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Abstract

Previous research has found that weather disasters contribute to significant social changes in cities exposed to severe weather. Severe weather-led social change is affected by non-random exposure to weather disasters and unequal recovery. In Chapter 2, I combine several strands of literature to explain how such social changes take place in American commuting zones using a structural equilibrium sorting model. An equilibrium sorting model can describe how households make decisions about where to live and compare the amenity-prices trade-off between different groups of households. I use three census years of household-level data from 1990-2010 to find household valuations of location-specific environmental amenities such as severe weather exposure. I allow for heterogeneous outcomes based on level of education and mobility behavior. I find that college-educated workers are willing to pay more to avoid an additional weather disaster and value location-specific amenities more compared to non-college-educated workers, and non-college-educated workers value real income gains more than college-educated households do. Non-college educated workers value safety from weather disasters too. However, their marginal willingness to pay for it is significantly lower than their college-educated colleagues. This vast difference in marginal willingness to pay indicates that non-college-educated workers are more likely to be exposed to severe weather and face difficulties recovering from damages.

The latest demography and economics literature on internal migration in the United States has raised concerns over the decline in mobility rates. While the decline is not rapid and not remarkable from a historical perspective, in the short-run the trend in mobility has been downward sloping for at least three consecutive decades. Seminal papers focusing on this decline have shown that the household mobility downturn is directly related to the labor market, and pointed to health insurance, technological advancements, and a homogeneous labor market as possible reasons. In Chapter 3, I focus on internal mobility in the United States and how it has been affected by household health insurance needs. I study a sample of heads-of-households with employer-based health insurance that is working full-time and provide health insurance coverage to their young-adult children. My findings suggest that despite efforts to increase its portability, health insurance still affects household mobility decisions. More specifically I show that Patient Protection and Affordable Care Act, while improving access to healthcare for young adults may have inadvertently created a mobility-lock for their parents. I show using a difference-in-difference analysis that employer-based health insurance can have mobility constraints for households who value health insurance. I propose a unique identification strategy using the timings of the young adult and employer mandates of the Affordable Care Act to establish the causal effect of health insurance on long-distance mobility. I propose several robustness scenarios that further establish my thesis.

I take up the issue of internal migration of working households in the United

States and flexible work arrangements in Chapter 4. Alongside declining long-distance mobility rates two other trends in internal migration have been evident in recent years; an increase in return-migration of households and increasing immobility. Before now, most literature on immobility and return-migration had taken the stance that it is a response to higher moving costs (psychological moving costs), increasing childcare costs, and the need for security that has made households return to their kith-and-kin. However, return-migration data show that it is not traditionally vulnerable groups that frequently move back to their birth states. With this background I seek to answer the question- does attachment to one's birth state contribute to return-migration and subsequent immobility? I answer this question using a sample of full-time workers employed in occupations that can be done remotely. With the main indicator variable that divides remote-workers and non-remote-workers, I show that when employment is not attached to the "workplace" households choose to move back to their birth states. This paper contributes to the literature on immobility where I show immobility is increasingly becoming voluntary and how that might affect interstate mobility in the United States at a time when work-from-home is becoming the norm. This work is descriptive. However, by carefully selecting the sample of workers and by using coefficient stability tests I am able to make somewhat reasonable causality claims.

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To the people of Sri Lanka whose tax rupees paid for an education that laid the foundation for this journey

Chapter 1

A broad overview of internal migration in the United States

1.1 Introduction

The United States has always been a mobile nation. Its people have moved across geographic boundaries for better opportunities compared to most other developed countries, which often is attributed to the "American exceptionalism". Americans were less constrained by roots and legacy compared to their European peers, in that individuals were constantly moving between social strata. This movement was based on wealth, and a culture that fostered the notion of an "American dream"; the notion that all people have the same opportunities that allow them to achieve their goals with enough effort[1]. However, this advantage seems to have run its course. After nearly 50 years of constant mass mobility, in recent decades there has been a decline in residential mobility. There are many reasons cited for this decline in recent publications (Molloy, Smith, and Wozniak (2011a), Kaplan and Schulhofer-Wohl (2012), and Kaplan and Schulhofer-Wohl (2017a)). Longer job tenures, better information flow, health insurance, and uptake in information technology resources are some of the main reasons cited by these authors. While these reasons are not necessarily alarming, lower mobility can have significant labor market effects and well-being consequences. The three chapters in this dissertation look at three motivations for household long-distance mobility (immobility). The objective of this chapter is to provide background information to better situate the main arguments.

In the next section, I will discuss measurements and data sources that are often used in understanding internal mobility. In the section that follows I will elaborate on common migration models as a supplementary methodological review. Because two of the main chapters attempt to understand mobility patterns in recent decades, the next section will situate overall mobility trends in the United States since the year 2000 as additional information for Chapters 3 and 4.

[1]The largest migration events in the past century has more nuance than moving for better opportunities. A sector of the American population was actively discriminated against and violence against them was a constant threat in some areas. I discuss this further in the sections that follow.

1.1.1 Measuring internal mobility

How internal mobility is measured is an important consideration when understanding geographic mobility. When I refer to geographic mobility I refer to households moving a qualitative distance from where they were before. By defining geographic mobility as such in this dissertation, I ignore households that only make housing changes perhaps in the same neighborhood. My reasons for this are twofold; first, changes in homes do not affect employment, travel, social networks, or schools. As a result, changing homes do not contribute to the distribution of neighborhood characteristics. Second, qualitative changes via mobility inform underlying motivations for moving, and the level of risk aversion in moving away from familiar surroundings. This is important to meaningfully understand "migration". However, this process erroneously eliminates a set of households that may have made a conscious move between geographies that do not fall outside of my strict elimination criteria. Although it is unlikely to affect the output in Chapter 3, it can create biases in the analysis in Chapter 4.

Geographic mobility can be measured by distance, by crossing administrative boundaries, or by a combination of them. Measuring mobility by distance is perhaps the most accurate way of understanding changes in employment, schools, access to amenities, and changes in social capital. However, measuring migration using distance is difficult to do. Most large-scale data products like the decennial Census, American Community Survey (ACS), and Current Population Survey (CPS) from the U.S. Census Bureau and data from the U.S. Internal Revenue Service

(IRS) cannot accurately provide this information. Even in small-scale products that can collect address information, privacy concerns make such data publicly unavailable (the same is true for Census data as well). Therefore, the next best alternative is to find the distances between centroids in small enough geographies.

But, this too has its shortcomings. For example, the smallest identifiable geographical unit in the Census (in the United States) is a Public Use Microdata Area (PUMA), and depending on the density of the population, PUMAS can be extremely large or extremely small. This is because PUMAs have no meaning except that they are divided by population for measurement convenience. PUMAs in high-density areas like New York, New Jersey, Connecticut, and Maryland, Washington D.C., and northern Virginia are some examples where PUMAs are extremely small. Larger PUMAs are common in the Mid-West and Western states where populations are sparsely distributed.

Measuring mobility by looking at those who have crossed administrative boundaries is another option that is commonly used. Movement within counties and across counties is a measurement that is often used by the U.S. Census Bureau in their data briefs, and data products like from the IRS are also based on crossing county boundaries. While crossing county boundaries are somewhat meaningful, it is difficult to determine qualitative changes arising from mobility if residents only moved a very short distance (households living closer to county boundaries may not have to give up any amenities they live with currently in their move). This is circumvented if one is interested in understanding interstate mobility patterns because even if the move would not constitute a long-distance move in terms of travel distance, changing state boundaries come with significant changes in tax liabilities, health insurance provisions, and other state-specific regulations.

With both such categories of mobility measurements not being ideal, I use a combination to meet distance thresholds and administrative boundary changes. In Chapter 2, I used commuting zones (CZs) as my geographic unit of analysis and in Chapters 3 and 4 I use a combination of a distance threshold and changes in administrative boundaries when isolating my sample of households/respondents. CZs combine counties that have heavy between-movements that center around a central business district. Moving between CZs then indicates that a household likely made a move between two labor market areas resulting in qualitative differences in the distribution of people in a given location. In chapter two, I test the interstate mobility effects of employer-based health insurance and isolate my sample of households to those who are long-distance movers. Long-distance movers were defined as those who moved over 70 miles from their origin in the previous year and across non-contiguous PUMAs. Due to data limitations, in the third chapter, I relax my sample of households to those who have made any movement between PUMAs over 70 miles in the previous year.

1.1.2 Individual and household samples and restrictions

Measuring migration also depends on whose migration one measures. Age-specific migration patterns and location-specific migration patterns exist in the United States that affect migration outcomes and how significantly they contribute to broader migration patterns (Wilson (2020) and Johnson, Winkler, and Rogers (2013)).

In all three of the main chapters of this dissertation, I have isolated specific samples to be included in the analyses. Reasons for this vary from data availability to analytical precision. In Chapter 2 I isolate my sample to heads of households that earn a wage income, between 25-64, and are full-time employed. The decision for this specific sample to be isolated is made based on the model used in the analysis. The structural spatial equilibrium model is defined for a household and it is convenient to make the head-of-household the representative agent that stands for the entire household. This also means that I make implicit assumptions that the head-of-household makes household mobility decisions and that household mobility decisions are based on the circumstances of heads-of-households. These assumptions may or may not be true, and can affect the analysis because I lose the information of the true decision-maker by excluding some members of households in the analysis (such as the spouse of the head-of-household). Therefore, the decision to make heads-of-households the representative member of a household is an arbitrary decision that is based on how previous research (such as Diamond (2016) and Fan, Klaiber, and Fisher-Vanden (2016)) had approached similar issues and for analytical convenience.

Similarly, in Chapters 3 and 4, I isolate my samples to any working individual within an age threshold. The reason is that if limit the sample by head-of-household status, it will severely limit my sample size. This determination implicitly assumes that migration is an individual decision and not a household one. However, this is unlikely to bias the results of my analysis unless the household size of each category is unequally distributed. Further, in Chapter 3, when I determined which households should be included in the sample, I decided to exclude households with young adults still living with their parents yet working full-time for wages. The objective of this elimination was to make sure that I isolate households that are responsible for providing health insurance and that I exclude young adults who may have their own health insurance and thereby not being the cause of their parents' mobility lock. However, an unintended consequence of this would be that I isolate a sample of households whose young adult children are more dependent on parents than their colleagues do.

Although these decisions seem arbitrary, they are based on how researchers have made similar decisions in the past. However, this is not to say that it does not create biases in the analyses. The relationship status of an individual informs the migration decisions of the partner regardless of how many individuals in the partnership are full-time employed. This is perhaps more important in the context of households in which both head-of-household and spouse are full-time working individuals. Their decisions making process is likely to be more costly than others where only one spouse works. Similar biases can occur in Chapters 3 and 4 as well. When excluding non-working household members from the analysis, I implicitly assume that household mobility decisions are based on working members of the household only. However, because my objective is to understand worker mobility decisions this is unlikely to affect the analysis, except when working members of households are influenced by non-working members in their mobility decisions.

Because of the analytical strategy in Chapter 3 this (biases arising from not identifying the true decision-maker of a household) is unlikely to affect the analytical results. However, this would affect the descriptive analysis in the chapter.

1.2 Theories and applications

Migration theories can be categorized as micro theories and macro theories. Micro theories look at individual migrants and their determinants of migration. Macro theories are aggregates of individuals and study interactions of aggregate populations across regions or counties.

As a macro model, the Gravity Model of migration asserts that the frequency of migration flows between two locations depend on how popular each location is and the distance between the two locations as per the thesis of H. C. Carey (1858-59). This argument is borrowed from Newtonian physics where particles in the universe attract one another in the product of their masses over the squared distance between the two particles. While the formal link was made by Carey, the central argument was first presented by E. G. Ravenstein in the 19th century where he interpreted urban growth to be a direct result of migration, and that migration between locations could be explained by physical distance and by the quality of accessibility (Greenwood, 2021; Poot et al., 2016). Gravity models were increasingly used to explain international trade and to a lesser extent migration. The most common form of the gravity equation can be written as follows (Poot et al., 2016)-

$$M_{ij} = G\frac{p_i^{\alpha} \times p_j^{\beta}}{D_{ij}^{\gamma}} \tag{1.1}$$

$$ln(M_{ij}) = G\ ln(\frac{p_i^{\alpha} \times p_j^{\beta}}{D_{ij}^{\gamma}}) \Rightarrow ln(M_{ij}) = \alpha\ ln(p_i) + \beta\ ln(p_j) - \gamma\ ln(D_{ij}) \tag{1.2}$$

We can think of internal mobility more clearly in equation 1.2 as the migration flow between locations i and j depends on the attractiveness of the two locations, or the share of the total population in a given year, and the distance between i and j. In the case of this paper, we can interpret distance as the cost of mobility which depends on the physical distance as well as other aspects such as state health insurance requirements, Medicaid eligibility and licensure laws, etc.

One of the most widespread theories of mobility came from Everett Lee, who theorized that people move because they are pushed from certain locations and pulled into others. According to Lee (1966), each location has characteristics that are perceived as positive or negative. Positive aspects keep people in place while negative aspects push people away. Extending this logic, Lee suggests that people move between locations from net negatives to net positives after accounting for moving costs. Lee also suggests that migrants have different qualitative characteristics that separate them from non-movers. Migration as an individual decision-making model that maximizes utility was introduced by Larry Sjaastad in 1962. The individual makes a migration decision based on earning potential and the cost of moving, and this is also one of the first to cite both monetary and non-monetary costs of migration[2]. The migration decisions are looked at in terms of an investment with expected-returns for the future, as a result, this model can explain some salient features in migration experiences such as reduced movement in older workers, and higher movement seen among educated workers. A similar theory was presented by Michael Todaro (1980) where workers migrated from a rural area to an urban area by maximizing expected wage returns. Kith and kin network facilitation of migration is another branch of migration theories that attempts to explain mobility patterns. Proponents of this theory argue that when people migrate they move to locations with which they have kith-kin networks because it reduces the cost of migration, and keeps progressively reducing the cost of migration for others yet to migrate (Nelson, 1959; McKenzie and Rapoport, 2006).

1.2.1 Spatial equilibrium and migration

A spatial equilibrium is one where the utility assigned to each location is equalized across locations. People living in each location have maximized their utility taking into account location-specific price levels and amenities. Any change to any of these characteristics redistributes the population such that it eventually arrives at another equilibrium state. Equilibrium sorting models describe the spatial equilibrium by decomposing average utilities assigned to each location into its characteristics (Lancaster, 1971). The equilibrium sorting model cannot describe migration behavior. However, by describing the spatial equilibrium over time it can describe

[2]Note that Lee (1966) theorized that there were migration costs. However, attention to non-monetary costs was explicitly focused on by Sjaastad (1962)

what amenities migrants find attractive, and what situations migrants are repelled from. I demonstrate this further by a simple example. Consider two location k and j and an individual i,

$$V_j^i = Wages_j + Rent_j + Amenities_j + \epsilon_j^i V_k^i = Wages_k + Rent_k + Amenities_k + \epsilon_k^i \tag{1.3}$$

whose indirect utility is a function of average *wages*, *rents*, and *amenities* such that $V_j^i = V_j + \epsilon_j^i$ and $V_k^i = V_k + \epsilon_k^i$. Individual i will choose to live in location j if $V_j^i > V_k^i$ and will choose to live in k if $V_j^i < V_k^i$. The spatial equilibrium framework was used by Rosen (1979) and Roback (1982) to construct a model that defined how households make trade-offs between prices and amenities in the equilibrium. The initial Rosen-Roback model did not account for individual heterogeneity, and it was later added by Bayer, Keohane, and Timmins (2009) allowing moving costs to be incorporated into the model. With this inclusion, the equilibrium sorting model is now able to describe determinants of mobility as well as mobility costs.

In a spatial equilibrium framework, changes in amenity levels accompany changes to wages and rental rates to remain in equilibrium. This is based on Roback's argument that housing is limited and any demand shock has to be accompanied by price changes to distribute the limited housing stock. In the case of positive amenity shocks, the real incomes are increased in compensation, and in the case of positive amenity shocks, real income levels decline in response to the excess demand.

1.3 Internal migration in the United States

1.3.1 Historical context

The United States, in its 250-odd years of history, has experienced mass migration movements that defined it as a county where people would travel to realize their dreams. The strongest motivation for internal migration in the county was therefore income and earning potential. There were several processes of movement that occurred between now the early 19th century. The "Westward expansion" operated from the early 19th century to the beginning of the 21st century where the largest internal mobility motivators were cheaper price levels in Western states compared to Eastern states, and wide wage differentials. The "Great migration" occurred from the early 20th century to the late 20th century and the strongest motivations were income too. Among these processes were the movement of people from rural to urban sectors and from the agriculture sector to the non-agriculture sector. In more recent years; from the late 20th century to the early 21st century internal mobility was motivated by cheaper housing costs and location-specific amenities. The broad context of internal migration in the United States is then the fact that people moved in an adjustment process that eventually reached an equilibrium. For this dissertation, the objective of this exercise is to acknowledge this fact and to provide context, within which the three chapters in this dissertation can be interpreted. In the next few paragraphs, I will elaborate on the many migration movements in the county.

What is known today as the "Great Migration" in the early 20th century, saw a mass exodus of people of African descent from the Southern states of the United States to the Northern parts of the United States. They moved to avoid racial violence and for better opportunities in the Northern states that were actively seeking more people to join its workforce (Hannah-Jones et al., 2021). This also gave Americans of African descent more opportunities to seek employment in non-agricultural sectors. This exodus from early 1900 to about 1940 is often described as the "First Great Migration." The second half of the 20th century saw another mass movement of Americans that is now known as the "Second Great Migration". This too was motivated by expanding opportunities for Americans of African descent whose civil liberties (won during Reconstruction) were reinstated after they broke down during "Jim Crow". However, this was not just an interstate movement. It was a combination of interstate movement from the South to other parts of the county, migration from rural to urban areas within Southern states (especially for Americans of African descent), and return migration of a people that fled the South in the first half of the century (Glaeser and Tobio, 2008; Tolnay, 2003). These movements of Southern-born populations largely contributed to the overall migration trends of the country (see Figure 1.1) and drove the image of the United States had cultivated as a "mobile nation".

Although the two movements of people during the first and second halves of the 20th century were discussed mainly in terms of how Americans of African descent moved, Glaeser and Tobio (2008) suggested that this was also a movement of all people to warmer areas of the country to make use of its large productivity potential and lax housing supply. This may have motivated some Americans of African descent to return to the South too, for even if they did not face daily violence in Northern states, they were not fully integrated into the otherwise white American societies of European descent (Massey, 1990; Pearcy, 2020). I discuss this more later.

At this time there were other patterns of migration as well. Among rural to urban migration was embedded migration from the agricultural sector to the non-agricultural sector that added its numbers to the "great migration" flow of people. The strongest motivation for the movement of people between agriculture and non-agriculture industries was the earnings differential between the two sectors (Caselli and Coleman II, 2001; Mundlak, 2005; Hathaway, 1960). Western states had more land that drove prices lower and more potential for higher incomes. Northern and mid-Western states also had more non-agriculture job opportunities to fill and higher earning possibilities that attracted people from the South to the Northern parts of the county.

The earnings differentials in the agriculture and non-agriculture sectors occurred in many ways. With the Agricultural Adjustment Act of 1933, landowners were offered financial benefits to reduce their agricultural production which led to Americans of African descent losing their employment (Heinicke, 1994; Hathaway, 1960). This was one of the main reasons for their mobility outside of the Southern states because most Americans of African descent were employed in the agricultural sector or involved in sharecropping. With government subsidies to large landowners at a time when prices for their products were falling, large landowners reduced farming in general and reduced sharecropping without any of the subsidies being directed towards their sharecroppers (Fligstein, 1983). The movement of people from the agricultural sector to the non-agricultural sector was not characterized by race alone. People in younger age groups (between 19-40) and more educated moved away from the agricultural sector faster than others did (Hathaway, 1960). This perhaps supports the thesis that agriculture to non-agriculture migration was motivated by skill acquisition (Caselli and Coleman II, 2001) as well. Caselli and Coleman II (2001) in evidence found that educational attainment in the agricultural sector was consistently lower than most non-agricultural sector employees' educational attainment. Authors such as Mundlak (2005) and Caselli and Coleman II (2001), their work showed how the movement of people away from agriculture improved the productivity of the sector. This is mainly because producers turned to mechanization instead of using labor in the interest of securing government subsidies. Secondly, this was the result of technologies that were "labor-saving" which created a wider wage differential between the agriculture and non-agriculture sectors.

In addition to these migration flows, there was still a strong flow from the Eastern states of the county to the West. What is known today as the "Westward migration" started earlier than 1910 and had been expanding with "pioneers" pushing the frontier westward. However, the 20th-century migration patterns also took a westward flow due to the Homestead Act of 1862, more employment opportunities (in mining), and because of efficient transportation (railroad) that made it easier to move. These were still true before the 20th century and much of the population that moved to expand the frontier were not of African descent.

The Westward movement of people in the United States may be the most nuanced in its history and continued to be active till about the early 21st century. Starting in the early 19th century, more and more people moved Westward and set up their "homesteads" beyond the Mississippi River, and the flow of movers included Americans of African descent. Perhaps one reason for this was that there was no exclusion of non-white citizens in the Homestead Act (which does not mean that there were no tensions. White "pioneers" were active in limiting Black people from competing for land in the new frontier (**pbsedwards2021homestead**; PBS-THIRTEEN, n.d.). With the acquisition of Texas, New Mexico, and California from Mexico this movement became stronger. There was potential for non-agricultural industries to thrive (such as gold mining) and the residents were largely anti-slavery and made Western territories more attractive (for some people) as well (Smith, 2011). However, similar to the South to North, later North to South, and agriculture to non-agriculture sector movement, the migration West was also motivated by income differentials. For example, Vandenbroucke (2008) shows how the West and East wage differentials correlate with the movement of people (see Figure 1.3) and Mitchener and McLean (1999) shows the flip-side of it by looking at price level differences. Even after the "great migration" flow, Americans were still (into the 21st century) moving across to Western states and warmer climates with vast land areas Arsenault, 1984; Biddle, 2012; Frey, 2016. On the one hand, this was a response to the untapped productivity potential in the Western and Sun-belt states and less restrictive land availability that could respond to increasing demand unlike in traditional cities in the North and East. On the other hand, this may have been a response to desirable amenities (Glaeser and Tobio, 2008; Diamond, 2016).

Internal migration in the United States has been a popular topic in recent years because migration rates, especially interstate and long-distance migration rates had continuously fallen. To put this in context, I present a graph published in Molloy, Smith, and Wozniak (2011a) in Figure 1.2 where the interstate migration rate for Americans has fallen in 2010 beyond the level observed in 1970 (the end of the great migration). Looking at this mobility downturn from a historical perspective, therefore, indicates that when arbitrage opportunities are no longer available people will naturally stop moving. In Molloy, Smith, and Wozniak (2011a), the authors found that mobility rates have been slacking and found low labor market churning to be the reason for it. A complementary study Kaplan and Schulhofer-Wohl (2012) found that homogeneous labor markets and better information contributed to the lack of long-distance mobility (and job mobility) as well. Both these suggest that the advantages of moving may have reached its peak and reasonably explain the current mobility decline in the country. However, having interstate mobility dip below the levels of 1970 perhaps also indicates that the current migration downturn is qualitatively different from before. To elaborate, there are additional costs to migration today than there may have been in the late 20th century.

The qualitative differences in migration that we see today may be understood by looking at several strands of literature. First, lack of mobility is attributed to skill-based and income-based segregation of workers (Diamond, 2016; Giannone, 2017; Sharp and Iceland, 2013). This segregation occurs because one sector of workers is more responsive to real income levels and the other to amenity levels, such that the new form of segregation is no longer along racial or urban-rural axes, but across earnings potential and education (Iceland, Sharp, and Timberlake, 2013). Diamond (2016) finds that skilled (and high-income) workers sort into high-amenity locations because they derive more utility from enjoying better amenities than from lower real incomes. Unskilled (low-income) workers on the other hand derive more utility from higher real wages. Although high-amenity locations are expensive, to begin with, by endogenously contributing to improving the amenity stock, skilled households drive prices higher with time. This forces unskilled workers to live in low amenity locations because high-amenity cities are increasingly becoming unattainable. This income and well-being gap between the two skill categories can contribute to lowering mobility because widening inequality locks workers into declining cities. Second, a related study Giannone (2017) found that wage inequality between skilled and unskilled workers existed because wage convergence between the two sectors ceased in 1980 and because skilled migrants have been seeking already skill-abundant cities as destinations. As the demand for skilled workers increases in the American economy, unskilled workers likely find that it is increasingly difficult to move and afford places with higher wages and better amenities.

In this dissertation, I largely study interstate migration and residential location choice. Their placement in history, then, is more recent, and I try to understand determinants of mobility (and immobility) in a post-1970 era. 1970 onward, the United States saw changes in technologies and cultures that influenced migration within this time. For example, the late 1990s saw the rapid rise in technology industries that was called the "dot-com boom" and its subsequent fall around the mid-2000s, lap-top and mobile phone usage increased with more portability of the machines during this same time. These advancements qualitatively changed the traditional workplace. At this same time American societies changed as well, healthcare costs in the county have steeply increased without much improvement in the health status of the population (Kurani et al., 2022) and young adults are facing more difficulties in managing their education expenditure, employment, and other socio-demographic functions compared to previous generations (Nau, Dwyer, and Hodson (2015), Chetty et al. (2014), and Kaplan (2012)). The objective, therefore, of this dissertation is to understand mobility within a limited and recent time frame.

1.4 Mobility (and immobility) in the United State: 2000-2019

Sociological, economic, and demographic literature has tried to explain household mobility choices from various angles. However, many of these studies have focused on those who are moving to determine what motivates their move. Schewel (2020) argues that this bias in focusing on the determinants of mobility does not entirely explain internal mobility and that determinants of "immobility" should be included in the conversation as well. In this section, I will discuss the broader trends in mobility (and immobility) from 2000 onwards to facilitate a better understanding of the background in which the three main chapters of this dissertation are situated.

1.4.1 Broader migration patterns

Although temporal migration patterns show that Americans are less mobile compared to several decades ago, internal mobility levels have plateaued in the last two decades. The period between 2000 and 2020 was marred with calamities in the United States such as a terrorist attack in 2001, a financial downturn in the same year, Hurricane Katrina in 2005, the 2008 financial crisis, hurricane Harvey in 2017, and the COVID-19 pandemic in 2019, etc. However, overall mobility patterns suggest that households have been somewhat consistent in their mobility behavior. There are two possible reasons for it; one, people have been mobile to subsequently be immobile. What I mean here is that people make semi-permanent mobility decisions. For example, this period has seen the largest share of young adult populations living with their parents (Fry, 2016), and the share of people moving back into their home states has also increased (I discuss this in detail in Chapter 4). Two; non-native immigrants may have taken up the mobility burden themselves (Basso and Peri, 2020).

Table 1.1 shows how total migration and interstate migration patterns in the United States between 2000-2019 have changed. Overall age groups 15-24 and over 65 have seen increases in their mobility compared to other ages. People with higher levels of education seem to have moved more, while they have also increased their interstate migration levels. In testing mobility behavior at different life stages, the table shows that persons that are never married or have separated from their partner (legally or in death) have been more mobile than their colleagues. This is not unexpected as life-course changes motivate mobility. Similarly, households that have new children (under 2 years) were less mobile over the years, which can be attributed to increasing costs associated with moving. Co-residence has also increased during this time. Adults (over 25) co-residents with their parents have increased by over 50%. While not as much, older adults have also increased their overall mobility levels between 2000 and 2019. While there is evidence to suggest that adult children continue to live with their parents for many reasons including health insurance and income smoothing (Fry, 2016; Kaplan, 2012; Chapter 4), whether older adults are moving to be with their children to share care responsibilities or to be cared for remains uncertain.

In the next three chapters, I will discuss three aspects that affect household mobility decisions. In the first chapter, I show, via a structural location choice model how different households respond to local price levels and their trade-off between real income and amenities. College-educated households yield more utility from positive amenities while non-college-educated households yield more utility from higher real incomes.

In the next three chapters, I focus on internal migration in the United States from several different angles. In Chapter 2, I look at household location choices to determine preferences for avoiding extreme weather. In the next two chapters, I use

Quasi-experimental methods to assess if health insurance is a hindrance to internal mobility (Chapter 3) and how remote-work affects household internal mobility patterns (Chapter 4).

1.5 Tables

TABLE 1.1: Mobility patterns in the United States 2000-2019

	Any mobility		Interstate mobility	
	2000	2019	2000	2019
Age 0-14	3.36	2.57	3.06	2.61
Age 15-24	3.44	3.09	3.20	3.94
Age 25-44	5.78	5.13	6.02	6.01
Age 45-64	1.97	2.27	2.23	2.67
Age65+	0.71	1.02	0.84	1.37
Some school	5.51	3.99	4.62	3.70
High school	6.99	6.77	6.58	7.58
College	2.76	3.31	4.14	5.32
Married	4.77	3.86	5.61	5.25
Seperated	0.48	0.34	0.37	0.31
Divorced	1.44	1.30	1.33	1.37
Widowed	0.40	0.43	0.41	0.48
Never married	8.18	8.15	7.62	9.19
New kids (<2)	2.19	1.58	1.97	1.66
Co-resident adults (>25)	0.40	0.60	0.66	1.01

Co-resident adults (>65)	0.41	0.48	14.48	12.35

Author calculations based on ACS 1 year samples from 2000-2019. Calculations for 2000 are based on average between 2000-2004 and calculations for 2019 are based on average between 2015-2019. All values are percentages. Any mobility refers to any change in residence, and Interstate mobility refers to any change in the state of residence. Variables co-resident adults respectively refer to adults living with parents that did not move during the perious year, and older adults that moved to live with their children who did not move in the previous year.

1.6 Figures

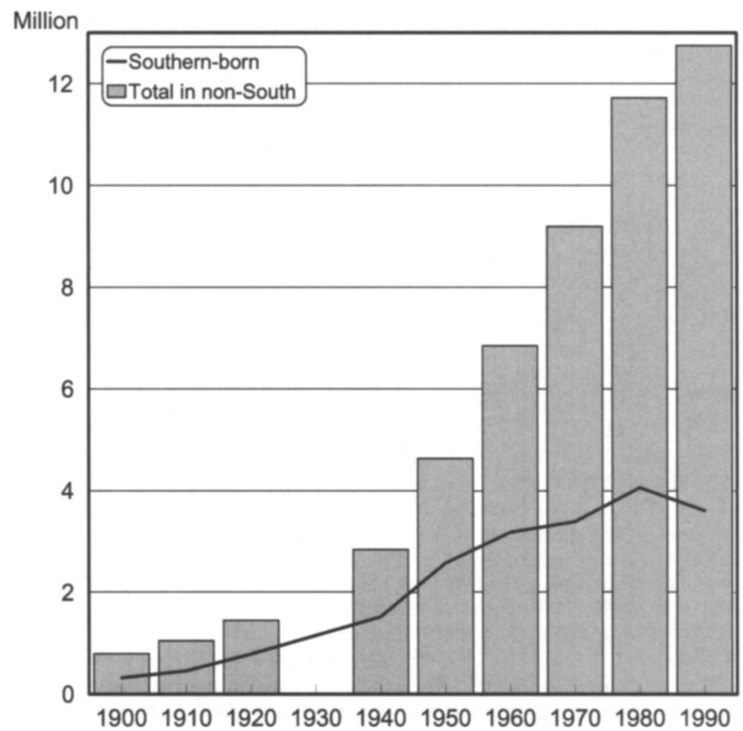
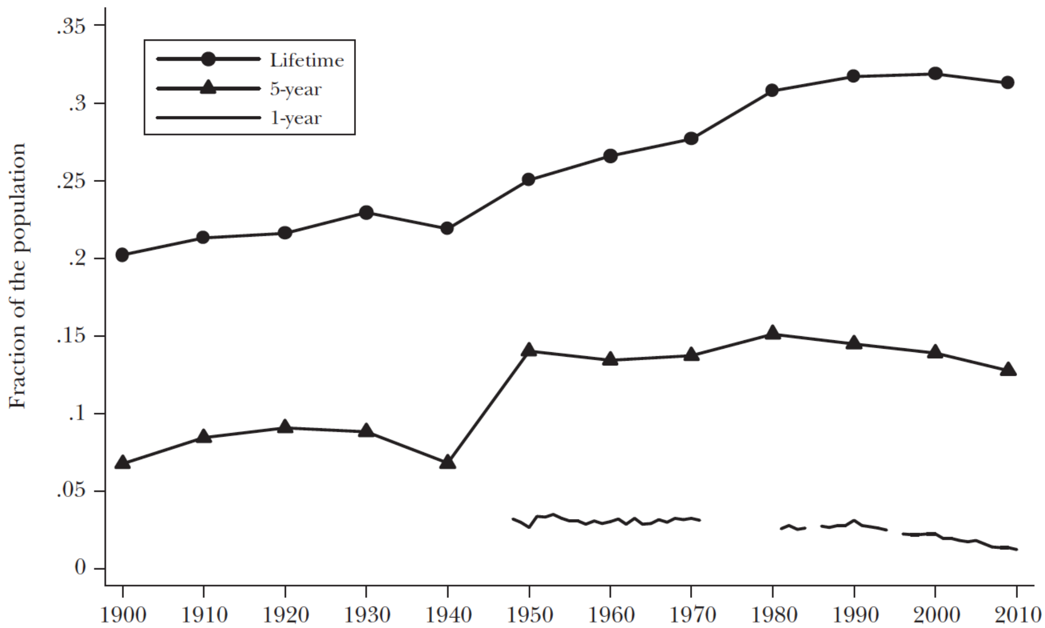


Figure 1 Number of African Americans (total and Southern-born) living in nonsouthern areas from 1900 to 1990. Data estimated from the Integrated Public Use Microdata Files available from the Minnesota Population Center (Ruggles & Sobek 2001).

