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Essays in the Economics of Aging

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ABSTRACT

ESSAYS IN THE ECONOMICS OF AGING

By

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In this dissertation, I explore how economic decisions diverge for different age groups. Two essays address the location decisions of older households while the third examines why different age cohorts donate to charities.

The first essay estimates how the age distribution of the population across cities will change as the number of older adults rises. I use a residential sorting model to estimate the location preference heterogeneity between younger and older households. I then simulate where the two household types will live in 2030. All MSAs end up with a higher proportion of older households in 2030, and only eight of 243 MSAs experience a decline in the number of older households. The results suggest that MSAs in upstate New York and on the west coast, particularly in California, will have the largest number of older households in 2030. Florida will remain a popular place for older households, but its relative importance may diminish in the future.

The second essay explores whether the basic motivations for charitable giving differ by age cohort. Using the results from a randomized field experiment[1], I test whether benefits to self or benefits to others drives the charitable giving decision for each age cohort. I find limited

[1] List, Price, and Murphy (2015)

heterogeneity for benefits to self. Individuals between the ages of 50 and 64 increase average donations more than any other age cohort in response to emphasizing warm glow, and this heterogeneity is exclusively driven by larger conditional gifts.

The third essay is preliminary joint work with H. Spencer Banzhaf and Carlianne Patrick. We build a unique data set of local homestead exemptions, which vary by generosity and eligibility requirements, for tax jurisdictions in Georgia. Using school-district-level Census data since 1970 along with the history of such exemptions, we will explore the impact of these exemptions, particularly exemptions targeting older households, on the demographic makeup of each jurisdiction and consider the impact of these laws on the relative levels of housing capital consumed by older and younger households.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Abbreviations

BKT	Bayer, Keohane, Timmins
CL	conditional logit
CMSA	Consolidated Metropolitan Statistical Area
DI	Disability Insurance
HH	household
IPUMS	Integrated Public Use Microdata Series
MSA	Metropolitan Statistical Area
MU	marginal utility
OASI	Old-Age Survivors Insurance
PFD	Permanent Fund Dividend
PUMA	public use microdata area
SS	Social Security
U.S.	United States

Introduction

According to Census projections, the number of persons over 65 years old is expected to grow from 43.1 million in 2012 to 72.8 million in 2030. In 2030, one in five people will be over the age of 65. In this dissertation, I explore how the economic decisions of older households differ from younger households in the context of location choice and charitable giving.

The first essay estimates how the age distribution of the population across cities will change as the number of older adults rises overall. That is, I predict where older and younger households will live in 20 years. While I am not the first to run such projections, I am the first, to my knowledge, to run such simulations on a national-scale using on micro-data[2] in a residential sorting model. Will Florida, Arizona, and other traditional retirement communities continue to attract the higher number of older households? I use a residential sorting model developed by Bayer, Keohane, and Timmins (2009) to estimate the utility associated with living in different cities for two cohorts of households: households with heads under 65 years old (younger households) and households with heads 65 and older (older households). The model accounts for differences in household incomes across metropolitan areas as well as the long-run psychological costs of living away from one's birth place. I then use these estimates to simulate where these households will live in the year 2030. Overall, all but eight metropolitan statistical areas (MSAs) in the simulation have an increase in the number older households between 2010 and 2030. As expected, the greatest increases occur in the largest MSAs in the Northeast (New York City, Boston, Washington, Buffalo, and Pittsburgh), around the Great Lakes (Chicago, Detroit, and Cleveland), on the West coast (Phoenix, Tucson, San Diego, Los Angeles, San Francisco, Portland, and Seattle), and in Texas (Dallas and Houston). MSAs in Florida have mostly modest

[2] I use data from the micro-data from the 2010 American Community Survey provided by Ruggles et. al. (2010).

gains in the number of older households, and their relative importance may diminish in the future. Further, the results suggest that MSAs on the West coast, particularly in California, and upstate New York will age more than other areas of the United States. The MSAs with highest net migration of older households were in the Rust Belt (Buffalo, Cleveland, Pittsburgh, Albany, Scranton), smaller MSAs in the Carolinas (Goldsboro, Wilmington, Greenville, Myrtle Beach), MSAs in Florida (West Palm Beach, Sarasota, Tampa, Fort Myers, Naples, Daytona Beach), relatively small MSAs in Texas (Beaumont, Brownsville, Tyler), MSAs in southern Arizona (Tucson and Phoenix), and most MSAs in California (Los Angeles, San Francisco, San Diego, Sacramento, Fresno, etc.). Large MSAs bordering the Atlantic Ocean in the Northeast (New York City, Philadelphia, Washington, and Boston) and along the Great Lakes in Illinois, Michigan, and Wisconsin (Detroit, Chicago, Green Bay, and Milwaukee) as well as a large number of Southern cities (Atlanta, Raleigh, Charlotte, Atlanta, Birmingham, Chattanooga, Nashville, Little Rock, New Orleans, Jackson, Dallas, Houston, and New Orleans) had the highest out-migration of older households.

The second essay examines how the motivations for charitable giving vary for different ages. Evidence suggests that charitable giving usually increases with age until it begins to decline between 65 to 75 years old. Further, economic theory proposes two basic drivers of charitable giving: benefits to self or benefits to others. I use data from a large scale field experiment described in recent manuscript by List, Murphy, and Price (2015) that was designed to directly disentangle pure (benefits to others) and impure (benefits to self) altruism. In the experiment, each household in Alaska eligible to collect a Permanent Fund Dividend (PFD) received a letter in the last week of December of 2013 asking them to donate a portion of their 2014 PFD to an eligible charity. The letters contained a randomized message either appealing to the concern for the benefits to others (“Make Alaska Better for Everyone”) or to the concern for the benefits to self (“Warm Your Heart”). Using linear regression, I extend the analysis of the field experiment by estimating the heterogeneous treatment effects for each treatment by age cohort. Examining the effect on average donations, I find limited treatment heterogeneity in the “Warm Your Heart” message, but no age cohort is affected heterogeneously by the “Make Alaska Better for Everyone” message. In particular, the results indicate that individuals between the ages of 50 and 64 years old increase average donations more than any other age cohort in response to the “Warm Your Heart” message, but the statistical difference between the Mature and Older cohorts disappears when controlling for whether the individual gave in 2013. Further, the response heterogeneity of the 50 and 64 years olds is exclusively driven by the intensive margin, larger average donations from people who gave something, as opposed to increasing the number of donors. Finally, individuals under 19 years old give less on average compared to other age cohorts when they receive the message emphasizing impure altruism. That is, they are less persuaded than other ages to donate by a message reminding them that giving could make them feel good about themselves. I also present back-of-the-envelope calculations to predict charitable giving in 2032 under a number of treatment scenarios. One question left unanswered by this analysis is if the results are driven by cohort effects or actual aging.

The third essay is joint work with H. Spencer Banzhaf and Carlianne Patrick and is still in the development phase. The most significant contribution of the essay is a unique data set of local homestead exemptions for tax jurisdictions in Georgia. To my knowledge, this is the first such data set in Georgia and possibly the United States. Local homestead exemptions in Georgia vary by generosity and eligibility. Further, many are targeted to older households. Using school-district-level Census data starting in 1970 along with the history of such exemptions, we will explore the impact of these exemptions, particularly exemptions targeting older households, on the demographic makeup of each jurisdiction. We would expect these subsidies to attract seniors to such jurisdictions (or prevent them from leaving), relative to control jurisdictions. Second, we will consider the impact of these laws on the levels of housing capital by testing whether the equilibrium ratio of housing consumption for seniors to younger households is higher in jurisdictions with age-targeted exemptions compared to control districts. We will test for such demographic "sorting” and heterogeneous housing consumption by age with a difference-in-difference-in-differences model.

On the whole, this work illustrates the heterogeneity between older and younger persons. While the first and third essays discuss how Tiebout (1956) sorting vary by age, they examine different questions and on different scopes. The first essay looks at location decisions between cities on a national scale and predicts future decisions; the third essay studies how particular laws affect location decisions and examine the location decisions at the school-district level within the state of Georgia. However, this does not mean that the two essays are not relatable. The first essay emphasizes the importance of cities being prepared for the coming demographic shift while the policies examined in the third essay may need to be reevaluated because of the demographic population shifts predicted by the first essay. Finally, the second essay expands upon the heterogeneity between different ages in a charitable giving context.

Chapter I

Location Preferences of Older Households

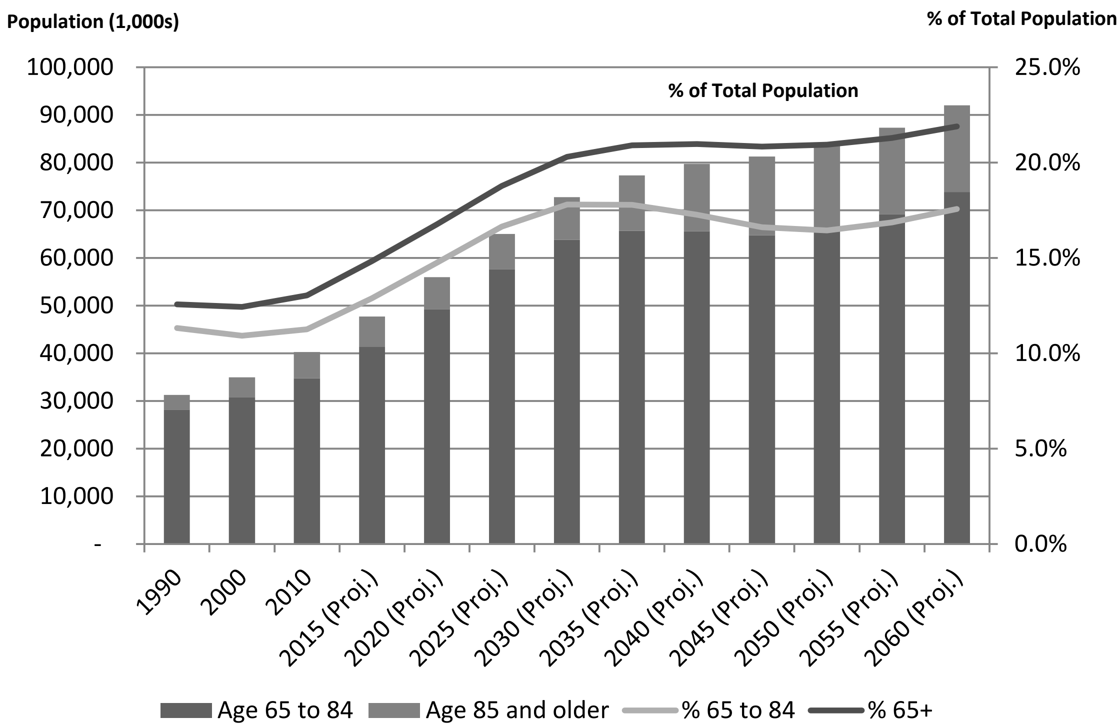
1. Introduction

The population in the United States is aging. According to the 2010 Census, persons 65 years and older accounted for approximately 40.3 million, or 13%, of the 308.7 million people in the United States (Howden and Meyer 2011). This segment of the population, whom I will refer to as older adults, grew 15.1% between 2000 and 2010 which is more than 50% faster than the overall U.S population growth rate of 9.7% over the same time period (Werner 2011) and second only to the 31.5% increase for persons between 45 to 64 years old who are mostly Baby Boomers (Howden and Meyer 2011). Figure 1 shows how the population has aged historically from 1990 to 2010 and highlights the projections of the population over 64 years old from 2015 to 2060 in 5-year increments[3]. The bars represent 1,000s of people 65 and older and are measured by the left axis; the dark gray (light gray) line characterizes the percent of the population 65 and older (between 65 and 84 years old) and is measured using the right axis. The percent of the population 85 and older can be calculated using the differences between the dark and light gray lines. The 2010 Census showed the largest proportion of the population 65 years old and older than any previous Census on record (Werner 2011). The proportion of the population in the United States over 64 years old will continue to grow as the Baby Boomer generation ages and overall population growth remains relatively slow. In fact, the Census Bureau estimates that there will be over 72.7 million persons 65 and older by 2030, representing 20.3% of the total population; this

[3]The data for 1990 to 2000 comes from Hobbs and Stoops (2002) while the source for 2010 is Howden and Meyer (2011). Finally, the projections for 2015 to 2060 were found in the 2015-2060 Projections: U.S. Census Bureau, Population Division. (2012).

number increases to over 92 million, or 21.9% of the population, in 2060 (U. S. Census Bureau, Population Division 2012).

Figure 1. Projected Population that is 65 Years Old and Older in the United States



Sources:
1900-2000 data: Hobbs and Frank 2000
2010 data: Howden and Meyer 2011
2015-2060 Projections: U.S. Census Bureau, Population Division. (2012) Table 12. Projections of the Population by Age and Sex for the United States: 2015 to 2060 (NP2012-T12).

As the number of older adults increase, the number of households (HHs) lead by older adults will rise. Older households are more likely to have a retired head and a higher proportion of income that is location independent as they are more likely to rely on a fixed income from Social Security benefits, pensions, accumulated wealth, and other retirement plans. Therefore, older households may face fewer financial constraints when making location decisions compared to working households which allows them to put more weight on other preferences, such as nice weather or living near relatives. While older households are less compelled to seek economic opportunity, they face other constraints to moving, such as health concerns and limited resources. Overall, older households are less likely to move than younger households; however, their reasons for moving and, therefore, their destinations may differ.

These demographic trends cause numerous social, economic, and political issues. Social Security and Medicare suffer from funding problems because tax revenue is failing to keep pace with the increasing benefits. Seniors also tend to require greater, more expensive levels of healthcare that put an upward pressure on costs for all. Further, some studies have found evidence of modest slowing in economic growth as populations age because of lower labor force participation rates and savings rates (e.g. Bloom, Canning, and Fink 2011). These national fiscal realities are well documented, but the implications of these demographic changes may also impact local governments and have other effects on society.

Local governments may not be prepared for the aging population. A survey administered by the MetLife Foundation in 2010 found that only 17% of local communities had a strategic plan in place for older adults (MetLife Foundation 2011). The same report cited that the top 3 challenges that local governments face in planning for the aging population are funding shortages, transportation, and housing. While markets may respond to the changing demographics over time, unprepared local governments may face a crisis if they do not begin to make plans now.

With these basic facts, the purpose of this paper is to predict where older households will live in the future. Specifically, I simulate how the age distribution of the population across metropolitan statistical areas (MSAs) will change as the number of older households rise. Will Florida, Arizona, and other traditional retirement communities continue to attract the largest number of older households? I use a residential sorting model developed by Bayer, Keohane, and

Timmins (2009) to estimate the utility associated with living in different cities for two cohorts of households: households with heads under 65 years old (younger households) and households with heads 65 and older (older households). The model accounts for differences in household incomes across metropolitan areas as well as the long-run psychological costs of living away from one's birth place. I then use these estimates to simulate predictions of where these households will live in the year 2030. Ultimately, I will predict which cities will age the most. Conventional wisdom tells us that older adults, retirees in particular, favor moving to places with nice weather and abundant sunshine, but rising housing prices in these locations may hinder many households from moving to these areas. The simulations will answer questions about which areas will continue to attract older households as their numbers increase and what new retiree destinations may emerge as the overall U.S. population ages.