FIGURE 1.1: Migration of Americans of African descent in the 20th century. Source:Tolnay, Stewart E. "The African American" great migration" and beyond." Annual Review of Sociology (2003): 209-232.

Interstate Migration Rates since 1900



Notes: Lifetime and five-year migration rates are from the denennial Census 1900–2000 and from the ACS for 2009. Five-year migration rates are estimated from microdata on the fraction of households with a four or five year-old residing outside of their birth state (Rosenbloom and Sundstrom, 2004). Annual migration rates are calculated from Current Population Survey microdata.

FIGURE 1.2: Interstate migration of Americans from 1900-2010. Source:Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. "Internal migration in the United States." Journal of Economic perspectives 25.3 (2011): 173-96.

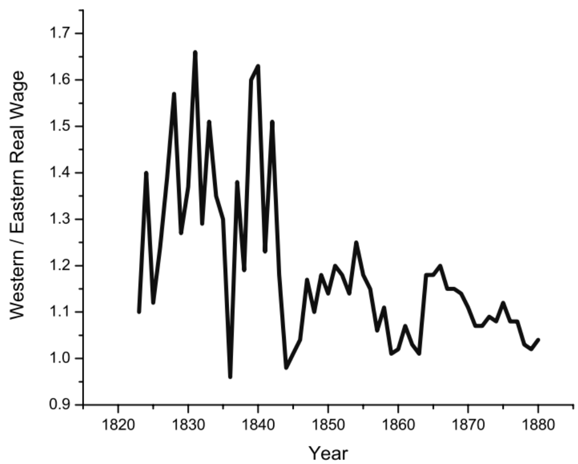


FIGURE 3

RATIO OF WESTERN TO EASTERN REAL WAGES, 1823–1880.

NOTES: THE SOURCE OF DATA IS COELHO AND SHEPHERD (1976) AND MARGO (2000). ONLY NORTHERN REGIONS, WHICH USED FREE LABOR THROUGHOUT THE ENTIRE PERIOD, ARE CONSIDERED. THE AVERAGE OF NEW ENGLAND AND MIDDLE ATLANTIC'S REAL WAGES REPORTED BY COELHO AND SHEPHERD (1976) ARE SPLICED WITH MARGO (2000)'S NORTHEASTERN REAL WAGES. THE AVERAGE OF EASTERN NORTH CENTRAL AND WESTERN NORTH CENTRAL REAL WAGES FROM COELHO AND SHEPHERD (1976) ARE SPLICED WITH MARGO (2000)'S MIDWEST REAL WAGES.

FIGURE 1.3: Ratio of Western states to Eastern states real wages 1820-1880. Source:Vandenbroucke, Guillaume. "The US westward expansion." International Economic Review 49.1 (2008): 81-110.

Chapter 2

Severe weather and social change in the United States

2.1 Introduction

Climate change and population growth in places that are disaster-prone have seen an increase in severe weather frequency and an increase in damages from such disasters. For example, billion-dollar weather disaster frequency in the United States has increased at a rate of five percent a year since 1980 and these losses account for about 80% of the total losses attributed to severe weather events each year (Smith and Katz, 2013). However, these severe weather events do not affect all people alike. Prior literature has found that weather disasters contribute to increased poverty (Boustan, Kahn, and Rhode, 2012; Davlasheridze and Fan, 2017), forced migration of people who cannot adapt to frequent disasters (Boustan, Kahn, and Rhode, 2012; Raker, 2020; Deryugina, 2017), and that such disaster-prone areas continuously attract poor households forcing them to be repeatedly exposed to weather calamities (Depro, Timmins, and O'Neil, 2015). These inequalities are exacerbated by the segregation of American households by the level of education and income (Markhvida et al., 2020). College-educated households are increasingly sorting into locations with similarly educated residents and contribute to higher rents and wage growth that force less-educated workers into places that have poor amenities and lower rents (Diamond, 2016). In this paper, I combine the skill-based sorting literature with works that assess household responses to severe weather to explain how household well-being is affected by severe weather exposure and skill-based sorting in the United States.

I examine unequal exposure to severe weather using an equilibrium sorting model of college and non-college workers' residential location choices. I estimate a two-stage sorting model similar to Berry, Levinsohn, and Pakes (1995), Bayer, Keohane, and Timmins (2009), Diamond (2016), Sinha, Caulkins, and Cropper (2018) and Fan, Klaiber, and Fisher-Vanden (2016). The model describes moves from 1990 to 2010 in decadal intervals across the continental United States. I use a fixed-effects research design to control for time-invariant attributes in residential locations and thus identify the effect of individual extreme weather events on workers' mobility decisions and marginal willingness to pay over each ten-year period. I separate workers by skill group based on college education status and consider multiple samples such as recent movers, non-movers, and a combined sample of households.

Going forward, this paper is separated into several sections. The following section will place this paper among related literature and discuss how I contribute to each strand of literature this paper is built on. In the section that immediately follows I discuss my data and variables creation. In the next section, I present a descriptive analysis using multiple reduced form regressions. In the section that follows, I discuss the structural model, then the estimation process, and later the instrumentation process. Next, I present my results and discuss alternative specifications and the robustness of my results. In the section that follows I make welfare calculations and interpretations. Finally, I discuss my findings and make concluding remarks.

2.2 Background and contribution

Research finds that workers in the United States have been sorting based on skill type for at least four decades. Cities with larger shares of college graduates tend to attract even more workers with college degrees compared to cities with smaller shares of college-educated workers (Diamond, 2016; Giannone, 2017; Fogli and Guerrieri, 2019). Equilibrium effects of skill-based sorting suggest that in cities with higher shares of college-educated workers wage rates and housing prices are expected to grow faster to account for higher productivity and greater demand for housing. Recent sorting literature has shown that such productivity improvements not only increase wage rates for other college-educated workers but also for non-college-educated workers due to spillover effects (Diamond, 2016; Autor, 2019). Both these effects create demand for the limited housing stock in a city and increase prices. College-educated workers have more flexibility in location choice and spend a larger share of their income to live in locations with desirable amenities (Diamond, 2016) and endogenously contribute to improving amenity levels. These patterns imply a widening gap between college and non-college-educated workers' access to environmental amenities that Diamond (2016) cites as a well-being gap. I contribute to this literature by showing how the well-being inequality between college and non-college workers is exacerbated by unequal exposure to severe weather disasters.

I graphically explore the widening of well-being inequality between college and non-college workers by presenting the change in college employment ratio as a function of disaster exposure. Figure 2.1 shows the change in log college employment ratio from 1990 to 2010 against the log average FEMA disaster declarations from 1981 to 1990. Figure 2.1 shows that growth in average disaster exposure is correlated with negative growth in college employment ratios. I note that although the linear fit is downward sloping, the change in college employment ratio is flatter pointing to less responsiveness. This is unsurprising as literature has noted that public assistance programs and disaster insurance has allowed wealthy households to recover faster from disasters. In Figure 2.2 I present the change in college employment ratio between 2010 and 2000 against the log average FEMA disaster declarations in 2000. The FEMA disaster declarations 1981-1990 and 1991-2000 are likely qualitatively different owing to the changes the declaration process underwent in 1988 with the Stafford Act. With the Stafford Act, Presidents were granted the power to unilaterally decide which claims are declared disasters. Therefore, average disaster declarations between 1991 and 2000 are likely a combination of severe weather exposure and political appeasement. This is evident in the fact that the change in college employment ratio is positively correlated with average disaster declarations between 1991-2000. This shows that disaster assistance via disaster declarations is not helping the sector of populations that most need them. Such findings are similar to Raker (2020) and similar in spirit to Boustan, Kahn, and Rhode (2012) and Deryugina (2017) because they too observe that cities with more disasters are unequal in their disaster recovery.

Household responses to severe weather often emphasize broader social change. Disaster exposure in the United States is often accompanied by wider inequality and recent studies have established several mechanisms from which such inequalities stem (Boustan, Kahn, and Rhode, 2012; Raker, 2020; Davlasheridze and Fan, 2017; Depro, Timmins, and O'Neil, 2015). Extreme weather events such as the ones that have been declared a disaster by Federal Emergency Management Agency (FEMA) have the potential to disrupt entire economic systems through physical damages to the built environment and infrastructure. Such damages increase local wages and decrease housing prices as household location choice decisions in a spatial equilibrium depend on maximizing returns to local wage rates, housing affordability, and the amenity stock in a given city. Higher wages compensate to hold workers in areas in which economic activities are affected by natural disasters, and lower housing prices compensate for the loss in local amenities. These price adjustments keep the population in equilibrium. However, these adjustments do not necessarily mean that qualitative attributes in populations are maintained in equilibrium. For example, increasing real wages (wages net of housing costs) as a result of natural disasters attract households that are drawn to lower housing costs and repel those who can afford higher housing prices in search of safer environmental amenities. Social change can also occur as a result of public assistance programs and unequal access to credit and other recovery means (Deryugina, 2017; Raker, 2020; Boustan, Kahn, and Rhode, 2012). Boustan, Kahn, and Rhode (2012) found that extreme disasters contributed to net out-migration of residents and lowered housing prices. Raker (2020) found supporting evidence by assessing tornado activities in the United States where average income levels post-disaster were generally higher suggesting the out-migration of residents that cannot recover from disasters.

This work is built on, and expected to contribute to the literature on environmental and social justice as well. There is a vast body of literature that captures the effects of unequal exposure to pollutants in minority and low-income households (see Banzhaf, Ma, and Timmins (2019) for a review of literature). My study contributes to this literature by documenting further evidence for low-income households sorting into locations with distasteful amenities; commonly known as "coming to the nuisance." My findings fit among studies such as Banzhaf and Walsh (2008) and Depro, Timmins, and O'Neil (2015) where high-income and majority-race households sort into locations with lower exposure to distasteful amenities while their poorer neighbors do the opposite.

2.3 Methodology

My spatial equilibrium model of household location choice is based on the framework developed in Roback (1982) and extended by Bayer, Keohane, and Timmins (2009) and Diamond (2016) to include household and location heterogeneity and moving costs. Unlike other sorting models that describe the spatial equilibrium from one time period to another, I model the changes in equilibrium behavior relative to a base period, which in this case is 1990. This model assumes that college and non-college workers have different sorting equilibria. I also allow households to have preferences for living in CZs that are in their states of birth. This proxy for psychological moving costs is assumed to be universal.

Each household i in year t and skill group $skill$, represented in my model is working age, head-of-household worker, that has chosen to live in location j which provides them with the highest level of utility from wages, rents, and amenities specific to j. Locations in my model are defined based on commuting zones (CZs) that cover the entire continental United States[1]. Each household supplies one unit of labor in return for a wage W_{jt}, which they use to consume a national good C, which has a price P_t, and a local good H_{jt}, which has a price of R_{jt}. The price of the national good- P_t is based on the CPI-U index estimated by the Bureau of

[1] CZ definitions are based on Autor and Dorn (2013). There are 741 CZs in the United States, and I use 722 CZs in the contiguous United States in this chapter.

Labor Statistics and provided in the United States Census data used to estimate the model. The household gains utility from consuming a bundle of local goods X_{jt}, and pays the moving cost M_{ijt} associated with choosing the current location. Each household in each skill category has Cobb-Douglas preferences for the local and national goods and maximizes utility subject to their budget constraint.

$$max_{CHj}\ ln(C)^{(1-\gamma)} + ln(H)^{\gamma} + X_{jt} + M_{ijt} \quad s.t.\ \ P_t C + R_{jt} H \leq W_{jt}^{skill} \tag{2.1}$$

where a household's relative taste for consuming the local good is provided by γ which lies between zero and one. Given the Cobb-Douglas preference structure, γ represents the expenditure share attributed to the local good. A key assumption here is that γ stays constant across locations and periods. However, I allow the two skill groups to have separate preference parameters for the national commodity and local goods.

Optimizing the household utility problem above, I obtain the demand functions for the national consumption good C^* and demand for local goods H^*. The demand for local goods indicate that the demand for housing ($HD_i jt$) is a constant share of income;

$$HD_{ijt}^{skill} = \gamma \frac{W_{jt}^{skill}}{R_{jt}} \tag{2.2}$$

By re-entering the optimum quantities of local and national good back into the utility function, I can express my indirect utility function as follows:

$$V_{ijt}^{skill} = ln(\frac{W_{jt}^{skill}}{P_t}) - \gamma ln(\frac{R_{jt}}{P_t}) + X_{jt} + M_{ijt} = ln(w_{jt}^{skill}) - \gamma ln(\rho_{jt}) + X_{jt} + M_{ijt} \tag{2.3}$$

Equation 2.3 assumes that all attributes that are variable by time and place are observable and complete and that workers are heterogeneous in their demand for wages and amenities. In empirically estimating equation 2.3 I make adjustments to the model by allowing a subset of location-specific attributes to be unobserved (ϵ_{jt}), and by allowing an idiosyncratic error term ζ_{ijt} that is independent of wages, rents, mobility costs, and local goods.

$$V_{ijt}^{skill} = ln(w_{jt}^{skill}) - \gamma ln(\rho_{jt}) + X_{jt} + \epsilon_{jt} + M_{ijt} + \zeta_{ijt} \tag{2.4}$$

2.3.1 Estimation

The household location choice model described in equation 2.4 is estimated in two stages. The first stage of the estimation process used a discrete choice model that maximizes household utility with respect to their choice of location. In this process, I collect components that are variable by time and place them into δ_{jt}^{skill} that enters into the equation as a full set of location-specific fixed effects as in equation 2.5.

$$V_{ijt}^{skill} = \delta_{jt}^{skill} + \alpha^M M_{ijt} + \zeta_{ijt} \tag{2.5}$$

I assume that ζ_{ijt} is independently and identically distributed and of type 1 extreme value. The probability statement for a household i choosing location j as the utility-maximizing location can be depicted as-

$$P(U_{ijt} \;\geq\; U_{ikt} \quad \forall\, j \neq k) = \frac{exp^{\delta_{jt}^{skill} + \beta^M M_{ijt}}}{\Sigma_1^J \; exp^{\delta_{jt}^{skill} + \beta^M M_{ijt}}}.$$

With 722 location fixed effects and other controls, the computational power needed for the estimation of equation 2.5 is vast. To circumvent this issue I used a contraction mapping routine (Berry, Levinsohn, and Pakes, 1995) to estimate δ_{jt} and β^M. After estimating equation 2.5 I am left with six sets of $j-1$ δs by year and skill type. Because δ_{jt}^{skill} enters as fixed effects the estimated alternative specific constants are estimated relative to a base location the final set of fixed effects count $j-1$ locations instead of j locations[2]. These fixed effects can be interpreted as relative average utilities assigned to each location. After estimating equation 2.5 I decompose the δs into wages, rents, and location-specific observable components in the second stage in equation 2.6.

$$\Delta\delta_{j\tau}^{skill} = \beta_p^{skill}(ln(\Delta w_{j\tau}^{skill}) - \gamma ln(\Delta\rho_{j\tau})) + \beta_X^{skill}\Delta X_{j\tau} + \epsilon_{j\tau} \tag{2.6}$$

Note that in equation 2.6, the subscript is no longer t but τ indicating that the second stage decomposition explains the change in average utilities from a base period, which in my case is 1990. This allows me to hold constant geographic and time-invariant aspects tied to each location, and decompose changes in utility into changes in wages, rents, and other location-specific amenities. Instead of estimating changes in wages (Δw_{jt}) and rental rates ($\Delta\rho_{jt}$) I estimate income net of local expenditure ($\Delta w_{jt} - \gamma\Delta\rho_{jt}$) and assume that γ is equal to 0.62 following Diamond (2016). The purpose of this restriction is twofold. First, it reduced the identification burden of the instrumental variables by only having to identify one parameter. Second, it holds the local expenditure share at a value that literature has found to be more realistic. I estimate equation 2.6 as a stacked model (of both skill groups)

[2]The base location value is equal to zero.

using a generalized Method of Moments (GMM) estimator.

2.3.2 Instrumentation

A key challenge in this work is the identification of the price parameters that are likely correlated with unobserved amenities. To address this issue, I deploy a Bartik instrument that interacts industry wages nationally with industry presence locally in each skill group. In each skill category, the national changes to industry productivity inform local wage levels in the same industry and the industry composition in the current period in each location depends on the industry composition at the base period. This instrument defines local wages as a function of national wages because national wage shocks influence local wage rates. However, national-level wage shocks are unlikely to translate into local wage changes of the same intensity. The strength of the national wage shock affecting local wage levels depends on the share of workers in the industries for which national wage shocks occurred.

I calculate changes in average national wages by industry between the current period and 1990 and interact them with the industry composition of the local economy in 1990. I calculate national wages for each location by taking the average over industry wages in all outside locations ($-j$). The subscript *ind* stands for industry category where I group industries into 15 broad categories. I exclude Agricultural and Military categories and am left with 13 categories that I use in the instrumentation procedure. Equation 2.7 defines my main Bartik instrument.

$$\Delta B_{j\tau}^{skill} = \Sigma_{ind}(w_{ind\ -j\ t}^{skill} - w_{ind\ -j\ 1990}^{skill}) \times \frac{N_{ind\ j\ 1990}}{N_{j\ 1990}} \tag{2.7}$$

In equation 2.7 $w^{skill}_{ind\ -j\ t}$ is the national average wage at time t, and industry ind for skill group $skill$. $\frac{N^{skill}_{ind\ j\ 1990}}{N^{skill}_{j\ 1990}}$ represents the share of people working in industry ind, at location j, and base time period in 1990.

To add more variation to the instrument, I interact equation 2.7 with local housing supply elasticities. Demand for housing in a location depends on the demand for labor in the same location, and how responsive housing supply is to such demands. These responses can vary due to land use constraints such as limitations in developable land, and other regulatory barriers (Saiz, 2010; Gyourko, Saiz, and Summers, 2008). By interacting with housing supply elasticity indicators and changes in industry-specific national productivity, I also address the criticism against using geography alone as an exogenous instrument in identifying local housing market responses (Davidoff, 2015).

Identification of natural disasters variables

After accounting for potential identification issues that may arise from unobserved location-specific attributes being correlated with price variables, I now turn to the identification of the main explanatory variable in the model- FEMA disaster declarations.

Coasts, water bodies, forests, mountains, etc. where natural calamities are likely to strike are dangerous as they are attractive for the natural amenities they provide. As a result, FEMA disaster declarations are likely to be correlated with unobserved location-specific attributes biasing the coefficient on natural disasters. The second identification issue of the FEMA disaster events variables arises because the process of declaring a disaster is somewhat political. FEMA disaster declarations were aimed at assisting states and local governments with managing disasters and were authorized by the United States Congress until 1988. With the Robert T. Stafford Disaster Relief and Emergency Assistance Act of November 1988, the authority of approving disaster declarations fell under the purview of the President of the United States. This shift in authority is strongly correlated with the frequency of disaster declarations, such declarations coinciding with election years, and the frequency of issuing declarations for politically competitive states (Reeves, 2011; Salkowe and Chakraborty, 2009; Gasper and Reeves, 2011; Saiz, 2019).

I account for these biases by including additional control variables in the second stage of the model. I include the variables $FedAssist$ and $WtrEvents$ in addition to $Disasters$ in the models to account for among others the political attractiveness and average disaster propensities in each location. The baseline severe weather propensities are accounted for in my models using $\Delta WtrEvents$. As many researchers had pointed out, FEMA disaster declarations were highly correlated with the political attractiveness of counties. I defined $FedAssist$ to be the share of FEMA disaster declarations ($Disasters$) over $WtrEvents$. The objective of this control variable is to capture the political attractiveness of each CZ given the baseline severe weather risk. I argue that if $\Delta FedAssist$ is positive it suggests that the change in political attention has become stronger given the baseline weather risk, and if the change in $\Delta FedAssist$ is negative then Presidential attention has diminished.

While control variables described earlier can capture some of the confounders in the model, how the variable *Disasters* is defined accounts for further biases that can push the coefficient of interest towards zero. FEMA disaster declarations are county-wide assessments and the President of the United States has the discretion to approve disaster declarations by specific county. If we assume that there is favoritism the outcome has to be that two counties with damages from a disaster are treated differently, such that one is offered federal assistance and the other is not. However, by aggregating counties into broader geographic locations (such as CZs in this study) the effect of the favoritism dissipates because clustered counties are assigned a disaster declaration if any one of the counties in the cluster were offered federal assistance. This accounts for counties that were not offered federal assistance despite being exposed to devastating calamities and captures worker decisions based on true exposure to disasters.

One caveat that needs to be mentioned is that despite not controlling for the political nature of the FEMA disaster declaration process, the results of my analyses are unlikely to be affected significantly. Evidence for this is presented in Table 2.3, where I show despite not accounting for baseline severe weather exposure and political attractiveness FEMA disaster events are on average negatively correlated with rents and college employment ratios and that are statistically significant.

2.4 Data

2.4.1 Economic data

This study uses 10% samples of census data from 1990 to 2000, and American Community Survey (ACS) data from 2006 to 2010 instead of census 2010 data (Ruggles et al., 2021). I use this data to form my sample of households represented by heads-of-households that are full-time wage employees (not self-employed) who are working in industries other than agriculture and the military, and not earning any additional farm or business income. As I focus on location choices of working households I exclude heads-of-households that are younger than 25 and over the retirement age (65).

I define full-time employment as those who have been working for at least 35 hours a week and 48 weeks in the previous year. I calculate the average wage using the IPUMS variable *incwage* and exclude those who have missing income information or zero wages in the previous year. I use IPUMS variable *rent*, *halueh*, *costelec* and *costgas* to generate my local rent variable. Households that own their dwelling are converted to renters by multiplying the value of the house by 7.85%. Both contract rent (*rent*) and imputed rents were added to utility costs to get the final local rent variable. Both price variables *income* and *rent* were converted to 1999 constant U.S. Dollars and used in the final analysis.

The sample of heads-of-households is grouped into college and non-college workers using their highest level of educated reported in the ACS. I categorized workers that have at least graduated from a four-year college as college-educated, and any other as non-college workers.

The moving cost indicator variable is assigned a value of 1 if the household lives in the same state as their birth and 0 otherwise. This indicator variable assumes that as long as one lives in the same state as the state of birth, the household incurs no mobility cost. If the household lives in a state outside of the state of birth, the household incurs the same mobility cost regardless of the relative proximity of their location choice.

I use a set of household characteristics in the first stage of the model that I interact with the moving cost variable. These variables include age groups of workers, sex, and the presence of children in the household. I assign any household that has children under the age of 10 (care-needing ages) a value of 1 and 0 otherwise. This indicator variable is included to account for moving costs associated with childcare.

2.4.2 Disaster events data

Disaster and weather events data for this study are collected from FEMA and NOAA. FEMA disaster declarations data are county-specific data that include event-by-type information for which federal disaster assistance is provided. I aggregate FEMA disasters by event and type for each CZ. This places equal weight on each observation regardless of how many counties within a CZ were provided with federal assistance. The main explanatory variable *Disasters* counts the number of the unique disasters in each CZ in the preceding decade per thousand residents in that

CZ. For example, the number of *Disasters* in 1990 counts the total number of FEMA disaster declarations between 1981 and 1990 over the population of 1990 (in thousands). *FedAssist* and *WtrEvents* respectively measure the share of FEMA disaster events over NOAA weather events and NOAA weather events per thousand residents. *WtrEvents* data were extracted from the Storm Events Database of the National Oceanic and Atmospheric Association (NOAA) of the United States (National Oceanic and Atmospheric Association, 2021).

2.4.3 Other amenities

Other amenity data comes from various sources. PRISM daily climate data published by Oregon State University are used to compute temperature variables in the second stage (PRISM Climate Group, n.d.). PRISM data is reported as four-kilometer grid points that correspond to points in the United States when overlayed. Grid points that fall within each geographic unit are extracted to create the climate variables used in the second stage of the model. Crime data for the models were obtained from USA County and City Data Book (U.S. Census Bureau, 2009) and Federal Bureau of Investigation (U. S. Department of Justice. Federal Bureau of Investigation, 2006a; U. S. Department of Justice. Federal Bureau of Investigation, 2006b; U. S. Department of Justice. Federal Bureau of Investigation, 2014). Local government expenditure shares on education and parks are extracted from the Annual Survey of State and Local Governments (U.S. Census Bureau and U.S. Department of Commerce, 2008; U.S. Census Bureau, 2019). Industry composition and industry presence data are downloaded from the County Business Patterns Database by Eckert et al. (2020).

2.4.4 Unit of analysis

The equilibrium sorting model in this paper uses CZs as the unit of analysis because it is functional and convenient. A CZ is a cluster of counties where population movement within a CZ is stronger than population movements between CZs. My analysis is based on the CZ definitions of Autor and Dorn (2013) who created 741 CZs for the country of which 722 CZs were in the contiguous United States[3]. I use CZs as my geographical unit because it is meaningful when studying working-age households that rely on wage/salary incomes. Another advantage of using this unit of analysis is that it covers the entire United States regardless of minimum population thresholds.

2.4.5 Amenity index

Although I have multiple climates, environmental, and other amenities included in the model not all of these variables are complete. As I aggregate county-wide measures into CZs missing observations are not apparent. However, many of the

[3]Autor and Dorn (2013)'s CZ measure, when being attributed to census and ACS data need to be translated from counties to PUMAs, for which definition files are publicly available. These definition files weight the frequency weights provided by the United States Census Bureau so that each CZ has portions of representative households/individuals that belong to one PUMA of which the boundary crosses more than one CZ.

variables suffer from incomplete county information that could affect the model estimation. To circumvent this issue I perform a principal component analysis (PCA) to create an index of amenities. I performed PCAs on amenities for each decade and used in each case the principal components that had eigenvalues greater than one (this was two for each decade). I then used the decadal amenity indices to create long-run differences in amenities by subtracting the index value in my base period (1990) from each of the subsequent decades. These amenities are listed in the analysis as PC1 and PC2.

Variable descriptions with their sources are reported in Table 2.1 and variables used in the analysis are reported in Table 2.2.

2.5 Descriptive analysis

Before I venture into the structural component of the model, I explore how social change occurs in CZs concerning disaster events and political attractiveness. I define social change as the change in the share of residents that can contribute to a shift in the socio-economic profile in each CZ. For example Boustan, Kahn, and Rhode (2012) found that poverty rates increased following extreme weather disasters in U.S. counties, Raker (2020) showed that income increased in U.S. counties following major tornadoes, and Davlasheridze and Fan (2017) found that share of minority households increased in places with the largest damages occurred from hurricane Katrina. What each of these studies informs is that inequality has increased in counties following major weather catastrophes potentially changing the social and economic profiles of U.S. counties. I explore this further by conducting a series of regression analyses explaining the current average income, average rental rate, and college employment ratio. My objective here is to establish in reduced-form that there is a relationship between the *Disasters* and other defining attributes of a CZ that can change the essential attributes of society. Results are reported in Table 2.3 and they suggest that larger changes in FEMA disaster declarations are negatively correlated with local prices and the employment ratio of college-educated workers and non-college-educated workers. These results point to the fact that after accounting for baseline exposure to potentially dangerous weather events and political attractiveness (albeit imprecisely), FEMA disasters affect the amenity stock enough for CZs to compensate for the loss in amenities via lower rental rates and push workers with more flexibility out of areas that are disaster-prone. The other side of this narrative is that vulnerable households remain in areas with high disaster propensities and continue to be exposed to such because they trade between safety from disasters and real income rates.

2.6 Results

The results of the structural location choice model are explained in several sections. In the first section, I discuss the first stage of the model where I estimate location-specific average utilities associated with each CZ. In the second stage, I decompose said average utilities into location-specific amenities and test alternative specifications to confirm the robustness of my results. These amenity coefficients can then be used to calculate average household valuations for them in terms of how much wage income workers are willing to forego/accept.

2.6.1 First-stage results

In the first stage of the model, I estimate equation 2.5 allowing households to yield utility from staying in a CZ in their state of birth, and by interacting this moving cost component with other demographic factors such as age, and sex of the heads-of-household. The first stage results of the conditional logistic model are reported in Table 2.4. Note that all coefficients are interacted with an indicator variable that notes if a household lives outside of the birth state of the head-of-household or not. The negative *Moving cost* variable suggests that living in a CZ outside of the birth-state yields negative utility for all households. Any interaction of the *Moving cost* variable also yields negative utility except for *Age 45-54* and *Age 55-64* variables.

This suggests that heads-of-households in these age groups living in CZs outside of the birth state provide positive utilities.

What I observe here is that regardless of skill level workers prefer to stay in their state of birth, and the effect is generally greater if one is a female head of household or if one has children of care-needing ages i.e. under 10 years old[4]. The highly significant mobility cost variables inform me of two aspects (1) that my findings are consistent with recent migration literature that suggests households have not been moving as much as they did several decades ago (Molloy, Smith, and Wozniak, 2011a; Kaplan and Schulhofer-Wohl, 2012). And (2) that kinship networks are a significant constraint when households move because a large share of the U.S. population depends on kinship networks for their childcare and other social needs (Laughlin, 2010).

2.6.2 Second-stage results

In the second stage of the sorting model, I collect the location-specific fixed effects estimated in the first stage and generate long-run differences from 1990, which I take as my base period. This model is estimated using a GMM estimator. Results of this exercise are reported in Table 2.5. In panel A I report coefficients of the analysis and in panel B I indicate ratios between coefficients to compare between models. I report two types of models in Table 2.5. Models 1 and 3 explicitly include all amenity variables and in Model 2 I include two principal components instead of

[4]This was determined based on the age of starting middle school when students stay an entire day at school as opposed to several hours in primary-school

a full list of amenities. On average, non-college workers' marginal utility of income is much stronger than the marginal utility of income for college workers indicating that higher income is more important for the former and that better amenities yield more utility for the latter. In all cases utility improves with higher income and stronger political attractiveness. Exposure to frequent weather events and FEMA disaster declarations results in lower utility. Effect sizes, although not meaningful to be compared except within the two groups (col. and non-col.) suggest that being in a CZ that is politically attractive yields more utility than reducing disaster exposure as the coefficient of the former is over five times larger than that of the latter on average. Households also yield utility from higher average temperatures and lower frequency of extreme heat days. When comparing the sizes of the coefficients, there are larger utility gains from living in CZs with higher average temperatures compared to avoiding CZs with more hot days. However, high average temperature areas are not necessarily the same places that have more extreme heat days. Non-college-educated workers yield more utility from higher local government expenditures for education and lower air quality. This is not to suggest that non-college workers gain utility from bad air quality; this suggests that because low air quality locations are more likely to be busy cities, non-college workers prefer such areas compared to better air quality locations that are correlated with rural and non-manufacturing areas. College workers showed a preference for greater shares of non-Hispanic white residents and both households derived utility from living in populous CZs.

In panel B of Table 2.5, I divided my coefficients of interest with the marginal utility of fixed income to compare between models. This measure reports the expenditure share on FEMA disasters. I find that the share of income on FEMA disasters was larger for college workers compared to non-college workers and that the pattern holds for the types of disasters as well.