Overall, all but eight MSAs in the simulation experience increases in the number of older households. As expected, the highest gains occurred in the largest MSAs in the Northeast (New York City, Boston, Washington, Buffalo, and Pittsburgh), around the Great Lakes (Chicago, Detroit, and Cleveland), on the West coast (Phoenix, Tucson, San Diego, Los Angeles, San Francisco, Portland, and Seattle), and in Texas (Dallas and Houston). Surprisingly, the largest percentage increases were concentrated in California and New York, excluding New York City. MSAs in Arizona (Flagstaff, Yuma), New Mexico (Albuquerque and Santa Fe), California (Visalia, Merced, Modesto, Stockton, Fresno, Redding, and Chico), Oregon (Eugene and Portland), Washington (Spokane, Bellingham, Seattle, and Yakima), South Carolina (Charleston, Augusta, and Myrtle Beach) , Illinois (Bloomington, Decatur, Springfield), and New York (Syracuse, Rochester, Buffalo, and Jamestown) along with Philadelphia, Cleveland, Detroit, Washington, and St. Louis, experienced large gains in the share of older households. MSAs in

Florida have mostly modest gains in the number of older households, the percent change in older households, and the change in the proportion of older households. This suggests that Florida will remain a popular place for older households. However, its relative importance may diminish in the future. The results suggest that MSAs on the west coast, particularly in California, and upstate New York will age more than other areas of the United States.

The population in a city can age through either its existing residence advancing in years or older households migrating into the city. I calculate the net migration for each MSA by removing the households that did not move in the simulation. The highest net migration of older households were from MSAs in the western portion of the Northeast (Buffalo, Cleveland, Pittsburgh, Albany, Scranton), smaller MSAs in the Carolinas (Goldsboro, Wilmington, Greenville, Myrtle Beach), MSAs in Florida (West Palm Beach, Sarasota, Tampa, Fort Myers, Naples, Daytona Beach), smaller MSAs in Texas (Beaumont, Brownsville, Tyler), MSAs in southern Arizona (Tucson and Phoenix), and most MSAs in California (Los Angeles, San Francisco, San Diego, Sacramento, Fresno, etc.). Large MSAs bordering the Atlantic Ocean in the Northeast (New York City, Philadelphia, Washington, and Boston) and along the Great Lakes in Illinois, Michigan, and Wisconsin (Detroit, Chicago, Green Bay, and Milwaukee) as well as a large number of Southern cities (Atlanta, Raleigh, Charlotte, Atlanta, Birmingham, Chattanooga, Nashville, Little Rock, New Orleans, Jackson, Dallas, Houston, and New Orleans) had the highest out-migration of older households.

The remainder of this paper begins with background and overview of the related literature. Section 3 discusses the proposed methodology while section 4 details the data used to estimate the model. Using the data as a backdrop, section 5 discusses the econometric implementation of the model. The results of the model are presented in section 6, and the simulations are discussed in section 7. Section 8 concludes.

2. Background And Related Literature

A household's migration pattern most often follows the life cycle[4,5]. Households are most likely to move when they experience a major life change such as a new job, marriage, the birth of a child, retirement, increasing health care needs, or the death of a spouse. Upon retirement, households often have more freedom to seek places that fit their amenity preferences because much of the household's income is no longer tied to a job or location. This freedom to move diminishes as the household's members age or their health declines.

Conventional wisdom, endless lists of top retirement communities[6], and research tells us that older adults, specifically younger, healthier retirees, seek places with nice weather (Duncombe, Robbins, and Wolf 2000) and more sunlight, but most people prefer good weather (Rappaport 2007). In addition to weather, retirees may also consider a location's relative cost of living (Graves and Knapp 1988; Graves and Waldman 1991a; Fournier, Rasmussen, and Serow 1988; Cebula and Clark 2013; Gabriel and Rosenthal 2004); crime rate (Stimson and McCrea 2004; Duncombe, Robbins, and Wolf 2000); public spending and taxes (Cebula and Clark 2013; Conway and Houtenville 1998; Duncombe, Robbins, and Wolf 2000; Conway and Rork 2013; Onder and Schlunk 2010; Conway and Rork 2012); access to transportation networks; access to high quality health care (Karner and Dorfman 2012); access to restaurants, theatres, movie theatres, parks, and golf courses; and cleaner air[7].

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[4] See Berkoz and Dokmeci (2000), Nijkamp, Van Wissen and Rima (1993), and Clark and Onaka (1983) for examples.

[5] Rossi (1955) was the first to incorporate the life course into mobility decisions.

[6] See (Bortz and Max 2014; Brandon 2012; MarketWatch 2014)

[7] Work in epidemiology suggests that populations over 65 years old are more sensitive to air pollutants than working age populations (Gouveia and Fletcher 2000; Fischer et al. 2003; Lee, Son, and Cho 2007; Cakmak, Dales, and

In a recent study, Chen and Rosenthal (2008) developed a set of the quality of life and quality of business indicators. To estimate the relative attractiveness of locations to retirees and workers, the authors regressed the difference between the log share of retirees in a location and the log share of workers in the same location on the quality of life and quality of business indicators. Their results suggest that retirees are attracted to areas with higher quality of life but repelled from areas with improving quality of business[8]. To address whether shifts in population may be driving the quality of life and business[9], the authors examined changes in the quality of life and quality of business for households that migrated between 1995 and 2000. The results suggest that households begin to move away from locations with high quality of business to locations with high quality of life beginning in their 50s and peaking in their 60s.

Previous literature has also looked at where older adults historically migrate. Longino and Bradley (2003) analyzed both the 1990 and 2000 Censuses. Their study found that Florida remained at the top of retirement destination state followed by Arizona and California, but the gap between Florida and the number two state shrank between 1990 and 2000. Nevada also entered the top 10 retirement destinations for the first time in 2000. In terms of the net number of retirement migration, the top three are Florida, Arizona, and North Carolina. A more recent study by Conway and Rork**,** examine how elderly migration has changed since 2000[10] (2013). Their results suggest that changes in the elderly migration rate are inconclusive, but the authors also note that the rankings by their elderly net immigration rate for Nevada and Florida have fallen

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Vidal 2007). Some studies did not find that the elderly were directly more sensitive to air pollutants, but they did find that health problems that may be more likely to occur in the elderly are associated with greater sensitivity to air pollution (Zanobetti, Schwartz, and Gold 2000).

[8] An earlier study by Gabriel and Rosenthal (2004) also found that retirees are repelled from places with high quality of business but attracted to places with high quality of life and low cost of living.

[9] Rosenthal and Strange (2004) show how changes in population affect quality of business and quality of life indirectly through agglomeration economies and consumer choices.

[10] See Feinstein and McFadden (1989) for another example of earlier elderly migration estimates and projections of U.S. elderly migration projections and Rogers (1988) for an international comparison.

from number 1 and 3, respectively, in 2000 to number 11 and 8 in 2010 while Georgia, Idaho, and the Carolinas have risen in the rankings. My main contribution to this literature is to use microdata to help predict the areas that will see large increases in the number of older households. To my knowledge, this is the first study to attempt to make such prediction in this manner.

3. Methodology[11]

3.1 Overview

I estimate a partially-dynamic, additive random utility model of residential sorting developed by Bayer, Keohane, and Timmins (2009) in a conditional logit framework. To identify location choice differences between younger and older households, I take the simplest approach and estimate the model separately for the two cohorts. This allows the marginal utility of income, the long-run psychological cost parameters, and the mean utility of MSAs to differ between the cohorts. While I cannot compare the magnitude of the estimated parameters for each cohort, I can contrast the relative MSA ranks between the two cohorts using the estimated mean utilities.

3.2 Bayer, Keohane, and Timmins (2009) model of residential sorting

The methodology follows the model of residential sorting by Bayer, Keohane, and Timmins (2009)[12] closely. Bayer, Keohane, and Timmins, henceforth BKT, made at least two key contributions. First, they showed that the traditional hedonic model biases the estimates of the marginal willingness to pay for a local amenity when what they call "mobility costs" is positive and vary with location. Their "mobility costs" represent the long-run psychological costs of a head of household living in a location outside of his or her birthplace; it is not a short run

[11] The description of the model largely follows Bayer, Keohane, and Timmins (2009).
[12] The BKT model is similar to the logit specification described in Berry (1994) and Berry, Levinson, Pakes (1995). While the conditional logit model has a number of strict assumptions, its convenience makes it a popular estimation model.

moving cost resulting from moving from one location to another[13]. Therefore, I will henceforth refer to these costs as long-run, psychological costs. When long-run costs are positive, the cost of moving must be compensated either through lower housing rents, higher wages, or a combination of the two. Therefore, the housing price and wage effects underestimate the value of a marginal change in an amenity. That is, the amenity minus the mobility cost is captured in the housing price and wage effects. Their second main contribution deals with instrumenting for each community's air quality which is not the emphasis of this paper[14].

The BKT model is estimated in two stages, but this paper focuses on the first stage[15]. The first stage recovers a housing price-adjusted baseline utility for each location independent of long-run costs and income, and the second stage decomposes these baseline utilities into the marginal indirect utilities of local amenities (or dis-amenities). The model begins with households maximizing their utility by choosing location *j*, consumption of numeraire good *C*, and housing *H* subject to a budget constraint:

$$max_{\{C,H,X_j\}} U\left(C,H,;X_j,M_j\right) \ s.t. I_j = C + \ \rho_j H \tag{1}$$

where I_j is income in location *j*; the price of the composite good *C* is normalized to one; ρ_j is a housing price index in location *j*; and M_j is a long-run cost that is described in section 5. Indirect utility equals a constant $\bar{V} \equiv V\left(I_j,\rho_j;X_j,M_j\right)$ in equilibrium because individuals would move if they could achieve a higher utility in another location[16]. The traditional hedonic approach of

[13] Households pay pecuniary costs to move; households that move have to pay for moving help or miss time working to move. I also believe that short-run psychological costs are important. Households who change cities may pay a psychological cost of leaving a familiar place where they may have built a social network.0 However, I cannot account for these costs in the current model as a household's last location is endogenous to their current location. Keenan and Walker (2011) develop a dynamic migration model that can account for return moves.

[14] BKT use pollution from distant sources to instrument for local air pollution.

[15] I will use the second stage in future research to see how older and younger households differ in their valuation of specific amenities.

[16] Bayer, Keohane, and Timmins compare this traditional hedonic model to their proposed model to show that he absence of mobility costs bias the estimates of the marginal willingness to pay for amenities.

totally differentiating $\bar{V}$ cannot be used to incorporate long-run costs because utility cannot be constant across locations when individuals are born in different places.

To resolve this problem, BKT suggest taking a step back by explicitly modeling the location decision prior to choosing the composite commodity and housing services. The intuition is that households first select a location (i.e. MSA) and then decide their housing and consumption bundle second based on this location choice. To implement this, I continue to follow their model by assuming the following utility function for household *i* in location *j*:

$$U_{i,j} = C_i^{\beta_c} H_i^{\beta_H} X_j^{\beta_X} e^{M_{i,j} + \eta_{i,j} + \xi_j} \tag{2}$$

where ξ_j captures unobserved characteristics of location *j*; $\eta_{i,j}$ describes the household idiosyncratic part of utility independent of long-run costs; and $M_{i,j}$ measures the long-run cost of not living in the location where the head of household *i* was born. Households maximize equation (2) subject to their budget constraint $I_j = C + \rho_j H$. After solving the demand for housing $H_{i,j}^{*}$[17], the following indirect utility is derived:

$$V_{i,j} = I_{i,j}^{\beta_I} e^{M_{i,j} + M_{i,j}^{SR} - \beta_H \ln(\rho_j) + \beta_X \ln(X_j)\ \eta_{i,j} + \xi_j}, \beta_I \equiv \beta_C + \beta_H \tag{3}$$

One of the benefits of their model is that the marginal willingness to pay is equal to the marginal rate of substitution between X_j and income[18].

Finally, I take the log of equation (3) to derive their estimation equation for step 1. This yields the following:

$$ln\, V_{i,j} = \delta_j + \beta_I ln I_{i,j} + M_{i,j} + \eta_{i,j} \tag{4}$$

[17] See appendix 1 for steps to solve for $H_{i,j}^{*}$.

[18] This is expressed in the following equation:

$$MWTP_i = \frac{\left(\frac{\beta_X}{X_j}\right)}{\left(\frac{\beta_I}{I_{ij}}\right)} = \left(\frac{\beta_X}{\beta_I}\right)\left(\frac{I_{ij}}{X_j}\right).$$

where

$$\delta_j = -\beta_H ln\rho_j + \beta_X lnX_j + \xi_j \tag{5}$$

δ_j symbolizes the mean, or baseline, utility of location *j* given income, long-run costs, and a mean of zero for the idiosyncratic error; it contains all individual-constant attributes of location *j* that individuals care about. It represents attributes such as weather, pollution, recreational amenities, natural amenities, and housing prices[19]. Since I do not observe the income that households would earn in all locations in practice, I estimate $I_{i,j}$ by decomposing it as a predicted mean $\hat{I}_{i,j}$ and an idiosyncratic error term, $\varepsilon^I_{i,j}$. Substituting this term into equation (4) gives the following:

$$\ln \mathrm{V}_{\mathrm{i,j}} = \delta_{\mathrm{j}} + \beta_{\mathrm{I}}\ln\hat{\mathrm{I}}_{\mathrm{i,j}} + \mathrm{M}_{\mathrm{i,j}} + \nu_{\mathrm{i,j}} \tag{6}$$

where

$$\nu_{i,j} = \eta_{i,j} + \beta_I \varepsilon^I_{i,j} \tag{7}$$

Assuming that $\nu_{i,j}$ are independently and identically distributed type I extreme value and given the results in McFadden (1974), equation (6) can be estimated using the conditional logit (CL) model where the probability that household *i* chooses in location *j* is:

$$P\left(ln\,V_{i,j} \geq ln\,V_{i,k} \forall\, k \neq j\right) = \frac{e^{\beta_I ln\hat{I}_{i,j} + M_{i,j} + \delta_j}}{\sum_{u=1}^{J} e^{\beta_I ln\hat{I}_{i,u} + M_{i,u} + \delta_u}} \tag{8}$$

This probability also represents the share of the population that lives in location *j*. $\hat{\delta}_j$'s are estimated from equation (8) using maximum likelihood and represent the indirect utilities for each location independent of income and mobility costs. The second stage disentangles the local amenities that drive the mean utility of a MSA by estimating equation (5).

[19] In future work, I plan on decomposing δ_j into the

4. Data

4.1 Primary Data

This study utilizes the census 1% microdata sample from the 2010 American Community Survey provided by the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2010). The data contains information on location, demographics, income, and residence of a household and its members. The unit of analysis is households over the age of 25 because location decisions are made at the household level. Each household takes on the characteristics of its head. That is, the head of the household's age, education level, marital status, birth location, and current location are assigned to the entire household. For simplicity, I drop individuals who lived in group quarters such as college dormitories, prisons, and mental institutions, because individuals in group quarters are often in these areas temporarily, and many are there involuntarily. While I only loose about 80,000 observations (approximately 6% of the sample), the downside is that I remove some older adults in nursing homes. Because the psychological costs of living outside a head's birth location cannot vary across locations[20], I have to drop all households with foreign born heads as each MSA in the choice set are outside of the head's birth location. I also drop households when their metropolitan area is unidentified in the data due to privacy concerns. After weighting the data, I am left with a little over 66.5 million households which is approximately 71% of all households living in MSAs in 2010 Census (93,924,511) and 57% of all households in the United States in the 2010 Census (116,716,291). The full sample is summarized in panel A of table 1.

[20] Estimating the conditional logit model requires within household variation across locations for the independent variables.