2.6.3 Alternative specifications

In Table 2.6 I report 5 models of alternative specifications to test the robustness of my results. Model 1 reports results after excluding region fixed effects from the basic model, and model 2 reports results for one that does not differentiate between college and non-college wage differences. Results of the former remain similar to that of the basic models reported in Table 2.6 suggesting that my results are robust to alternative specifications. In the case of the latter, the marginal utility of income was higher for college workers than non-college workers confirming that college-educated workers who have greater potential for higher incomes yield more utility from amenities than real incomes. In model 3 I limit my analysis to locations with a college employment ratio over 26% (the average college employment ratio). The objective of this model was to test the relative differences in utility decomposition in locations that are likely to be attractive due to agglomeration economies, and better baseline levels of amenities. Here too the FEMA disaster declarations variable was negative and significant suggesting robust results. Model 4 reports a basic model with only the FEMA disaster declarations variable and excludes baseline weather exposure and the proxy for political attractiveness. The objective of including this model was to test if the additional control variables *WtrEvents* and *FedAssist* helped the precision of the coefficient on *Disasters*, and I find this to be true after comparing the expenditure shares between model 4 and others in panel B of Table 2.6. Finally, I repeat the exercise in model 4 in model 5 and include FEMA disaster declarations by type.

2.7 Household mobility effects

Although I account for household preferences for living closer to their kin and other social networks in the first stage, this model realistically combines two distinct samples: "movers" and "stayers." Households that are averse to moving long-distance may overstate the importance of amenities because they are tied to "location". "Movers" on the other hand may exhibit the true valuation for an amenity because they are not inordinately attached to place (Sinha, Caulkins, and Cropper, 2018). Using this rationale, I re-estimate the basic models in Table 2.5 by household mobility risk preferences and report my results in Table 2.7 and 2.8. I define "movers" to have made some change in residence (within the last five years for 1990 and 2000, and within the last year for 2010). To avoid including households that made mere housing moves (without moving from the same location) I include only those who moved between non-contiguous PUMAs. All others I categorize as "stayers." Both college and non-college-educated "movers" have somewhat similar preferences for higher real incomes although the effect is slightly stronger in the former category than in the latter. Both types of workers preferred not to experience FEMA disasters and enjoyed greater federal attention. "Stayers" too enjoyed higher wages, political attention, and lower exposure to FEMA disasters. On average non-college worker "stayers" indicated lower marginal utility of income compared to college workers indicating that college-educated "stayers" have greater utility from amenities compared to non-college workers.

2.8 Welfare

I conduct my welfare analysis by calculating marginal willingness to pay (MWTP) values for my parameter of interest- *Disasters* according to equation 2.8. I report my calculation in Table 2.9.

$$MWTP^{skill} = \frac{\beta^{skill}_{Disasters}}{\beta^{skill}_{p}} \times Avg.Wage^{skill} \tag{2.8}$$

The MWTP values indicate the trade-off between income and an amenity, and in this case, the interpretation is how much of annual wage income a worker is willing to part with for each unit of FEMA disaster exposure reduction. I find that the MWTP for avoiding an additional disaster event (per 1000 residents) is $1022 for an average college-educated household and $392 for an average non-college-educated household. I also find that models without baseline severe weather control variable (*WtrEvents*) and changes in political attractiveness (*FedAssist*) have a lower MWYP compared to models with said control variables. This points to the fact that welfare losses are somewhat mitigated by political attention placed on CZs by Presidents. After dividing the sample by household preferences for mobility risk, I find that college-educated "movers" are willing to pay $702 and that "stayers" are willing to pay $1326 to avoid an additional disaster event. Such a large range in the MWTP likely points to the importance of "place" these households place on their utility-maximizing location choice. Similar trends are observed between non-college "movers" and "stayers" too, albeit in a much tighter range.

In Table 2.10, I report differential effects of MWTP values for population categories in my sample. I selected each of these categories to show how vulnerable populations and low-income groups are disproportionately subject to enduring extreme weather disasters. For example, full-time employed white heads of households pay on average $100 more than black or Hispanic heads of households. Similarly, asset ownership also indicates that affluent households are paying to live in CZs that have lower risks of being exposed to extreme weather disasters.

2.9 Discussion

The objective of this paper was to explain how social change following exposure to weather disasters occurs within American communities. Using a structural spatial equilibrium model of location choice by full-time employed households of their working-age, I show that college-educated workers place a much larger importance on safety from natural disasters compared to non-college-educated workers.

This is not to say that non-college-educated workers prefer disaster risk. My findings show that non-college-educated workers place a much higher value on real incomes compared to their more educated colleagues. This re-iterates the "coming to the nuisance" argument that suggests low-income and vulnerable populations are disproportionately exposed to environmental dis-amenities because they prioritize real incomes over attractive amenities.

Methodologically, my strategy allows for heterogeneous preferences in the model following Diamond (2016) and I identify the model on temporal changes in wages and amenities like in the case of Diamond (2016) and Bayer, Keohane, and Timmins (2009). Compared to other studies that valued climate and environmental amenities such as Fan, Klaiber, and Fisher-Vanden (2016), Klaiber and Phaneuf (2010), and Sinha, Caulkins, and Cropper (2018) a key difference in my model is that it takes into account amenity changes over three census years and estimates long-run marginal utilities. Another key aspect of this design is that it allows comparing between coefficients. By estimating the second-stage models for college and non-college workers as a stacked model, I estimate the marginal utilities at the same time. This allows for comparing between coefficients of the two skill groups. Coefficient comparisons allow us to see that college workers on average are less responsive to income changes than non-college workers and that the opposite is true in terms of amenities.

In the regression models that I have presented in Tables 2.5 and 2.6, I show that college-educated households dedicate a larger share of their income to amenities and how non-college-educated households place a greater value on real incomes. While the model as it is describes the spatial equilibrium and makes the valuation of amenities, it could be reasonably argued that my MWTP values do not reflect the correct value of amenities. For example, households that are extremely risk-averse to making long-distance moves may have a higher valuation of amenities that partly captures attachment to "place" as well as the true valuation for the amenity. Sinha, Caulkins, and Cropper (2018) uses a sample of households that moved between MSAs to circumvent this issue and I follow this example and divide my sample into households that moved at least between non-contiguous PUMAs ("movers") in the previous years and households that did not ("stayers"). In Table 2.7 the marginal utility of income for college-educated households and non-college-educated households remain somewhat similar indicating that households move to realize higher incomes. However, the share of income willing to be spent on avoiding weather disasters is much greater in college-educated households than in non-college-educated households indicating that the former is more likely to move to locations that provide better income and positive amenities. Results in Table 2.8 indicate that out of households disinclined to move, non-college workers place a much higher value on average real income compared to college-educated workers that place a much higher value on amenities.

My MWTP values remain on par with other similar studies that value climate and environmental amenities. My results suggest that college-educated workers spend around 2.5% of their wage income per year and non-college workers spend about 1.5% of their annual wage income to avoid an additional unit of disaster exposure. Studies such as Albouy et al. (2016) and Sinha, Caulkins, and Cropper (2018) found that long-run extreme temperature changes remain traded for between 1% and 4% of income. Given that I account for three census years of data, and that my estimates lie around 2% of income, I remain confident that my estimates are comparable to most long-term amenity assessments. However, compared to studies such as Fan, Klaiber, and Fisher-Vanden (2016), Klaiber and Phaneuf (2010), and Bayer, Keohane, and Timmins (2009) that indicate environmental amenities are valued around 1% of income, my estimates are slightly larger. For example, Bayer, Keohane, and Timmins (2009) finds that a unit decrease in air pollution is valued at 0.95% of income and Fan, Klaiber, and Fisher-Vanden (2016) finds that an additional hot day is traded for 0.41% of income and that an additional cold day is traded for 0.26% of income. The large difference in income share may be due to multiple reasons including the study sample, and the model design.

2.9.1 MWTP and social change

I use the MWTP calculations for different population groups in an attempt to explain post-disaster social change as shown by Boustan, Kahn, and Rhode (2012), Davlasheridze and Fan (2017), Deryugina (2017) and Raker (2020). Post-disaster social change occurs when the likelihood of one population sector is exposed to more (less) disasters than others and is less (more) able to recover than others. I have discussed the broader implications of my results in the previous section and here I will go into further detail to show how my results can explain broader social change following disaster exposure.

From results in Table 2.9, college-educated "stayers" indicated that they were willing to pay twice as much as "movers" were willing to pay to avoid weather disasters and yielded more utility from amenities than incomes. Non-college-educated "stayers" on the other hand gained more utility from local wages and their valuation for amenities did not change significantly from non-college "movers." This suggests that "stayers" that are not college-educated are more likely to be poorer. When locations that have similar population distributions attract more residents the higher local prices affect poor and vulnerable residents first driving them away to locations with lower local prices and perhaps higher disaster risk increasing their risk of being exposed to more disasters and reducing their ability to negotiate the recovery process post-disaster.

I demonstrate this further in Table 2.10 where I apply the basic pooled model to the sample of households to find the average MWTP by social attributes such as race, age, sex, and home ownership. Younger heads-of-households, white, male, and homeowners on average paid more to live in CZs with less disaster risk compared to their neighbors. These population categories are also likely to have more access to means for recovery after disasters struck compared to others.

2.9.2 Contribution to the literature

The strongest contribution of this paper is to the amenity valuation literature because this study uses a somewhat new data source to find the value of avoiding disaster exposure in college and non-college-educated households. Amenities, like price variables, are also endogenously determined, and extreme weather disasters in the form of FEMA disaster declarations are especially so because of its relationship to party politics. By definition, a variable such as severe weather exposure is endogenously determined because the severity of weather events is understood in terms of how costly it is for humans. Because of this, for a variable such as severe weather to be considered truly exogenous, I need to instrument for it, which is difficult to achieve because of data limitations and would have to take into account the different types of weather events to be accurately determined. In this light, accounting for biases arising from using FEMA disaster declarations in its current form using additional control variables contributes to the larger understanding of how biases result in significant differences in welfare valuations. I show this further in Table 2.9 where line *No baseline weather controls* indicates that the MWTP values were 5 percent lower for college workers while it was 8 percent lower for non-college workers. Compared to studies such as Bayer, Keohane, and Timmins (2009), the differences in estimates are not large in this study, however, this study has shown the importance of accounting for possible biases in amenities when making welfare measurements.

Although this project was aimed at understanding the process in which social changes occur in American societies some of the robustness scenarios showed that my results are somewhat sensitive to different samples. For example, when dividing the same by "movers" and "stayers", the expectation was to see stronger preferences for avoiding severe weather in "movers" and a marked difference between college and non-college workers' marginal utilities for fixed income. This was not the case in my models. The fixed income coefficient was positive and significant and was virtually equal suggesting that both college and non-college households have the same preferences for higher real incomes. Perhaps this suggests that mobile college workers are at the lower end of the skilled-income distribution and that their location choice objectives are similar to non-college workers. College-educated "stayers" on the other hand yielded much less utility from increasing real incomes compared to non-college workers and enjoyed the same level of utility gains from reducing disaster exposure. This would suggest that college-educated "stayers" have a preference for "place" and that preference is not a financially motivated one.

2.10 Conclusion

Weather disasters do not affect all persons alike and prior literature has shown that exposure to weather disasters is accompanied by significant social changes.

Using a spatial equilibrium model that uses data over three census years, and allowing for heterogeneous preferences for college-educated workers, non-college-educated workers, "movers", and "stayers" I show how such social changes occur in the United States.

My results show that households require significant compensation to endure severe weather that can be categorized as disastrous. The MWTP values for avoiding such disasters lie between 1.5%-3% of annual wage income with college-educated workers willing to pay more than non-college-educated workers to reduce their exposure to weather disasters. I explore such heterogeneous welfare effects further to explain how social changes occur as a result of repeated exposure to weather disasters.

2.11 Tables

TABLE 2.1: Variable Descriptions and data sources used in the analysis

Variable name	Description and source

Ln(Income skilled)	Log real mean wage income of heads of households age 25-64 that have college degrees. Sample restricted to full-time (worked 35 hours a week and 48 weeks a year) wage employees with no farm or business income. – (Ruggles et al., 2021)
Ln(Income unskilled)	Log real mean wage income of heads of households age 25-64 that do not have college degrees. Sample restricted to full-time (worked 35 hours a week and 48 weeks a year) wage employees with no farm or business income. – (Ruggles et al., 2021)
Ln(Rent)	Log real mean gross rental rates. Gross rent is calculated using contract rent and utilities expenditure. Owned home values are converted into rental rates using a discount factor of 7.58% – (Ruggles et al., 2021)
Disasters	Number of FEMA disaster declarations in the preceding decade per 1000 residents. – (Federal Emergency Management Agency, n.d.)
WtrEvents	Severe weather events recorded from 1981-2010. Note that from 1981-1996 severe weather events only counted Thunderstorm Winds, Tornadoes, and Hail events. – (National Oceanic and Atmospheric Association, 2021)

FedAssist	FEMA disaster events as a share of total severe weather events. Severe weather events in this case is limited to Thunderstorm Winds, Tornadoes, and Hail events to ensure consistency in the shares.– (National Oceanic and Atmospheric Association, 2021, Federal Emergency Management Agency, n.d.)
Hot days	Average number of days over 90F over the preceding decade. – (PRISM Climate Group, n.d.) Climate Group
Avg. temp	Average temperature in the preceding decade. Temperature measured in F. – (PRISM Climate Group, n.d.)
Population	Number of households in thousands – (Ruggles et al., 2021)
Violent crm.	Violent crime per 1000 residents. – (U. S. Department of Justice. Federal Bureau of Investigation, 2006a, U. S. Department of Justice. Federal Bureau of Investigation, 2006b, U. S. Department of Justice. Federal Bureau of Investigation, 2014)
Property crm.	Property and non-violent crime per 1000 residents. – (U. S. Department of Justice. Federal Bureau of Investigation, 2006a, U. S. Department of Justice. Federal Bureau of Investigation, 2006b, U. S. Department of Justice. Federal Bureau of Investigation, 2014)

Exp. Edu	Average share of local government expenditure on education. – (U.S. Census Bureau and U.S. Department of Commerce, 2008, U.S. Census Bureau, 2019)
Exp. Parks	Average share of local government expenditure on parks and recreation – (U.S. Census Bureau and U.S. Department of Commerce, 2008, U.S. Census Bureau, 2019)
Air quality	Number of "good" air quality days (Air Quality Index value 0-50) as a share of total days measured. – (U.S. Environmental Protection Agency, n.d.)
Share white	Average share of heads-of-households identifying themselves as non-Hispanic White.– (Ruggles et al., 2021)
Retail emp.	Workers employed in the retail sector as a share of total employment. – (Eckert et al., 2020)

TABLE 2.2: Summary statistics for variables used in the second-stage of the sorting model of residential choice

	1990		2000		2010	
	Mean	SD	Mean	SD	Mean	SD
Ln(Income skilled)	8.19	0.18	8.21	0.18	8.14	0.18
Ln(Income unskilled)	7.77	0.13	7.76	0.13	7.64	0.14
Ln(Rent)	7.02	0.30	6.96	0.26	7.06	0.26
Disasters	0.10	0.60	0.57	2.25	0.46	1.34
WtrEvents	14.31	22.61	36.24	69.12	61.69	126.52
FedAssist	0.02	0.07	0.04	0.17	0.02	0.14
Hot days	36.18	31.62	33.44	32.45	35.21	31.64
Avg. temp	53.19	8.44	53.43	8.58	53.90	8.37
Population	48.61	124.40	54.37	129.49	56.30	131.97
Violent crm.	2.51	2.03	2.76	2.41	2.60	1.84
Property crm.	30.06	15.39	25.76	15.14	23.80	11.72
Exp. Edu	0.47	0.13	0.48	0.11	0.61	0.15
Exp. parks	0.01	0.01	0.01	0.01	0.01	0.01
Air quality	0.76	0.10	0.72	0.11	0.74	0.11
Share white	0.91	0.09	0.89	0.10	0.88	0.11
Retail emp.	0.25	0.06	0.22	0.05	0.17	0.03

Price variables $Ln(income)$, $Ln(Incomeskilled)$, $Ln(Incomeunskilled)$ and $Ln(Rent)$ are in 1999 constant U.S. Dollars. $Disasters$, $WtrEvents$, $Violentcrm.$ and $Propertycrm.$

are calculated per 1000 residents. $FedAssist$, $Exp.edu$, $Exp.parks$, $Airquality$, $Share\ white$ and $Retailemp$. are shares. Temperature variables are measured in F. Data sources and variable descriptions are listed in Table 2.1.

TABLE 2.3: Reduced-form evidence of how exposure to severe weather affects social change in the United States

	$\Delta ln(Income)$	$\Delta ln(Rent)$	$\Delta ln(Col.emp)$
$\Delta ln(Income)$		0.5767***	0.5036***
		(0.0863)	(0.0544)
$\Delta Disasters$	0.0011	-0.0108***	-0.0081***
	(0.0008)	(0.0030)	(0.0018)
$\Delta PCA1$	0.0038	-0.0162***	-0.0245***
	(0.0024)	(0.0049)	(0.0038)
$\Delta PCA2$	-0.0014	-0.0169***	0.0139***
	(0.0017)	(0.0040)	(0.0023)
T	-0.0774***	0.1427***	0.1177***
	(0.0017)	(0.0072)	(0.0051)
Intercept	0.0336***	-0.0738***	0.0309***
	(0.0021)	(0.0043)	(0.0023)
N	1444	1444	1444
R^2	0.2909	0.2280	0.3966

Standard errors in parentheses. Standard errors are clustered at CZ level. Significance levels *<0.1 **<0.05 ***<0.001 All models use a 10% sample of Census data for 1990 and 2000, and ACS data 2006-2010 in lieu of census 2010. The sample of households are represented by heads-of-households that are between 25-64, working full-time in wage employment with no supplementary income.

TABLE 2.4: First-stage logistic model results

	1990		2000		2010	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Kids under 10	-0.1578***	-0.0785***	-0.1217***	-0.0402***	-0.1443***	-0.0579***
	(0.0194)	(0.0117)	(0.0187)	(0.0025)	(0.0164)	(0.0133)
Age 35-44	-0.0481***	-0.0052	0.113***	0.0262***	0.1549***	0.0892***
	(0.0192)	(0.0123)	(0.0140)	(0.0125)	(0.0112)	(0.0145)
Age 45-54	0.1272***	0.0606***	0.0349***	0.0198	0.1592***	0.0704***
	(0.0178)	(0.0144)	(0.0129)	(0.0134)	(0.0128)	(0.0142)
Age 55-64	0.0884***	-0.0119	0.2483***	0.1071***	0.1822***	0.1156***
	(0.0205)	(0.0165)	(0.0163)	(0.0159)	(0.0148)	(0.0154)
FemaleHH	-0.0671***	0.0722***	-0.0559***	0.0413***	-0.2049***	-0.0306***
	(0.0202)	(0.0121)	(0.0184)	(0.0110)	(0.0138)	(0.0100)
Moving cost	-3.5557***	-4.3783***	-3.6839***	-4.385***	-3.7142***	-4.4064***
	(0.0131)	(0.0108)	(0.0081)	(0.0094)	(0.0106)	(0.0124)

Standard errors in parentheses. Significance levels *<0.1 **<0.05 ***<0.001 All models use a 10% sample of Census data for 1990 and 2000, and ACS data 2006-2010 in lieu of census 2010. The sample of households are represented by heads-of-households that are between 25-64, working full-time in wage employment with no supplementary income.

TABLE 2.5: Second-stage sorting model results: decomposing average utilities into location specific amenities

Panel A	Estimates of marginal utilities					
	(1)		(2)		(3)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Fixed income	1.2962***	1.6724**	1.5544***	1.5594**	1.3089***	1.6512**
	(0.4223)	(0.7302)	(0.4344)	(0.6928)	(0.4258)	(0.7697)
Disasters	-0.0310***	-0.0241***	-0.0329***	-0.0234***		
	(0.0080)	(0.0079)	(0.0088)	(0.0078)		
Fire events					-0.0156	-0.0444**
					(0.0516)	(0.0219)
Flood events					-0.0670**	-0.0333*
					(0.0303)	(0.0181)
Winter events					0.0114	-0.0141
					(0.0534)	(0.0479)
Storm events					-0.0159	-0.0554

					(0.0161)	(0.0374)
Coastal events					-0.0605	-0.0004**
					(0.0707)	(0.0001)
WtrEvents	-0.0004***	-0.0004***	-0.0004**	-0.0004***	-0.0005***	-0.0168
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0124)
FedAssist	0.2063***	0.1729***	0.2463***	0.1776***	0.2136***	0.1821***
	(0.0540)	(0.0605)	(0.0603)	(0.0666)	(0.0633)	(0.0628)
Hot days	-0.0064*	-0.0089***	-0.0073*	-0.0106***	-0.0059*	-0.0089***
	(0.0034)	(0.0029)	(0.0038)	(0.0027)	(0.0034)	(0.0029)
AvgTemp	0.1372***	0.1174***	0.1328***	0.1233***	0.1393***	0.1167***
	(0.0414)	(0.0383)	(0.0446)	(0.0346)	(0.0416)	(0.0394)
Population	0.0017***	0.0013***			0.0016***	0.0013***
	(0.0006)	(0.0005)			(0.0006)	(0.0005)
Parks	0.1194	1.0653			0.2138	1.0707
	(0.7464)	(0.7377)			(0.7839)	(0.7682)
Violent crime	-0.0002	0.0043			-0.0007	0.0042
	(0.0089)	(0.0094)			(0.0090)	(0.0097)

Education	0.0644	0.1238**			0.0706	0.1234**
	(0.0905)	(0.0611)			(0.0904)	(0.0609)
Air quality	-0.2223	-0.3628***			-0.2244	-0.3552***
	(0.1629)	(0.1337)			(0.1614)	(0.1371)
RetailEmp	0.0531	-0.0296			-0.0345	-0.1101
	(0.4393)	(0.2743)			(0.4307)	(0.2754)
White	1.3023***	0.1994			1.3494***	0.2535
	(0.4419)	(0.3629)			(0.4426)	(0.3803)
T	0.1208*	0.3027***	0.1463**	0.2925**	0.1150*	0.2964**
	(0.0630)	(0.1157)	(0.0575)	(0.1200)	(0.0612)	(0.1213)
PCA1			0.0496***	0.0295**		
			(0.0182)	(0.0116)		
PCA2			0.0342**	-0.0224**		
			(0.0167)	(0.0092)		
Intercept	-0.2395***	-0.4268***	-0.2882***	-0.4047***	-0.2449***	-0.4263***
	(0.0836)	(0.0780)	(0.0880)	(0.0709)	(0.0848)	(0.0804)
N	1425		1425		1425	
p(Hansen’s J)	0.2633		0.2402		0.2544	

Panel B	Ratios of marginal utilities					
	(1)		(2)		(3)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Disasters	-0.0239	-0.0144	-0.0212	-0.0150		
Fire events					-0.0119	-0.0269
Flood events					-0.0512	-0.0202
Winter events					0.0087	-0.0085
Storm events					-0.0121	-0.0336
Coastal events					-0.0462	-0.0002

Standard errors in parentheses. Standard errors are clustered at CZ level. Significance levels *<0.1 **<0.05 ***<0.001 All models use a 10% sample of Census data for 1990 and 2000, and ACS data 2006-2010 in lieu of census 2010. The sample of households are represented by heads-of-households that are between 25-64, working full-time in wage employment with no supplementary income. Model 1 is the basic model where all control variables are explicitly included, in Model 2, instead of the control variables an amenity index is included in the model and in Model 3, along with separate control variables, the FEMA disaster events variable is decomposed into type of disaster.

TABLE 2.6: Alternative specification and robustness check of residential sorting model

Panel A	Second-stage alternative model results									
	(1)		(2)		(3)		(4)		(5)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Fixed income	1.1114***	2.2784***	3.5401***	1.9926***	1.4218**	0.3592	1.4632***	2.1495**	1.4452***	2.1071**
	(0.3968)	(0.7929)	(1.0835)	(0.6602)	(0.6189)	(0.3410)	(0.4506)	(0.8562)	(0.4545)	(0.8775)
Disasters	-0.0285***	-0.0247***	-0.0543***	-0.0294***	-0.0464***	-0.0143***	-0.0330***	-0.0283***		
	(0.0071)	(0.0089)	(0.0148)	(0.0077)	(0.0153)	(0.0039)	(0.0079)	(0.0095)		
Fire events									-0.0380	-0.0655**
									(0.0577)	(0.0293)
Flood events									-0.0462	-0.0179
									(0.0292)	(0.0192)
Winter events									-0.0129	-0.0498

									(0.0508)	(0.0479)
Storm events									-0.0295**	-0.0269**
									(0.0143)	(0.0136)
Coastal events									-0.0609	-0.0523
									(0.0810)	(0.0481)
WtrEvents	-0.0002	-0.0000	-0.0002	-0.0003***	-0.0005	-0.0002*				
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0001)				
FedAssist	0.1426*	0.0587	0.2040***	0.2300***	0.2484***	0.1910**				
	(0.0758)	(0.0865)	(0.0396)	(0.0739)	(0.0549)	(0.0752)				
Hot days	-0.0090***	-0.0146***	-0.0099***	-0.0087***	-0.0086	-0.0039	-0.0096***	-0.0119***	-0.0093**	-0.0116***
	(0.0031)	(0.0034)	(0.0038)	(0.0023)	(0.0052)	(0.0026)	(0.0036)	(0.0031)	(0.0036)	(0.0032)
AvgTemp	0.1450***	0.1380***	0.1631***	0.0878***	0.1028*	0.0857**	0.1526***	0.1444***	0.1527***	0.1369***
	(0.0409)	(0.0471)	(0.0450)	(0.0268)	(0.0529)	(0.0393)	(0.0450)	(0.0429)	(0.0452)	(0.0437)
Population	0.0019***	0.0012**	0.0001	0.0000	0.0017**	0.0013***	0.0017***	0.0014***	0.0017***	0.0014**

	(0.0006)	(0.0006)	(0.0010)	(0.0007)	(0.0007)	(0.0004)	(0.0007)	(0.0005)	(0.0007)	(0.0005)
Parks	1.1562	1.9198*	-0.2101	1.5888***	2.0602	1.8415**	0.5116	1.0990	0.5684	1.0353
	(1.0109)	(1.1587)	(1.0929)	(0.5881)	(1.7102)	(0.8206)	(0.8472)	(0.9018)	(0.8688)	(0.9061)
Violent crime	0.0004	-0.0042	-0.0125	0.0088	-0.0080	0.0210***	-0.0038	-0.0008	-0.0040	-0.0007
	(0.0085)	(0.0138)	(0.0115)	(0.0072)	(0.0127)	(0.0076)	(0.0093)	(0.0105)	(0.0093)	(0.0106)
Education	0.0642	0.1385*	0.2767**	0.2061***	0.0457	0.1317	0.0219	0.1108	0.0273	0.1136
	(0.0858)	(0.0765)	(0.1238)	(0.0677)	(0.1757)	(0.0903)	(0.0970)	(0.0718)	(0.0964)	(0.0714)
Air quality	-	-	-	-	-	-0.1699	-	-	-	-
	0.3623**	0.5588***	0.3057*	0.2930***	0.3777*		0.3371*	0.4636***	0.3280*	0.4420***
	(0.1579)	(0.1525)	(0.1637)	(0.1062)	(0.2183)	(0.1672)	(0.1725)	(0.1570)	(0.1706)	(0.1594)
RetailEmp	-0.2290	-	-0.0213	0.2130	0.2889	0.1505	-0.0463	-0.1728	-0.1187	-0.2303
		0.7485*								
	(0.3797)	(0.4006)	(0.4861)	(0.2210)	(0.7637)	(0.3286)	(0.4733)	(0.3027)	(0.4595)	(0.3014)
White	1.4317***	0.0864	0.7679	0.1972	1.1349	1.0141***	1.3168***	0.0604	1.3605***	0.1016
	(0.4071)	(0.4205)	(0.5548)	(0.2925)	(0.8063)	(0.2944)	(0.4610)	(0.4417)	(0.4577)	(0.4536)
T	0.0802	0.3664***	0.3912***	0.2875***	0.1287	0.0940*	0.1291*	0.3628***	0.1223*	0.3589**
	(0.0503)	(0.1123)	(0.1377)	(0.0836)	(0.0894)	(0.0534)	(0.0679)	(0.1380)	(0.0650)	(0.1409)

Intercept	-0.1336***	-0.2638***	-0.6146***	-0.5805***	-0.2310**	-0.3080***	-0.2273**	-0.4620***	-0.2296**	-0.4566***
	(0.0404)	(0.0446)	(0.1753)	(0.1062)	(0.1003)	(0.0517)	(0.1050)	(0.0944)	(0.1056)	(0.0953)
N	1425		1425		1425		1425		1425	
p(Hansen's J)	0.1822		0.2678		0.5734		0.2414		0.2327	
Panel B	Rations of marginal utilities									
	(1)		(2)		(3)		(4)		(5)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Disasters	-0.0256	-0.0108	-0.0153	-0.0148	-0.0326	-0.0398	-0.0226	-0.0132		
Fire events									-0.0263	-0.0311
Flood events									-0.0320	-0.0085
Winter events									-0.0089	-0.0236
Storm events									-0.0204	-0.0128
Coastal events									-0.0421	-0.0248

Standard errors in parentheses. Standard errors are clustered at CZ level. Significance levels *<0.1 **<0.05 ***<0.001 All models use a 10% sample of Census data for 1990 and 2000, and ACS data 2006-2010 in lieu of census 2010. The sample of households are represented by heads-of-households that are between 25-64, working full-time in wage employment with no supplementary income. In Model 1 I exclude regional fixed effects, in Model 2 college and non-college wages are calculated using a pooled sample of both college and non-college workers. Model 3 limits the analysis to CZs with over 26% of college employment (against non-college employment). Model 4 reports results for the basic model without baseline weather events data and political attractiveness data, and in Model 5 the same model as Model 4 is estimated with FEMA events by type.

TABLE 2.7: Alternative specification of residential sorting model: decomposing average location specific utilities of "Movers"

Panel A	Estimates of marginal utilities					
	(1)		(2)		(3)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Fixed income	1.6875***	1.6562**	1.7765***	1.1870*	1.7020***	1.6946**
	(0.5951)	(0.7792)	(0.5585)	(0.7010)	(0.5974)	(0.8318)
Disasters	-0.0277**	-0.0208***	-0.0301***	-0.0185***		
	(0.0112)	(0.0077)	(0.0117)	(0.0068)		
Fire events					-0.0043	-0.0117
					(0.0476)	(0.0187)
Flood events					-0.0472	-0.0296**
					(0.0329)	(0.0143)
Winter events					0.0430	-0.0204
					(0.0574)	(0.0472)
Storm events					-0.0326*	-0.0920***

					(0.0188)	(0.0327)
Coastal events					-0.1139	-0.0004***
					(0.0796)	(0.0001)
WtrEvents	-0.0002	-0.0004***	-0.0003	-0.0005***	-0.0002	-0.0130
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0105)
FedAssist	0.2047***	0.1843***	0.2193***	0.2031***	0.2362***	0.2093***
	(0.0587)	(0.0464)	(0.0520)	(0.0620)	(0.0701)	(0.0504)
Hot days	-0.0110**	-0.0108***	-0.0131***	-0.0125***	-0.0104**	-0.0109***
	(0.0044)	(0.0030)	(0.0046)	(0.0027)	(0.0043)	(0.0031)
AvgTemp	0.1915***	0.1191***	0.2155***	0.1176***	0.1929***	0.1206***
	(0.0511)	(0.0396)	(0.0521)	(0.0341)	(0.0515)	(0.0416)
Population	0.0029***	0.0030***			0.0029***	0.0030***
	(0.0008)	(0.0005)			(0.0008)	(0.0005)
Parks	1.1504	1.0310			1.2484	0.9899
	(0.8822)	(0.7446)			(0.8795)	(0.7843)
Violent crime	-0.0063	0.0044			-0.0060	0.0039
	(0.0113)	(0.0102)			(0.0114)	(0.0107)

Education	0.1444	0.2035***			0.1488	0.2043***
	(0.1100)	(0.0611)			(0.1105)	(0.0620)
Air quality	-0.3238	-0.3087**			-0.3083	-0.3104**
	(0.2231)	(0.1420)			(0.2222)	(0.1477)
RetailEmp	0.4517	0.0321			0.3482	-0.0590
	(0.5625)	(0.2716)			(0.5354)	(0.2809)
White	1.2511***	0.0436			1.3116***	0.0741
	(0.4601)	(0.3957)			(0.4621)	(0.4192)
T	0.2124**	0.2199*	0.1982***	0.1622	0.2113**	0.2245*
	(0.0921)	(0.1233)	(0.0741)	(0.1214)	(0.0889)	(0.1312)
PCA1			-0.0180	0.0247*		
			(0.0217)	(0.0133)		
PCA2			-0.0009	-0.0138		
			(0.0160)	(0.0098)		
Intercept	-0.4543***	-0.3522***	-0.4979***	-0.2966***	-0.4602***	-0.3565***
	(0.1020)	(0.0803)	(0.1051)	(0.0707)	(0.1037)	(0.0840)
N	1425		1425		1425	
p(Hansen's J)	0.8020		0.7256		0.7914	

Panel B	Ratios of marginal utilities					
	(1)		(2)		(3)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Disasters	-0.0164	-0.0126	-0.0169	-0.0156		
Fire events					-0.0025	-0.0069
Flood events					-0.0277	-0.0175
Winter events					0.0253	-0.0120
Storm events					-0.0192	-0.0543
Coastal events					-0.0669	-0.0002

Standard errors in parentheses. Standard errors are clustered at CZ level. Significance levels *<0.1 **<0.05 ***<0.001 All models use a 10% sample of Census data for 1990 and 2000, and ACS data 2006-2010 in lieu of census 2010. The sample of households are represented by heads-of-households that are between 25-64, working full-time in wage employment with no supplementary income. "Movers" are defined as ones that moved between non-contiguous PUMAs and over 70miles last year. Model 1 is the basic model where all control variables are explicitly included, in Model 2, instead of the control variables an amenity index is included in the model and in Model 3, along with separate control variables, the FEMA disaster events variable is decomposed into type of disaster.

TABLE 2.8: Alternative specification of residential sorting model: decomposing average location specific utilities of "Stayers"

Panel A	Estimates of marginal utilities					
	(1)		(2)		(3)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Fixed income	0.7224*	1.7285**	0.9324**	1.3185*	0.6997*	1.8309**
	(0.4171)	(0.8591)	(0.4102)	(0.7945)	(0.4159)	(0.9336)
Disasters	-0.0224**	-0.0228**	-0.0250**	-0.0197**		
	(0.0093)	(0.0105)	(0.0100)	(0.0095)		
Fire events					-0.0330	-0.0393
					(0.0357)	(0.0246)
Flood events					-0.0361	-0.0181
					(0.0281)	(0.0251)
Winter events					0.0221	-0.0596
					(0.0511)	(0.0644)
Storm events					-0.0231	-0.0818*

					(0.0186)	(0.0454)
Coastal events					-0.1131	-0.0004**
					(0.0775)	(0.0002)
WtrEvents	-0.0004**	-0.0005***	-0.0005***	-0.0006***	-0.0004***	-0.0166
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0177)
FedAssist	0.1430**	0.2169***	0.1665***	0.2337***	0.1756**	0.2373***
	(0.0563)	(0.0480)	(0.0577)	(0.0604)	(0.0707)	(0.0526)
Hot days	-0.0086***	-0.0118***	-0.0106***	-0.0132***	-0.0083***	-0.0124***
	(0.0032)	(0.0031)	(0.0033)	(0.0028)	(0.0031)	(0.0033)
AvgTemp	0.1555***	0.1419***	0.1810***	0.1427***	0.1537***	0.1451***
	(0.0395)	(0.0432)	(0.0424)	(0.0375)	(0.0393)	(0.0464)
Population	0.0033***	0.0027***			0.0033***	0.0027***
	(0.0007)	(0.0005)			(0.0007)	(0.0005)
Parks	0.6203	1.0448			0.6410	0.9299
	(0.6772)	(0.6560)			(0.7223)	(0.7199)
Violent crime	0.0075	0.0079			0.0074	0.0064
	(0.0084)	(0.0109)			(0.0084)	(0.0116)

Education	0.0831	0.1888***			0.0845	0.1875***
	(0.0836)	(0.0656)			(0.0825)	(0.0679)
Air quality	-0.1426	-0.3729***			-0.1213	-0.3816***
	(0.1598)	(0.1393)			(0.1577)	(0.1477)
RetailEmp	0.1374	-0.3811			0.0134	-0.4727*
	(0.4370)	(0.2720)			(0.4069)	(0.2860)
White	0.7786**	-0.1783			0.8637**	-0.1784
	(0.3632)	(0.4162)			(0.3581)	(0.4472)
T	0.0071	0.2865**	0.0245	0.2590*	0.0030	0.3023**
	(0.0637)	(0.1360)	(0.0546)	(0.1371)	(0.0609)	(0.1464)
PCA1			0.0096	0.0342**		
			(0.0161)	(0.0139)		
PCA2			-0.0019	-0.0260**		
			(0.0114)	(0.0113)		
Intercept	-0.0593	-0.4954***	-0.0877	-0.4321***	-0.0586	-0.5036***
	(0.0824)	(0.0895)	(0.0829)	(0.0812)	(0.0831)	(0.0954)
N	1425		1425		1425	
p(Hansen's J)	0.2174		0.3623		0.2293	

Panel B	Ratios of marginal utilities					
	(1)		(2)		(3)	
	Col.	Non-col.	Col.	Non-col.	Col.	Non-col.
Disasters	-0.0310	-0.0132	-0.0268	-0.0149		
Fire events					-0.0472	-0.0215
Flood events					-0.0516	-0.0099
Winter events					0.0316	-0.0326
Storm events					-0.0330	-0.0447
Coastal events					-0.1616	-0.0002

Standard errors in parentheses. Standard errors are clustered at CZ level. Significance levels *<0.1 **<0.05 ***<0.001 All models use a 10% sample of Census data for 1990 and 2000, and ACS data 2006-2010 in lieu of census 2010. The sample of households are represented by heads-of-households that are between 25-64, working full-time in wage employment with no supplementary income. "Stayers" are defined to be households that did not make a significant enough move (or did not move) during the previous year. Model 1 is the basic model where all control variables are explicitly included, in Model 2, instead of the control variables an amenity index is included in the model and in Model 3, along with separate control variables, the FEMA disaster events variable is decomposed into type of disaster.

TABLE 2.9: Marginal willingness to pay for avoiding severe weather

	Col.	Non-col.
Pooled models		
Main	$ 1,021.70	$ 392.01
Amenity index	$ 1,094.76	$ 294.22
No baseline weather controls	$ 964.46	$ 358.00
By mobility risk preference		
Movers	$ 701.68	$ 341.04
Stayers	$ 1,325.47	$ 358.19
By disaster type		
Fire events		$ 730.96
Flood events	$ 2,189.44	$ 546.93
Winter events		
Storm events		
Coastal events		

Values are 1999 constant U.S. Dollars per year to avoid an additional event per decade. Average college educated worker's annual wage income in my sample is $42746.56 and average non-college educated worker's annual wage income is $27154.99. MWTP values are reported for coefficients that are statistically significant.

TABLE 2.10: Differential welfare effects by population components: exposure to severe weather and social change

	Average MWTP
Race	
White	$ 609.97
Black	$ 524.21
Hispanic	$ 520.03
Home ownership	
Owner	$ 610.23
Renter	$ 562.53
Sex	
Male	$ 598.58
Female	$ 592.54
Age	
Age 25-34	$ 606.87
Age 35-44	$ 599.72
Age 45-54	$ 591.84
Age 55+	$ 581.76
Moving cost	
CZ in birth state	$ 559.86
CZ outside birth state	$ 651.66
CZ in birth state×Race	
White	$ 570.44

Black	\$ 502.56
Hispanic	\$ 506.82
CZ outside birth state×Race	
White	\$ 667.64
Black	\$ 558.66
Hispanic	\$ 549.73

Values are 1999 constant U.S. Dollars. Average welfare values are calculated by applying the MWTP values reported in Table 2.9 to the sample of heads-of-households by their level of education.

2.12 Figures

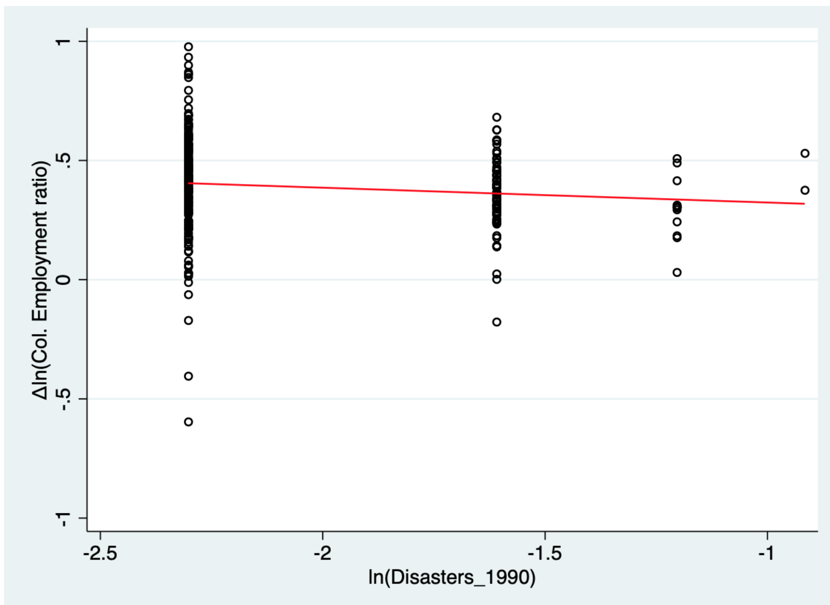


FIGURE 2.1: Changes in college employment ratio and extreme disaster events in the U.S. 1990-2010— Source: Data consist of 10% samples from 1990 and 2000 decennial census, and 2006-2010 American Community Survey (ACS) in lieu of 2010 census data. All data were downloaded from IPUMS.org (Ruggles et al., 2021). Disaster declaration data (Disasters) from FEMA Disaster Declarations 1981-2010 (Federal Emergency Management Agency, n.d.). Disasters data are counts per CZ for the preceding decade.

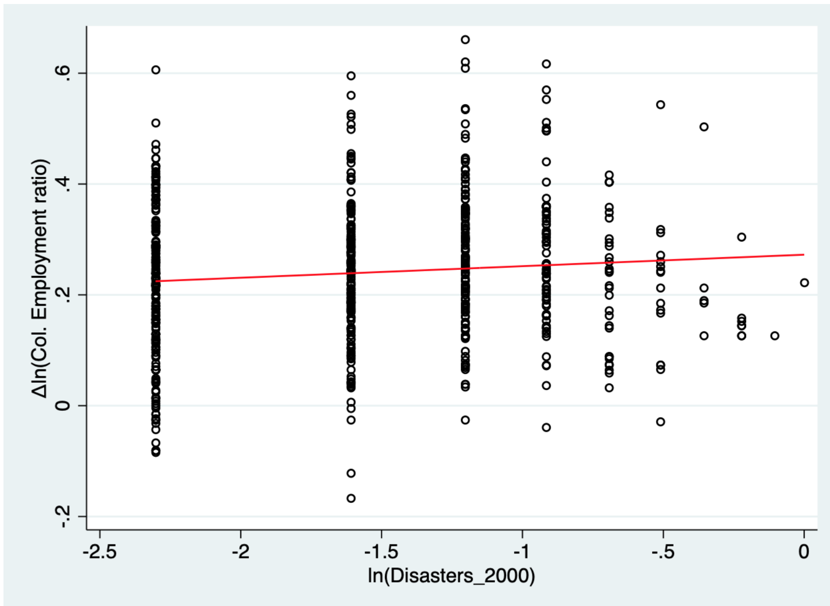


FIGURE 2.2: Changes in college employment ratio and extreme disaster events in the United States 2000-2010— Source: Data consist of 10% samples from 1990 and 2000 decennial census, and 2006-2010 American Community Survey (ACS) in lieu of 2010 census data. All data were downloaded from IPUMS.org (Ruggles et al., 2021). Disaster declaration data (Disasters) from FEMA Disaster Declarations 1981-2010 (Federal Emergency Management Agency, n.d.). Disasters data are counts per CZ for the preceding decade.

Chapter 3

Does health insurance affect interstate mobility? Exploring evidence of mobility-lock using employer-based health insurance recipients

3.1 Introduction

Health insurance and residential mobility are profoundly connected in the United States through the workplace because a majority of working, non-poor households obtain health insurance via their employers. This has important economic implications because labor markets depend on the efficient movement of workers between firms to attract the best skills and thereby improve individual earnings. There is a large literature on how health insurance affects job mobility and retirement decisions, however not much has been done to understand if this translates into long-distance residential mobility as well. The difference between long-distance residential mobility and job mobility is that people who are considering long-distance moves are almost always changing jobs, and crossing state boundaries could mean workers to be affected by different state mandates such as continued coverage and limitations coverage for dependents. In this paper, I explore if interstate mobility in the United States is affected by health insurance-related risk aversion when significant steps to ensure health insurance portability has been taken in recent years.

Recent literature on long-distance mobility has shown that population movement in the United States has been slow for largely labor market related reasons. Kaplan and Schulhofer-Wohl (2017b) found that the reduction in residential mobility was due to labor markets being homogeneous across geographies and because better information flows have made multiple moves to find the utility-maximizing location a redundant exercise. However, Wozniak (2010) found that some workers were more responsive to interstate labor market opportunities compared to the rest. And Molloy, Smith, and Wozniak (2011b) showed that lower mobility is correlated with longer job tenure and the general reluctance to change employers. What all of this suggests is that there may be a stronger connection between labor market mobility and long-distance mobility because some of the long-distance mobility determinants have strong ties to the labor market such as health insurance. As such, lower mobility rates have significant economic consequences because a sluggish labor market affects economic productivity and growth as well as human well-being

(Azzopardi et al., 2020).

Compared to other members of the Organization for Economic Co-operation and Development (OECD), the United States spends the most on healthcare and yields the least from it. The United States has the largest obese population, tops the list in preventable deaths, has the largest chronic disease burden, and has the lowest life expectancy at birth among comparable counties (Tikkanen and Abrams, 2019). All these points to a large segment of the population that has their healthcare and health insurance need unmet. The combined effects of this unmet demand for healthcare and dependence on firms to provide that healthcare at a reasonable cost, have led to inefficiencies in the labor market by slowing worker transition and thereby worker mobility (Gruber and Madrian, 1994; Madrian, 2006). Health insurance is strongly tied to labor market outcomes in the United States because a large share of the working-age, non-poor households get health insurance through their employers, and because healthcare is too expensive without health insurance (Collins, Radley, and Baumgartner, 2019). Large employers or unions can negotiate better group plans because they can generate sizable risk pools. Individuals outside of such a setting are rarely able to negotiate for better premiums because there is little opportunity to form large enough risk pools. Even with this advantage, offers of health insurance along with employment had declined in the last twenty years, but have remained constant for those in higher wage income categories (Long et al., 2016). Therefore, workers that are offered health insurance in their remuneration are more likely to be college-educated, and full-time employed. Although college-educated and full-time employed workers have an advantage in the labor market (in that they are likely to find employment without incurring a substantial search cost), these workers are still less likely to change jobs than employees that do not have health insurance benefits (Bansak and Raphael, 2008; Dey and Flinn, 2005).

However, health insurance and access to healthcare is an important part of American life that some households change employers in search of health insurance benefits (Bradley, Neumark, and Motika, 2012; Madrian, 2006; Chute and Wunnava, 2015). Yet, it is questionable if this translates into internal mobility. State health insurance programs can make it harder for interstate mobility because there are coverage losses during the transition, due to waiting periods, and because eligibility has to be maintained. This is evident in the fact that there is little evidence to suggest households move across state boundaries in search of health insurance (Bansak and Raphael, 2008; Schwartz and Sommers, 2014; Goodman, 2017). This is noteworthy because there is other evidence suggesting that households move across administrative boundaries in other circumstances such as in search of welfare assistance (Bailey, 2005; Brueckner, 2000). All of this evidence suggests that health insurance and mobility connections cannot be understood entirely by how the job market responds to health insurance.

One of the main issues in ascertaining the effect of health insurance on mobility is that it is difficult to determine who has more value for health insurance. The extent to which households value health insurance is somewhat individual-specific. Those who value healthcare more than what it costs to provide it can inform researchers on the effect of health insurance on mobility when compared to a control group. Many have assessed the severity of job-lock by studying how health insurance affects retirement decisions, labor force participation, and job mobility. For example; there are rents associated with EBHI that make employment more attractive than retirement[1], and these rents are especially high for older employees because risk pooling makes their premiums much less expensive (Gruber and Madrian, 2002). The same principle applies to people with EBHI who are eligible to get health insurance for their families through the employer's group plan. The rents associated with the employer group insurance for their families may be higher for some employees, and these employees may not be inclined to change jobs. The reasons such rents are higher may be due to pre-existing conditions, special health needs, and the number of family members that need coverage (general costs associated with changing insurers and healthcare providers). This non-random assignment of some households valuing health insurance more than others may be one of the reasons why workers with employer-sponsored health insurance have low job turnover, even while taking wage discounts compared to those that do not have health insurance[2].

Throughout the last few decades, there have been some attempts to ease the transition of workers from one firm to another. The Consolidated Omnibus Budget

[1]When retirees seek health insurance outside of their workplace, they are more likely to be among other retirees, or candidates otherwise ineligible for EBHI. This brings the distribution of potential healthcare costs to the right-hand side imposing higher premiums.

[2]Changing health insurance comes with its complications. Besides the cost factor, changes in co-pays, deductibles, and possibly changes in doctors, and medical facilities are a hassle when it comes to changing health insurance while the household had dependent children or older adults. In addition, wait times between health insurances, and coverage differences such as coverage for pre-existing conditions also factor in when households decide to change health insurances.

Reconciliation Act (COBRA) in 1985 allowed some workers to continue health insurance coverage via their ex-employer's group plan for 18 months after the termination of employment. For interstate movers, COBRA may not be suited if the ex-employer's health plan's in-network providers are state-specific. The Health Insurance Portability and Accountability Act (HIPAA) of 1996 is another example of an attempt to make health insurance portable across employers. This extended some provisions that COBRA offered without significant changes. Most recently, the Patient Protection and Affordable Care Act (hereafter referred to by ACA) of 2010 was an attempt to make health insurance accessible and affordable for all people with significant provisions that could improve health insurance portability. The ACA, bringing significant changes to the health insurance market was expected to make changes to the labor market as well (Abraham and Royalty, 2017). Because ACA's provisions were not entirely tied to firms, it affected interstate mobility decisions independently as well as via the labor market. However, evidence to suggest that the U.S. labor market changed due to the ACA is scarce with weak evidence (Chatterji, Brandon, and Markowitz, 2016; Dillender, Heinrich, and Houseman, 2016; Bailey and Chorniy, 2016). I suspect this is a result of two opposing effects canceling each other out in the aggregate. Take for example workers who are often offered EBHI and those who are not. The former is likely to depict the effects of health insurance regulation by being reluctant to move between firms. The latter is likely to show the attractiveness of obtaining EBHI via frequently changing employers in search of health insurance coverage. If we assume these effects are identical with opposing signs, it is unlikely to change labor market outcomes in the aggregate. However, this is not to say that there has been no mobility effect from it. First, job mobility has in many ways little to do with residential mobility, especially when it comes to interstate and long-distance mobility. This is because interstate movers are almost always changing jobs and negligible job mobility effects do not inform residential mobility. Second, the ACA's provisions were not only affecting employed populations and their families. The ACA changed coverage standards for young adult dependents, increased spending on public health insurance, and increased access to non-group health insurance access via the health insurance marketplace. These are less likely to be seen in the labor markets although their effects are more likely to be apparent in residential mobility decisions.

My focus in this paper is on long-distance mobility because it is most meaningful in explaining the true effects of increased access to health insurance. I define long-distance as a combination of crossing a distance threshold and crossing an administrative boundary. A given distance threshold is important because it separates workers who are "movers" versus "non-movers" as it indicates a separation from local social capital (Johnson and Kleiner, 2020). I discuss this further in the methodology section that will follow. Administrative boundaries let me isolate meaningful mobility that could have significant health insurance-related consequences. Further, because I am interested in the mobility behavior of people who participate in the labor market, the ideal definition for mobility is also one that takes into account the movement from one labor market to another. A close approximation for this is a metropolitan statistical area (MSA), where a populous cluster is defined around an urban center. The disadvantage here is that it does not cover the entire country and ignores rural areas. The other possible definition is the movement between counties. However, administrative boundaries such as counties are not meaningful without sufficient labor market-based criteria to cluster them. A commuting zone (CZ) is a viable alternative given that it covers the entire country and is based on county aggregations that are relatively easy to determine. A CZ is a labor market-based geographic definition and indicates a movement from one labor market area to another. CZs are defined based on heavy within movement and light between movement of people (Autor and Dorn, 2013), and they are sufficiently large areas that moving between CZs indicates a change in residence as well as employment in most cases.

I measure short-distance mobility as people's movement within and between public use microdata areas (PUMAs) within a single state boundary. The American Community Survey (ACS) measures migration at different levels, the smallest unit of analysis being a PUMA. A PUMA is not an ideal short-distance metric as the size of the PUMA depends on the population density, and because it does not have administrative importance that is sometimes significant when households make short-distance mobility decisions (such as between school districts). However, I do not pursue a more meaningful short-distance metric because I focus on long-distance household movements.

In this paper, I look at recent residential mobility patterns and attempt to explain such trends with changes in relation to EBHI access. I hypothesize that employment-based health insurance is correlated with the decline in the mobility of working-age households. Towards this end, I first turn to available data sources in the United

States that give information on household mobility to understand residential mobility patterns between 2010 and 2019. I use this period to pick up the discussion from where Molloy, Smith, and Wozniak (2011b) and Kaplan and Schulhofer-Wohl (2017b) have left off. This period also coincides with the recovery from the 2008/2009 financial crisis, and with a time when major health insurance reforms were introduced to the county via the ACA. These two effects occurring at the same time could cause potential identification issues that I circumvent using a combination of policy provisions in the ACA.

3.2 Methodology

The ACA and its young adult mandate provide a unique opportunity to test my thesis that health insurance has been a large component in the decline in long-distance mobility. The ACA was introduced in May of 2010, which overhauled the health insurance system making federal requirements on health insurance accessibility, and affordability. Among others, it allowed adult dependents' continued coverage until age 26. However, access to health insurance did not significantly improve until 2015, when all the provisions in the ACA went into effect. Towards identifying how access to health insurance affects long-distance mobility, I present a DiD model of long-distance mobility using individuals who have EBHI, have no publicly provided health insurance, and are over 35 years of age. EBHI is a good measure of health insurance accessibility for non-poor households. Although they are more likely to be mobile than households with other sources of health insurance, there are within-group differences in mobility rates depending on household value placed on health insurance. For example, a household that consists of two working individuals with EBHI and three dependents may be more mobile than households that have public health insurance. However, the former may be less mobile compared to a household with one working adult with EBHI. I make a case that improving health insurance access to those who highly value health insurance decreases their long-distance mobility. In doing so I face several challenges; (1) identifying those who have a higher valuation for health insurance, (2) identifying a measure that is a proxy for access to health insurance, and (3) ensuring validity in this exercise.

Identifying to what extent mobility is affected by the individual value placed on health insurance requires a strategy that will isolate the part that indicates the value of health insurance divorced from other attributes that correlate with lower mobility. I draw parallels with the extensive job-lock literature that looks at EBHI and the likelihood of voluntary job turnover. Literature on worker job-lock has shown that workers are reluctant to change jobs with EBHI not just because of their need for health insurance (and the costs associated with changing healthcare providers), but also because the firms that provide EBHI are also likely to provide other benefits that are attractive to workers (Chute and Wunnava, 2015). I propose to overcome this issue by concentrating on households with adult dependents in residence to identify health insurance needs. Young adults in their early twenties have been a historically underinsured sector of the population that was assured coverage by the ACA. In the pre-ACA era, adult dependents would have only received insurance coverage through their parents' health insurance subject to conditions such as residency, studentship, and age. A majority of non-full-time student dependents would have lost insurance between ages 19 and 21. This, I argue affects household mobility decisions because major labor market milestones would have to have been postponed for households to ensure insurance coverage for their adult dependents.

I use the ACA employer shared responsibility provision (the employer mandate) to indicate access to health insurance, and I assign 2010-2014 as the pre-treatment period and 2015-2019 as the post-treatment period. In the pre-treatment period between 2010 and 2015, EBHI holders were still offered health insurance as determined by their employer. This changed in the post-treatment period when large firms with over 100 employees were required to provide health insurance to their workers (Economic Advisers, 2021). This removed some of the non-randomness of having EBHI (Rae et al., 2020) and increased access to health insurance.

Before the ACA any long-distance mobility study would have had to account for state insurance mandates in origin and destination states to conduct analyses such as mine. Different states have different requirements of minimum coverage for EBHI policies and while they still have those differences, the ACA largely regulated the policy minimums that were relevant to this study thus removing a significant complication. Focusing on between states mobility, I am faced with a potential validity problem due to unobserved quality characteristics that make an individual a short or long-distance mover (White and Mueser, 1988). I follow recent literature to determine short and long-distance mobility by excluding movers within a distance boundary (Johnson and Kleiner, 2020). My boundary radius is 70 miles and this is based on the geographic centers of PUMAs. I determined that individuals that moved within this boundary to be short-distance movers although some of such moves may be across state boundaries and excluded them from my analysis.

$$s2s_{it} = \beta_1 T_t + \beta_2 YA_{it} + \beta_3 (YA_{it} \times T_t) + \beta_4 X_{it} \tag{3.1}$$

In the model described in equation 3.1; $s2s_{it}$ refers to whether individual i moved across states between this year and the previous year, T_t is an indicator variable for the treatment, which in this case is an indicator variable for pre and post-2015. YA_{it} is an indicator variable for those with adult dependents in the household, andX_{it} is a matrix of individual and time-varying attributes that are included to control for other aspects that affect state-to-state movement such as full-time employment status, occupation category, race and age among others.

The DiD strategy, in the absence of additional identification issues, can show how health insurance affects long-distance mobility because the estimator measures the differences in average outcomes between the treatment and control groups before and after the intervention. To make sure that the DiD strategy is valid, two assumptions must be satisfied; (1) that the ACA is a true natural experiment, and (2) paralleled trends. The former is a reasonable assumption to make because no household before deciding to have children would have known about future health insurance provisions. The meaning of the latter is that in the absence of the intervention, the movement of people before and after the treatment would have been the same, or that the designated control group is the true control for this experiment. Before the ACA adult dependents in the household that was at most over 23 years old would have not constrained household mobility because adult dependent coverage does not extend to those who are not full-time students. With the ACA, all EBHI policies were required to provide health insurance to adult dependents constraining mobility in households with adult dependents that are not full-time students nor employed to obtain EBHI on their own. Therefore I define my treatment group to be households with adult dependents between ages 24 and 25, while households with adult dependents between ages 21 and 23 are assigned to the control group. I confirm in Figure 3.1, that the pre-treatment trends of the treatment and control groups are the same.

3.3 Data

The ACS (via IPUMS.org) from 2008-2019 (Ruggles et al., 2021) is the main data source for my empirical analysis. The main reasons for selecting the ACS are its coverage of health insurance access, and mobility. I use ACS data from 2010 to 2019 in my empirical analysis and use data from 2008 onward for my descriptive analysis. The ACS started its coverage on health insurance-related aspects in 2008 and continues to do so. It is extensive in that the ACS collects data on most types of health insurance and records information on participation in state and federal health insurance programs such as Medicaid, and Medicare. I use the

HINSEMP[3] and HCOVPUB[4] to make exclusion on my sample for the empirical analysis. Variable HINSEMP indicates if an individual has EBHI and HCOVPUB reports those who have some form of public insurance coverage. In my sample, I isolate those who have EBHI and no public insurance coverage. The main migration variables I use are MIGRATE1, MIGPLAC1[5], and MIGPUMA1[6]. Variable MIGRATE1[7] records non-movers, within PUMA, between PUMAs, and between state movers. I compare PUMA (coupled with STATEFIP[8]) and MIGPUMA1 (coupled with MIGPLAC1) to determine origin to destination combinations in my data that is then used to determine if a move is a short-distance one or a long-distance one.

One large part of the analysis is the determination of adult dependents. I define adult dependents as those who are children to the head of the household, between ages 19-25, working less than 20 hours a week on average and for less than 40 weeks a year (or not employed at all). I use RELATE[9] in the IPUMS data to determine dependent status, and UHRWORK[10] and WKSWORK[11] to determine financial dependency. I record households with dependent adults that are in each aged from 19 to 25 and create my treatment and control groups using this information. Here, there is potential for one household to be in both the treatment and control groups.

[3]HINSEMP is an indicator variable in IPUMS that reports if an individual has EBHI.
[4]HCOVPUB is an indicator variable that reports if an individual has public health insurance coverage.
[5]MIGPLAC1 is the State from which each individual migrated in the previous year.
[6]MIGPUMA1 is the PUMA from which each individual migrated in the previous year.
[7]Reports each individual's migration status.
[8]State FIPS code
[9]RELATE reports each individual's relationship to the head of the household.
[10]UHRWORK reports the usual number of hours a week one works.
[11]WKSWORK reports how many weeks an individual usually works in a year.

In this event, I exclude those households from my analysis.

3.3.1 Descriptive observations - mobility in the U.S.

In this section, I make a case for health insurance-related losses in mobility by demonstrating long-distance migration patterns by social and economic components. I analyze annual migration patterns for individuals in various age groups, education levels, and racial groups, etc. differentiated by health insurance status. I use annual ACS data for this analysis from 2008 to 2019 (see Appendix B, Table B.1). The descriptive analysis indicated that both within the state and between states migration was lower for those who had employer-based health insurance. This is not surprising as they are likely to experience higher costs when relocating. Within each group of persons with and without employer-based health insurance older age groups saw less migration than younger age groups. Mobility increased with the level of education and was higher for renters than for homeowners. Mobility decreased with the presence of children in the household, and with each additional full-time employed member in the household. These findings are consistent with most similar literature.

CZ to CZ mobility within each category saw a sharp drop between 2011 and 2012 and continued on a generally declining trend. However, the group with no-EBHI saw a faster decline than those with EBHI, and the latter also saw a slight recovery in their numbers. State-to-state mobility was more nuanced. EBHI holders saw an increase in their mobility over the years while those with no-EBHI observed a declining trend. While both between CZs and between states mobility is considered long-distance in this chapter, the differences in mobility trends inform us that between states mobility is more nuanced than between CZs mobility because the latter does not necessarily mean moving away from one's state of residence, and the former may be affected by state-level health insurance provisions.

Two key components can be identified in this descriptive exercise. One of which is that between states mobility is on a path of convergence for the two health insurance groups. I demonstrate this by taking the difference in mobility rates in each health insurance group. The differences have declined in most cases and in some cases, the EBHI group's mobility rates overtook that of the no-EBHI group. The latter was observed in college-educated persons, those who are employed full-time, and in the age group 19-24. I also calculate the growth in mobility in each group between 2008 and 2019; mobility rates grew by 13.3% for those with EBHI and declined by 18.7% in the no-EBHI group. Between CZs mobility differences between the health insurance groups also declined, and for the most part followed the same trends. Both groups showed a negative growth and the no-EBHI group's mobility levels dropped faster (-34.2%) than that of their peers with EBHI (-16.4%).

3.4 Results

3.4.1 Descriptive results

Table 3.1 reports descriptive statistics of adult migrants in whose households at least one adult dependent lived. Between pre and post-treatment periods total mobility levels declined for households with adult dependents. However, between states, mobility increased except for individuals in households with at least one adult dependent between ages 24-25. This tells us that health insurance access may have been an important consideration when individuals decided to migrate, and the level of responsiveness depended on how valuable health insurance coverage is to the household. Table 3.1 also presents a breakdown of mobility rates. Total mobility rates (out of total population) fell for lower education levels between pre and post-treatment periods and rose for those with higher education levels. Comparing this with between states mobility- although overall the trend seemed the same, the increase in-between states mobility is only slight. Total mobility and between states mobility also decreased between treatment periods for those with labor force participation. Like in the case of education, the decline was much greater for those who moved between states. The combined interpretation of all this is that increasing access to health insurance increased long-distance mobility, and the extent of that mobility improvement depended upon how valuable health insurance coverage is for households. My claim that a greater need for health insurance is reflected in the presence of adult dependents in the household and that it will be reflected in the decline in mobility for individuals that have 24-25-year-old adult dependents in the household is somewhat supported by this preliminary study. An increase in the median age of migrants also supports my theory, where the median age for those who moved between states increased while it did not change the total mobility rate. This suggests that perhaps the increase in the median age in between states movers was offset by much younger people increasing their mobility within the state.