Table 1. Summary statistics of the IPUMS data

	Unit	Mean	Std. Dev.	Min	Max
Variable	Panel A: Full Weighted Sample (66,590,500 observations)				
Log of HH Inc.	HH	11.022	0.616	7.59	14.08
Married	Head	0.481	0.500	0	1
White	Head	0.834	0.372	0	1
Age	Head	52.639	16.106	26	95
65 and Older	Head	0.233	0.423	0	1
HS Drop.	Head	0.085	0.279	0	1
HS Diploma	Head	0.249	0.433	0	1
Some College	Head	0.239	0.426	0	1
Assoc. Degree	Head	0.083	0.276	0	1
Bach. Degree	Head	0.210	0.408	0	1
Adv. Degree	Head	0.134	0.341	0	1
Moved	HH	0.107	0.309	0	1
Moved States	HH	0.015	0.122	0	1
Moved MSA	HH	0.021	0.144	0	1
	Panel B: Younger HH Weighted Sample (51,059,402 observations)				
Log of HH Inc.	HH	11.048	0.641	7.04	14.08
Married	Head	0.499	0.500	0	1
White	Head	0.820	0.384	0	1
Age	Head	45.759	10.829	26	64
65 and Older	Head	0.000	0.000	0	0
HS Drop.	Head	0.062	0.241	0	1
HS Diploma	Head	0.226	0.418	0	1
Some College	Head	0.248	0.432	0	1
Assoc. Degree	Head	0.094	0.292	0	1
Bach. Degree	Head	0.232	0.422	0	1
Adv. Degree	Head	0.139	0.345	0	1
Moved	HH	0.127	0.333	0	1
Moved States	HH	0.017	0.130	0	1
Moved MSA	HH	0.024	0.153	0	1
	Panel C: Older HH Weighted Sample (15,531,098 observations)				
Log of HH Inc.	HH	10.765	0.577	8.54	13.98
Married	Head	0.423	0.494	0	1
White	Head	0.878	0.327	0	1
Age	Head	75.257	7.714	65	95
65 and Older	Head	1.000	0.000	1	1
HS Drop.	Head	0.159	0.366	0	1
HS Diploma	Head	0.327	0.469	0	1
Some College	Head	0.209	0.406	0	1
Assoc. Degree	Head	0.047	0.211	0	1
Bach. Degree	Head	0.140	0.347	0	1
Adv. Degree	Head	0.119	0.324	0	1
Moved	HH	0.043	0.202	0	1
Moved States	HH	0.008	0.088	0	1
Moved MSA	HH	0.011	0.106	0	1

Source: Ruggles et al (2010)

The mean log household income is 11.022 ($55,126) per year with a standard deviation of 0.616 ($56,981)[21]. Almost half (47.8%) of the household heads were married, and 80% of them were white. The average age of householder was just over 50 years old which clearly demonstrates the Baby Boomers generation aging toward retirement. Interestingly, a little over 20% of the household heads in the sample are 65 years old and older which is quite higher than the 13% of the population over 65. This anomaly makes sense because household heads tend to be older than the average household member, and the youngest household head is 25 years old. The percent of household heads with less than a high school diploma, a high school diploma, some college, an associate's degree, a bachelor's degree, and an advanced degree are 12%, 24%, 23%, 8%, 20%, and 13%, respectively. Finally, approximately 13% of the sample moved between 2009 and 2010, but only 1.8% and 2.6% changed states or MSAs, respectively.[22]

Panels B and C of table 1 show the summary statistics for the young and old cohorts, respectively. On average, younger households earn more, are more educated, are more likely to be married, and less likely to be white than older households. Young households are also much more likely to move within a MSA and between a MSA.

4.2 Geography

The microdata from IPUMS provide the household location in 2000 public use microdata areas (PUMAs). I aggregate the PUMAs into metropolitan areas using the Metropolitan Statistical Areas (MSA) or Consolidated Metropolitan Statistical Area (CMSA) as defined in

[21]I estimate the income equations using the log of household income. To adjust for negative values, I rescale income by adding the minimum income to each household's income.

[22]In future work, I plan on using data from the 2000 Census to test for cohort effects. The 2000 Census data and the 2010 ACS are some important differences. The two most important are the questions asked and the timeframe that the questions refer. The questions vary slightly between the ACS and the 1990 and 2000 long form decennial Census. For example, the ACS asks where an individual lived 1 year ago while the decennial Census asks where the individual lived 5 years ago. The other major difference is that the ACS is conducted throughout the year and asks about the previous 12 months while the decennial Census asks about the previous calendar year. This can significantly affect the way the two surveys measure annual income.

1999 by the Office of Management and Budget[23,24]. The PUMAs do not map perfectly into MSAs because MSAs are defined using county borders while PUMAs may cross county borders. Subsequently, I only assign households to a MSA if I know they reside in the MSA with certainty[25]. In the end, I use 243 MSAs in the analysis which are listed in Appendix A.

5. Econometric Implementation

5.1 Estimation of Income by location

The model requires household income for each location choice, but the data only provides what a household makes in its current location. Economically, households, particularly those with workers, would expect to earn heterogeneous incomes in each city because each location has distinct characteristics, such as the cost of living and amenities (and disamenities), that affect wages. Older households may earn differentiated incomes in different locations because public benefits vary by state. Econometrically, the conditional logit model requires that all explanatory variables vary over location j and disallows household characteristics that only vary over i. In essence, location invariant independent variables drop out of the logit estimation. Therefore, I need to measure predicted household income for each household in each MSA. This is done in two steps. First, I estimate a MSA-specific, log-linear regressions of household income on household head attributes. Second, I predict household income for each household in each MSA using these estimates.

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[23] The Missouri Census Data Center provides cross-walks between different geographies.
[24] I will simply refer to these as MSAs. When I discuss specific MSAs, I will use the first city listed in the MSA name to refer to the whole MSA.
[25] In future research, I will improve upon the geographic assignment to increase the scope of the study in two ways. First, I will combine MSAs that share a PUMA. Second, I will expand the borders of an MSA if it contains a PUMA that overlaps with a rural area. I also want distinguish whether a household lives in the central city or suburb of an MSA. IPUMS provides an indicator for whether a household resides in the central city of an MSA, but many of the PUMAs are not classified as either. I am exploring other possibilities to assign central city status including the population density, number of businesses per square mile, distance to city town hall, and density of public transportation.

I use the following log-linear income model to estimate how household income changes by household characteristics:

$$
\begin{aligned}
ln\hat{I}_{\,i,j} = {} & \alpha_{0,i,j} + \alpha_{Married,j}\, MARRIED_i + \alpha_{Female,j} FEMALE_i + \alpha_{White,j} WHITE_i \\
& + \alpha_{AGE,j}\, AGE_i + \alpha_{Age^2,j}\, AGE_i^2 + \alpha_{Age65,j}\, Age65_i \\
& + \alpha_{HSDROP,j} HSDROP_i \\
& + \alpha_{SOMECOLL,j} SOMECOLL_i + \ \alpha_{ASSOCDEG,j} ASSOCDEG_i \\
& + \alpha_{BACHDEG,j} BACHDEG_i + \alpha_{ADVDEG,j} ADVDEG_i \\
& + \alpha_{P1,j,t} P(R_B, R_D|EDU) + \alpha_{P2,j,t} P(R_B, R_D|EDU^2) + \beta_I \varepsilon_{i,j}^I
\end{aligned} \tag{9}
$$

$P(R_B, R_D|ED)$ is Dahl's (2002) semi-parametric controls for non-random sorting:

$$
\begin{aligned}
& P(R_B, R_D|EDU) \\
& \qquad = \ HSDROP_i \cdot P(R_B, R_D|HSDROP) + HSGRAD_i \\
& \qquad \cdot P(R_B, R_D|HSGRAD) + SOMECOLL_i \cdot P(R_B, R_D|SOMECOLL) \\
& \qquad + ASSOCDEG_i \cdot P(R_B, R_D|ASSOCDEG_i) + BACHDEG_i \\
& \qquad \cdot P(R_B, R_D|BACHDEG) + ADVDEG_i \cdot P(R_B, R_D|ADVDEG_i)
\end{aligned} \tag{10}
$$

$P(R_B, R_D|EDU)$ denotes the probability of an individual with education level EDU is born in Census Region R_B and moves to Census Region R_D. That is, it controls for self-selection of higher educated individuals moving to locations with higher returns to education. The estimates from equation (9) are then used to generate the predicted incomes for each household in each location, $\hat{I}_{ij}$[26].

5.2 Long-run Psychological Moving Costs

The final piece required to estimate the first stage is a proxy for mobility costs. These costs are not financial and therefore, do not appear in the budget constraint. Instead, the costs are

[26] I am making a several implicit assumptions about income that are not necessarily true in the real world. First, I am estimating household income as purely a function of the attributes of the head of the household; households with two income earners are the obvious violation of this assumption Second, I am assuming the younger and older household's incomes behave the same. Older households are more likely to have a greater portion of their income fixed across locations (except possibly from tax differences). This is one reason why they often migrate to high amenity, low-cost of living areas. I am working to relax these assumptions in a future version.

purely psychological. The long-run psychological costs measure the cost to live outside of the household head's birth state, division, or region using the following equation:

$$M_{i,j} = \omega_S d_{i,j}^S + \omega_D d_{i,j}^D + \omega_R d_{i,j}^R \qquad (11)$$

where $d_{i,j}^S$ equals one if location *j* is outside of household *i*'s birth state and zero otherwise, $d_{i,j}^D$ is one if location *j* is outside household *i*'s birth census division and zero otherwise, and $d_{i,j}^R$ equals one if location *j* is outside household *i*'s birth census region and zero otherwise. We expect the long-run costs of each to decline as the scope geographic area increases. That is, we expect the parameters of $M_{i,j}$ to be negative and for $\omega_S < \omega_D < \omega_R$[27].

5.3 Estimation

I estimate the model separately for two age cohorts: households with heads less than 65 years old and households with heads 65 years old and older. The parameters for equation (11) are estimated in the first stage along with the marginal indirect utility of income and location aging-in-place utilities δ_j using the following likelihood function:

$$L(\omega_S, \omega_D, \omega_R, \beta_I, \delta) = \prod_i \prod_{j=1}^{J} \left[\frac{e^{M_{i,j}+\delta_j+\beta_I \ln(\hat{I}_{i,j})}}{\sum_{k=1}^{J} e^{M_{i,k}+\delta_k+\beta_I \ln(\hat{I}_{i,k})}} \right]^{\chi_{i,j}}. \qquad (12)$$

where $\chi_{i,j}$ is one if household *i* chooses location *j* and 0 otherwise.

Specifically, I estimate the parameters and aging-in-place utilities by nesting the contraction mapping technique conceived by Berry (1994) into a likelihood maximization algorithm. The contraction mapping recovers the $\delta_j's$ given an initial guesses of the parameters $\left(\omega_S^q, \omega_D^q, \omega_R^q, \psi_{MSA}^q, \psi_D^q, \psi_R^q, \beta_I^q\right)$ by matching the predicted shares of individuals in each MSA to the actual shares. I normalize the delta values by setting δ_j for Yuma, AZ to zero. Assuming that

[27] I could also model costs of moving away from the spouse's and children's birthplace. This may allow me to see part of the locational history of some of the families.

$\nu_{i,j}$ is independently and identically distributed type I extreme value and given initial guess of parameters and aging-in-place utilities $\left[\delta_j^{m,q}\right]_{j=1}^{J}$, the probability that individual *i* chooses location *j* is the following:

$$P_{i,j}^{m,q} = \frac{e^{\beta_I^q ln\hat{I}_{i,j} + M_{i,j}^q + M_{i,j}^{SR,q} + \delta_j^{m,q}}}{\sum_{u=1}^{J} e^{\beta_I^q ln\hat{I}_{i,u}^q + M_{i,u}^q + M_{i,j}^{SR,q} + \delta_u^{m,q}}} \tag{13}$$

where the *m* subscript shows the iteration for recovering the $\delta_j{}'s$ and the *q* subscript denotes the iteration for finding the remaining parameters. The purpose of equation (14) is to predict the share of population who choose each location which is given by:

$$\hat{\sigma}_j^{m,q} = \frac{1}{N}\sum_i P_{i,j}^{m,q} \tag{15}$$

Letting σ_j indicate the actual share of households choosing location *j* in the data, the $\delta_j's$ that equate observed and predicted shares are recovered by the following iterative procedure:

$$\delta_j^{m+1q} = \delta_j^{m,q} + \left(\ln\sigma_j - \ln\hat{\sigma}_j^{m,q}\right). \tag{16}$$

The recovered $\delta_j's$ given the guess of the parameters are then used in the following maximum likelihood equation:

$$L\left(\omega_S^q, \omega_D^q, \omega_R^q, \beta_I^q, \delta^{*,q}\right) = \prod_i \prod_{j=1}^{J} \left[P_{i,j}^{*,q}\right]^{\chi_{i,j}}. \tag{17}$$

where $\chi_{i,j}$ is one if household *i* chooses location *j* and 0 otherwise. New values of $\left(\omega_S^{q+1}, \omega_D^{q+1}, \omega_R^{q+1}, \beta_I^{q+1}\right)$ and the recovered $\left[\delta_j^{m,q}\right]_{j=1}^{J}$ are used until equation (18) is maximized at $\left(\omega_S^*, \omega_D^*, \omega_R^*, \psi_{MSA}^*, \psi_D^*, \psi_R^*, \beta_I^*, \left[\delta_j^*\right]_{j=1}^{J}\right)$. In summary, the following steps are taken to recover the parameters in the first stage:

1. Make an initial guess of the parameters $\left(\omega_S^q, \omega_D^q, \omega_R^q, \beta_I^q\right)$ and recover the corresponding $\delta_j's$ using equations (19), (20), and (21).

2. Use the initial $\left(\omega_S^q, \omega_D^q, \omega_R^q, \beta_I^q\right)$ and corresponding recovered $\delta_j' s$ to calculate the likelihood of the observed data given by equation (22).

3. Repeat steps 1 and 2 to recover the parameters $\left(\omega_S^*, \omega_D^*, \omega_R^*, \beta_I^*,\ [\delta_j^*]_{j=1}^J\right)$ that maximize equation (23).

Table 2. Income regression for Atlanta

Variable	Coef.	St. Err.	P-Value
Constant	10.14290	0.04943	0.00000
Married	0.41542	0.00888	0.00000
Female	-0.08360	0.00865	0.00000
White	0.14639	0.00904	0.00000
Age	0.02045	0.00186	0.00000
Age Squared	-0.00019	0.00002	0.00000
65 and Older	-0.12072	0.01834	0.00000
High school dropout	-0.15070	0.01672	0.00000
Some College	0.13112	0.01281	0.00000
Associates Degree	0.16417	0.01792	0.00000
Bachelor Degree	0.39861	0.01428	0.00000
Advanced Degree	0.54499	0.01710	0.00000
Observations			14,252
R-squared			0.394

Dep. Var.: Log of annual household income

6. Sorting Results

6.1 Household Income Estimation

The results from the income regression of equation (24) mostly follow conventional wisdom. On average, married households earn more than single households; households with female heads earn slightly less than households with male heads while households with white heads earn slightly more than other races. The results also suggest that households earn more as they age which may result from work experience, but the earnings growth tends to diminish with age. Finally, we see that household heads that dropped out of high school earn less than high school graduates, and earnings increase as the head of household's education level rises. The results for Atlanta are presented in table 2[28].

6.2 Estimates from the Sorting Model

Using the predicted incomes estimates based on the results from the MSA-specific income regressions, I estimate the residential sorting model using the procedure outlined in section 5.3. Table 3 shows the results from the first stage estimation of equation (16) by age cohort.

As expected the marginal utility of income is positive for both age groups. The long-run psychological costs of not living in one's birth state also have the correct sign, but we unexpectedly find that $\omega_D > \omega_R$. Under conventional standard errors, the parameters are statistically significant at the one percent level.

Table 3. Residential sorting results

Variable	Under 65 years old		65 and older	
	Coefficient	Std. Error	Coefficient	Std. Error
Marginal Utility of Income (β_I)	3.0870***	0.031969	2.9610***	0.05004
Long-run Physc. Costs				
State (ω_S)	-2.6115***	0.0050251	-2.5628***	0.00849
Division (ω_D)	-0.5223***	0.0060437	-0.6193***	0.01003
Region (ω_R)	-0.9835***	0.0051552	-0.7801***	0.00843

*** p < .01, ** p < .05, * p < .1

To illustrate the results from the estimated mean utilities, I use them to rank the desirability of each MSA for younger and older households. Table 4 reports the top ten MSAs ranked by mean utility for both older and younger households. Younger and older households rank MSAs similarly, but this is expected as both household types value amenities. MSAs in the Southwest and Florida rank high for older households most likely for their natural amenities such

[28] The results for the remaining MSAs are available from the author.

as weather. MSAs in the Pacific Northwest, coastal MSAs in the Northeast, MSAs bordering the Great Lakes, MSAs in North Carolina, and MSAs in Colorado are also ranked high for older households. For both cohorts, larger MSAs dominate the top 25, and smaller cities in the, especially land-locked MSAs in the Midwest, Southeast, and Northeast, tend to be ranked the lowest. Los Angeles, CA; New York City; Phoenix, AZ; Philadelphia; Tampa, FL; San Francisco; Portland, OR; Seattle, WA; Boston; and Dallas, TX make up the top 10 for older households. The top 10 for younger households are New York City; Los Angeles, CA; Phoenix, AZ; Philadelphia; Atlanta, GA; Portland, OR; Dallas, TX; Seattle, WA; Chicago, IL; and Tampa, FL. Surprisingly, many traditional retiree cities in Florida are further down on the list for older households with Orlando, Miami, West Palm Beach, Sarasota, Jacksonville, Fort Myers, and Melbourne ranked 21, 22, 24, 27, 36, and 42, respectively. Other MSAs in the Sun Belt, such as Atlanta (15); Tucson, AZ (16); Houston, TX (17); Las Vegas (19); and San Diego (20), were ranked in the top 20 for older households.

Table 4. Top 10 MSAs ranked by mean utilities (δ)

Panel A: Top 10 for Older Households	
Los Angeles-Riverside-Orange County, CA (C)	3.32096828
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	3.315929583
Phoenix-Mesa, AZ	2.879711686
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	2.573941631
Tampa-St. Petersburg-Clearwater, FL	2.534203074
San Francisco-Oakland-San Jose, CA (C)	2.49021256
Portland-Salem, OR-WA (C)	2.455673492
Seattle-Tacoma-Bremerton, WA (C)	2.449092495
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	2.389214317
Dallas-Fort Worth, TX (C)	2.253129361
Panel B: Top 10 for Younger Households	
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	3.735485428
Los Angeles-Riverside-Orange County, CA (C)	3.403939149
Phoenix-Mesa, AZ	3.145991487
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	3.048074711
Atlanta, GA	2.976338757
Portland-Salem, OR-WA (C)	2.948411355
Dallas-Fort Worth, TX (C)	2.932753648
Seattle-Tacoma-Bremerton, WA (C)	2.916591682
Chicago-Gary-Kenosha, IL-IN-WI (C)	2.845610395
Tampa-St. Petersburg-Clearwater, FL	2.818008388

Because of the similarities between the MSA rankings of older and younger households, I calculate the difference between the rankings[29] for each MSA by cohort to illustrate the variation in rankings between the cohorts. These differences are reported in table 5[30] and figure 2[31].

Table 5. MU rank for each MSA by HHs age cohort

	Older HH Rank	Younger HH Rank	Diff. in Rank
Panel A: MSAs that Older Households Prefer			
Naples, FL	121	191	-70
San Luis Obispo-Atascadero-Paso Robles, CA	108	178	-70
Chico-Paradise, CA	99	165	-66
Barnstable-Yarmouth, MA	168	233	-65
Punta Gorda, FL	86	150	-64
Yakima, WA	149	213	-64
Santa Barbara-Santa Maria-Lompoc, CA	111	174	-63
Yuma, AZ	127	188	-61
Modesto, CA	90	147	-57
Ocala, FL	62	119	-57
Panel B: MSAs that Younger Household Prefer			
Auburn-Opelika, AL	226	156	70
Clarksville-Hopkinsville, TN-KY	225	161	64
Fayetteville, NC	203	143	60
Savannah, GA	167	113	54
Columbus, GA-AL	178	126	52
Tallahassee, FL	146	95	51
Biloxi-Gulfport-Pascagoula, MS	162	115	47
Madison, WI	191	144	47
Lincoln, NE	177	131	46
El Paso, TX	132	87	45

Note: The difference is: Rank of Older Households - Rank of Younger Households. A negative value means that older households preferred the MSA more relative to younger households while younger households prefer MSAs with a positive value.

A negative value means older households ranked the MSA higher relative to younger households while a positive value indicates that older households ranked the MSA lower than younger households. In general, MSAs in California, coastal Florida, Arizona, Washington, and the

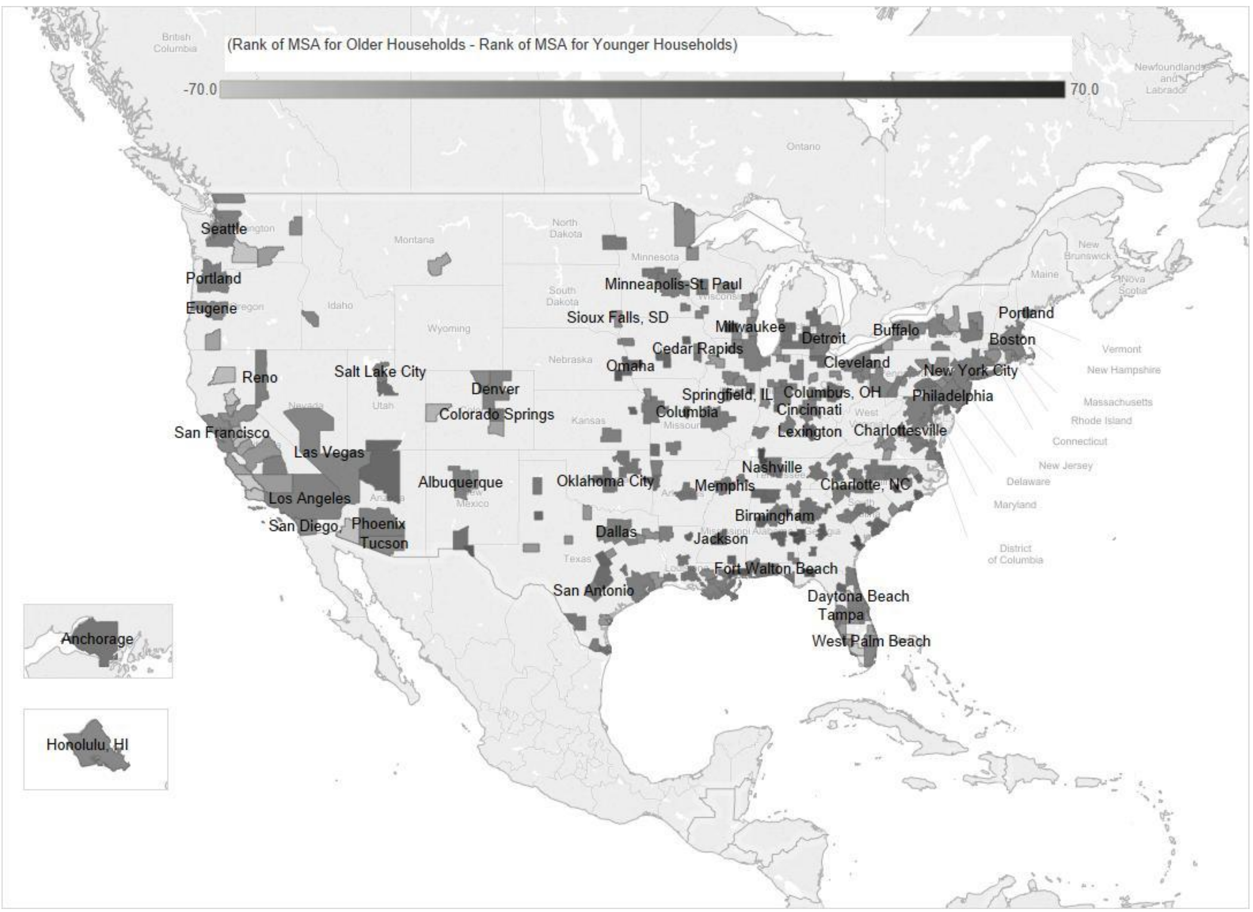
[29] $\text{Rank Difference} = \text{MSA Rank}_{\text{Old}} - \text{MSA Rank}_{\text{Young}}$

[30] Appendix A contains tables that report the same information for all MSAs as the top and bottom ten tables in tables.

[31] Appendix B contains full-page, color maps that duplicate the information for all gray-scale maps in the text of Chapter 1. I recommend that you view those as they are easier to read and contrast differences between MSAs.

Northeast tend to be ranked higher by older households. We would expect that MSAs that are ranked higher by older households to also attract the most households that are older as the population ages, but these rankings do not tell the whole story. To investigate where older households will live in the future, I run simulations to project the population for each MSA in 2030. These simulations are explored in the next section.

Figure 2. Difference in MSA rank between older and younger HHs



7. Simulations

7.1 Overview of Simulation

I run two population simulations to predict how the age profile of MSAs will change as the population ages. The first simulation, which I will refer to as the aging-in-place simulation, takes the population age distribution as given and does not allow household sorting. The second simulation, henceforth the sorting simulation, allows households to move as their utility for each MSA changes with age. The population dynamics are the same for both simulations. Each head of household is aged two periods of ten years. I calculate the probability of a household head dying over each ten year period using the Social Security Administration's Actuarial Life Table[32]. A household is removed from the sample when its head is predicted to pass away[33]. I then replace the youngest cohort of households that aged from 26 to 35 years old to 36 to 45 years old with the 2010 sample for 26 to 35 year olds. To account for additional household growth, I let the number of households increase by a conservative one percent every 10 years.

Table 6 illustrates the population dynamics under both simulations. The simulations start with 66,590,500 households; 15,531,098 (23.3%) have household heads 65 years old and over, and 51,059,402 (76.7%) have heads between 26 and 64 years old. By 2030, the simulation has 69,002,238 of which 24,357,770 (35.3%) are 65 and over and 44,644,468 (64.7%) are under 65. Over the 20 year period, the number of older households increases by approximately 57% which is below the projected 80% increase in the number of older adults, but I wouldn't expect the number of older households to increase as fast as the number of adults. Finally, the number of

[32] Found at the following web address http://www.ssa.gov/oact/STATS/table4c6.html.

[33] This simplification will cause an overestimation of the number of households dropping from the simulation because households do not always disappear when the head dies. Younger households are more affected by this simplification because someone within the household is more likely to take over as head than in an older household. I am working on an improvement that allows a household to take on the characteristics of a spouse, if present, when the household dies to help mitigate some of the unrealistic household reductions.

younger household shrinks in the simulation because the model ignores immigration and birth rates are below the population replacement rate in the United States.

Table 6. Population dynamics in the simulations

Variable	Younger Households	Older Households	Total Households
Number HH in 2010	51,059,402	15,531,098	66,590,500
% of HH in 2010	76.7%	64.7%	-
Number HH in 2030	44,644,468	24,357,770	69,002,238
% of HH in 2030	64.7%	35.3%	-
Change in Number of HH	-6,414,934	8,826,672	2,411,738
Change in % of HH	-12.56%	56.83%	3.62%

Note: The Total Population Dynamic is the same for the aging-in-place and sorting simulations. Each head of household is aged two periods of ten years. A household is removed from the sample when its head is predicted to pass away. I then replace the younger households that aged from 26 to 35 years old to 36 to 45 years old with themselves. To account for additional household growth, I let the number of households increase by a conservative one percent every 10 years.

Table 7[34] and figure 3 report the number of older households living in each MSA in 2010[35]. Large MSAs have the greatest number of older households with New York City, Los Angeles, Chicago, Philadelphia, Washington, San Francisco, Detroit, Boston, Dallas, and Tampa in the top ten. The proportions of older households in each MSA in 2010 shown in Table 8 and Figure 4 tell a slightly different story. Florida MSAs take 9 of the top ten spots. The top ten are Punta Gorda, FL; Naples, FL; Sarasota, FL; Ocala, FL; West Palm Beach, FL; Fort Myers, FL; Barnstable, MA; Fort Pierce, FL; Daytona Beach, FL, and Lakeland, FL.

[34] The tables in the text will show the top and bottom 10 MSAs for the variable in question. Tables with results for all MSAs can be found in Appendix A.

[35] Appendix A Table 3 shows the total older population, total younger population, and the ratio of the MSAs population that is 65 and older in 2010 for all MSAs in the analysis

Table 7. Number of older HHs in 2010

Panel A: Top 10	
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	1,203,082
Los Angeles-Riverside-Orange County, CA (C)	780,789
Chicago-Gary-Kenosha, IL-IN-WI (C)	556,853
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	487,202
Washington-Baltimore, DC-MD-VA-WV (C)	481,714
San Francisco-Oakland-San Jose, CA (C)	397,991
Detroit-Ann Arbor-Flint, MI (C)	384,361
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	374,892
Dallas-Fort Worth, TX (C)	296,884
Tampa-St. Petersburg-Clearwater, FL	254,674
Panel B: Bottom 10	
Laredo, TX	5,785
Flagstaff, AZ-UT	6,493
Iowa City, IA	7,042
Bryan-College Station, TX	7,355
Jacksonville, NC	7,624
Clarksville-Hopkinsville, TN-KY	7,720
Hattiesburg, MS	8,244
Auburn-Opelika, AL	8,367
Sioux City, IA-NE	8,523
Jackson, TN	8,554