3.4.2 Analytical results

The DiD results on the effect of increased access to health insurance on interstate mobility are reported in Table 3.2. The models in Table 3.2 and others are linear probability models that test the probability of interstate mobility out of all long-distance movers. The coefficients indicate the percentage point changes to a baseline average probability in each case. Results of the models show that the interstate mobility decline due to health insurance is around 3 percentage points. That is the probability of long-distance movers making a cross-state move declines by 3 percentage points if they have greater health insurance needs than comparable categories of households. Results suggest that the baseline probability of interstate mobility is about 17 for the control group of households with 21-23-year-old dependents in the pre-intervention period. This baseline probability increases by about 4 percentage points in the treatment group (indicated by positive coefficients in *Adults 24-25*). Additionally, interstate mobility probability further increases by another 4 percentage points in the treatment period for both categories of households. However, the interaction term that suggests the additional probability of interstate mobility for the treatment group in the post-intervention period is negative and significant. This is what suggests that there is a mobility-lock that occurs with health insurance for those who are most in need of it.

I estimate several versions of the main model described in equation 3.1 above. All models account for controlling factors that affect interstate mobility and consist of a full set of origin dummy variables that reports last year's state of residence. After these controlling factors, it is clear that individuals who have adult dependents between the ages of 24-25 years reduce their interstate mobility compared to individuals in households with adult dependents between 21-23 years. I alter the treatment period to 2016-2019 from 2015-2019 in model 2, because the employer mandate of the ACA went into effect in two stages, and because it is useful to see how model results would change as a result of altering the treatment period. Firms with over 100 workers were mandated to provide health insurance in 2015, while firms with over 50 workers were mandated to start providing health insurance in 2016 (Economic Advisers, 2021). I argued in the previous section that 2015 made the largest contribution in providing access to health insurance in this paper because it defined a new era of health insurance provisions and healthcare accessibility. I change this determination in model 2 to check how sensitive my basic model is to this change. With the same number of controls, and fixed effects the coefficient of interest is still negative, and highly significant. In model 3, I truncate the treatment period to 2015 and 2016. The presidential election and the subsequent change in the ruling party brought with it expectations that will change the ACA (Mach, 2017). This may have affected the health insurance markets because the American Health Care Act (AHCA) of 2017 among others suggested eliminating large employer (over 50 employees) tax penalties associated with not providing employees with health insurance, and largely suggested nullifying the changes made by the ACA. Evidence of this is perhaps apparent in the number of insurers leaving the health insurance marketplace post-2016 (McDermot et al., 2016). These suggested changes may have contributed to some changes in mobility behavior and especially in households with young adults over the age of 23. To account for this, I perform the same analysis in equation 3.1 after limiting the treatment group to 2015 and 2016. Results suggest that my findings are not affected by the change in presidential policies on health insurance and the interstate mobility probability reductions remained around 3 percentage points. All other coefficients too remained largely similar across the models.

3.4.3 Robustness of results

The robustness of my results is tested using alternative control age groups. The main part of the analysis used 21-23 young adult resident households, and in this section, two other control groups are considered; households with young adult dependents of age groups 19-23 and 27-29. These results are reported in Table 3.3 and show that compared to the 19-23 age group households of 24-25-year-old dependents were less likely to make interstate moves, and the reduced probability was

3.63 percentage points; not different from the results of the main model in Table 3.2. In the model that juxtaposed interstate mobility between the 24-25-year-old treatment group and the 27-29-year-old control group indicated that it is statistically indistinguishable from zero that the treatment group households reduced their interstate mobility compared to the control group.

Previous studies such as Johnson and Kleiner (2020) tested for the robustness of their results by accounting for multi-level clustering of standard errors. I adopt this method and Table 3.4 shows how accounting for birth state-level clustering and accounting for the birth state in the model change the significance of the coefficients. Results show that households of 24-25-year-old young dependents are less likely to move across states compared to households of comparable age groups and that the effect sizes remained closer to the ones reported in the main models in Table 3.2. These establish that my results are robust to changes in specifications and exacting estimation standards.

3.5 Alternative analyses

Previous studies such as this have relied on alternative data sources to perform robustness analyses (Johnson and Kleiner, 2020). In this case, I am severely constrained by not having enough observations to run a comparable DiD model to establish the robustness of my earlier results using alternative data such as the CPS.

However, I can test my hypothesis in an alternative sample in the ACS by making use of state-wide healthcare provision mandates.

By the time the ACA young adult mandate was introduced, over 30 states had introduced extended health insurance coverage mandates to ensure that adult dependents have access to health insurance (Noble, 2016). These mandates being state-specific have residency requirements in addition to other eligibility requirements such as marital status, studentship, financial dependence, and age. Many states that have extended dependent health insurance coverage mandates require eligible dependents to be residents in the same state as their parents, or even in the same household as their parents. In such events, the ACA dependent care mandate relieved much of the mobility constraints adult dependents would have experienced. It is possible that financial dependency and marital status eligibility (most such eligibility requirements call for unmarried dependents with no dependents of their own) also contributed to the lack of mobility in young adults. This too was eliminated with the ACA. However, by 2016, seven states (Florida, Illinois, New Jersey, New York, Pennsylvania, South Dakota, and Wisconsin) with extended dependent health insurance mandates covered eligible dependents over the age of 26 (Noble, 2016). In these states, we would expect to see more restrictive mobility patterns in adult dependents than in other states, even after the ACA. Recent studies have found evidence of this effect, and have also found that young adult dependents were 3% more likely to be living with their parents due to state-wide extended dependent coverage mandates (Chatterji, Brandon, and Markowitz, 2016).

While state-wide extended dependent health insurance mandates directly affect adult-dependent mobility rates, they can also affect the mobility patterns of their parents; which is the primary research design in this paper. Members of households with adult dependents possibly are constrained in their mobility between states due to state-wide dependent coverage mandates because of differences in state-specific eligibility requirements. In addition, because most state-wide mandates call for residency requirements and studentship, other household members may also experience constraints in their mobility because non-dependent and dependent members in the household have to coordinate efforts to relocate across state boundaries. We make use of this information to identify the effect ACA's young adult mandate has had on household mobility by isolating the study sample to states that have state-wide extended dependent coverage mandates. We then apply the DiD strategy we used in our main empirical section to assess the robustness of our main results.

3.5.1 Alternative scenario 1

In this scenario, I limit my study sample to households with young adult dependents (AD_{it}) in states that have had state-wide extended dependent coverage mandates, based on the states these households were living in the previous year. I make this determination because the state of origin is informative of restrictive mobility behavior. Unlike the main DiD model, I proposed in equation 3.2, in this model (equation3) the treatment period will be from 2011-2014 (τ_t). I am not including years onward of 2014 because the employer mandates of the ACA changed the composition of individuals who were offered EBHI and changed the uniformity of the sample of households. Similar to the main models, I include other control variables such as full-time employment status, age group, occupation, and controls for the state of residence one year ago. These control variables are included in X_{it}. This model assesses the linear probability of moving between states when households have adult dependents.

$$s2s_{it} = \beta_1 \tau_t + \beta_2 DA_{it} + \beta_3 (DA_{it} \times \tau_t) + \beta_4 X_{it} \tag{3.2}$$

Results of this exercise are reported in Table 3.5 Model 1 and show that the introduction of the ACA is correlated with improving mobility levels for households with young adult children living in states with extended dependent coverage mandates (states that would have otherwise restricted interstate mobility). In Model 2, I change the treatment time to 2011-2019 temporarily relaxing identification issues arising from including the period after the employer mandate. This model also established that in states with extended dependent coverage mandates the ACA made state-to-state mobility less restrictive.

3.5.2 Alternative scenario 2

In this scenario, I take into account states that have extended dependent coverage mandates for eligible dependents over the age of 26. I argue that these states create lock-in effects in households with eligible dependents over the age of 26. Similar to models 1 and 2 in Table 3.5, I isolate the sample to those who were residing in states that have state-wide extended dependent coverage mandates and to households with adult dependents between ages 27 and 29. In this model, my variable of interest is an indicator for residence in a state with extended dependent coverage mandates with eligibility for young dependents over the age of 26. This model is presented in equation 3.3.

$$s2s_{it} = \beta_1 \tau_t + \beta_2 SM_{it} + \beta_3 (SM_{it} \times \tau_t) + \beta_4 X_{it} \tag{3.3}$$

Results indicate that among states that have extended dependent coverage, households living in states with eligibility extending to adult dependents over the age of 26 experience rigidities in between-states mobility compared to households with adult dependents of other ages.

3.6 Discussion

Health insurance is an important part of American life that has significant mobility consequences. In this paper, I explore how long-distance mobility is affected by rents associated with EBHI. The ACA with its young adult and employer mandates created a unique opportunity to test this thesis without significant identification concerns. The young adult mandate of the ACA was introduced to provide health insurance coverage to a sector of the population that has historically been uninsured and under-insured. Although the ACA was introduced in 2010, a major accessibility gap was bridged with the employer mandate that went into effect in two stages in 2015 and 2016. With the employer mandate, employees that were traditionally not offered EBHI were offered health insurance indirectly extending the availability of health insurance for adult dependents in those households. Previous studies have found this to have been successful (Akosa Antwi, Moriya, and Simon, 2013; Bailey and Chorniy, 2016).

The objective of this exercise was to determine if there were mobility consequences of EBHI even after significant health insurance portability issues were addressed by the ACA. Before the introduction of the ACA, this would have been understood using workers with pregnant spouses or workers with young children in their households. In a post-ACA era, this would not be possible because many of the provisions that were previously unavailable to all EBHI recipients were mandated by the ACA by imposing minimum coverage guidelines. However, the young adult mandate, despite mandating insurance plans to cover young dependents up to age 26 since 2010, did not increase access until 2015 when large employers were mandated to provide health insurance to all their employees regardless of occupation category. As a result, after 2015 many categories of workers would have newly gotten access to health insurance via the workplace allowing me to study how EBHI affects interstate mobility.

I found that among households with young adult dependents, households with 24-25-year-old adult dependents reduced their mobility after the young adult mandate went into effect by about 3 percentage points. I interpret this as the mobility lock households of young adult dependents face as a result of the young adult mandate that allowed parents to cover their children's health insurance for at least two additional years. I test the sensitivity of my models and their robustness by isolating the analysis to states with state-wide extended dependent coverage mandates. My results indicated that long-distance mobility declined by about 3 percentage points in households (with adult dependents) that were residents of states with extended dependent coverage mandates. Results suggest that my main findings are not sensitive to differences in specifications and robust to alternative analyses.

The contribution of this paper to the existing literature is twofold. First, it exhibits interstate mobility constraints that are attributed to EBHI, and second, this study depicts how important health insurance is for households with adult dependents who have historically been under-insured or uninsured.

With aging populations, even workers that are older and closer to traditional retirement ages remain competitive in the labor markets (Dychtwald, Erickson, and Morison, 2004). Therefore, mobility constraints of older populations have important labor market implications. By showing how EBHI affects worker mobility decisions, I can show the lock-in effects of households that have adult dependents to continue to provide health coverage. The latter contribution of this paper is to show how important health insurance is for young adults that have completed their full-time education but are not in employment that offers EBHI. This group of individuals has unique healthcare needs and literature has found that after the introduction of the young adult mandate of the ACA utilization of insurance has increased for said health concerns (Antwi, Moriya, and Simon, 2015; O'Reilly et al., 2020; Golberstein et al., 2015). This paper also contributes methodologically to the "job-lock" literature by introducing a new method of instrumenting for healthcare needs. According to Gruber and Madrian (2002), most health instrumentation strategies used to test for "job-lock" does not adequately address "healthcare need." For example, testing for job-lock using workers with pregnant spouses is unlikely to provide accurate estimates because these health events are rare and not likely to occur regularly. Similarly, testing for job-lock in households with only one spouse as the primary health insurance holder is also unlikely to be an adequate proxy for health insurance needs because workers could anticipate changes to health insurance providers before making job changes. In this regard, the current instrumentation strategy is superior because health insurance needs for young adult dependents are constant and continuous.

While this paper covers one of the inadequately studied areas in internal migration literature, the estimates of mobility reduction may be underestimated. The main reason for this is that the data does not allow me to identify workers that provide health insurance for young adults living outside of the home[12]. This excludes most college students that do not live in dormitories (in the ACS dormitory students are counted in their parents' household). Another shortcoming of this study is that the coefficients may be confounded by retirement decisions. Most households that rely on one member of that household to provide health insurance for the entire household will often find that one spouse becomes eligible for Medicare

[12]In the ACS, students living in dormitories are identified as if they are living at their parent's home. However, students that live outside of their parents' homes and outside of dormitories are counted as separate households even if they share their dwelling with other non-relative individuals.

sooner than the other. If the younger spouse is unemployed or relies on the older spouse for health insurance, often the older spouse may postpone retirement, and by extension postpone mobility temporarily. The sample of workers in my sample may also fall into this category and I have not accounted for that in the main analysis. However, this has been tested by including all household members in a family as opposed to only working members and those who are over the age of 64 to see if mobility patterns remain robust to this change in specification. This exercise (not reported in this study) showed that older workers and their spouses reduced their interstate migration by about 60 percentage points.

Although this study shows that households with young adult dependents change their migration behavior because of additional health-insurance responsibilities, the declining rate of migration for households with 24-25-year-old adult dependents indicates that there is some form of adjustment that occurs in these households. One possibility could be that their retirement decisions and mobility decisions overlap due to facing mobility constraints. With aging populations and low birth rates, older workers are still competitive employees in the workplace, and as a result, their interstate movements may not exactly match their life-course changes. However, given that there is evidence for retirement postponing due to spousal health insurance coverage difficulties, the two additional years of immobility may coincide with the time retirement postponing occurs. The combined effects may be a compounded mobility-lock that creates a downward slope in working adults' interstate mobility patterns after 2015.

The second possibility is that the model captures a disproportionately larger proportion of young adults that are more dependent on their parents than others; which is somewhat similar to a selection issue. While this might be true as per the literature that suggested young adults were more frequently returning to their parents' homes. Reasons for such dependency may not be due to changes in young adult psyche and rather a response to income and employment shocks they face now more than previous generations did. What bolsters my confidence that this study does not suffer from a selection issue is that in the pre-treatment period, both treatment and control group households moved in the same direction.

3.7 Conclusion

The objective of this study was to understand the interstate migration effects of health insurance. If EBHI is only as valuable as how much it costs, most households will not be constrained by EBHI in their migration decisions. In reality, some households value health insurance more than the financial cost of providing it. Therefore instrumenting for this "healthcare need" remains one of the important aspects of studying residential mobility or job-mobility about health insurance. In this paper, I suggest a new instrument that makes use of the young adult and employer mandates of the ACA. I find that households with young adult dependents (24-25) reduce their mobility by about three percentage points compared to households with young adult members of comparable age groups (19-23 and 27-29). However, these estimates are likely to be lower bounds of the true estimates of mobility-lock because I do not capture young adults that are not living in their parents' home (yet dependent on them for health insurance coverage) in my sample.

3.8 Tables

TABLE 3.1: Mobility trends of households with EBHI and at least one young adult dependent in the household

	Within and between states							
	2010-2014				2015-2019			
	19-25	19-23	21-23	24-25	19-25	19-23	21-23	24-25
Total	0.160%	0.142%	0.073%	0.019%	0.135%	0.117%	0.064%	0.018%
Education								
No school	3	3.02	3.32	3.24	1.71	1.73	1.8	1.54
Some school	20.69	20.64	21.26	22.01	8.55	8.45	9.03	9.31
Hight school	30.93	30.76	30.61	31.36	25.7	25.44	24.72	27.24
Some college	25.02	25.1	23.66	23.92	28.62	28.39	28.75	30.53
College	20.36	20.47	21.16	19.48	35.42	35.99	35.7	31.38
Labor								
Not in LF	13.45	12.94	13.47	16.87	14.03	13.48	14.07	17.61
LF	86.55	87.06	86.53	83.13	85.97	86.52	85.93	82.39
Race/Age								

NH White	55.44	55.1	55.32	56.6	58.83	58.95	58.54	57.27
NH Black	23.64	23.52	24.15	24.69	19.34	19.46	21.04	18.55
Hispanic	20.92	21.38	20.53	18.71	21.82	21.59	20.42	24.18
Median age	48.83	48.37	49.62	52.04	49.51	49.08	50.32	52.29
Income								
Bottom 50%	63.54	63.62	62.91	63.16	48.84	48.49	47.17	51.8
Top 50%	36.46	36.38	37.09	36.84	51.16	51.51	52.83	48.2
Between states								
	2010-2014				2015-2019			
	19-25	19-23	21-23	24-25	19-25	19-23	21-23	24-25
Total	0.016%	0.013%	0.007%	0.003%	0.020%	0.018%	0.010%	0.003%
Education								
No school	0.73	0.8	0.36	0.3	0.46	0.45	0.47	0.7
Some school	3.83	3.08	3.07	7.21	4.68	5.09	2.48	4.31
Hight school	23.78	22.62	23.42	28.18	22.53	21.5	27.69	23.29
Some college	26.15	26.89	24.77	22.85	25.7	25.72	27.05	29.08
College	45.51	46.6	48.38	41.46	46.63	47.24	42.3	42.62

Labor								
Not in LF	22.32	22.63	21.7	19.23	22.82	21.77	20.79	27.52
LF	77.68	77.37	78.3	80.77	77.18	78.23	79.21	72.48
Race/Age								
NH White	72.79	75.25	78.88	59.51	70.65	72.63	72.49	59.37
NH Black	16.48	16.04	13.01	20.44	15.29	15.82	18.1	13.38
Hispanic	10.74	8.71	8.11	20.05	14.05	11.54	9.41	27.25
Median age	50.57	50.04	51.51	53.25	51.14	50.55	51.84	54.41
Income								
Bottom 50%	45.78	46.76	47.06	42.58	39.85	38.46	39.77	50.03
Top 50%	54.22	53.24	52.94	57.42	60.15	61.54	60.23	49.97

This table summarizes some key characteristic of people who are moving over 70 miles away from their origin in the previous year. These are author calculations and data comes from 2010-2019 ACS from IPUMS-USA. *Total* refers to persons 35 years of age, with EBHI, no public insurance coverage that moved as a percentage of the total population. These summary statistics belong to individuals over 35 years of age, with EBHI, no public insurance coverage holders in the households, and with at least one adult dependent in the household. Income categories are defined using real total family income (*ftotinc*) at 1999 constant U.S. dollars.

TABLE 3.2: DiD results: the effect of increasing access to health insurance on interstate mobility in households of adult dependents

	(1)	(2)	(3)
	21-23	21-23	21-23
Treatment	0.0381***	0.0383***	0.0336***
	(0.0008)	(0.0009)	(0.0011)
Adults 24-25	0.0440***	0.0406***	0.0445***
	(0.0012)	(0.0011)	(0.0012)
Treatment × Adults 24-25	-0.0313***	-0.0302***	-0.0282***
	(0.0018)	(0.0019)	(0.0024)
Intercept	0.1735***	0.1778***	0.1761***
	(0.0016)	(0.0016)	(0.0018)
Obs	690,245	690,245	491,700
Controls	Y	Y	Y
Destination FE	Y	Y	Y
Standard errors are in parenthesis			
*** p<0.01, ** p<0.05, * p<0.1			

DiD models reported above are linear probability models using the OLS estimator. Data for models are from ACS 2010-2019 (IPUMS-USA). Sample consist of adults over the age of 40, with EBHI, belong to households with none participating in public health insurance programs, and have moved at least 70 miles away from the PUMA of origin (last year's PUMA). Control group young adult age category is reported below model numbers. Models differences are based on treatment time period; Model 1 treatment was 2015-2019, Model 2 treatment was 2016-2019, and Model 3 treatment time was 2015-2016. All models include a complete set of control variables (age, race and Hispanic origin, full-time employment, year dummy variables, and broad occupation definitions), and a full set of indicator variables for the state of origin (state of residence last year. Robust standard errors were assumed when estimating the models.

TABLE 3.3: Robustness check: the effect of increasing access to health insurance on interstate mobility in households of adult dependents by multiple control groups

	(1)	(2)
	19-23	27-29
Treatment	0.0363***	0.0096***
	(0.0006)	(0.0016)
Adults 24-25	0.0466***	0.0098***
	(0.0012)	(0.0015)
Treatment × Adults 24-25	-0.0368***	-0.0041
	(0.0017)	(0.0022)
Intercept	0.1597***	0.3154***
	(0.0011)	(0.0031)
Obs	1,320,788	322,968
Controls	Y	Y
Destination FE	Y	Y
Standard errors are in parenthesis		
*** p<0.01, ** p<0.05, * p<0.1		

DiD models reported above are linear probability models using the OLS estimator. Data for models are from ACS 2010-2019 (IPUMS-USA). Sample consist of adults over the age of 40, with EBHI, belong to households with none participating in public health insurance programs, and have moved at least 70 miles away from the PUMA of origin (last year's PUMA). Control group young adult age category is reported below model numbers. All models include a complete set of control variables (age, race and Hispanic origin, full-time employment, year dummy variables, and broad occupation definitions), and a full set of indicator variables for the state of origin (state of residence last year. Robust standard errors were assumed when estimating the models.

TABLE 3.4: Robustness check: the effect of increasing access to health insurance on interstate mobility in households of adult dependents with cluster standard errors

	(1)	(2)	(3)
	21-23	19-23	27-29
Treatment	0.0393***	0.0377***	0.0306
	(0.0101)	(0.0075)	(0.0206)
Adults 24-25	0.0458**	0.0491**	0.0238
	(0.0170)	(0.0179)	(0.0206)
Treatment × Adults 24-25	-0.0375*	-0.0397*	-0.0282
	(0.0179)	(0.0195)	(0.0303)
Intercept	0.1671***	0.1516***	0.2808***
	(0.0173)	(0.0118)	(0.0485)
N	690,245	1,320,788	322,968
Controls	Y	Y	Y
Destination FE	Y	Y	Y

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

DiD models reported above are linear probability models using the OLS estimator. Data for models are from ACS 2010-2019 (IPUMS-USA). Sample consist of adults over the age of 40, with EBHI, belong to households with none participating in public health insurance programs, and have moved at least 70 miles away from the PUMA of origin (last year's PUMA). Control group young adult age category is reported below model numbers. All models include a complete set of control variables (age, race and Hispanic origin, full-time employment, year dummy variables, and broad occupation definitions), and a full set of indicator variables for the state of origin (state of residence last year. Robust standard errors were assumed when estimating the models.

TABLE 3.5: Alternative analysis: mobility consequences of ACA in states with extended young adult dependent health coverage requirements

	(1)	(2)
	Any YA	Any YA
Treatment	-0.0093***	-0.0030***
	(0.0005)	(0.0004)
YA Adults	-0.0354***	-0.0375***
	(0.0006)	(0.0006)
Treatment × YA Adults	0.0263***	0.0348***
	(0.0008)	(0.0007)
Intercept	0.2142***	0.2008***
	(0.0008)	(0.0006)
Obs	2,620,051	4,693,006
Controls	Y	Y
Destination FE	Y	Y
Standard errors are in parenthesis		
*** p<0.01, ** p<0.05, * p<0.1		

Model 1 describes how the ACA young adult mandate relieved the mobility-lock state-wide extended coverage mandates have created and the treatment period was from 2011-2014. Model 2 is identical to Model 1, but the treatment period was altered to 2011-2019.

DiD models reported above are linear probability models using the OLS estimator. Data for models are from ACS 2010-2019 (IPUMS-USA). Sample consist of adults over the age of 40, with EBHI, belong to households with none participating in public health insurance programs, and have moved at least 70 miles away from the PUMA of origin (last year's PUMA). Control group young adult age category is reported below model numbers. All models include a complete set of control variables (age, race and Hispanic origin, full-time employment, year dummy variables, and broad occupation definitions), and a full set of indicator variables for the state of origin (state of residence last year. Robust standard errors were assumed when estimating the models.

TABLE 3.6: Alternative analysis: mobility consequences of ACA in states with extended young adult dependent health coverage requirements for adults over 26 years

	(1)
	Extended Mandate
Treatment	0.0458***
	(0.0024)
SM 26+	
Treatment × SM 26+	-0.0705***
	(0.0050)
Intercept	0.3634***
	(0.0047)
Obs	119,964
Controls	Y
Destination FE	Y
Standard errors are in parenthesis	
*** p<0.01, ** p<0.05, * p<0.1	

Model 1 describes how state-wide extended coverage mandates with eligibility over 26 years of age affected between states mobility in households of 27-29 year old dependents. DiD models reported above are linear probability models using the OLS estimator. Data for models are from ACS 2010-2019 (IPUMS-USA). Sample consist of adults over the age of 40, with EBHI, belong to households with none participating in public health insurance programs, and have moved at least 70 miles away from the PUMA of origin (last year's PUMA). Control group young adult age category is reported below model numbers. All models include a complete set of control variables (age, race and Hispanic origin, full-time employment, year dummy variables, and broad occupation definitions), and a full set of indicator variables for the state of origin (state of residence last year. Robust standard errors were assumed when estimating the models.

3.9 Figures

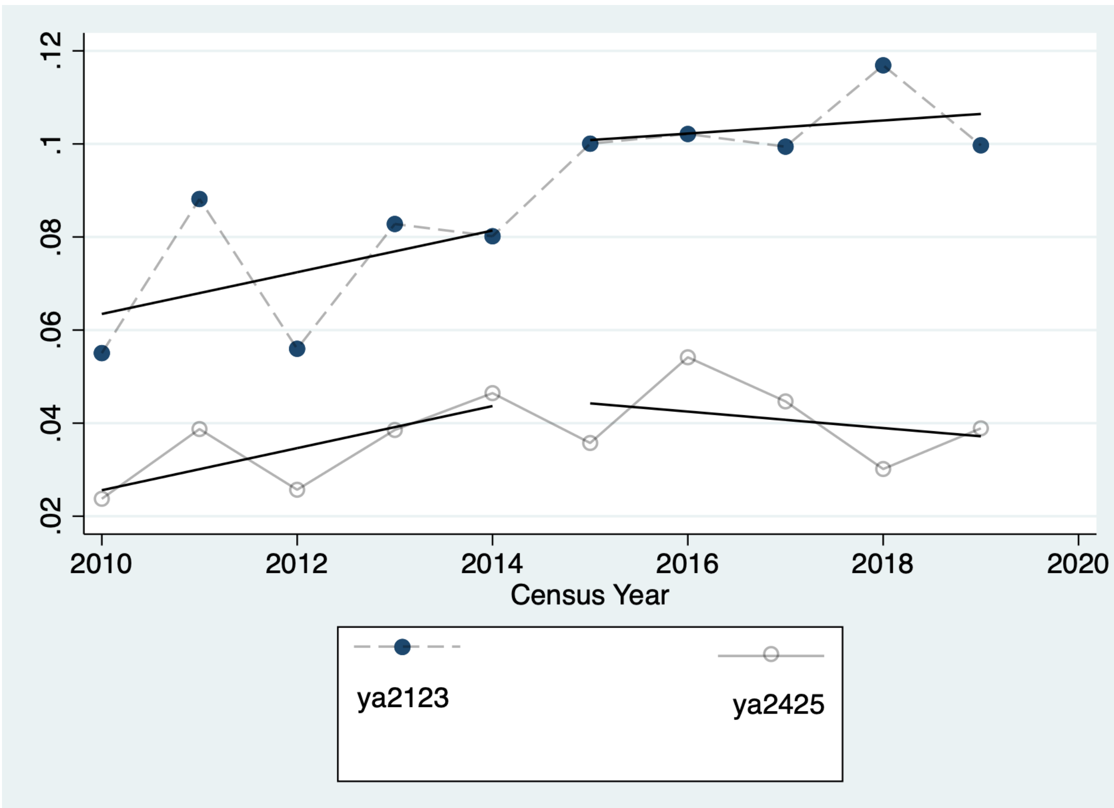


FIGURE 3.1: Share of between states movers with EBHI and over 35 years old by the presence of adult dependents in the household.

The employer mandate of the ACA increased access to health insurance to workers that previously would not have been offered EBHI. With this, their dependents were also eligible for health insurance as adult dependents. Most households with EBHI would have had dependent coverage benefits as long as eligible dependents were full-time students. Age 23 being the most common age for students to have graduated from four year college, households with 24-25 year old dependents would have been most affected by the young adult mandate of the ACA. In the above graphic, I show how mobility trends in persons with adult dependents (age 21-23) in the households have largely continued even after accessibility of EBHI improved as a result of the employer mandate of the ACA. Mobility in households with adult dependents (ages 24-25) show a clear decline.

Chapter 4

Working from home and its effect on return-migration in the United States

4.1 Introduction

Alongside the decline in interstate mobility in the United States, there has also been a movement of people into their birth states. This is stronger than the movement of people venturing out of their birth-states[1]. Previous literature has explained such return-migration trends as household responses to increasing care responsibilities and consumption smoothing. However, this may not be a complete explanation because households that choose to move to their birth states are not all traditionally vulnerable groups. High-wage earning, and educated households seem to be making such moves as much as others, perhaps even more.

[1] see Figure 4.1 and explanation later in the introduction

Is it attachment to one's birth state, relationship with kith-and-kin, and familiar surroundings that drive return-migration in the United States? The objective of this paper is to attempt to answer this question. Using descriptive methods and a unique sample of full-time workers that work from home, the results of this exercise contribute to the understanding of how interstate mobility could change in the foreseeable future with remote work becoming a viable alternative to in-person employment in some sectors. This study is also expected to contribute to the discussion of immobility, which most migration literature seems to have ignored.

More recently, The Covid-19 pandemic seems to have exacerbated the trend of moving home. However, much of the evidence to this effect is anecdotal. Researchers have long been focusing on the internal mobility of American households (since 1970) and have put forth several explanations for the reluctance to leave one's birth state and for return migration, among which are increasing care responsibilities owing to widening dependency, and increasingly longer employment tenures. However, research into the determinants of return-migrations and determinants of immobility are sparse with a few notable exceptions such as Leibbrand et al. (2019), Compton and Pollak (2014), Kahn, Goldscheider, and García-Manglano (2013), Schewel (2020) and Kaplan (2012). In this paper, I attempt to contribute to the discussion of immobility and return-migration in working American households by trying to understand how Americans are connected to their birth states and kinship networks. I find evidence to challenge the idea that immobility and return-migration are related in their motivations. Instead, I find that voluntary immobility has increased because workers have lost gains from mobility owing to wages equalizing and labor markets being homogeneous.

Internal migration in the United States has been the focus of social scientists because mobility rates have been dwindling in recent decades. Perhaps this is not surprising in a historical sense, as the United States has always experienced booms and busts of migration. Therefore, I focus on internal mobility in the short-run. A detailed discussion of mobility trends is offered in Chapter 1. Many of the highly cited studies found that labor market conditions closely mimicked migration patterns and went on to suggest that lower labor market churning and changes in the labor markets themselves were driving the increase in immobility. For example, Molloy, Smith, and Wozniak (2011a) found that slow labor market churning and slow job mobility was causing the mobility downturn, while Kaplan and Schulhofer-Wohl (2017a) found that better information flows and homogeneous return to labor were making repeated migration redundant. Others postulated that low internal migration is a response to increasing access to information technology and telecommunication, rise in dual-earner households, changes in family structure, dependence on social networks for sharing care responsibilities, preferences for amenities similar to that one grew up with, cultural preferences, and rising income inequality (Cooke, 2013; Cooke, Mulder, and Thomas, 2016; Wozniak, 2010; Albouy, Cho, and Shappo, 2021; Fan, Klaiber, and Fisher-Vanden, 2016). Parallel location choice trends of sorting by skill levels (Diamond, 2016), increasing probabilities of co-residence with parents (Fry, 2017; Smits, 2010), and evidence of better labor market performance of workers with physical family ties (Compton and Pollak, 2014) suggest that internal migration may also be affected by attachment to family and birthplace[2].

However, out of those that are still mobile, especially mobile across administrative boundaries, there is a clear rise in those who choose to move back to their birth-states. Figure 4.2 shows the migration rates of the total population in the United States, and how migrants within and outside of their birth states contribute to the overall trend. This figure shows two obvious points of interest: (1) residents already living in their birth states are moving less[3], and (2) a larger portion of intrastate movers move to live in their birth states and once arrived, seemingly move within its boundaries more often than they venture out. Logically, if more interstate movers are those living outside of their birth state, they must be moving to locations that are closer to their states of birth. I test this hypothesis in Figure 4.3 where I show return migration in the previous year as a share of the total population that moved across state boundaries. This figure can support the hypothesis that more movers have been moving back to their states of birth. This provides some evidence that mobility contribution from individuals not living in their birth-states towards interstate migration is positively correlated with the growth in individuals returning to their birth-states. Coupled with rising immobility in people already living in their birth states, and increasing shares of interstate movers moving to their birth states suggests that immobility and mobility (especially return-migration) cannot be entirely separated when trying to understand their determinants.