Figure 3. Number of Older HHs in 2010

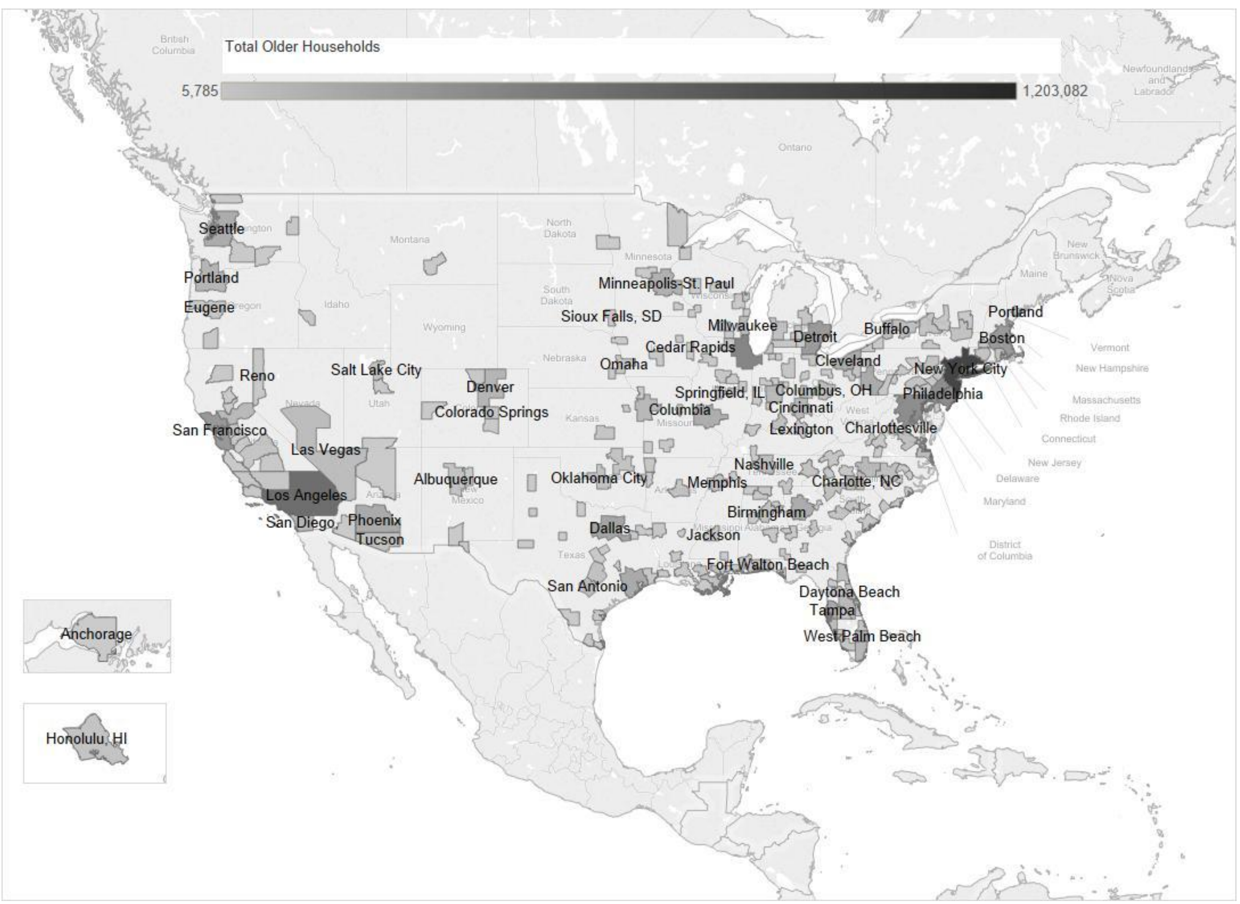
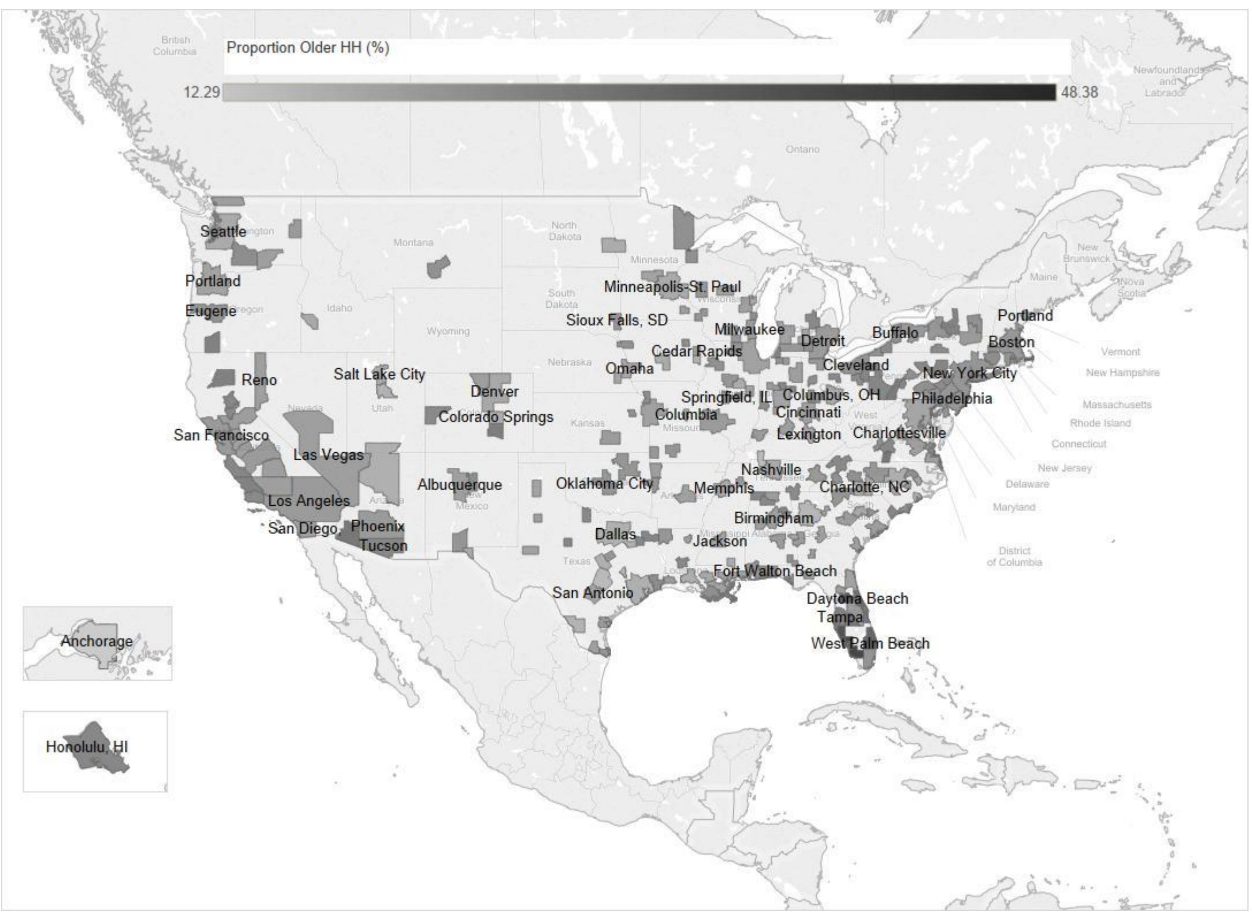


Table 8. Proportion of MSA's HHs that are older in 2010

Panel A: Top 10	
Punta Gorda, FL	48.38%
Naples, FL	47.35%
Sarasota-Bradenton, FL	43.90%
Ocala, FL	41.52%
West Palm Beach-Boca Raton, FL	39.36%
Fort Myers-Cape Coral, FL	38.54%
Barnstable-Yarmouth, MA	38.10%
Fort Pierce-Port St. Lucie, FL	37.38%
Daytona Beach, FL	34.58%
Lakeland-Winter Haven, FL	32.82%
Panel B: Bottom 10	
Anchorage, AK	12.29%
Clarksville-Hopkinsville, TN-KY	15.52%
Austin-San Marcos, TX	15.90%
Atlanta, GA	16.90%
Bryan-College Station, TX	17.29%
Laredo, TX	17.61%
Provo-Orem, UT	18.14%
Colorado Springs, CO	18.18%
Jacksonville, NC	18.22%
Dallas-Fort Worth, TX (C)	18.23%

Figure 4. Proportion of MSA's HHs that are older in 2010



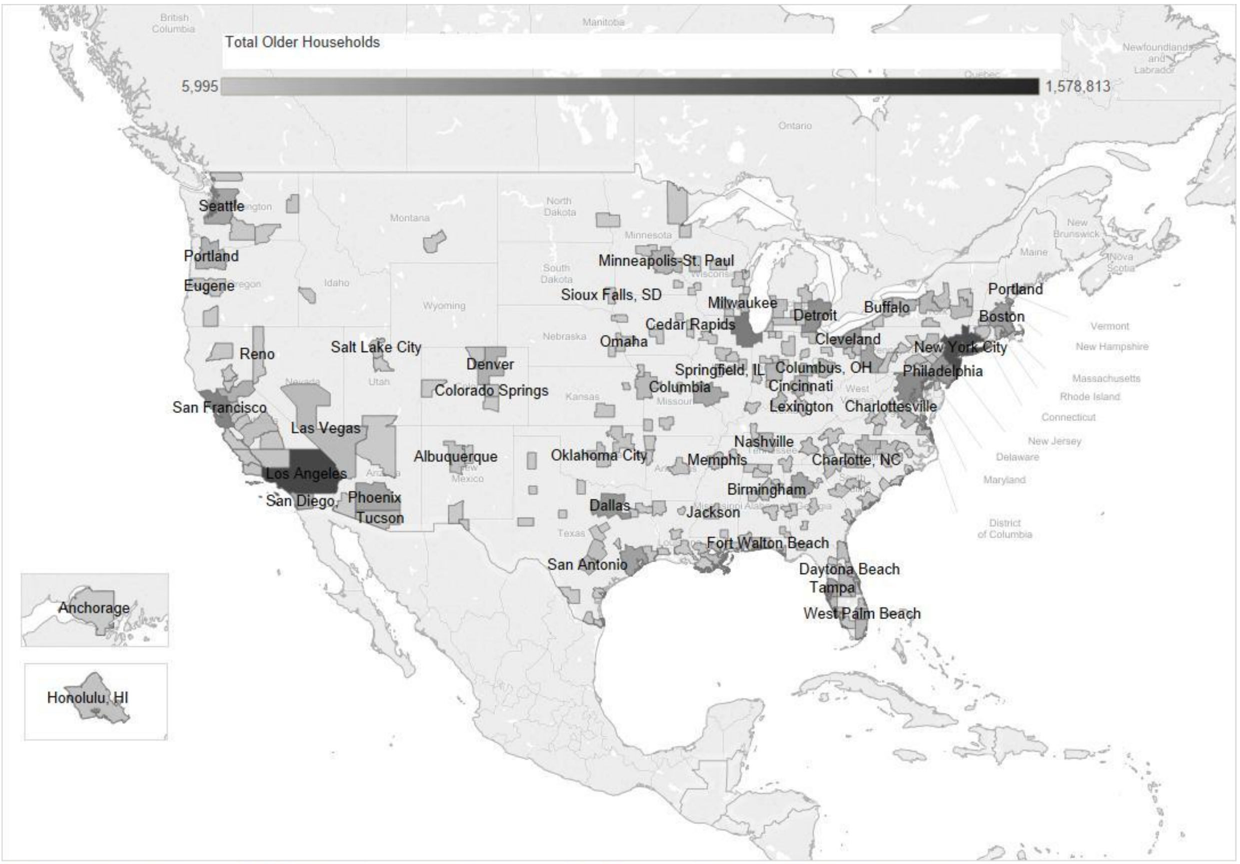
The age-in-place model predicts what happens if households age in place, and the sorting simulation allows households to change locations based on their predicted utility. After each 10 year period, the sorting simulation updates each household's income and assigns a mean utility for each MSA based on the head of the household's age. When a household head reaches 65 years old, they are assigned the mean utility for older households. Based on the updated incomes and mean utilities, I predict the probability of a household living in each MSA using equation (25), simulate the idiosyncratic preferences, and assign households to MSAs. We expect some households to change locations upon reaching 65 years old because their probabilities of choosing different MSAs change with changes in their relative utilities.

7.2 Results of Sorting Simulation

This section discusses the results from the sorting simulation and the differences between 2010 and 2030. The numbers of older households in 2030 for each MSA is reported in figure 5 and table 9, and figure 6 and table 10 show the proportion[36] of households that are older in each MSA in 2030 in the sorting simulation. The top ten cities in terms of older households in 2030 remained roughly the same as in 2010. They are, with their 2010 rank in parenthesis, Los Angeles (2), New York City (1), Chicago (3), San Francisco (6), Washington (5), Detroit (8), Dallas (9), Philadelphia (4), Cleveland (11), and Boston (8). In 2030, Los Angeles had the most older households in the simulation at 1,578,813, and the Iowa City had the smallest number of older households at 5,995. Florida MSAs dominate the top ten MSAs by the proportion of older households in 2030 with some surpassing over 50% of households having heads over 64 years old. While the patterns in 2030 seem similar to those in 2010, the differences between the years are more pronounced when we examine the changes between the two years.

[36] Proportion of Older Households $= \frac{\text{\# HH 65 and Over in MSA}}{\text{Total \# HH in MSA}}$

Figure 5. Number of older HHs in 2030 under the sorting simulation

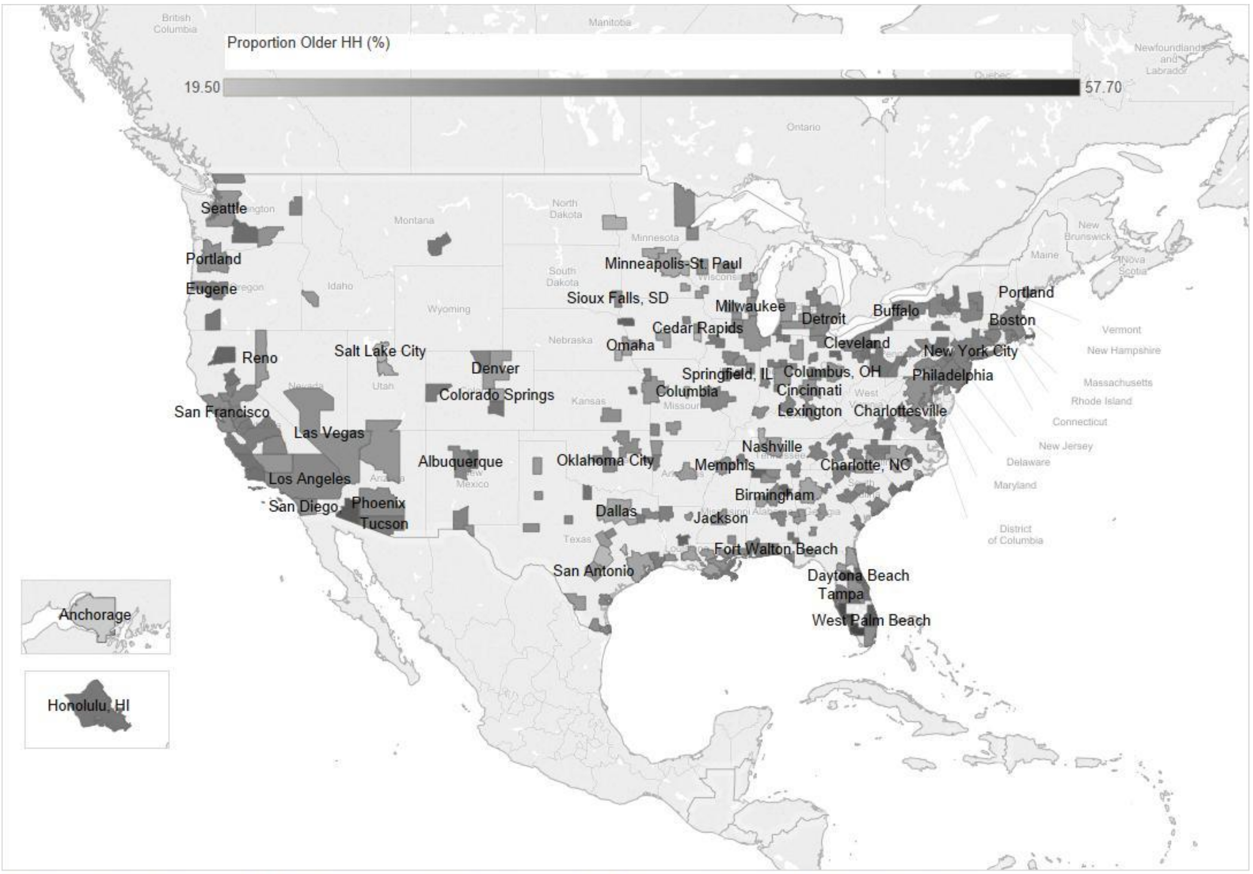


Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Table 9. Number of older HHs in 2030 under the sorting simulation