[2]I note that there may be cases where people moved away from their birth-state at an age not old enough to form location-specific attachments. However, with over 80% of all children under the age of 15 still living in their birth states, this is unlikely to affect the thesis of this project.

[3]Although both categories of people are moving less, those living in their birth states are reducing their mobility at a steeper rate compared to those living outside of their birth-states

Mobility and immobility are two profoundly related subjects that have nuances over and above one being the inverse of the other. In a recent paper by Schewel (2020), the author argues that migration studies are biased against immobility. Using an aspirations-capabilities framework, the author shows that there are as many reasons for immobility as there are for mobility and need further examination. The increasing frequency of interstate movers choosing to move back home perhaps is a commentary on how related mobility and immobility are. I demonstrate this further using figure 4.1 where I show how movers to and from their birth states have changed over the years. The top panel shows figures that indicate the relationship between return migrants and those who left their birth-states in the previous year. The top right-hand side panel, which uses a sample of the working-age population has a steeper increase in their return-migration compared to others (top left-hand side). The overall increase in return migration can occur either by increasing return migration or decreasing those who leave their birth state. The bottom panel of figures shows that it is a combination of both that had created an overall increase in return-migration suggesting that return migrants subsequently become immobile.

Researchers have established that household location choice decisions are made by maximizing utility over location-specific wages, housing costs, amenities, and moving costs (Bayer, Keohane, and Timmins, 2009; Rosen, 1979; Sjaastad, 1962). Kinship ties affect this household problem by affecting moving costs. Moving costs are both financial in the short-distance and emotional in the long-distance (Sjaastad, 1962). Since Sjaastad (1962), a large body of literature, especially outside of economics has gone on to show the importance of family ties as a significant determinant of immobility; both voluntary and involuntary (Bengtson, 2001; Greenwell and Bengtson, 1997; Grundy and Shelton, 2001; Knijn and Liefbroer, 2006; Michielin, Mulder, and Zorlu, 2008; Pettersson and Malmberg, 2009). Emotional costs of moving away from kin and familiar surroundings often exist when individuals are dependent on their kin to share care responsibilities. (Spring et al. (2017)) show that close relatives residing closer to each other are less likely to move away while proximity to aging parents, and children encourages movement close to each other. (Gillespie and Mulder (2020)) also show similar motivations. Although most such research classifies kinship networks as a motivation for internal migration separate from moving for economic motives, in reality, it is hard to do so. For example, according to the United States Census Bureau, a large share of childcare responsibilities in American families are borne by grand-parent and relatives Bureau (2013), and grand-parents physical proximity has been positively attributed to female labor force participation (Compton and Pollak, 2014). As childcare can be a significant burden, this is likely to affect the migration choices of households who rely on their kin for care responsibilities. Similarly, population aging contributes to longer relationships between older adults and their adult children (Cooke, 2013) which is also expected to contribute to significant migration costs. Others such as Grundy and Shelton (2001), Knijn and Liefbroer (2006), and Michielin, Mulder, and Zorlu (2008) and Pettersson and Malmberg (2009) also find that proximity to kin increases the chances of gaining support from them, which can be a powerful motivation for remaining closer to one's kinship network.

In this light, a broad question arises as to what drives return-migration (and immobility thereafter). A survey of literature on determinants of return-migration showed a common theme: moving to reduce care costs. Increasing childcare costs (Landivar, Ruppanner, and Scarborough, 2021; Ruppanner, Moller, and Sayer, 2019; Ruppanner et al., 2021) and an aging population (Pettersson and Malmberg, 2009) demanding more care from the working-aged (dependency) may have contributed to a redistribution of populations across locations. Similarly, Kaplan (2012) finds that returning home acts as a risk mitigation mechanism for young adults. In Table 4.1 I show some basic statistics of residents living in their states of birth and returning to their states of birth. What is obvious to see is that residence in the birth state on average decreased for most categories suggesting that people are not moving into their birth states. After interacting some of these demographic categories with the "college education" component (as a proxy for lower economic vulnerability) I find that the reverse is true. Therefore, recent mobility patterns do provide evidence to suggest that individuals who are moving into their birth states and continue to live in their birth states do not belong to traditionally vulnerable populations.

By challenging the consensus that immobility and return migration to one's birth state is involuntary and is a response to the economic vulnerability I seek to show to what extent attachment to one's birthplace affects household residential location choice. In doing so I am immediately faced with the challenge of finding a strategy that allows for the identification of preference for living closer to one's birthplace divorced from competing motivations such as economic vulnerability and social necessity. Drawing on the Covid-19 pandemic experience, I find that remote workers and workers with flexible work arrangements can answer the question of how important birthplace is in the determination of residential location choice of working households in the United States.

Remote workers (including before the Covid-19 pandemic) and workers with flexible work arrangements are often those that are more educated, belong to the majority race, and are generally not considered vulnerable populations (Irlacher and Koch, 2021; Mongey and Weinberg, 2020; Arntz, Sarra, and Berlingieri, 2019). They work in industries and occupations that are dominated by a college-educated workforce and generally enjoy higher wages (Althoff et al., 2022). As a result, they are less likely to be burdened with situations that make it necessary for them to depend on their kin for day-to-day support. This group, therefore, can represent a reasonable control group against a treatment group of remote workers to test my thesis that workers are increasingly finding it preferable to live closer to their kin and birth-states and that subsequent immobility is not a response to economic vulnerability. In doing so I answer the following research question: how important is the birthplace in household location choice decisions?

In doing so, I first define proximity to family to be a variable that describes how geographically near an individual is to one's state of birth. I use this definition because most nationally representative data sources (such as the American Community Survey and the Current Population Survey) birthplace is recorded at most at the state level. However, I concede the point that while birth-state records provide some information, it is insufficient to make a meaningful assessment of the true motivations for moving into (or close to) one's state of birth and that moving into one's birth state does not necessarily mean geographical proximity to kin and familiar social networks. However, location choice literature has shown that amenities in the birth-states have a bearing on preferences for amenities when individuals make location choice decisions (Fan, Klaiber, and Fisher-Vanden, 2016; Sinha and Cropper, 2013). Other similar studies have found that individuals have preferences for living among others that are racially, culturally, and socioeconomically similar (Bayer, Fang, and McMillan, 2014; Albouy, Cho, and Shappo, 2021). This evidence suggests that, although state-of-birth is limited in the amount of information it can provide in terms of understanding proximity to kin, it can be a close approximation.

In the next section of this paper, I will attempt to explain worker preferences for living closer to family using a combination of full-time working non-poor households commuting to work and working from home to show how flexible working arrangements re-order household priorities. This work is expected to contribute to the broader literature on internal migration in the United States, and the understanding of mobility costs in household location choice. To a lesser extent, this work is expected to contribute to the understanding of the future expectations of internal mobility at a time when working-from-home is expected to be a mainstream labor market experience.

4.2 Methodology

In the absence of post-pandemic migration data to test if newly appointed remote workers are more likely to be mobile across state boundaries and if those interstate movers are more likely to be moving back to their states of birth, I turn to pre-pandemic remote workers and their mobility decisions. My estimation strategy exploits pandemic period work-from-home arrangements to establish a pool of occupations that are equipped to deal with remote workers by isolating occupations in which over 50% of workers worked from home during the pandemic. I categorize these occupations as "high remote potential" (hereafter referred to as HRP) jobs because these occupations are more likely to be continued as remote or hybrid employment even after the pandemic ends. Based on this classification of occupations, I limit my sample to workers of HRP occupations. I do this to ensure that the models are not confounded by the mobility decisions of workers of "lower remote potential" occupations.

4.2.1 Timeline

Although the preceding section discussed return-migration in the past two decades, when attempting to study how return-migration may be affected by flexible employment, I need to pay attention to the timeline. For reasons that I will explain shortly, I will focus on 2008-2019 going forward as the timeline for the main part of the analysis.

The remote potential of jobs increased with advancements in technology such as broadband internet, portable computing devices, and telecommunication (such as Microsoft teams, Skype, or Zoom). This, however, happened at least after 2005, when the United States for the first time had more broadband connections than dial-up (Horrigan, 2005). Unrelated to the viability of remote work, in 2005, the United States faced one of the most deadly hurricanes in its history that changed the migration patterns of people that I study; those who might be leaving or returning to their birth state. Therefore, for an analysis that looks at how flexible-employment affects migration, I am forced to use data from after 2008 and onward.

4.2.2 "Movers" versus "Non-Movers"

In this analysis, one of the essential pre-analysis steps is to establish the distinction between a "short-distance" mover and a "long-distance" mover (see Chapter 1 for a discussion). Using detailed migration information from the ACS I further limit my sample to movers who migrated long distances between the previous year and the year of enumeration. This is aimed at excluding "non-movers" from the sample because they can confound the estimates of the analysis. Using the migration data provided in the ACS I defined "movers" to be those who relocated from any one place of residence to another. I define "long-distance movers" as those who relocated between non-contiguous Public Use Microdata Areas (PUMAs). While this indicates movers are less risk-averse to migration than "non-movers," their level of risk acceptance depends on the size of the PUMAs. For example, PUMAs in New York City and Northern New Jersey are small and closer together that movers between non-contiguous PUMAs may not depict the qualitative differences between "movers" and "long-distance movers." Therefore, I include a distance cut-off following studies such as Diamond (2016)[4] and Johnson and Kleiner (2020)[5] of 70 miles between the origin and destination of movers who migrated between non-contiguous PUMAs. The distance threshold was imposed to ensure that it reflects an unreasonable distance for a daily commute, as such, movers over 70 miles are likely to have changed employers as well as residences.

I account for another potential source of bias; that some workers may be attached to one's state of birth already that they are averse to moving away. These segments of workers may be for the most part accounted for in limiting the sample to long-distance movers. However, to account for any residual biases, I further limit my sample to workers that lived in states outside of their birth in the previous year. By accounting for workers who have made long-distance moves and remained within their state of birth I am preventing my estimates from being larger than they are.

[4]Diamond (2016) uses a 70-mile distance cut-off in her calculation of national wages when creating her instrumental variables. This cut-off was intended to exclude the immediate periphery of a local city.

[5]Johnson and Kleiner (2020) uses a distance cut-off of 50 miles to determine "movers" versus "non-movers"

4.2.3 Estimation

With these exclusions, the sample used in the analysis consists of households of which heads-of-households are full-time wage employees between 25 and 64, and not living in their birth states. These workers are employed in HRP occupations and moved over 70 miles and across PUMA boundaries in the previous year.

My primary estimation equation, which is a linear probability model of inter-state return-migration takes the following form:

$$rtn_i = \beta Remote_i + \alpha X_i + (S \times T) + B + \epsilon_i \tag{4.1}$$

Where, *rtn* stands for return-migration of household i, which is explained by *remote* which is an indicator variable for the head-of-household's remote-work status that takes the value 1 if true and 0 otherwise. The term X stands for an array of observable individual and household level characteristics such as age, income, sex, children in the households, marital status, etc. $S \times T$ is a list of state-by-year fixed effects, B is a list of birth state fixed effects, and ϵ is a conventional error term.

After defining the samples used for the analysis my coefficients of interest β indicate a causal effect between full-time remote work and return-migration under two assumptions. One, that remote workers are divorced from physical connections to the workplace, and two, that there exist no other biases in the samples than what has already been accounted for.

The first assumption relies on identifying workers who are true remote workers over those who work from home on an irregular basis. While I have no method of establishing this distinction, I note that over two-thirds of all remote workers live in households in which all full-time working adults are remote workers. This indicates that a majority of remote workers and their households are qualitatively similar, providing suggestive evidence to ignore the concern of potentially having included non-remote workers in the samples[6].

The second assumption relies on how well I have controlled for sources of bias in the analysis. I include a rich set of control variables and exclusions to account for most biases that can be controlled using observable characteristics. However, this is not to say that there are no other selection issues that may cause estimates to be biased. One such instance may be workers selecting into remote work because they form stronger attachments to their kin or because they are unable to work on-site, such as disabled workers Schur, Ameri, and Kruse, 2020. I partly account for this when I exclude those who were already living in the birth state and by including only those who moved longer distances between the year of enumeration and the one before. I make the case that those who are self-selecting into firms and occupations that are offering remote work because they want to move back home are unlikely to have left home or would only have traveled a shorter distance in the first place. In essence, I argue that the sample consisted of heads-of-households that traveled over 70 miles, moved between non-contiguous PUMAs, and moved across state boundaries that also did not live in their birth state in the previous year sufficiently satisfy the conditions to establish reasonable causality.

[6]However, this also suggests that remote workers make a conscious decision to work from home and may be different (perhaps more attached to birth-state) from other households that are in similar occupations and industries.

4.3 Data

A majority of the analysis in this paper is carried out using the American Community Survey (ACS) one-year surveys from 2008 to 2019 (Ruggles et al., 2021). In the ACS there exists a variable TRANWORK that asks people about their mode of transportation for their place of employment. This variable has an option assigned to indicate if one works from home. I use this indicator coupled with EMPSTAT[7] and CLASSWKR[8] to determine wage-employees working from home. EMPSTAT assures that the individual is active in the labor market, and CLASSWKR allows me to exclude those who are self-employed.

Although working from home is now an essential part of the labor market experience for some workers, before the Covid-19 pandemic, working-from-home only described about 4% of full-time wage working adults between the ages 25 and 64[9]. This number, however, has been increasing for the last two decades, albeit gradually, and by 2020 the share of remote working adults described 17% of all full-time wage workers between 25 and 64. However, a majority of these remote workers were forced to work from home due to the Covid-19 pandemic and are unlikely to continue to do so.

[7]EMPSTAT reports the labor market status of each individual.
[8]CLASSWKR reports if each individual works for wages/salaries or if one is self-employed.
[9]Author calculations using the 2019 American Community Survey.

4.3.1 Variables

My empirical analysis in this paper relies on ACS and CPS data from IPUMS (Ruggles et al., 2021; Flood et al., 2021). I use ACS data from 2008 to 2019 and CPS basic monthly survey data from 2020 to 2021. Main individual and household level data samples are derived from IPUMS-USA where I limit the sample to heads-of-households, 25-64 years of age who are full-time wage employees with no farm or business income. I define full-time workers as those who worked over 48 weeks a year and 35 hours a week in the previous year. I exclude workers who are self-employed in this analysis and individuals under 25 years even if they are full-time employed.

There are two variables of interest in this study; (1) indicator for interstate movers, and (2) indicator for return-migrant. I define an interstate mover as one who crossed state boundaries last year out of all that moved over 70 miles and between non-contiguous PUMAs last year. Using the MIGRATE1D[10] variable, I define any mover who moved between contiguous and non-contiguous states to be an interstate mover assigning a value of 1 and assigned 0 to any other mover that moved over 70 miles in the last year but not across state boundaries. I define a return migrant as one that moved across state boundaries in the previous year into his/her state of birth (in addition to moving over 70 miles between origin and destination in the previous year) and assigns a value of 1 for those who fall into

[10]MIGRATE1 is an IPUMS variable that reports the migration status

this category and assign 0 to others. I use ACS variables BPL[11] and STATEFIP[12] to make this determination.

The main variable of interest is the indicator variable that defines a remote worker. I define a remote worker as one that worked from home during the week before enumeration. I also define a variable that indicates heads-of-households in which all full-time working members of each household are working-from-home, I refer to them as remote households. The indicator variables for these would take the value of 1 if true and 0 otherwise. Both remote-worker and remote-household indicator variables were created using the mode of transportation question in the ACS- TRANWORK. The question asked which mode of transportation each working member of the household used to travel to work in the previous week. Among the answers was an option to indicate if that worker worked from home.

My empirical strategy is based on identifying movers that traveled long distances and lived in a state other than the state of birth. I use the variables PUMA, MIGPUMA1 BPL, MIGRATE1, and MIGPLAC1[13] to create these distinctions. First I use MIGRATE1, PUMA, and MIGPUMA1[14] to calculate the distance traveled from the origin (in the previous year) to the destination (residence this year) to identify those who traveled over 70 miles. Out of those who moved over 70 miles, I keep in the sample those who moved between contiguous PUMAs. Next, I use BPL and

[11]BPL is an IPUMS variable that reports the state-of-birth if within the United States and county code if outside of the United States.

[12]STATEFIP is an IPUMS variable that reports the state FIPS codes.

[13]MIGPLAC1 is an IPUMS variable that reported the state of residence one year ago.

[14]MIGPUMA1 is an IPUMS variable that reported the PUMA of residence one year ago.

MIGPLAC1 to identify who lived in their state of birth in the year before enumeration, and I exclude them from the sample.

One of the ways I control the sample for this study is by identifying occupations that are more likely to offer work-from-home opportunities or HRP occupations. Not controlling for this would bias my results towards zero because some occupations are geographically specific and tied to a workplace. For this, I use the CPS- OCC1990 and isolate a list of occupations in which people worked from home during the Covid-19 pandemic. I then calculated the share of all employed persons in each of the OCC1990 categories that worked from home. I then isolated occupations in which over 50% of all employment during the pandemic was done remotely. This list of OCC1990 would proxy for a list of occupations that are most equipped to allow remote work. I apply these occupations to the pre-pandemic remote-worker sample from the ACS to isolate the group of workers I test my thesis on based on the same variable- OCC1990 in the ACS. A list of these occupations is reported in Table 4.2.

Table 4.3 reports some characteristics of pre-pandemic and post-pandemic remote workers using the ACS and the CPS data. In the pre-Covid-19 period, in almost all categories, remote workers have been increasing as a share of the total employed population. College-educated and full-time employed remote workers have seen the largest increase in the shares, and the same overall trends could be observed in the post-Covid-19 period as well. However, any juxtaposition with the pre-Covid-19 period is unlikely to be meaningful because most remote workers in the post-Covid-19 period were responding to an active pandemic situation.

4.4 Results

4.4.1 Descriptive analysis

In Table 4.4 I present basic descriptive statistics for heads-of-households moved between states in the previous year. Most heads-of-households that made interstate moves are college-educated, younger, and predominantly white. The same trends exist for remotely working heads-of-households and heads-of-households in remotely working households. I now take the share of return-migrants as a share of interstate migrants in each category by taking the ratio between *Remote-households* and *Remote worker* columns in Table 4.4 (unreported). As a share of those who moved between states, return-migrants belonged to lower education levels, had younger children, were female, and were largely non-white. This alters itself when considering heads-of-households that worked from home and heads-of-households in remotely working households. In both these cases return migrants were more likely to be high-school educated, belonged to minority races, were female, and remained young. These overall observations are consistent with the literature where minority races, women, and less-educated workers have the highest valuation of living closer to their kinship network and places of birth.

In Table 4.5 I report overall migration trends as a preamble for the analytical results. Between heads-of-households that worked from home and heads-of-households in *remote-households*, the share of migrants that traveled over 70 miles within the state and between states increased supporting my thesis that remote work will induce a new wave of interstate migrants in the United States. Perhaps the strongest support for my claims comes from the increase in the share that moved to their birth-states alongside their remote-work status.

4.4.2 Analytical results

The effects of remote work on interstate mobility are reported in Table 4.6. Compared to the control group of full-time wage employee heads-of-households, working in HRP occupations in person, heads-of-households that were working remotely were 4.6 percentage points more likely to move back to their birth states. In Model 2 I differentiate remote workers by their interstate migration decisions; *RemoteLD* and *RemoteSD* respectively indicate workers that moved between non-contiguous and contiguous states. After accounting for this, the variable of interest *Remote* is negative and significant indicating that base-level mobility does not favor return-migration, rather than deliberate choices in migrating between states are taken with greater probability when workers choose to return to their birth state. Effect sizes suggest that remote workers who moved between contiguous and non-contiguous states increased their return migration probability by 22-30 percentage points. With such deliberate movement being more frequent in recent years, what this further informs us is that return-migration choices are not "just another" migration decision, but rather a calculated move that eventually results in greater immobility. Model 3 is a version of Model 1 where I limit my sample to those who made interstate moves in the previous year, and among them, remote workers are almost

12 percentage points more likely to return-migrate compared to non-remote workers. The intercept term here suggests that return-migration of interstate movers at the base level is about 83 percent and it increases by an additional 12 percentage points if the mover is a remote worker.

As my analysis is based on manually accounting for biases in the data, I adopt a method introduced by Altonji, Elder, and Taber (2005) and later developed by Oster (2019) that tests the sensitivity of my coefficient of interest with regards to observable and unobserved selection bias. This method uses the coefficients and the coefficients of determination between the fully defined model and a basic naive model (with no controls) to show how strong the unobserved selection bias has to be for the coefficient of interest to be equal to zero. I find that for the coefficient of interest *Remote* to be equal to zero in Model 1 Table 4.6 any unaccounted bias has to be 45 times more important to the analysis than the biases already controlled in the model. I test this for a potential maximum R^2 of 0.1770 following Oster's suggestion of $R^2_{max} = R^2 \times 1.3$. In Model 2 for the coefficient of interest to be zero, unaccounted bias has to be 2.42 times more important than the biases already accounted for, and the unobserved bias has to be negatively correlated with the remote-work indicator given $R^2_{max} = 0.1880$. Coefficient stability statistics suggest that when accounted for a reasonably large R^2 the unobserved biases have to be about twice as much important as the biases already accounted for in the models. What it means for this analysis is that my coefficients are likely true causal effects of interstate and return migration of remote workers.

I test for robustness to the alternative specification of the models in Table 4.7 following Johnson and Kleiner (2020) who tested two-way clustered standard errors. Table 4.7 is estimated identical to the specification used in Table 4.6 except standard errors are clustered by birth-state and industry category[15].

Differential effects

In Tables 4.8, 4.9, and 4.10 I test for differential effects of interstate and return migration. These differential effects are tested for my preferred model; Model 1 in Table 4.6. Table 4.8 suggests that college-educated remote workers are significantly more likely to move back to their birth states. According to the models reported in Table 4.9, the impact on return-migration was positive and significant for remote workers in all age groups and increased by four to six percentage points. Similar observations could be made for differential effects by industry categories as well (Table 4.10). Except for $Manufacturing$ sector workers, remote workers in all other categories increased their probability of moving back to their birth states.

[15] I tested other versions of the models such as different cutoff thresholds of post-Covid-19 work-from-home shares (35% and 60%), and by further limiting my sample to those who work for large employers (by limiting the sample for those who get employer-based health insurance). In almost all cases, the results remained similar to what Table 4.6 and 4.7 reported and had similar coefficient stability results.

4.5 Discussion

The objective of this paper was to understand how remote-working conditions in the post-pandemic period would affect interstate and return migration in the United States. To this end, I used pre-pandemic remote worker data assuming that pre-pandemic remote workers would behave the same way post-pandemic remote workers would in the future. However, this is an unreasonable assumption to make given that several qualitative changes have occurred in the labor market before and after the first Covid-19 lockdown order in March 2020. Therefore, pre-pandemic remote worker data are likely to exhibit selection biases. In this study, I account for those selection biases by controlling for occupations, risk aversion to migration, and attachment to one's state of birth and establish causality by further testing the stability of the coefficients of interest in the models.

My results suggest that remote workers are statistically significantly more likely to have moved between states and returned to their states of birth compared to the control group. Analyzing differential effects, I further establish that it is not just the traditionally vulnerable groups that choose to return to their birth states. These findings have a place in the discussion on American immobility and on the effectiveness of place-based policies. On the one hand, this study shows that immobility is fast becoming a choice rather than a response to a lack of opportunity. On the other hand, this study shows that connection to place is stronger in American households, and providing tailored assistance to places may serve the people it intends to serve.

4.5.1 Return-migration and immobility

One of the main motivations for this project is the need to explain American immobility alongside return-migration. As discussed earlier in Table 4.1 in most categories of the population return-migration has increased, and this is also true for those who have not made any residence changes in the previous year (not shown but understood in the general decline in mobility). What this suggests is that once households return to their birth states they then increasingly do not move elsewhere. This seems more of a choice than an inevitability unlike immobility studies have pointed out before (Foster, 2017). Recall Schewel (2020), who suggested that demographic work should focus on immobility as much as it does mobility; this work contributes to Schewel (2020) this discussion by showing that the category of immobility and the aspiration to be immobile (voluntary immobility) perhaps is generally greater than involuntary immobility.

4.5.2 Place-based policies

The opposition to place-based policies mainly stems from the fact that factor productivity is split equally between spillover effects from agglomeration economies and endogenous sorting of firms, and that depressed areas have no resources to sustain such productive standards (**rodriguez2017revamping**; Gaubert, 2018). However, my results would suggest that if working-from-home take-up continues to expand as suggested by recent publications (Barrero, Bloom, and Davis, 2021b), inducement for firms to relocate to depressed areas may not be as unproductive as it once would have been. Further, because the return-migrants are likely to be high-skilled, and largely employed in a professional capacity, the difference in agglomeration elasticity is unlikely to be the same across regions (Diamond, 2016), which often is used to show that place-based policies only increase productivity in the favored location by the same level that it decreases it in other locations (Kline and Moretti, 2014).

A common response to this argument is that if people who are moving back home are those that work remotely there is no incentive for industries and businesses to relocate. I can reconcile with this because when remote-workers move (like any other mover) they move with their families and those families demand better amenities that endogenously grow with the population. At the same time, movers to birth states due to remote work suggest that they did not have the same kinds of jobs available in their current destination. However, if their presence and their family members can create a demand for in-person jobs, the same workers who work remotely now will have more in-person options in the future. This is somewhat speculative and related to some ideas put forth by Richard Florida in his "creative class" arguments (**florida2003cities**; **florida2019rise**).

To elaborate on the potential for place-based policies in the future, in Appendix **??** Table E.1 I show the results of a basic OLS regression that explains the changes in local rents, incomes, and college employment shares. Results show that after accounting for temporal changes and after accounting for CZ level characteristics that are common across time, higher shares of non-native populations are correlated with higher rents, incomes, and amenities. Therefore, return-migrants could not necessarily move for greater real incomes. Here I argue that therefore, return migration is a choice that will eventually result in voluntary immobility that can affect how successful place-based interventions could be.

4.5.3 Caveats

This study is a descriptive one, and the analytical results presented here should be interpreted with caution. One reason for this is that I could not have entirely eliminated biases arising from self-selection. Although my results are robust to changes in specification and samples, and Oster bounds are reasonably higher, pre-Covid-19 was a time when working from home was a negotiated perk that was not the norm. As described in the body of the text, there are mitigating facts; for example, most workers in my sample who work from home are highly educated and work in positions with authority and flexibility. Therefore, it is possible that the natural progression of employment induced their work-from-home behavior rather than them actively seeking such arrangements. However, these are speculative arguments and cannot be confirmed either way.

My results also revealed some surprising details. Differential effects showed that non-college-educated workers were not particularly interested in moving to their birth-states compared to college-educated workers. This perhaps works in favor of my argument that self-selection may not be biasing my results too much, because we would expect to see both college and non-college workers equally likely to move to their birth states if all workers who worked from home were also those who self-selected into jobs that offered remote-working opportunities.

As evidenced by the results of my model and its many specifications, remote work can only explain a small share of the variation in household interstate and return migration in the pre-Covid-19 period. However, given that my exercise was aimed at explaining some of the possible migration patterns we can expect in the future, it is likely that this model can explain a larger share of the variation in return-migration in the post-pandemic period. My confidence stems partly from the fact that remote work is expected to be more of a norm in the future than the exception (Barrero, Bloom, and Davis, 2021a; Barrero, Bloom, and Davis, 2021b), and partly because the pandemic has made individuals value family and extended family relationships more (Ahmed, Buheji, and Fardan, 2020).

4.6 Conclusion

It has become abundantly clear in recent times that Americans are getting reluctant to move long distances. Although this has only been noticed in the last decade, interstate mobility effects have been lagging since the mid-1990s (Kaplan and Schulhofer-Wohl, 2012). There are several explanations most often cited as reasons, many of which are labor market related (Molloy, Smith, and Wozniak, 2011a; Kaplan and Schulhofer-Wohl, 2017a) while some point to increasing mobility costs that force people to depend on their kinship network for support (Chatterji, Liu, and Yoruk, 2017; Kaplan and Schulhofer-Wohl, 2012). Motivated by how readily both employers and workers have embraced working remotely coupled with the significant mobility constraints Americans are facing, the objective of this paper was to explore if working from home would induce remote workers to return to their states of birth as their occupations and wages remain unattached to place. In doing so I establish that remote work encourages return-migration to their birth states.

Assuming that pre-Covid-19 remote-workers exhibit the same mobility choices post-Covid-19 remote workers would exhibit in the future, I analyzed the pre-Covid-19 remote-worker likelihood of return-migration to see if these choices will re-distribute a skilled workforce into places that were previously unattractive to them. This paper shows that fully-remotely working households are 5.5 percentage points more likely to return to their birth state compared to households with only some remote workers, and compared to non-remote workers remote workers were 1.8 percentage points more likely to move to their state of birth. These results are not intended to measure the extent of the movement of people, but to establish the causal effect of remote work on interstate and return migration. However, if I am to speculate on the extent of people's movement, these estimates are likely to be in the lower regions of the actual distribution as the remote working model has been largely successful and its adoption of it is expected to be widespread.

In the absence of data to test how Covid-19 will shape the labor market to identify the effects of remote work on interstate and return migration, I employ this novel method of controlling for self-selection using CPS data for remote workers during the active pandemic period, by including a rich set of controls variables and by imposing rigid exclusion criteria for the samples. Although the sample restrictions are unlikely to have completely eliminated biases arising from self-selection, they are likely to have minimized its effect. Further, I also test the robustness of my coefficients of interest using Oster's coefficient stability test which suggested that the unobserved (and unaccounted for biases) in the models have to be larger for my estimates to be equal to zero.

4.7 Tables

TABLE 4.1: People living in their state-of-birth as a percentage of total population, and return-migrants to their states-of-birth as a percentage of total interstate movers.

	Birth-state		Return	
	2010	2019	2010	2019
Working age	53.05	52.33	51.02	52.32
Full-time	30.31	31.90	27.65	31.67
FemaleHH	17.06	18.48	14.63	15.85
Children in household				
<18	47.66	43.34	39.03	35.54
<14	40.40	36.78	35.45	32.55
<10	32.12	29.01	30.63	28.10
Race				
Hispanic	15.47	18.04	12.43	13.55
non-Hispanic white	65.25	60.67	66.69	63.94
non-Hispanic black	12.14	12.35	12.65	11.66
non-Hispanic other	7.14	8.94	8.23	10.85
Age group				
>65	12.71	15.63	5.80	8.15
55-64	11.17	12.86	6.25	7.57
45-54	14.52	12.98	8.89	8.35

35-44	14.05	12.70	13.19	12.33
25-34	13.30	13.79	22.69	24.08
<25	34.24	32.04	43.19	39.53
Education				
High-school	46.70	46.81	47.29	45.55
Some school	34.25	30.40	26.87	22.49
College	19.05	22.79	25.83	31.96
Interactions				
FemaleHH × college	4.56	6.14	5.94	7.80
Children in household				
<18 × college	6.71	7.33	6.54	7.61
<14 × college	5.66	6.15	6.05	6.95
<10 × college	4.52	4.81	5.45	6.15
Age group				
>65 × college	2.52	4.27	1.51	2.68
55-64 × college	3.31	3.76	2.22	2.80
45-54 × college	4.06	4.21	2.82	3.23
35-44 × college	4.29	4.59	5.07	5.68
25-34 × college	4.00	4.92	10.06	12.73

Percentages are calculated fr each category (the denominator changes for each category). ACS data 2006-2010 combined to create "2010" data and ACS data 2015-2019 to create "2019" data.

TABLE 4.2: List of occupations of which over 50% of employees worked from home during the Covid-19 pandemic.