Panel A: Top 10	
Los Angeles-Riverside-Orange County, CA (C)	1,578,813
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	1,430,803
Chicago-Gary-Kenosha, IL-IN-WI (C)	848,847
San Francisco-Oakland-San Jose, CA (C)	757,172
Washington-Baltimore, DC-MD-VA-WV (C)	654,073
Detroit-Ann Arbor-Flint, MI (C)	583,516
Dallas-Fort Worth, TX (C)	546,742
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	501,871
Cleveland-Akron, OH (C)	468,625
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	453,350
Panel B: Bottom 10	
Iowa City, IA	5,995
Anchorage, AK	7,527
Sioux Falls, SD	7,651
Fargo-Moorhead, ND-MN	8,356
Bryan-College Station, TX	9,967
La Crosse, WI-MN	10,550
Houma, LA	10,607
Rochester, MN	11,690
Sioux City, IA-NE	11,702
Laredo, TX	11,833

Figure 6. Proportion of MSA's HHs that are older in 2030 under the sorting simulation



Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Table 10. Proportion of MSA's HHs that are older in 2030 under the sorting simulation

Panel A: Top 10	
Naples, FL	57.70%
Punta Gorda, FL	57.18%
Sarasota-Bradenton, FL	55.93%
Barnstable-Yarmouth, MA	50.86%
Yuma, AZ	50.36%
Fort Myers-Cape Coral, FL	49.32%
Fort Pierce-Port St. Lucie, FL	48.79%
Ocala, FL	48.46%
West Palm Beach-Boca Raton, FL	47.95%
Anniston, AL	47.78%
Panel B: Bottom 10	
Anchorage, AK	19.50%
Bryan-College Station, TX	22.98%
Columbia, MO	23.50%
Austin-San Marcos, TX	23.70%
Iowa City, IA	23.92%
Salt Lake City-Ogden, UT	25.40%
Portland, ME	26.39%
Fargo-Moorhead, ND-MN	26.51%
Green Bay, WI	26.56%
Clarksville-Hopkinsville, TN-KY	26.57%

Tables 11 and 12, complemented by figures 7 and 8, show the changes in the number[37] of older households and the changes in the proportion of all US Households that are older in each MSA[38], respectively. On average, MSAs gained 36,324 older households between 2010 and 2030; Los Angeles gained the most at 798,024, and the most lost was 5,689 by Portland, ME. Only eight MSAs had fewer older households in 2030 than in 2010, and twenty-one MSAs gained over 100,000 older households. Most of the largest gains occurred in big cities located in the Northeast, around the Great Lakes, and the Pacific coast. Figure 8 and table 12 essentially show the changes in the distribution of all older households in the US. Clearly, additional older households will live in west coast MSAs, especially in California, and MSAs in the western half of the Northeast. Most of the Midwest and MSAs on the eastern side of the Northeast have fewer older households in 2030. The most striking result is that Florida also seems to be losing some of its importance to older households.

Table 11. Change in Number of older HHs under the sorting simulation

Los Angeles-Riverside-Orange County, CA (C)	798,024
San Francisco-Oakland-San Jose, CA (C)	359,181
Chicago-Gary-Kenosha, IL-IN-WI (C)	291,994
Dallas-Fort Worth, TX (C)	249,858
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	227,721
Cleveland-Akron, OH (C)	214,726
Detroit-Ann Arbor-Flint, MI (C)	199,155
Houston-Galveston-Brazoria, TX (C)	180,835
Washington-Baltimore, DC-MD-VA-WV (C)	172,359
San Diego, CA	160,458
Panel B: Bottom 10	
Portland, ME	-5,689
Lincoln, NE	-3,337
Anchorage, AK	-2,974
Sioux Falls, SD	-2,316
Des Moines, IA	-2,001
Fargo-Moorhead, ND-MN	-1,175
Milwaukee-Racine, WI (C)	-1,147
Iowa City, IA	-1,047
Rochester, MN	839
Cedar Rapids, IA	902

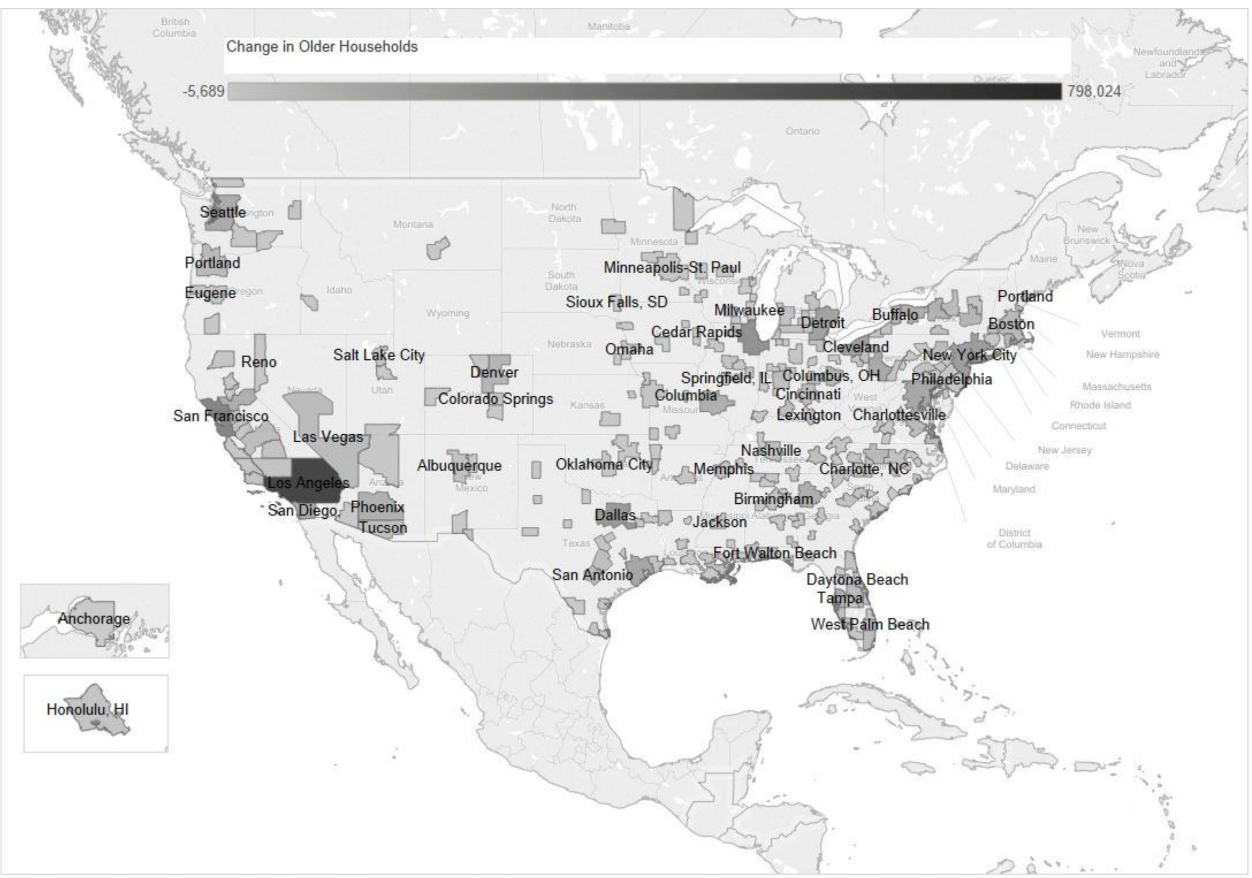
[37] $\Delta \mathrm{HH}_{2030} = \mathrm{HH}_{2030} - \mathrm{HH}_{2010}$

[38] $\Delta \mathrm{PropUSHHO65}_{2030} = \frac{\text{HH Over 65 in MSA in 2030}}{\text{Sum of All HH in US Over 65 in 2030}} - \frac{\text{HH Over 65 in MSA in 2010}}{\text{Sum of All HH in US Over 65 in 2010}}$

Table 12. Change in % of All U.S. HH that are older in an MSA under the sorting simulation

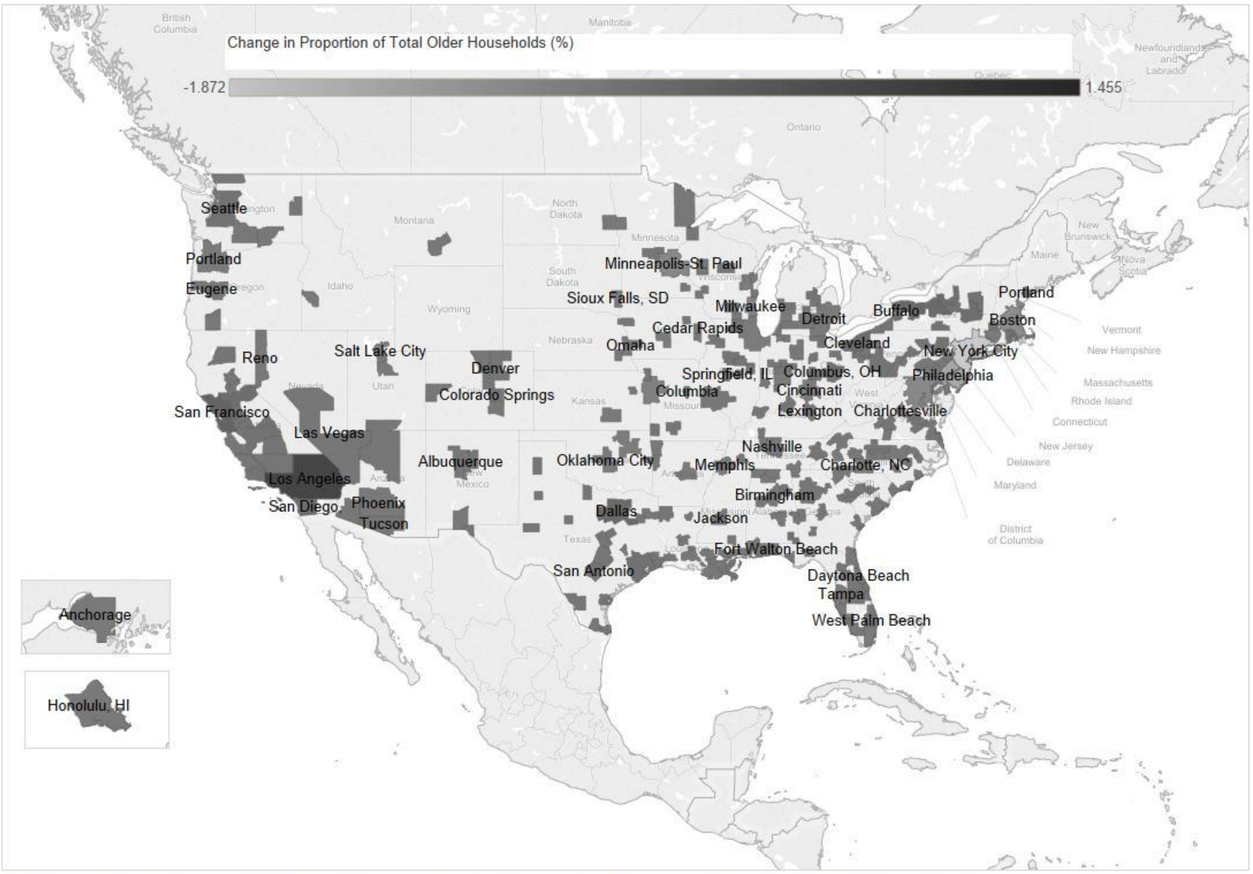
Panel A: Top 10	
Los Angeles-Riverside-Orange County, CA (C)	1.45%
San Francisco-Oakland-San Jose, CA (C)	0.55%
Rochester, NY	0.35%
Syracuse, NY	0.34%
Dallas-Fort Worth, TX (C)	0.33%
San Diego, CA	0.30%
Cleveland-Akron, OH (C)	0.29%
Buffalo-Niagara Falls, NY	0.27%
Sacramento-Yolo, CA (C)	0.26%
Albany-Schenectady-Troy, NY	0.24%
Panel B: Bottom 10	
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	-1.87%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	-1.08%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	-0.55%
Washington-Baltimore, DC-MD-VA-WV (C)	-0.42%
Minneapolis-St. Paul, MN-WI	-0.41%
Milwaukee-Racine, WI (C)	-0.33%
Kansas City, MO-KS	-0.22%
Tampa-St. Petersburg-Clearwater, FL	-0.14%
West Palm Beach-Boca Raton, FL	-0.13%
Tulsa, OK	-0.11%

Figure 7. Change in number of Older HHs under the sorting simulation



Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 8. Change in % of All US HHs that are Older under the sorting simulation



Sorting scenario: Changes to household composition as a result of aging in place and household migration.

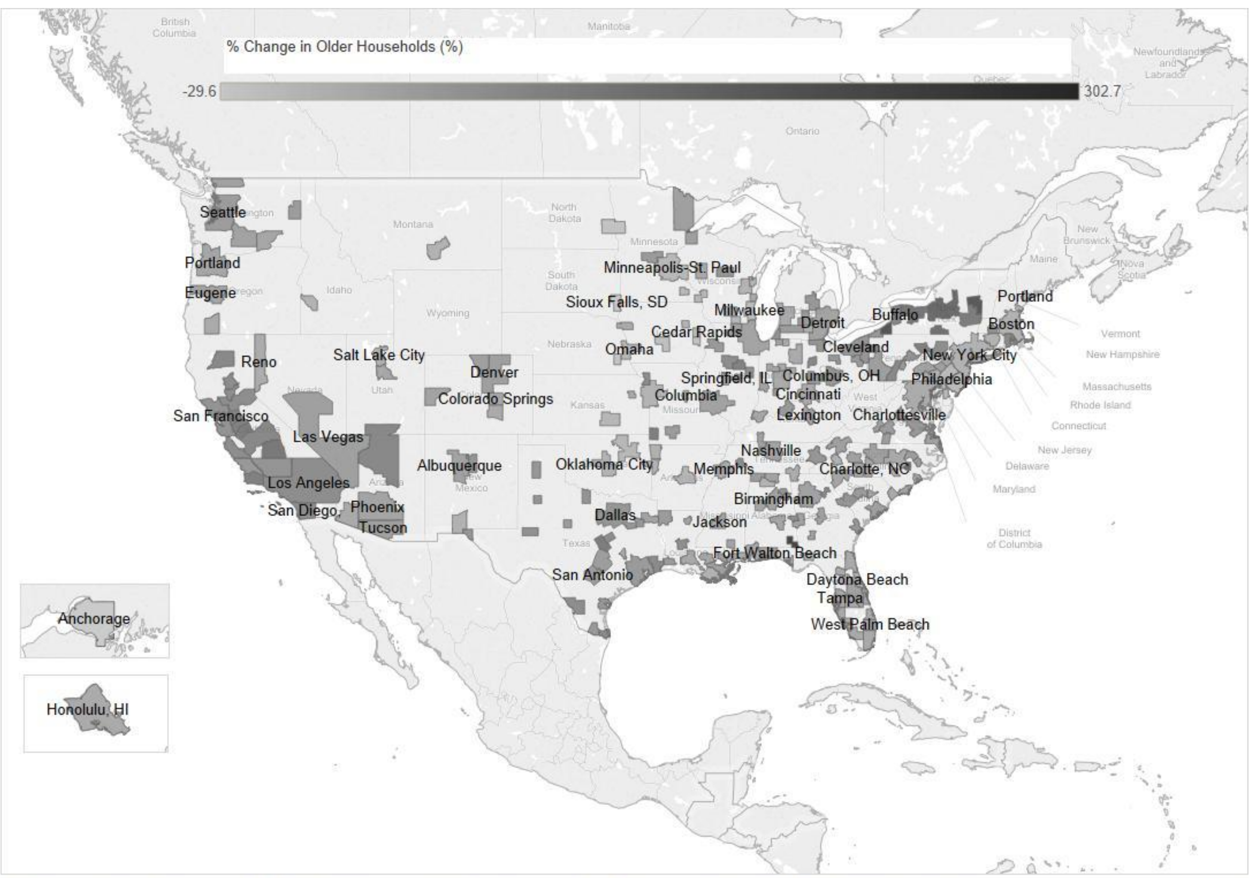
Figure 9 and table 13 summarize the percent change[39] in older households. The average percent change in number of older households in the twenty year period was 64.7% which is below the predicted growth rate of 80.7% for older people. Forty-two MSAs had the number of older households more than double between 2010 and 2030. MSAs in the Northeast, particularly New York state, California, and Texas, made up the majority of the MSAs with extreme aging. MSAs in Florida only had modest increases in the percent change of older households because they had a large number of older households to begin with in 2010.

[39] $\%\Delta \mathrm{HH}_{2030} = \frac{\Delta \mathrm{HH}_{2030}}{\mathrm{HH}_{2010}}$

Table 13. Percent change in Number of older HHs

Panel A: Top 10	
Dothan, AL	302.75%
Jamestown, NY	250.24%
Glens Falls, NY	238.02%
Syracuse, NY	190.29%
Goldsboro, NC	189.31%
Utica-Rome, NY	188.99%
Binghamton, NY	173.38%
Rochester, NY	159.30%
Visalia-Tulare-Porterville, CA	150.50%
Sharon, PA	149.64%
Panel B: Bottom 10	
Portland, ME	-29.58%
Anchorage, AK	-28.32%
Sioux Falls, SD	-23.24%
Lincoln, NE	-17.59%
Iowa City, IA	-14.87%
Fargo-Moorhead, ND-MN	-12.33%
Des Moines, IA	-7.26%
Milwaukee-Racine, WI (C)	-0.83%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	3.01%
Cedar Rapids, IA	5.02%

Figure 9. % Change in Older HHs under the sorting simulation



Sorting scenario: Changes to household composition as a result of aging in place and household migration.

It is also interesting to examine the changes in the proportion[40] of households in a MSA that are older; these changes are summarized in table 14 and figure 10. The share of older households increases for all MSAs in the period even though some MSAs have fewer older households in 2030. MSAs that lost older households had even more young households move out. At a 3.1% increase, Houma, LA (26.3% of households are older in 2010 and 29.4% in 2030) had the smallest increase in the proportion of older households; Sioux City, IA-NE had the largest increase in the simulation at 21.7% (25.8% in 2010 and 47.5% in 2030). The average change was an 11.8% increase. MSAs in the Arizona (Flagstaff, Yuma), New Mexico (Albuquerque and Santa Fe), California (Visalia, Merced, Modesto, Stockton, Fresno, Redding, and Chico), Oregon (Eugene and Portland), Washington (Spokane, Bellingham, Seattle, and Yakima), South Carolina (Charleston and Myrtle Beach) , Georgia (Athens, Augusta, and Savannah), Illinois (Bloomington, Decatur, Springfield), and New York (Syracuse, Rochester, Buffalo, and Jamestown) along with Philadelphia, Cleveland, Detroit, Washington, and St. Louis, experienced the largest gains in the share of older households. Florida MSAs only had modest gains in the proportion of older households because these MSAs have higher starting proportions. Most of the cities Iowa, Wisconsin, Minnesota, and Michigan also only see moderate increases in the share of older households.

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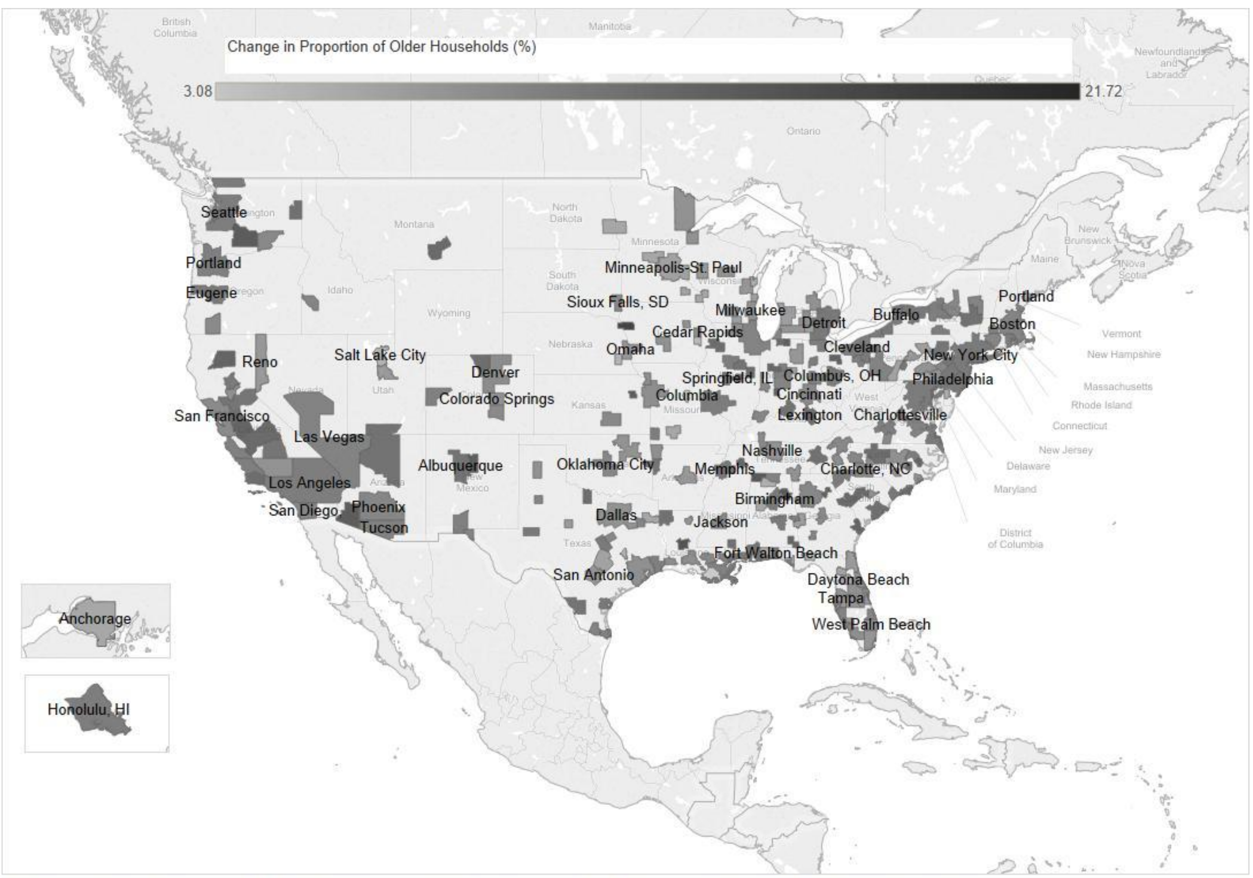
[40] $\Delta \mathrm{Prop65}_{2030} = \mathrm{Prop65}_{2030} - \mathrm{Prop}_{2010}$

Table 14. Change in the proportion of MSA's HHs that are older

Panel A: Top 10	
Sioux City, IA-NE	21.72%
Anniston, AL	21.15%
Alexandria, LA	19.05%
Florence, AL	18.64%
Gadsden, AL	17.93%
Yakima, WA	17.79%
Yuma, AZ	17.69%
Topeka, KS	17.63%
Santa Fe, NM	17.44%
Elkhart-Goshen, IN	17.42%
Panel B: Bottom 10	
Houma, LA	3.08%
Columbia, MO	3.17%
Iowa City, IA	5.07%
Tallahassee, FL	5.36%
Portland, ME	5.51%
Bryan-College Station, TX	5.69%
Salt Lake City-Ogden, UT	5.81%
Lincoln, NE	5.92%
Pensacola, FL	6.10%
Dover, DE	6.31%

Figure 10. Change in % of Older HHs under the sorting simulation



Sorting scenario: Changes to household composition as a result of aging in place and household migration.

7.3 Sorting vs. Aging-in-Place

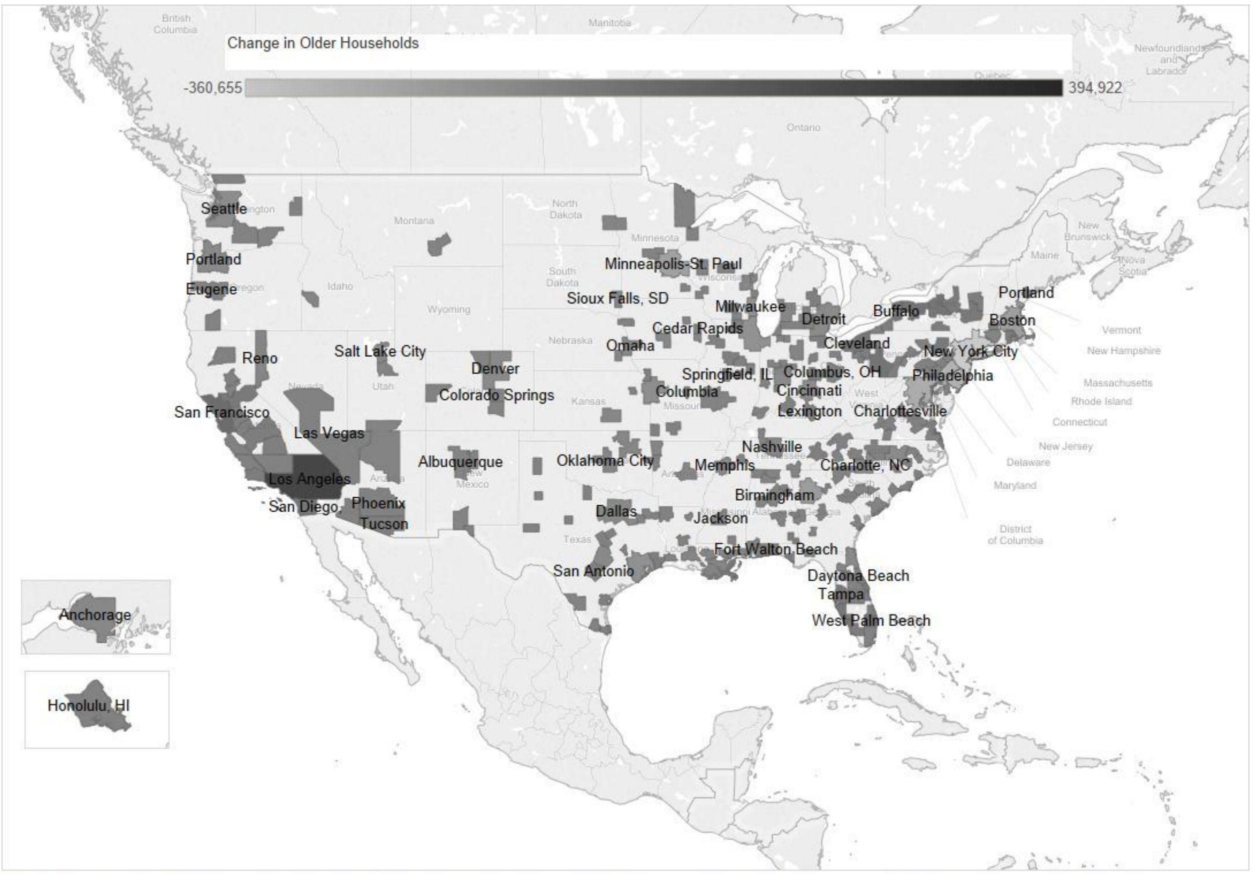
A MSA's population can age one of two ways. Households already in the MSA stay as they age or additional older households migrate to the city. Many households that are older do not move which makes "aging in place" important. While my model picks up both movers and stayers, the patterns of household movers are the most interesting. In this sub-section, I compare the results from the sorting and aging-in-place simulations by subtracting the aging-in-place results from the sorting simulation. Recall that the aging-in-place simulation disallows moving between MSAs for households while the sorting simulation allows households to stay in their locations or move. By netting out the aging-in-place simulation, I am able to capture net migration.

Figure 11 shows the net migration[41] of older households between 2010 and 2030. One hundred, forty MSAs gained an average of 19,156 older households through migration, and one hundred, three lost an average of 26,038 older households through migration. The top ten in-migration MSAs and top 10 out-migration MSAs are presented in table 15. Los Angeles gained the highest number of older households from migration while New York City lost the most. In general, older households moved out of large MSAs bordering the Atlanta Ocean in the Northeast (New York City, Philadelphia, Washington, and Boston) and along the Great Lakes in Illinois, Michigan, and Wisconsin (Detroit, Chicago, Green Bay, and Milwaukee) as well as a large number of Southern cities (Atlanta, Raleigh, Charlotte, Atlanta, Birmingham, Chattanooga, Nashville, Little Rock, New Orleans, Jackson, Dallas, Houston, and New Orleans). Older households moved to MSAs in the western portion of the Northeast (Buffalo, Cleveland, Pittsburgh, Albany, Scranton), smaller MSAs in the Carolinas (Goldsboro, Wilmington, Greenville, Myrtle Beach), MSAs in Florida (West Palm Beach, Sarasota, Tampa, Fort Myers,

[41] $\text{Net Migration in MSA} = \#\ \text{HH in MSA under sorting} - \#\ \text{HH in MSA under aging-in-place}$

Naples, Daytona Beach), smaller MSAs in Texas (Beaumont, Brownsville, Tyler), MSAs in southern Arizona (Tucson and Phoenix), and most MSAs in California (Los Angeles, San Francisco, San Diego, Sacramento, Fresno, etc.).

Figure 11. Net migration of older HHs



Migration scenario: Changes to household composition as a result of household migration; total values measure Net Migration.

Table 15. Net migration of older HHs

Panel A: Top 10	
Los Angeles-Riverside-Orange County, CA (C)	394,922
San Francisco-Oakland-San Jose, CA (C)	128,928
Syracuse, NY	83,472
Rochester, NY	82,437
Pittsburgh, PA	80,964
Buffalo-Niagara Falls, NY	80,748
Cleveland-Akron, OH (C)	76,248
West Palm Beach-Boca Raton, FL	69,178
San Diego, CA	66,755
Sarasota-Bradenton, FL	65,627
Panel B: Bottom 10	
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	-360,655
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	-246,967
Washington-Baltimore, DC-MD-VA-WV (C)	-214,133
Minneapolis-St. Paul, MN-WI	-162,528
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	-143,340
Atlanta, GA	-135,143
Chicago-Gary-Kenosha, IL-IN-WI (C)	-80,251
Milwaukee-Racine, WI (C)	-79,821
Houston-Galveston-Brazoria, TX (C)	-71,661
Kansas City, MO-KS	-61,334

Note: Net Migration is calculated by subtracting the number of HHs that aged in place from the number of HHs in the Sorting Simulation

Finally, I examine the changes in the proportion of households that are older due to migration by netting out the effect of “aging in place”. The share of older households can change on two dimensions: changes in the number of older households and changes in the number of younger households. That is, the share of older households can increase through either an increase in older households or a decrease in younger households. Therefore, some MSAs may have gained older households but experienced a decline in the share of older households because of a larger increase in younger households. Figure 12 and table 16 summarize these results. One hundred, sixteen MSAs see the share of older households increase due to migration while the share of older households falls due to migration in one hundred, twenty-seven. Of the MSAs with net in-migration, the average gain was 3.9% while the average loss for the MSAs that had a decrease in the share of older households due to migration was -2.8%. Yuma, AZ had the largest increase in the share of older households by far with migration accounting for a 20.6% increase.