Occupation 1990 classification	Share of remote-workers
Managers/specialists in marketing, advertising, and public relations	52.12%
Insurance underwriters	60.74%
Other financial specialists	52.54%
Management analysts	60.10%
Business and promotion agents	56.94%
Management support occupations	50.69%
Architects	60.69%
Electrical engineer	50.59%
Computer systems analysts and computer scientists	54.04%
Operations and systems researchers and analysts	54.96%
Actuaries	77.71%
Mathematicians and mathematical scientists	68.92%
Physicists and astronomers	65.77%
Atmospheric and space scientists	58.06%
Geologists	56.22%

Physical scientists	60.48%
Medical scientists	54.26%
Subject instructors (hs/college)	57.64%
Economists, market researchers, and survey researchers	62.66%
Social scientists	66.58%
Urban and regional planners	64.48%
Lawyers	63.76%
Writers and authors	53.13%
Technical writers	63.29%
Actors, directors, producers	51.42%
Editors and reporters	53.57%
Computer software developers	66.33%
Financial services sales occupations	51.49%
Sales engineers	52.98%
Eligibility clerks for government programs; social welfare	52.31%
Statistical clerks	57.34%

Source: CPS 2020-2021 (Flood et al., 2021). Out of all people working in these occupations during the

Covid-19 pandemic, over 50% of them worked remotely. This shows that people working in such occupations have a greater potential for conducting their job-responsibilities from outside of the physical work-place.

TABLE 4.3: Comparison of remote-worker characteristics pre and post Covid-19

	ACS				CPS
Year	2008	2012	2016	2019	2020/2021
Full-time employed	1.66	2.07	2.81	3.56	2.71
College educated	1.23	1.53	2.06	2.72	22.71
Highschool diploma	0.52	0.60	0.70	0.88	1.83
Age 35-44	0.61	0.66	0.82	1.08	6.20
Age 45-54	0.68	0.82	0.98	1.12	5.19
Age 55-64	0.51	0.68	0.89	1.14	4.15
Age 65 plus	0.21	0.29	0.40	0.57	1.36
Male	1.13	1.37	1.75	2.20	10.54
Female	1.28	1.54	1.97	2.54	12.17
Average annual income	27,174	28,265	31,926	32,444	52,540

Source: ACS 2008-2019 Ruggles et al., 2021 and CPS 2020-2021 Flood et al., 2021. All values except *Avg. annual income* are percentages of total population employed, recieving a income from an employer (not self-employed) and over the age of 25. *Avg. annual income* report real incomec in 1999 U.S. Dollars.

TABLE 4.4: Descriptive statistics by household type, from 2008-2019

	Total		Remote worker[a]		Remote household[b]	
	Interstate	Return	Interstate	Return	Interstate	Return
Education						
Some school	0.35	0.18	0.21	0.02	0.14	0.01
High-school	20.70	6.06	18.18	3.83	20.91	6.16
College	59.06	13.57	64.66	13.11	58.95	13.80
Race						
nHisp white	64.22	15.59	72.73	14.00	68.59	16.26
non-Hisp black	7.85	1.96	4.09	0.50	5.28	1.14
non-Hisp native	0.24	0.13	-	-	0.10	0.12
non-Hisp Other	3.30	0.92	2.62	0.99	2.24	1.03
Hipsanic	4.53	1.26	3.61	1.46	3.81	1.41
Age						
25-34	36.22	9.40	39.62	9.51	28.66	7.29
35-44	19.47	4.87	24.01	4.26	20.67	5.92
45-54	13.98	3.28	13.62	2.12	14.69	3.53
55-64	9.00	2.00	5.27	1.05	12.88	2.80
65+	1.47	0.30	0.53	-	3.13	0.42
Median	36	35	35	33	39	38
Mean	39.09	38.44	37.57	36.3	41.99	40.84
Sex						
Female	32.211	8.84	48.49	10.13	32.39	9.62

Male	47.933	11.02	34.56	6.82	47.64	10.35
Wage ('000)						
Median	48.580	43.09	52.63	53.44	57.72	54.45
Mean	48.66	43.82	49.57	51.26	57.51	55.18
Children						
$<$ 18 in HH	20.88	6.13	29.80	7.18	21.04	6.37
$<$ 5 in HH	11.87	3.52	19.92	4.50	12.22	3.17
$<$ 10 in HH	16.63	4.95	25.47	5.82	17.18	5.39

Source: ACS data from 2008-2019 Ruggles et al., 2021. All values except mean and median incomes, and median and mean age, are percentages of all heads-of-households in each category. Heads-of-households are full-time wage employees, over the age of 25 with no farm or business income. [a] Remote workers are heads-of-households that are remote workers. [b] Remote households are heads-of-households that in which all adult full-time employed members working from home. Remote households and households with some remote-workers- because households with some non-remote workers face higher costs when moving long-distances, heads of these households could not be expected to reflect the true impact remote-work has on interstate mobility and return-migration.

TABLE 4.5: The effect of remote-work on interstate migration

	Total	Remote worker[a]	Remote household[b]
All movers	12.34	11.69	13.53
Moved 70+ miles & within state	9.41	7.55	8.16
Moved 70+ miles & between states	1.94	3.19	4.38
Moved to birth state	0.45	0.86	1.43

Source: ACS data from 2008-2019 Ruggles et al., 2021. All values are percentages in each category. Heads-of-households are full-time wage employees, over the age of 25 with no farm or business income. [a] Remote workers are heads-of-households that are remote workers. [b] Remote households are heads-of-households that in which all adult full-time employed members worked from home.

TABLE 4.6: The effect of remote-work on return-migration

	(1)	(2)	(3)
Remote	0.0461***	-0.1335***	0.1170***
	(0.0143)	(0.0223)	(0.0373)
RemoteLD		0.2190***	
		(0.0366)	
RemoteSD		0.2948***	
		(0.0347)	
Intercept	0.5253*	0.5395*	0.8321***
	(0.2748)	(0.2811)	(0.2924)
N	1,449,535	1,449,535	147,282
R^2	0.1361	0.1444	0.5036
State $\times$ Time FE	Y	Y	Y
Birth state FE	Y	Y	Y
R^2_{max}	0.1770	0.1880	14.0658
δ	45.2161	-1.2729	0.6550

Source: ACS data from 2008-2019 Ruggles et al., 2021. Standard error are reported in parentheses and are clustered at birth-state. Significance levels: * $<$ 0.1 ** $<$ 0.05 *** $<$ 0.001. Sample includes full-time employed heads-of-households between ages 25-64, working in HRP occupation, that moved between non-contiguous PUMAs, and moved over 70 miles between origin and destination during the previous year.

Sample excludes households that are working in *Agriculture* and *Mining* industries, self-employed workers, and those who lived in their birth-state in the previous year. Data from IPUMS-USA (Ruggles et al., 2021). Model 1 test the effect of remote-work arrangements on return-migration, Model 2 tests the effect of remote work on return migration after accounting for remote workers that have moved between contiguous *RemoteSD* and non-contiguous *RemoteLD* states. Model 3 restricts the sample to interstate movers (not just long-distance movers). The control group consist of heads-of-households that are not working remotely, but employed in HRP occupations.

TABLE 4.7: The effect of remote-work on return-migration with two-way clustered standard errors

	(1)	(2)	(3)
Remote	0.0464***	-0.1502***	0.0947***
	(0.0137)	(0.0054)	(0.0330)
RemoteLD		0.2351***	
		(0.0191)	
RemoteSD		0.3247***	
		(0.0377)	
Intercept	0.8278***	0.8312***	-0.1686
	(0.2446)	(0.2453)	(0.2912)
N	1,449,535	1,449,535	147,282
R^2	0.0093	0.0199	0.0463
State $\times$ Time FE	Y	Y	Y
Birth state FE	Y	Y	Y
R^2_{max}	0.1750	0.1860	0.6520
δ	107.3517	-1.2780	20.8322

Source: ACS data from 2008-2019 Ruggles et al., 2021. Standard error are reported in parentheses and are clustered at birth-state and industry level. Significance levels: * $<$ 0.1 ** $<$ 0.05 *** $<$ 0.001. Sample includes full-time employed heads-of-households between ages 25-64, working in HRP occupation, that moved between non-contiguous PUMAs, and moved over 70 miles between origin and destination during the previous year. Sample excludes households that are working in

Agriculture and *Mining* industries, self-employed workers, and those who lived in their birth-state in the previous year. Data from IPUMS-USA (Ruggles et al., 2021). Model 1 test the effect of remote-work arrangements on return-migration, Model 2 tests the effect of remote work on return migration after accounting for remote workers that have moved between contiguous *RemoteSD* and non-contiguous *RemoteLD* states. Model 3 restricts the sample to interstate movers (not just long-distance movers). The control group consist of heads-of-households that are not working remotely, but employed in HRP occupations.

TABLE 4.8: Differential effects of return-migration on level of education

	<College	College
Remote	0.0339	0.0508***
	(0.0244)	(0.0142)
Intercept	0.4132**	0.1244
	(0.1849)	(0.1603)
N	261,746	1187,789
R^2	0.3846	0.1486
State $\times$ Time FE	Y	Y
Birth state FE	Y	Y

Source: ACS data from 2008-2019 Ruggles et al., 2021. Standard error are reported in parentheses and are clustered at birth-state and industry level. Significance levels: * $<$ 0.1 ** $<$ 0.05 *** $<$ 0.001. Sample includes full-time employed heads-of-households between ages 25-64, working in HRP occupation, that moved between non-contiguous PUMAs, and moved over 70 miles between origin and destination during the previous year. Sample excludes households that are working in *Agriculture* and *Mining* industries, self-employed workers, and those who lived in their birth-state in the previous year.

TABLE 4.9: Differential effects of return-migration by age group

	25-34	35-44	45-54	55-64
Remote	0.0362**	0.0486**	0.0423**	0.0602**
	(0.0182)	(0.0201)	(0.0211)	(0.0235)
Intercept	0.0099	-0.0356	-0.1544	1.6018***
	(0.1630)	(0.1945)	(0.1999)	(0.3725)
N	736733	372415	216162	124225
R^2	0.1870	0.2994	0.4124	0.5540
State $\times$ Time FE	Y	Y	Y	Y
Birth state FE	Y	Y	Y	Y

Source: ACS data from 2008-2019 Ruggles et al., 2021. Standard error are reported in parentheses and are clustered at birth-state and industry level. Significance levels: * $<$ 0.1 ** $<$ 0.05 *** $<$ 0.001. Sample includes full-time employed heads-of-households between ages 25-64, working in HRP occupation, that moved between non-contiguous PUMAs, and moved over 70 miles between origin and destination during the previous year. Sample excludes households that are working in *Agriculture* and *Mining* industries, self-employed workers, and those who lived in their birth-state in the previous year.

TABLE 4.10: Differential effects of return-migration by industry category

	Finance&Business	Manufacturing	Professional	Other
Remote	0.0476**	0.0093	0.0590***	0.0430*
	(0.0185)	(0.0328)	(0.0188)	(0.0229)
Intercept	1.0531***	1.6486***	-0.1808	-0.0052
	(0.2177)	(0.3101)	(0.3786)	(0.1659)
N	430809	162138	504932	351656
R^2	0.2662	0.4853	0.2016	0.2959
State × Time FE	Y	Y	Y	Y
Birth state FE	Y	Y	Y	Y

Source: ACS data from 2008-2019 Ruggles et al., 2021. Standard error are reported in parentheses and are clustered at birth-state and industry level. Significance levels: * $<$ 0.1 ** $<$ 0.05 *** $<$ 0.001. Sample includes full-time employed heads-of-households between ages 25-64, working in HRP occupation, that moved between non-contiguous PUMAs, and moved over 70 miles between origin and destination during the previous year. Sample excludes households that are working in *Agriculture* and *Mining* industries, self-employed workers, and those who lived in their birth-state in the previous year.

4.8 Figures

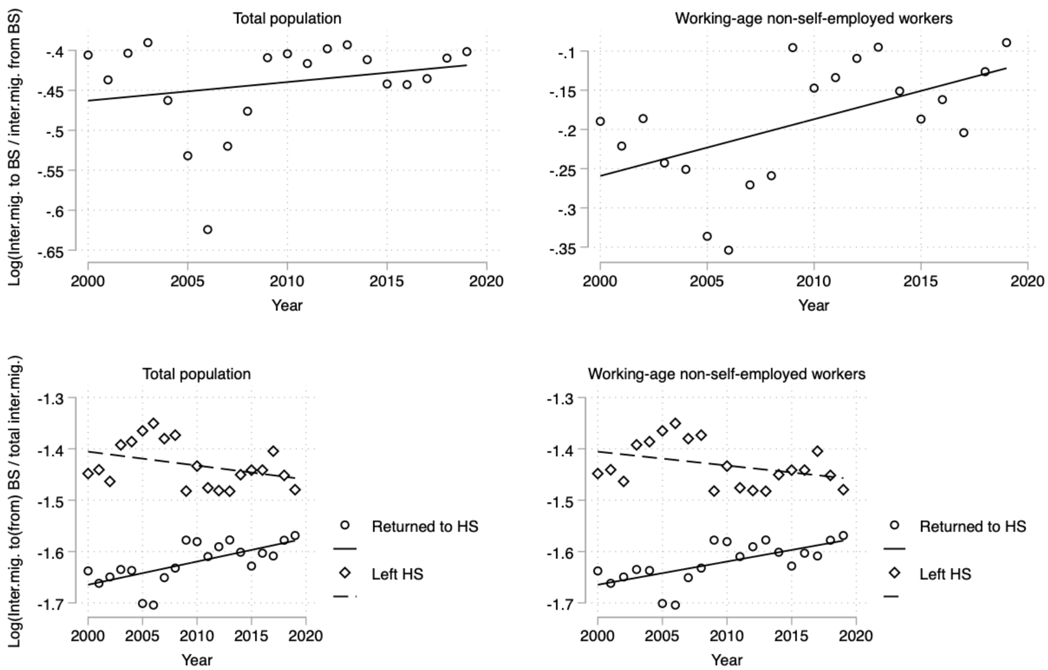


FIGURE 4.1: Interstate migrants to and from birth-state (BS)
This figure shows how interstate migrants to and from their respective birth-states have changed from 2008-2020. The sample used to produce the left-hand side upper and lower figures consist of all interstate movers. The left-upper figure shows the share of return migrants to the interstate migrants who moved away from their birth-state. The left-lower figure shows return-migrants (and migrants who left their birth-state) as a share of total interstate movers in each year. The sample used to produce the right-hand side upper and lower figures consist of all interstate movers between ages 25-64, non-self-employed, and working. The right-upper figure shows the share of return migrants to the interstate migrants who moved away from their birth-state. The right-lower figure shows return-migrants (and migrants who left their birth-state) as a share of total interstate movers in each year.

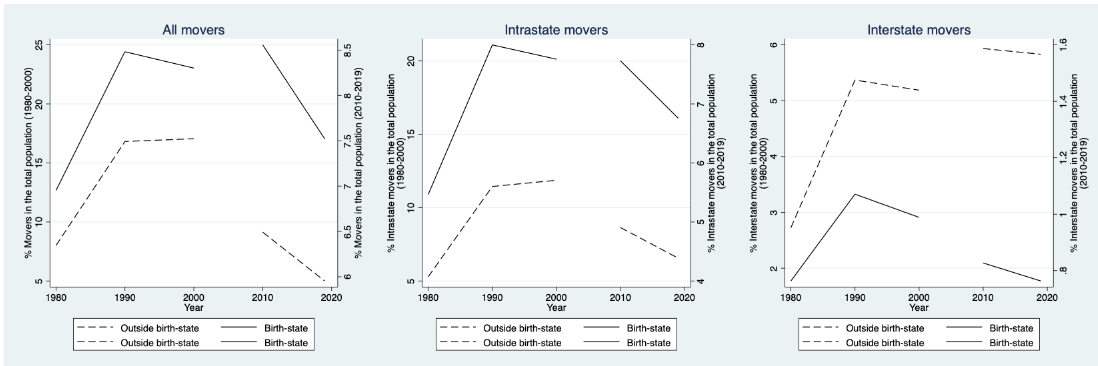


FIGURE 4.2: Migration patterns of residents living within and outside of birth-states.

Source: Decennial Census data from 1980-2000 and ACS data from 2007-2019 Ruggles et al., 2021. ACS data from 2007-2010 used to calculate 2010 census data equivalent and ACS data from 2015-2019 used to calculate 2019 census data equivalent. Graphs show the percentage of any movers "All movers," "intrastate" and "interstate" movers as of the total population in that year. Left-hand side vertical axis shows the percentages of movers five years ago. Right-hand side vertical axis shows the percentage of movers one year ago. All figures show that the decline in mobility is steeper for those who live in their birth-state compared to those who live outside of their birth state.

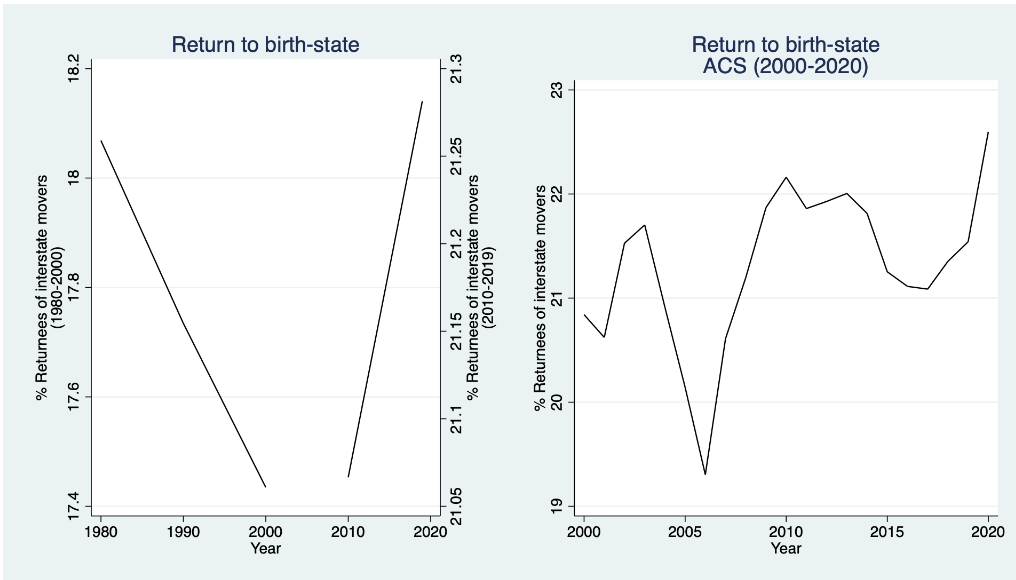


FIGURE 4.3: Return-migration patterns of interstate movers

Source: Decennial Census data from 1980-2000 and ACS data from 2007-2019 Ruggles et al., 2021. ACS data from 2007-2010 used to calculate 2010 census data equivalent and ACS data from 2015-2019 used to calculate 2019 census data equivalent. The graph in the left-hand side show the percentage of return-migrants out of all interstate movers in that year. Of the left-hand side figure, the left-hand side vertical axis shows the percentages of returnees from five years ago. Right-hand side vertical axis shows the percentage of returnees from one year ago. Note that 2005 hurricane Katrina and its aftermath and the 2010 financial crisis has made the trends of return migration more severe (steeper) than it might have been without these shocks. The right-hand side figure use ACS data from 2000-2020 and show the percentage of return-migrants of all interstate movers. ACS data indicate those who has moved between locations one year apart.

Appendix A

Derivation of indirect utility function for Chapter 2

$max_{CHj}\, C^{(1-\gamma)} H^{\gamma} e^{X_{jt}+M_{ijt}} \quad s.t.\ P_t C + R_{jt} \leq W_{ijt}$

$$L = C^{(1-\gamma)} H^{\gamma} e^{X_{jt}+M_{ijt}} + \lambda(W_{ijt} - PC - R_{jt} H)$$

$$\frac{\partial L}{\partial C} = (1-\gamma) C^{-\gamma} H^{\gamma} e^{X_{jt}+M_{ijt}} = P_t \lambda$$

$$\frac{\partial L}{\partial H} = (\gamma) C^{1-\gamma} H^{\gamma-1} e^{X_{jt}+M_{ijt}} = R_{jt} \lambda$$

$$\frac{\partial L}{\partial \lambda} = W_{ijt} - P_t C - R_{jt} H = 0$$

$$\frac{\frac{\partial L}{\partial C}}{\frac{\partial L}{\partial H}} = \frac{(1-\gamma) C^{-\gamma} H^{\gamma} e^{X_{jt}+M_{ijt}}}{(\gamma) C^{1-\gamma} H^{\gamma-1} e^{X_{jt}+M_{ijt}}} = \frac{P_t \lambda}{R_{jt} \lambda}$$

$= \frac{1-\gamma}{\gamma}\frac{H}{C} = \frac{P_t}{H_{jt}}$

$H = \frac{P_t}{R_{jt}}\frac{\gamma}{1-\gamma}C$

Insert H to $\frac{\partial L}{\partial \lambda}$ to get the demand function for C indicated by C^*;

$W_{ijt} = P_t C + R_{jt}[\frac{P_t}{R_{jt}}\frac{\gamma}{1-\gamma}C]$

$= P_t C[1 + \frac{\gamma}{1-\gamma}] = W_{ijt} = P_t C\frac{1}{1-\gamma}$

$C^* = \frac{W_{ijt}}{P_t}(1-\gamma)$

Insert C^* into H to get the demand function H^*;

$H = \frac{P_t}{R_{jt}}\frac{\gamma}{1-\gamma}[\frac{W_{ijt}}{P_t}(1-\gamma)]$

$H^* = \frac{W_{ijt}}{R_{jt}}\gamma$

Insert C^* and H^* into the utility statement to get indirect utility function;

$U = [\frac{W_{ijt}}{P_t}(1-\gamma)]^{1-\gamma}\ [\frac{W_{ijt}}{R_{jt}}\gamma]^{\gamma}\ \ e^{(}X_{jt} + M_{ijt})$

$$= [(1-\gamma)^{1-\gamma}\gamma^{\gamma}]\ (\frac{W_{ijt}}{P_t})\ (\frac{R_{jt}}{P_t})^{-\gamma}\ e^{(}X_{jt} + M_{ijt})$$

$$ln(U) = ln(\frac{W_{ijt}}{P_t})\ -\ \gamma ln(\frac{R_{jt}}{P_t})\ +\ (X_{jt} + M_{ijt}) + ln[(1-\gamma)^{1-\gamma}\gamma^{\gamma}]$$

$$ln(U) = \delta_{jt} + M_{ijt}$$

Appendix B

Population migration patterns by EBHI status to accompany Chapter 3

TABLE B.1: Annual migration patterns between residents with and without EBHI, by year, social and demographic characteristics

year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	Within PUMA within state																							
	no EBHI												EBHI											
Age																								
0-18	3.760	3.819	3.706	3.683	3.543	3.313	3.092	2.995	2.851	2.674	2.627	2.410	1.733	1.710	1.741	1.659	1.615	1.658	1.656	1.598	1.608	1.599	1.515	1.491
19-24	2.124	2.099	2.020	1.869	1.728	1.636	1.474	1.359	1.306	1.199	1.140	1.102	1.292	1.300	1.268	1.302	1.377	1.377	1.396	1.370	1.348	1.309	1.280	1.190
25-44	3.831	3.970	3.819	3.749	3.641	3.446	3.288	3.137	3.014	2.848	2.779	2.643	2.962	2.975	3.060	2.897	2.943	3.019	3.095	3.169	3.182	3.238	3.153	3.133
45-64	1.614	1.631	1.690	1.723	1.721	1.653	1.598	1.567	1.520	1.461	1.414	1.390	1.156	1.137	1.235	1.172	1.220	1.243	1.265	1.266	1.279	1.293	1.263	1.203
65 over	0.872	0.774	0.739	0.772	0.797	0.873	0.896	0.914	0.947	0.957	0.985	0.999	0.239	0.219	0.231	0.234	0.252	0.258	0.265	0.258	0.265	0.270	0.269	0.258
25-64	5.446	5.601	5.509	5.472	5.362	5.099	4.886	4.705	4.533	4.309	4.192	4.033	4.119	4.111	4.294	4.070	4.163	4.262	4.360	4.435	4.461	4.532	4.417	4.335
Race																								
White	6.120	5.892	5.568	5.479	5.378	5.183	4.979	4.828	4.673	4.460	4.287	4.138	4.845	4.787	4.825	4.690	4.863	4.982	4.928	4.946	4.919	4.902	4.682	4.500

Black	2.376	2.422	2.291	2.257	2.184	2.107	2.013	1.884	1.798	1.718	1.642	1.583	0.990	0.930	0.940	0.877	0.873	0.871	0.916	0.921	0.928	0.885	0.881	0.860
Hispanic	2.869	3.100	3.192	3.152	2.958	2.730	2.485	2.414	2.328	2.191	2.214	2.072	0.984	1.013	1.079	1.068	1.033	1.015	1.094	1.060	1.102	1.158	1.104	1.140
Education																								
No school	0.733	0.769	0.717	0.737	0.723	0.686	0.606	0.574	0.547	0.500	0.512	0.462	0.232	0.236	0.224	0.227	0.217	0.227	0.228	0.197	0.213	0.209	0.206	0.197
Some school	4.463	4.423	4.315	4.198	3.984	3.714	3.433	3.293	3.093	2.937	2.792	2.594	1.584	1.514	1.551	1.472	1.428	1.447	1.425	1.423	1.398	1.372	1.287	1.272
High school	2.946	2.904	2.791	2.745	2.660	2.551	2.479	2.367	2.314	2.219	2.199	2.165	1.408	1.324	1.310	1.281	1.284	1.316	1.340	1.343	1.345	1.343	1.300	1.252
Some college	1.948	2.006	2.000	2.034	1.982	1.971	1.859	1.783	1.753	1.636	1.561	1.504	1.857	1.863	1.920	1.864	1.907	1.888	1.893	1.852	1.836	1.800	1.714	1.604
College	0.845	0.877	0.884	0.885	0.906	0.924	0.943	0.969	0.980	0.971	1.011	0.988	1.631	1.745	1.886	1.806	1.958	2.029	2.136	2.216	2.242	2.358	2.356	2.351
Household																								
Children 0-5	3.615	3.732	3.590	3.537	3.390	3.055	2.772	2.689	2.548	2.322	2.308	2.059	1.774	1.782	1.779	1.702	1.694	1.760	1.746	1.678	1.730	1.707	1.595	1.584
Children 0-18	6.175	6.334	6.207	6.098	5.851	5.403	4.949	4.800	4.533	4.247	4.104	3.759	3.461	3.415	3.520	3.340	3.307	3.412	3.433	3.345	3.352	3.346	3.187	3.111
Children 19-25	3.444	3.639	3.613	3.459	3.135	2.973	2.636	2.411	2.187	2.032	1.895	1.797	1.494	1.595	1.644	1.653	1.694	1.702	1.702	1.632	1.568	1.516	1.491	1.385
owner	2.582	2.474	2.351	2.250	2.249	2.352	2.275	2.336	2.384	2.420	2.391	2.319	2.930	2.740	2.804	2.565	2.649	2.928	3.032	3.172	3.359	3.541	3.406	3.326

renter	8.727	9.008	8.915	8.845	8.440	7.843	7.348	6.930	6.537	6.026	5.874	5.547	4.251	4.389	4.519	4.499	4.548	4.415	4.443	4.305	4.137	3.990	3.893	3.783
Employment																								
FT employed	2.458	2.184	1.984	1.986	2.006	1.936	1.910	1.888	1.886	1.805	1.830	1.813	3.725	3.606	3.669	3.487	3.628	3.715	3.838	3.943	3.993	4.099	3.984	3.930
1 FTE adult	4.479	4.344	4.158	4.199	4.093	3.936	3.710	3.657	3.585	3.370	3.353	3.167	3.558	3.583	3.689	3.568	3.551	3.620	3.608	3.544	3.506	3.508	3.353	3.241
2 FTE adult	1.546	1.437	1.249	1.212	1.255	1.235	1.231	1.246	1.269	1.245	1.261	1.245	2.162	2.038	2.066	1.993	2.099	2.228	2.372	2.433	2.523	2.571	2.521	2.523
≥3 FTE adults	0.364	0.280	0.279	0.237	0.268	0.253	0.271	0.258	0.280	0.282	0.267	0.269	0.324	0.276	0.269	0.245	0.272	0.304	0.331	0.367	0.383	0.431	0.406	0.413
Income																								
Lowest 50%	7.570	7.594	7.384	7.176	6.851	6.666	6.307	6.015	5.830	5.510	5.263	5.204	2.849	2.749	2.705	2.674	2.700	2.838	2.905	2.878	2.868	2.764	2.623	2.713
Top 50%	4.631	4.700	4.589	4.619	4.578	4.255	4.041	3.958	3.807	3.629	3.682	3.340	4.533	4.591	4.830	4.592	4.706	4.717	4.772	4.783	4.814	4.946	4.857	4.561

Between PUMAs within state

	no EBHI												EBHI											
Age																								
0-18	0.837	0.817	0.784	0.758	0.724	0.707	0.703	0.673	0.687	0.671	0.660	0.687	0.560	0.569	0.581	0.548	0.500	0.548	0.580	0.534	0.532	0.559	0.543	0.553
19-24	0.749	0.729	0.709	0.606	0.574	0.563	0.521	0.518	0.499	0.465	0.465	0.479	0.576	0.550	0.563	0.598	0.628	0.613	0.633	0.627	0.625	0.609	0.626	0.604

Some college	High school	Some school	No school	Education	Hispanic	Black	White	Race	25-64	65 over	45-64	25-44
0.631	0.991	1.117	0.157		0.630	0.680	2.081		1.805	0.259	0.520	1.285
0.664	0.916	1.051	0.150		0.618	0.663	1.991		1.752	0.216	0.517	1.235
0.655	0.868	0.982	0.148		0.608	0.631	1.877		1.682	0.206	0.499	1.183
0.630	0.837	0.952	0.137		0.596	0.594	1.806		1.669	0.220	0.518	1.151
0.623	0.789	0.881	0.142		0.562	0.586	1.706		1.585	0.220	0.504	1.081
0.618	0.801	0.834	0.138		0.552	0.555	1.717		1.559	0.245	0.483	1.076
0.604	0.772	0.837	0.131		0.539	0.542	1.692		1.543	0.259	0.494	1.049
0.592	0.777	0.800	0.119		0.519	0.540	1.653		1.498	0.280	0.494	1.004
0.583	0.754	0.794	0.127		0.521	0.517	1.651		1.480	0.287	0.495	0.985
0.587	0.774	0.772	0.123		0.575	0.521	1.591		1.507	0.311	0.483	1.024
0.580	0.793	0.762	0.119		0.557	0.534	1.577		1.500	0.326	0.485	1.015
0.575	0.792	0.775	0.132		0.558	0.539	1.592		1.473	0.330	0.474	0.999
0.609	0.460	0.360	0.065		0.245	0.285	1.772		1.277	0.073	0.341	0.937
0.595	0.415	0.332	0.060		0.224	0.259	1.719		1.208	0.067	0.327	0.880
0.586	0.392	0.344	0.061		0.234	0.263	1.721		1.212	0.072	0.335	0.877
0.617	0.392	0.327	0.064		0.240	0.269	1.731		1.219	0.075	0.358	0.861
0.627	0.383	0.299	0.052		0.242	0.248	1.699		1.192	0.070	0.349	0.843
0.615	0.400	0.333	0.057		0.265	0.261	1.779		1.286	0.083	0.371	0.915
0.633	0.414	0.358	0.068		0.278	0.282	1.810		1.315	0.080	0.370	0.945
0.633	0.416	0.331	0.062		0.287	0.283	1.785		1.362	0.087	0.390	0.973
0.641	0.429	0.341	0.062		0.331	0.285	1.789		1.409	0.094	0.395	1.014
0.619	0.448	0.360	0.063		0.342	0.305	1.797		1.456	0.089	0.422	1.034
0.618	0.440	0.353	0.067		0.366	0.288	1.780		1.462	0.092	0.407	1.055
0.602	0.443	0.362	0.068		0.364	0.326	1.737		1.468	0.092	0.404	1.065

Income	≥3 FTE adults	2 FTE adult	1 FTE adult	FT employed	Employment	renter	owner	Children 19-25	Children 0-18	Children 0-5	Household	College
	0.087	0.404	1.074	0.628		1.902	0.838	1.030	1.209	0.691		0.371
	0.062	0.329	1.018	0.512		1.862	0.828	1.055	1.180	0.669		0.351
	0.069	0.304	0.984	0.487		1.841	0.778	1.053	1.174	0.699		0.346
	0.066	0.288	0.937	0.474		1.827	0.703	0.900	1.115	0.641		0.339
	0.052	0.283	0.915	0.462		1.688	0.716	0.855	1.035	0.588		0.332
	0.070	0.301	0.930	0.470		1.655	0.741	0.849	1.010	0.566		0.354
	0.064	0.307	0.892	0.468		1.614	0.745	0.774	0.997	0.565		0.350
	0.073	0.304	0.900	0.481		1.525	0.773	0.744	0.941	0.527		0.355
	0.073	0.322	0.866	0.476		1.484	0.800	0.710	0.934	0.519		0.372
	0.072	0.343	0.907	0.511		1.432	0.860	0.668	0.947	0.562		0.381
	0.075	0.356	0.874	0.506		1.417	0.878	0.664	0.909	0.510		0.387
	0.095	0.364	0.907	0.541		1.416	0.892	0.658	0.921	0.529		0.393
	0.089	0.650	1.056	1.120		1.245	0.950	0.623	0.873	0.490		0.695
	0.080	0.570	1.002	1.014		1.188	0.864	0.617	0.809	0.468		0.666
	0.069	0.550	1.029	0.989		1.181	0.903	0.652	0.827	0.457		0.705
	0.082	0.572	1.028	1.014		1.277	0.847	0.673	0.827	0.457		0.720
	0.085	0.572	0.994	1.008		1.272	0.800	0.688	0.751	0.419		0.723
	0.092	0.619	1.077	1.082		1.290	0.913	0.683	0.836	0.459		0.783
	0.095	0.672	1.093	1.111		1.305	0.978	0.704	0.886	0.506		0.806
	0.113	0.707	1.069	1.169		1.274	1.027	0.697	0.848	0.461		0.843
	0.122	0.747	1.091	1.224		1.262	1.101	0.686	0.863	0.474		0.868
	0.133	0.793	1.111	1.275		1.228	1.195	0.676	0.908	0.507		0.897
	0.144	0.816	1.084	1.291		1.249	1.193	0.682	0.907	0.508		0.918
	0.140	0.812	1.105	1.300		1.238	1.201	0.657	0.906	0.501		0.925

Lowest 50%	2.575	2.485	2.343	2.230	2.135	2.112	2.072	2.042	2.015	1.986	1.972	2.029	1.101	1.079	1.084	1.096	1.096	1.156	1.193	1.181	1.190	1.175	1.148	1.206
Top 50%	1.076	1.029	1.038	1.023	0.968	0.962	0.955	0.926	0.938	0.968	0.978	0.940	1.385	1.314	1.344	1.343	1.294	1.373	1.416	1.429	1.470	1.538	1.575	1.512

Between states

	no EBHI												EBHI											
Age																								
0-18	0.499	0.481	0.436	0.424	0.407	0.416	0.413	0.419	0.409	0.390	0.407	0.363	0.312	0.287	0.263	0.272	0.284	0.299	0.296	0.305	0.302	0.300	0.295	0.287
19-24	0.412	0.386	0.367	0.335	0.313	0.326	0.302	0.279	0.269	0.279	0.279	0.258	0.225	0.220	0.209	0.250	0.253	0.269	0.266	0.272	0.275	0.278	0.272	0.277
25-44	0.681	0.673	0.633	0.640	0.617	0.610	0.596	0.572	0.564	0.570	0.546	0.527	0.535	0.488	0.444	0.489	0.500	0.545	0.571	0.618	0.609	0.616	0.629	0.638
45-64	0.276	0.272	0.273	0.282	0.279	0.281	0.285	0.283	0.269	0.273	0.261	0.247	0.232	0.202	0.215	0.229	0.225	0.234	0.242	0.258	0.263	0.252	0.270	0.253
65 over	0.137	0.138	0.135	0.141	0.155	0.177	0.188	0.206	0.212	0.211	0.227	0.215	0.062	0.050	0.061	0.061	0.068	0.068	0.069	0.071	0.074	0.073	0.076	0.076
25-64	0.958	0.945	0.907	0.921	0.896	0.891	0.882	0.855	0.834	0.843	0.807	0.774	0.767	0.690	0.659	0.718	0.725	0.779	0.813	0.876	0.873	0.868	0.898	0.891
Race																								
White	1.242	1.217	1.109	1.078	1.061	1.071	1.084	1.034	1.020	1.010	1.006	0.943	0.995	0.909	0.856	0.940	0.959	1.010	1.012	1.040	1.023	1.027	1.022	1.020
Black	0.277	0.253	0.253	0.262	0.241	0.253	0.231	0.247	0.219	0.214	0.213	0.203	0.122	0.108	0.102	0.106	0.106	0.111	0.125	0.134	0.132	0.117	0.134	0.133

Hispanic	0.329	0.324	0.338	0.318	0.316	0.322	0.300	0.309	0.307	0.320	0.331	0.293	0.111	0.101	0.097	0.113	0.117	0.125	0.133	0.151	0.160	0.163	0.170	0.169
Education																								
No school	0.089	0.093	0.072	0.074	0.077	0.072	0.073	0.074	0.072	0.074	0.071	0.061	0.040	0.034	0.026	0.030	0.035	0.032	0.035	0.034	0.038	0.037	0.033	0.032
Some school	0.500	0.459	0.431	0.420	0.395	0.414	0.373	0.377	0.373	0.353	0.347	0.316	0.204	0.179	0.166	0.175	0.173	0.192	0.191	0.206	0.197	0.194	0.198	0.187
High school	0.496	0.457	0.443	0.428	0.407	0.414	0.416	0.400	0.391	0.390	0.385	0.373	0.187	0.161	0.157	0.167	0.172	0.186	0.185	0.193	0.193	0.201	0.197	0.201
Some college	0.370	0.389	0.358	0.366	0.374	0.369	0.361	0.352	0.340	0.353	0.352	0.324	0.259	0.236	0.228	0.247	0.244	0.257	0.266	0.281	0.262	0.266	0.266	0.263
College	0.325	0.330	0.326	0.334	0.322	0.346	0.357	0.360	0.364	0.375	0.379	0.361	0.538	0.502	0.480	0.544	0.564	0.606	0.622	0.666	0.685	0.678	0.704	0.699
Household																								
Children 0-5	0.458	0.440	0.402	0.380	0.379	0.373	0.369	0.377	0.359	0.350	0.341	0.319	0.314	0.266	0.246	0.249	0.268	0.277	0.289	0.313	0.311	0.293	0.283	0.286
Children 0-18	0.805	0.782	0.723	0.692	0.679	0.684	0.659	0.660	0.640	0.629	0.619	0.569	0.543	0.468	0.441	0.456	0.472	0.509	0.523	0.556	0.561	0.533	0.533	0.519
Children 19-25	0.512	0.516	0.498	0.478	0.463	0.446	0.422	0.389	0.360	0.361	0.345	0.309	0.265	0.254	0.254	0.305	0.302	0.317	0.316	0.329	0.324	0.323	0.311	0.304
Owner	0.536	0.541	0.506	0.471	0.450	0.480	0.493	0.513	0.541	0.552	0.565	0.549	0.523	0.423	0.392	0.387	0.402	0.455	0.474	0.521	0.530	0.552	0.587	0.581
Renter	1.208	1.199	1.126	1.121	1.140	1.144	1.102	1.052	0.993	0.975	0.962	0.875	0.736	0.705	0.689	0.793	0.804	0.840	0.855	0.895	0.890	0.856	0.846	0.837

Employment																								
FT employed	0.473	0.401	0.350	0.352	0.349	0.373	0.361	0.357	0.353	0.378	0.380	0.369	0.536	0.468	0.429	0.478	0.491	0.550	0.572	0.623	0.633	0.646	0.666	0.674
1 FTE adult	0.786	0.755	0.687	0.696	0.665	0.661	0.675	0.653	0.667	0.665	0.659	0.627	0.676	0.599	0.558	0.624	0.636	0.697	0.704	0.718	0.727	0.701	0.731	0.708
2 FTE adult	0.247	0.223	0.182	0.178	0.187	0.205	0.197	0.211	0.192	0.207	0.225	0.205	0.262	0.220	0.203	0.215	0.241	0.268	0.289	0.334	0.326	0.345	0.343	0.360
$\geq$3 FTE adults	0.064	0.045	0.040	0.033	0.037	0.039	0.043	0.044	0.043	0.050	0.048	0.045	0.042	0.036	0.028	0.032	0.035	0.041	0.042	0.058	0.066	0.071	0.071	0.066
Income																								
Lowest 50%	1.260	1.211	1.155	1.125	1.079	1.112	1.097	1.070	1.043	1.041	1.022	0.984	0.558	0.526	0.490	0.551	0.550	0.599	0.594	0.617	0.622	0.603	0.602	0.639
Top 50%	0.745	0.739	0.691	0.696	0.691	0.698	0.688	0.689	0.681	0.681	0.698	0.627	0.808	0.721	0.701	0.749	0.779	0.817	0.848	0.906	0.902	0.917	0.939	0.893

	Between CZs																							
	no EBHI												EBHI											
Age																								
0-18	2.744	2.668	2.525	2.490	2.061	2.021	1.948	1.919	1.849	1.758	1.757	1.655	1.432	1.367	1.354	1.331	1.053	1.097	1.112	1.067	1.091	1.084	1.025	1.021
19-24	2.015	1.940	1.799	1.635	1.291	1.262	1.168	1.117	1.063	1.016	1.006	0.962	1.259	1.224	1.197	1.298	1.059	1.066	1.098	1.088	1.091	1.068	1.079	1.037
25-44	3.298	3.159	3.037	2.999	2.476	2.390	2.320	2.249	2.191	2.172	2.099	2.041	2.225	2.023	1.975	2.032	1.632	1.732	1.765	1.868	1.896	1.887	1.905	1.863

College	Some college	High school	Some school	No school	Education	Hispanic	Black	White	Race	25-64	65 over	45-64
0.929	1.707	2.641	3.229	0.513		1.508	1.624	6.368		4.648	0.733	1.350
0.922	1.726	2.439	3.040	0.502		1.502	1.574	6.058		4.477	0.647	1.317
0.908	1.669	2.336	2.876	0.456		1.555	1.491	5.649		4.360	0.622	1.323
0.908	1.664	2.288	2.809	0.469		1.499	1.494	5.515		4.370	0.639	1.372
0.730	1.387	1.929	2.316	0.396		1.211	1.196	4.650		3.645	0.589	1.169
0.777	1.395	1.883	2.237	0.392		1.198	1.202	4.555		3.533	0.668	1.144
0.801	1.346	1.866	2.129	0.362		1.107	1.152	4.462		3.463	0.699	1.144
0.811	1.326	1.821	2.053	0.348		1.118	1.112	4.363		3.372	0.734	1.123
0.826	1.286	1.797	2.002	0.338		1.127	1.070	4.257		3.305	0.761	1.115
0.842	1.267	1.771	1.894	0.320		1.101	1.059	4.099		3.264	0.755	1.092
0.866	1.235	1.769	1.851	0.321		1.141	1.037	3.999		3.181	0.797	1.082
0.836	1.188	1.727	1.763	0.305		1.092	1.016	3.862		3.080	0.797	1.039
1.563	1.449	1.126	1.066	0.175		0.467	0.601	4.585		3.130	0.215	0.905
1.489	1.367	1.009	0.950	0.159		0.441	0.537	4.290		2.863	0.186	0.840
1.521	1.353	0.973	0.965	0.149		0.463	0.526	4.235		2.862	0.209	0.887
1.619	1.417	0.983	0.945	0.161		0.496	0.534	4.340		2.934	0.211	0.903
1.319	1.126	0.836	0.756	0.123		0.391	0.415	3.530		2.379	0.183	0.747
1.400	1.127	0.851	0.788	0.127		0.409	0.429	3.634		2.485	0.196	0.753
1.430	1.159	0.882	0.799	0.134		0.436	0.469	3.659		2.539	0.195	0.775
1.511	1.164	0.893	0.783	0.124		0.458	0.484	3.644		2.669	0.196	0.801
1.563	1.161	0.908	0.795	0.138		0.480	0.505	3.697		2.730	0.206	0.834
1.562	1.134	0.910	0.781	0.128		0.505	0.485	3.616		2.706	0.198	0.818
1.623	1.128	0.898	0.757	0.119		0.532	0.487	3.568		2.742	0.209	0.837
1.594	1.083	0.863	0.730	0.123		0.528	0.491	3.461		2.659	0.205	0.795

Household					Employment				Income
Children 0-5	Children 0-18	Children 19-25	owner	renter	FT employed	1 FTE adult	2 FTE adult	$\geq$3 FTE adults	Lowest 50%
2.548	4.309	2.870	2.483	6.233	1.996	3.544	1.164	0.250	6.678
2.456	4.182	2.891	2.380	6.085	1.643	3.274	1.011	0.162	6.385
2.310	4.011	2.797	2.217	5.931	1.477	3.054	0.868	0.166	6.064
2.241	3.915	2.600	2.088	5.885	1.459	3.049	0.846	0.151	5.868
1.842	3.230	2.044	1.802	4.810	1.260	2.562	0.736	0.135	4.825
1.745	3.108	1.977	1.891	4.650	1.249	2.504	0.747	0.146	4.808
1.638	2.959	1.829	1.874	4.456	1.233	2.461	0.760	0.142	4.679
1.637	2.885	1.705	1.925	4.268	1.252	2.448	0.790	0.147	4.564
1.540	2.758	1.563	1.982	4.048	1.240	2.392	0.798	0.161	4.461
1.479	2.638	1.450	2.003	3.843	1.272	2.361	0.792	0.164	4.331
1.473	2.578	1.443	2.028	3.773	1.268	2.328	0.832	0.152	4.220
1.372	2.418	1.344	1.994	3.576	1.293	2.267	0.811	0.168	4.191
1.354	2.492	1.394	2.422	3.118	2.643	2.807	1.478	0.192	2.680
1.231	2.238	1.368	2.065	3.014	2.342	2.576	1.275	0.150	2.536
1.174	2.226	1.408	2.071	2.993	2.260	2.530	1.233	0.138	2.464
1.190	2.237	1.509	1.992	3.241	2.356	2.643	1.302	0.152	2.549
0.949	1.797	1.195	1.613	2.623	1.934	2.113	1.091	0.132	2.049
0.997	1.882	1.208	1.786	2.618	2.040	2.225	1.149	0.149	2.168
1.013	1.930	1.236	1.878	2.634	2.094	2.201	1.248	0.165	2.226
1.017	1.926	1.216	1.969	2.639	2.229	2.223	1.320	0.189	2.239
1.059	1.973	1.198	2.086	2.639	2.308	2.290	1.362	0.211	2.252
1.034	1.955	1.164	2.154	2.500	2.318	2.233	1.382	0.225	2.181
0.966	1.872	1.178	2.189	2.483	2.359	2.193	1.435	0.225	2.132
0.972	1.820	1.089	2.172	2.368	2.315	2.145	1.412	0.214	2.191

Top 50%	3.461	3.347	3.241	3.266	2.763	2.675	2.600	2.577	2.518	2.461	2.522	2.303	3.357	3.104	3.157	3.226	2.625	2.677	2.718	2.781	2.865	2.875	2.923	2.730

Source: ACS data from 2008-2019 (Ruggles et al., 2021). All values are percentages of total population in each category.

Appendix C

Complete regression results for difference−in−difference estimates reported in Chapter 3

TABLE C.1: Complete DiD results for output reported in Table 3.2

	(1)	(2)	(3)
	21-23	21-23	21-23
Treatment	0.0381***	0.0383***	0.0336***
	(0.0008)	(0.0009)	(0.0011)
Adults24-25	0.0440***	0.0406***	0.0445***
	(0.0012)	(0.0011)	(0.0012)
Treatment × Adults 24-25	-0.0313***	-0.0302***	-0.0282***
	(0.0018)	(0.0019)	(0.0024)

Age45-64	0.0151***	0.0148***	0.0268***
	(0.0009)	(0.0009)	(0.0010)
Age65+	0.0042	0.0051	0.0377***
	(0.0039)	(0.0039)	(0.0051)
Non-hispanic-black	-0.0236***	-0.0241***	-0.0146***
	(0.0012)	(0.0012)	(0.0013)
Non-hispanic-native	-0.0321***	-0.0327***	-0.0407***
	(0.0010)	(0.0010)	(0.0011)
Non-hispanic-other	0.0043	0.0009	0.0729***
	(0.0053)	(0.0053)	(0.0077)
Hispanic-white	0.0149*	0.0163*	0.0428***
	(0.0067)	(0.0067)	(0.0080)
Hispanic-black	-0.1013***	-0.1035***	-0.0918***
	(0.0025)	(0.0025)	(0.0033)
Hispanic-native	-0.0297***	-0.0302***	-0.0170***
	(0.0013)	(0.0013)	(0.0015)
Hispanic-other	-0.0352***	-0.0349***	-0.0307***
	(0.0015)	(0.0015)	(0.0017)
Full-time	-0.0637***	-0.0635***	-0.0699***
	(0.0012)	(0.0012)	(0.0014)
Technical	-0.0506***	-0.0511***	-0.0629***
	(0.0010)	(0.0010)	(0.0011)
Service	-0.0586***	-0.0595***	-0.0713***

	(0.0011)	(0.0011)	(0.0012)
Farming	-0.0680***	-0.0679***	-0.0803***
	(0.0029)	(0.0029)	(0.0040)
Production	-0.0332***	-0.0334***	-0.0357***
	(0.0015)	(0.0015)	(0.0017)
Laborers	-0.0582***	-0.0589***	-0.0732***
	(0.0012)	(0.0012)	(0.0013)
Intercept	0.1735***	0.1778***	0.1761***
	(0.0016)	(0.0016)	(0.0018)
Obs	690,245	690,245	491,700

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

TABLE C.2: Complete DiD results for output reported in Table 3.3

	(1)	(2)
	19-23	27-29
Treatment	0.0363***	0.0096***
	(0.0006)	(0.0016)
Adults24-25	0.0466***	0.0098***
	(0.0012)	(0.0015)
Treatment × Adults 24-25	-0.0368***	-0.0041
	(0.0017)	(0.0022)
Age45-64	0.0241***	-0.0590***
	(0.0006)	(0.0022)
Age65+	-0.0044	-0.1034***
	(0.0026)	(0.0039)
Non-hispanic-black	-0.0375***	0.0186***
	(0.0008)	(0.0019)
Non-hispanic-native	-0.0356***	-0.0544***
	(0.0007)	(0.0015)
Non-hispanic-other	-0.0039	0.1498***
	(0.0039)	(0.0153)
Hispanic-white	-0.0590***	-0.0075
	(0.0040)	(0.0076)
Hispanic-black	-0.0742***	-0.0237*
	(0.0039)	(0.0120)

Hispanic-native	-0.0166***	0.0011
	(0.0010)	(0.0020)
Hispanic-other	-0.0407***	-0.0343***
	(0.0010)	(0.0021)
Full-time	-0.0513***	-0.0809***
	(0.0008)	(0.0018)
Technical	-0.0416***	-0.0880***
	(0.0007)	(0.0016)
Service	-0.0574***	-0.1110***
	(0.0008)	(0.0017)
Farming	-0.0366***	-0.1312***
	(0.0022)	(0.0043)
Production	-0.0381***	-0.0836***
	(0.0010)	(0.0022)
Laborers	-0.0729***	-0.1140***
	(0.0008)	(0.0018)
Intercept	0.1597***	0.3154***
	(0.0011)	(0.0031)
Obs	1,320,788	322,968

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

TABLE C.3: Complete DiD results for output reported in Table 3.4

	(1)	(2)	(3)
	21-23	19-23	27-29
Treatment	0.0393***	0.0377***	0.0306
	(0.0101)	(0.0075)	(0.0206)
Adults24-25	0.0458**	0.0491**	0.0238
	(0.0170)	(0.0179)	(0.0206)
Treatment × Adults 24-25	-0.0375*	-0.0397*	-0.0282
	(0.0179)	(0.0195)	(0.0303)
Age45-64	0.0185	0.0242**	-0.0430
	(0.0101)	(0.0078)	(0.0294)
Age65+	0.0039	-0.0109	-0.0668
	(0.0444)	(0.0273)	(0.0592)
Non-hispanic-black	-0.0134	-0.0295	0.0106
	(0.0291)	(0.0159)	(0.0260)
Non-hispanic-native	-0.0335*	-0.0326**	-0.0343
	(0.0148)	(0.0098)	(0.0234)
Non-hispanic-other	0.0066	0.0020	0.1830
	(0.0599)	(0.0451)	(0.1754)
Hispanic-white	0.0041	-0.0484	-0.0382
	(0.0576)	(0.0400)	(0.1034)
Hispanic-black	-0.0887***	-0.0651	-0.0308
	(0.0178)	(0.0386)	(0.1105)

Hispanic-native	-0.0423	-0.0100	0.0442
	(0.0292)	(0.0252)	(0.0311)
Hispanic-other	-0.0191	-0.0321	-0.0278
	(0.0292)	(0.0185)	(0.0249)
Full-time	-0.0669***	-0.0512***	-0.0855**
	(0.0148)	(0.0104)	(0.0271)
Technical	-0.0429**	-0.0347***	-0.0825**
	(0.0140)	(0.0091)	(0.0256)
Service	-0.0493**	-0.0522***	-0.1015***
	(0.0157)	(0.0098)	(0.0275)
Farming	-0.0844***	-0.0442	-0.1308*
	(0.0243)	(0.0317)	(0.0542)
Production	-0.0258	-0.0314*	-0.0752*
	(0.0178)	(0.0129)	(0.0305)
Laborers	-0.0470**	-0.0640***	-0.1117***
	(0.0161)	(0.0106)	(0.0226)
Intercept	0.1671***	0.1516***	0.2808***
	(0.0173)	(0.0118)	(0.0485)
Obs	690,245	1,320,788	322,968

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

TABLE C.4: Complete DiD results for output reported in Table 3.5

	(1)	(2)
	Any YA	Any YA
Treatment	-0.0093***	-0.0030***
	(0.0005)	(0.0004)
YA Adults	-0.0354***	-0.0375***
	(0.0006)	(0.0006)
Treatment×YA Adults	0.0263***	0.0348***
	(0.0008)	(0.0007)
Age45-64	0.0161***	0.0121***
	(0.0004)	(0.0003)
Age65+	-0.0448***	0.0119***
	(0.0020)	(0.0019)
Non-hispanic-black	-0.0364***	-0.0251***
	(0.0007)	(0.0005)
Non-hispanic-native	-0.0473***	-0.0351***
	(0.0005)	(0.0004)
Non-hispanic-other	0.1158***	0.0749***
	(0.0043)	(0.0029)
Hispanic-white	-0.0483***	0.0410***
	(0.0026)	(0.0026)
Hispanic-black	0.0451***	0.0263***
	(0.0065)	(0.0043)

Hispanic-native	0.0187***	0.0137***
	(0.0009)	(0.0007)
Hispanic-other	-0.0213***	-0.0286***
	(0.0009)	(0.0007)
Full-time	-0.0617***	-0.0521***
	(0.0006)	(0.0004)
Technical	-0.0430***	-0.0345***
	(0.0005)	(0.0004)
Service	-0.0746***	-0.0723***
	(0.0006)	(0.0004)
Farming	-0.1021***	-0.0792***
	(0.0015)	(0.0013)
Production	-0.0577***	-0.0441***
	(0.0007)	(0.0006)
Laborers	-0.0678***	-0.0634***
	(0.0006)	(0.0005)
Intercept	0.2142***	0.2008***
	(0.0008)	(0.0006)
Obs	2,620,051	4,693,006

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

TABLE C.5: Complete DiD results for output reported in Table 3.6

	(1)
	Extended Mandate
Treatment	0.0458***
	(0.0024)
SM 26+	
Treatment×SM 26+	-0.0705***
	(0.0050)
Age45-64	-0.0731***
	(0.0036)
Age65+	-0.1382***
	(0.0061)
Non-hispanic-black	-0.0915***
	(0.0026)
Non-hispanic-native	-0.0556***
	(0.0024)
Non-hispanic-other	-0.0491***
	(0.0097)
Hispanic-white	-0.0691***
	(0.0050)
Hispanic-black	0.3993***
	(0.0430)

Hispanic-native	0.0232***
	(0.0047)
Hispanic-other	-0.0490***
	(0.0039)
Full-time	-0.0596***
	(0.0029)
Technical	-0.1529***
	(0.0027)
Service	-0.1546***
	(0.0029)
Farming	-0.0161
	(0.0110)
Production	-0.1378***
	(0.0039)
Laborers	-0.1588***
	(0.0030)
Intercept	0.3634***
	(0.0047)
Obs	119,964

Standard errors are in parenthesis

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix D

Complete regression results for estimates reported in Chapter 4

TABLE D.1: Complete results for output reported in Table 4.6

	(1)	(2)	(3)
Remote	0.0461***	-0.1335***	0.1170***
	(0.0143)	(0.0223)	(0.0372)
Female	0.0062	0.0063	0.0575**
	(0.0086)	(0.0084)	(0.0270)
Age 35-44	-0.0034	-0.0024	0.0243
	(0.0077)	(0.0080)	(0.0291)
Age 45-54	-0.0094	-0.0081	0.0349
	(0.0082)	(0.0081)	(0.0366)
Age 55-64	-0.0052	-0.0043	0.0447

	(0.0091)	(0.0087)	(0.0544)
nH black	0.0153	0.0164	0.0892*
	(0.0181)	(0.0178)	(0.0494)
nH native	0.0120	0.0145	0.3284
	(0.0653)	(0.0639)	(0.2126)
nH other	0.0029	0.0019	0.1946**
	(0.0194)	(0.0191)	(0.0738)
Hispanic	0.0147	0.0124	0.1168
	(0.0199)	(0.0194)	(0.0896)
Some school	-0.2312	-0.2260	-0.1229
	(0.2287)	(0.2353)	(0.1530)
High-school	-0.3568*	-0.3582*	0.1199
	(0.2062)	(0.2129)	(0.1634)
College	-0.3607*	-0.3631*	0.0943
	(0.2071)	(0.2137)	(0.1638)
Manufacturing	0.0508	0.0538	0.0113
	(0.0391)	(0.0404)	(0.1808)
Transport	0.0530	0.0577	0.0722
	(0.0387)	(0.0398)	(0.1775)
Wholesale	0.0276	0.0287	0.0333
	(0.0460)	(0.0471)	(0.1833)
Retail	0.0159	0.0186	0.0435
	(0.0423)	(0.0427)	(0.1918)

Finance	0.0512	0.0560	0.0510
	(0.0414)	(0.0426)	(0.1779)
Business	0.0378	0.0411	0.0435
	(0.0384)	(0.0394)	(0.1805)
Personal	0.0618	0.0683	0.1035
	(0.0533)	(0.0529)	(0.2095)
Entertainment	0.0680	0.0688	0.0272
	(0.0597)	(0.0612)	(0.2162)
Professional	0.0219	0.0252	0.0030
	(0.0399)	(0.0410)	(0.1796)
Pub.Admin	0.0291	0.0336	0.0963
	(0.0378)	(0.0392)	(0.1875)
Children	0.0208	0.0216	-0.0149
	(0.0151)	(0.0145)	(0.0480)
No of children	0.0076	0.0064	0.0351**
	(0.0065)	(0.0063)	(0.0142)
Children <5	-0.0230	-0.0204	-0.0178
	(0.0144)	(0.0149)	(0.0436)
Log(wage)	-0.0189**	-0.0203**	-0.0052
	(0.0091)	(0.0089)	(0.0187)
RemoteLD		0.2190***	
		(0.0366)	
RemoteSD		0.2948***	

		(0.0347)	
Intercept	0.6729**	0.6857**	-0.0055
	(0.2626)	(0.2697)	(0.2776)
N	1,449,535	1,449,535	147,282
R^2	0.1361	0.1444	0.5036

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

TABLE D.2: Complete results for output reported in Table 4.7

	(1)	(2)	(3)
Remote	0.0461***	-0.1335***	0.1170***
	(0.0126)	(0.0118)	(0.0394)
Female	0.0062	0.0063	0.0575***
	(0.0087)	(0.0086)	(0.0219)
Age 35-44	-0.0034	-0.0024	0.0243
	(0.0088)	(0.0087)	(0.0317)
Age 45-54	-0.0094	-0.0081	0.0349
	(0.0111)	(0.0111)	(0.0379)
Age 55-64	-0.0052	-0.0043	0.0447
	(0.0120)	(0.0116)	(0.0492)
nH black	0.0153	0.0164	0.0892
	(0.0155)	(0.0153)	(0.0545)
nH native	0.0120	0.0145	0.3284
	(0.0604)	(0.0599)	(0.2224)
nH other	0.0029	0.0019	0.1946**
	(0.0166)	(0.0165)	(0.0779)
Hispanic	0.0147	0.0124	0.1168
	(0.0193)	(0.0192)	(0.0913)
Some school	-0.2312	-0.2260	-0.1229
	(0.2232)	(0.2281)	(0.1394)
High-school	-0.3568*	-0.3582*	0.1199

	(0.2059)	(0.2120)	(0.1270)
College	-0.3607*	-0.3631*	0.0943
	(0.2064)	(0.2126)	(0.1185)
Manufacturing	0.0508	0.0538	0.0113
	(0.0376)	(0.0382)	(0.1828)
Transport	0.0530	0.0577	0.0722
	(0.0375)	(0.0379)	(0.1831)
Wholesale	0.0276	0.0287	0.0333
	(0.0450)	(0.0451)	(0.1921)
Retail	0.0159	0.0186	0.0435
	(0.0385)	(0.0389)	(0.1844)
Finance	0.0512	0.0560	0.0510
	(0.0373)	(0.0379)	(0.1737)
Business	0.0378	0.0411	0.0435
	(0.0367)	(0.0372)	(0.1780)
Personal	0.0618	0.0683	0.1035
	(0.0517)	(0.0512)	(0.2138)
Entertainment	0.0680	0.0688	0.0272
	(0.0704)	(0.0706)	(0.2433)
Professional	0.0219	0.0252	0.0030
	(0.0363)	(0.0369)	(0.1795)
Pub.Admin	0.0291	0.0336	0.0963
	(0.0382)	(0.0388)	(0.1873)

Children	0.0208	0.0216	-0.0149
	(0.0192)	(0.0188)	(0.0493)
No of children	0.0076	0.0064	0.0351**
	(0.0079)	(0.0077)	(0.0177)
Children <5	-0.0230	-0.0204	-0.0178
	(0.0148)	(0.0149)	(0.0510)
Log(wage)	-0.0189***	-0.0203***	-0.0052
	(0.0072)	(0.0071)	(0.0229)
RemoteLD		0.2190***	
		(0.0232)	
RemoteSD		0.2948***	
		(0.0331)	
Intercept	0.6729***	0.6857***	-0.0055
	(0.2261)	(0.2319)	(0.3270)
N	1,449,535	1,449,535	147,282
R^2	0.1361	0.1444	0.5036

Standard errors are in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Appendix E

Supplementary analysis to accompany place-based policies discussion in Chapter 4

TABLE E.1: OLS results explaining changes in average rent, wage income, and college employment ratio since 1980 in commuting zones

	d ln(Avg.income)	d ln(Rent)	d ln(College emp.)
d ln(Non-native share)	0.07***	0.07***	0.08***
	(7.54)	(5.34)	(4.09)
d ln(Col-emp-share)	0.14***	0.08***	
	(9.20)	(3.71)	
d ln(Adult pop)	0.11***	-0.07*	-0.17***
	(4.70)	(2.51)	(3.95)

d ln(Eatery emp share)	0.01	0.07***	0.08***
	(1.00)	(4.61)	(3.49)
d ln(Grocery emp share)	-0.01	-0.05***	0.03***
	(1.47)	(4.00)	(1.53)
d ln(Daycare emp. share)	-0.02***	-0.00***	0.05***
	(5.11)	(0.46)	(4.90)
d(Avg.winter temp)	-0.00*	0.01***	0.03***
	(2.27)	(3.47)	(9.89)
d(Avg. summer temp)	-0.02***	-0.01*	0.02**
	(5.57)	(2.52)	(2.99)
2000	0.04***	0.05***	0.09***
	(6.04)	(6.54)	(5.59)
2010	-0.02*	0.23***	0.41***
	(2.02)	(17.19)	(24.30)
2019	-0.04***	0.17***	0.55***
	(3.82)	(11.19)	(33.09)
d ln(Avg.income)		0.34***	0.71***
		(7.67)	(9.24)
Intercept	-0.07***	-0.03***	0.16***
	(20.13)	(5.79)	(20.94)
N	2888	2888	2888

Values are 1999 constant U.S. Dollars. Differences are indicated by letter "d" preceding the text (variable name), and indicate that values are $t - t_1980$. Robust standard errors are assumed.

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PUBLICATIONS

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