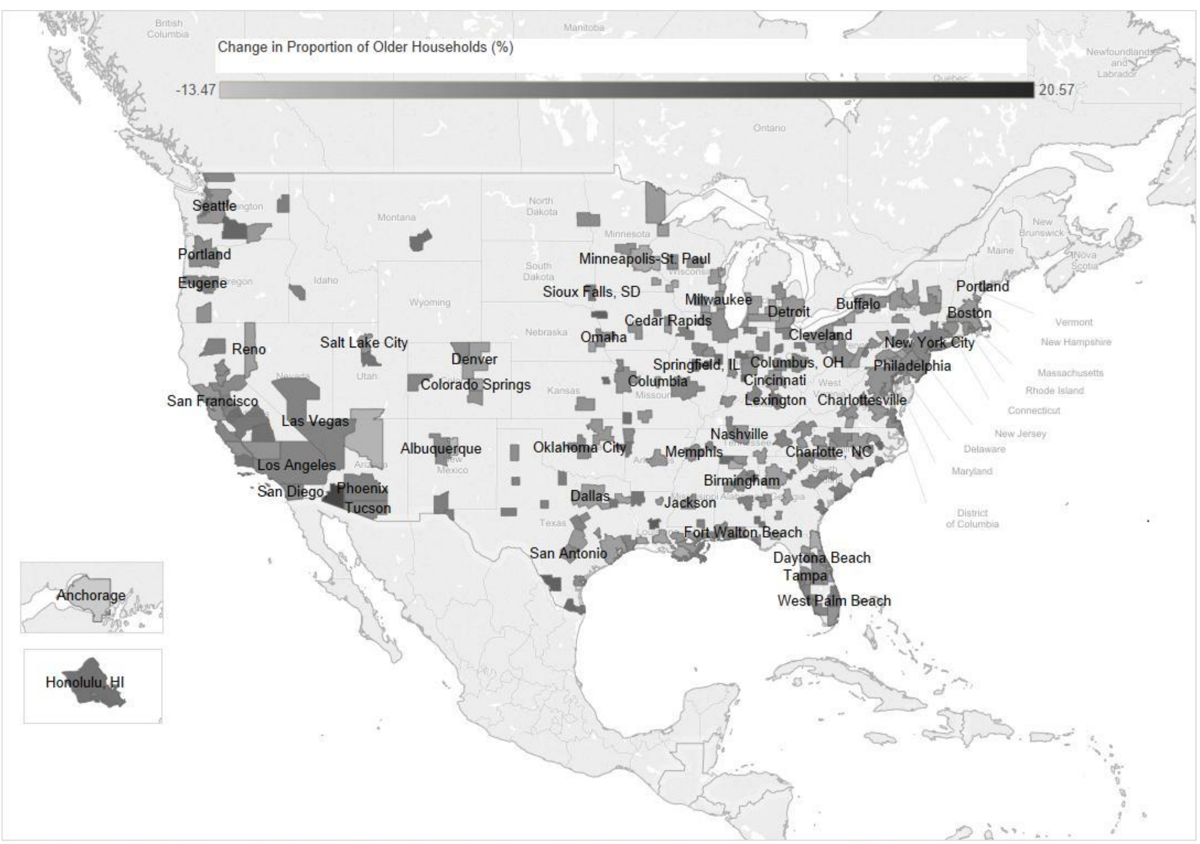
The share of older households in Anchorage, AK fell by 13.5% due to migration which is the largest fall in the simulation. Fewer general patterns emerge than in the results from figure 11 partly because the share of older households also depends on the migration of younger households. Almost all of the MSAs in the Northeast, excluding New York City; Albany, NY; and Scranton, PA, have declines in the share of older households. MSAs in the western portion of New York and Pennsylvania such as Buffalo, NY, saw increases in the number of older households due to migration, but the share of older households fell due to high in-migration of younger households as well. The share of older households also fell in large MSAs in Michigan, Wisconsin, and Minnesota and many of the MSAs in the South which is expected because these MSAs had net out-migration of older households. MSAs in Florida follow a similar pattern as figure 11. Those that gain older households have a slight increase in the share of older households while MSAs that lose older households have declines in the share of older households. Most of the MSAs in California, Arizona, Nevada, Oregon, and Washington have increases in the proportion of older households. Notable exceptions are San Francisco, CA; Bakersfield, CA; and Flagstaff, AZ which all attracted large numbers of younger households.

Table 16. Change in proportion of MSA's HHs that are older due to migration

Panel A: Top 10	
Yuma, AZ	20.57%
Alexandria, LA	13.10%
Laredo, TX	12.08%
Sioux City, IA-NE	11.81%
Bloomington, IN	10.71%
Yakima, WA	10.36%
Anniston, AL	9.82%
Greenville, NC	9.73%
Florence, AL	9.21%
McAllen-Edinburg-Mission, TX	8.94%
Panel B: Bottom 10	
Anchorage, AK	-13.47%
Portland, ME	-11.03%
Santa Fe, NM	-10.23%
Flagstaff, AZ-UT	-8.53%
Dover, DE	-8.31%
Decatur, AL	-7.35%
Tallahassee, FL	-7.19%
Jackson, MI	-7.02%
Columbia, MO	-6.65%
Minneapolis-St. Paul, MN-WI	-6.55%

Note: Net Migration is calculated by subtracting the number of HHs that aged in place from the number of HHs in the Sorting Simulation

Figure 12. Change in % of Older HHs due to Net Migration



Migration scenario: Changes to household composition as a result of household migration; total values measure Net Migration.

8. Conclusion

The number of older households is increasing dramatically as the Baby Boom generation continues to age and retire. This paper examines the location preferences of older adults through a residential sorting model. The sorting model estimates household-constant attributes of location *j* that are relevant to household utility, the marginal utility of income, and the marginal cost of living outside a household head's birth location for old and young households. The results confirm that older and younger households value have heterogeneous location preferences.

The estimates from the sorting model are then used to run simulations that predict where households will live in 2030 based on their age. As the households age, their income and mean utility for each MSA are updated, and they select a location based on the new relative utilities of each MSA. The number of older households declines in only 8 of the 243 MSAs, but the share of households in a MSA that are older increases for all MSAs. MSAs in California and upstate New York gain the largest amount of older households while New York City, Philadelphia, Washington, Chicago, Detroit have the largest decreases.

MSAs in the Arizona (Flagstaff and Yuma), New Mexico (Albuquerque and Santa Fe), California (Visalia, Merced, Modesto, Stockton, Fresno, Redding, and Chico), Oregon (Eugene and Portland), Washington (Spokane, Bellingham, Seattle, and Yakima), South Carolina (Charleston and Myrtle Beach) , Georgia (Athens, Augusta, and Savannah), Illinois (Bloomington, Decatur, and Springfield), and New York (Syracuse, Rochester, Buffalo, and Jamestown) along with Philadelphia, Cleveland, Detroit, Washington, and St. Louis, had the largest gains in the proportion of households that are older. While MSAs in Florida continue have high concentrations of older households, the results suggest that their relative importance is taking a backseat to cities such as Los Angeles and Buffalo.

When I remove the impact of households aging in place, some of the same patterns discussed above emerge. Californian MSAs, upstate New York MSAs, and MSA on the coast of Florida along with Cleveland and Pittsburgh experience the largest in-migration of older households. The MSAs with the largest out-migration of older households were Boston, New York City, Philadelphia, Washington, Atlanta, Detroit, Chicago, Dallas, Houston, Raleigh, Charlotte, Minneapolis, and Seattle.

While these patterns of older household migration are interesting, the next step in this research agenda is to begin looking at the details of what is driving these location decisions. Specifically, I will decompose the mean utilities by regressing the mean utilities on various local amenities. This will allow me to estimate the differences between older and younger households in the marginal willingness to pay for specific local amenities. Further, I will be able to simulate how changes in a city's amenities will change its attractiveness to different households.

Chapter II

Age and the Motivations for Charitable Giving

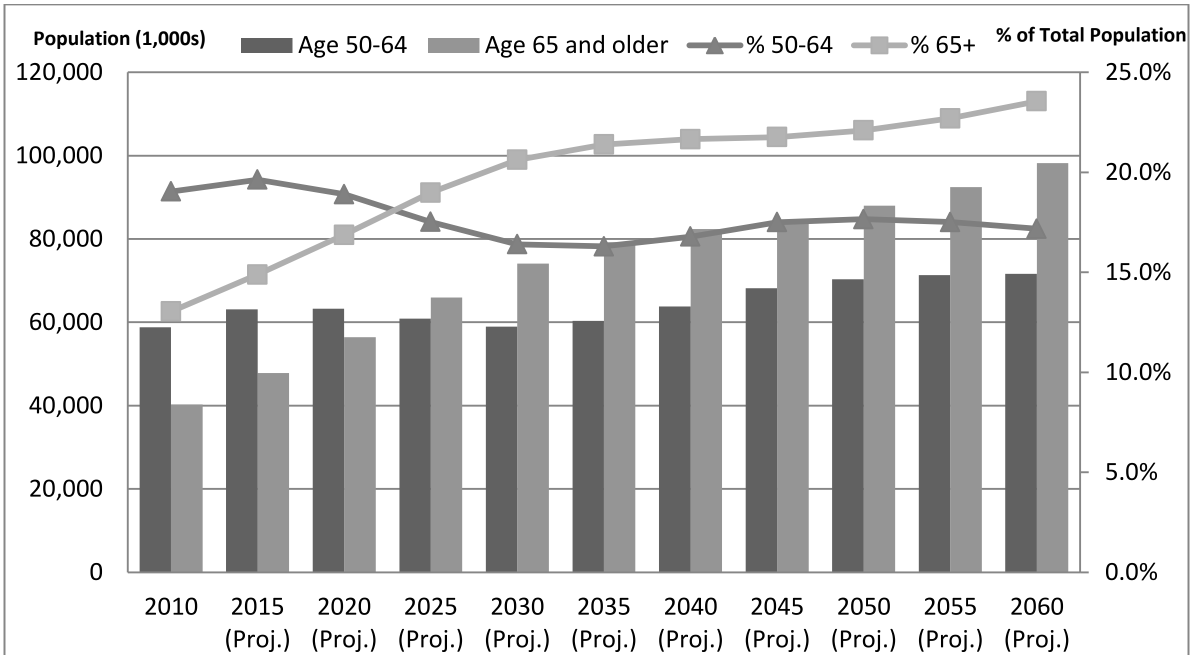
1. Introduction

The United States population is aging rapidly as the Baby Boomer generation began turning sixty-five years old in 2011. As figure 13[42] illustrates, demographers expect major shifts in the populations for ages 50 to 64 and 65 and older. In 2010, 58.8 million people (19% of the total population) in the United States were between 50 and 64 years old, and over 40.2 million (13%) people in the United States were over the age of 65 (Howden and Meyer 2011). By 2025, the Census Bureau projects that the size of the over 65 population will surpass the size of the aged 50-64 population (U. S. Census Bureau 2014). In 2060, the U.S. will have almost 100 million residents over 65 or roughly 23.6% of the population. According to the same projections, the population between 50 and 64 years old will total approximately 71.6 million people and account for only about 17.2% of the population. Many older households rely significantly on Social Security (SS) benefits. In fact, Social Security payment increases significantly reduced poverty rates among the elderly from 1967 to 2000 (Engelhardt and Gruber 2004). Unfortunately, SS as we know it may not continue forever. The Congressional Budget Office projects that outlays will exceed noninterest revenues by 12% on average over the next decade and projects that under current law the combined trust fund of disability insurance (DI) and the Old-Age Survivors Insurance (OASI) will be exhausted in fiscal years 2031 (Congressional Budget Office 2013). If the trust fund balance falls to zero and benefits exceed income as projected, federal law requires that Social Security payments be reduced. Although the above

[42] 2010 data is from the U.S. Census Bureau (2011), and the population projections are from U.S. Census Bureau, Population Division (U. S. Census Bureau, Population Division 2014).

scenario is unlikely, it seems reasonable to assume that SS beneficiaries will see reduced payments in the future as the population ages. This scenario could significantly alter the needs of older households and the goals of many charities.

Figure 13. Population Projections for ages 50-64 and 65 and older



Source for 2010 Data: U.S. Census Bureau 2011
Source for 2015-2060 Projections: U.S. Census Bureau, Population Division 2014

Literature has shown that charitable giving has an inverse u-shape relationship with age (Bekkers and Wiepking 2011; List 2004). A person's charitable giving increases as he or she ages but then declines at older ages, typically between sixty-five and seventy-five years old. These demographic shifts and fiscal realities combined with potentially lower aggregate charitable giving due to aging may put more pressure on private charities to help prevent low income households who rely on SS benefits from falling into poverty while their available diminish due to lower donations from population aging.

Another branch of the charitable giving literature examines the donor's motivation for giving. Ultimately, the literature proposes two primary mechanisms for donations: concern for benefits to others (pure altruism) and concern for benefits to self (impure altruism). In this chapter, I use data from a large scale field experiment described in recent manuscript by List, Murphy, and Price (2015) that was designed to directly disentangle pure and impure altruism through messaging to a large population of potential donors. In the experiment, postcards with different messaging asking households to donate a portion of their 2014 Alaskan Permanent Fund Dividend (PFD) to an eligible charity were mailed in the last week of December of 2013. The postcard contained one of two messages randomly assigned based on the household's zip code. One message emphasized the to concern for benefits to others ("Make Alaska Better for Everyone") while the other appealed to the concern for benefits to self ("Warm Your Heart"). A third group who did not receive a postcard served as the control.

Using the results from this randomized field experiment, I extend the analysis by estimating the heterogeneous treatment effects for each treatment by age cohort. The age cohorts are the following: Young are under 19 years old; Middle Aged are 19 to 49 years old; Mature are 50 to 64 years old; and Older are 65 years old and older. These cohorts largely follow List (2004) with the exception of breaking the oldest cohort used by List into two to account for the demographic shift of an aging population.

Examining the effect on average donations, I find limited treatment heterogeneity in the "Warm Your Heart" message, but no age cohort is affected heterogeneously by the "Make Alaska Better for Everyone" message. The results indicate that individuals between the ages of 50 and 64 years old increase average donations more than any other age cohort in response to the "Warm Your Heart" message, but the statistical difference between the Mature and Older cohorts disappears when controlling for whether the individual gave in 2013. Further, the heterogeneity in response by the Mature cohort is exclusively driven by the intensive margin, people who give donating larger gifts, on average, instead of increasing the number of total donors. Finally, individuals under 19 years old give less on average compared to other age cohorts when they receive the message emphasizing impure altruism. That is, they are less persuaded to give by a message reminding them that donating could make them feel good about themselves than other ages. While this chapter focuses on age as being the main driver of any heterogeneous treatment effects, a generational effect is also a plausible explanation, and one could even argue that differences in generations is the driving factor. Unfortunately, age and generational effects can only be separated using a long panel data set. With this caveat, the discussion will focus on the age effects.

2. Related Literature

2.1. Charitable Giving and Age

Psychologists, sociologists, and economists have long studied the link between age and charitable giving. The consensus is that philanthropy increases on both the intensive and extensive margin with age, but the majority of studies that allow for quadratic trends find that giving tends to decrease at higher ages, typically between 65 and 75 (Wiepking and James 2013; Bekkers and Wiepking 2011)[43]. Many of the early studies found the giving increased with age (Feldstein and Clotfelter 1976; Feldstein and Taylor 1976; Boskin and Feldstein 1977; Clotfelter 1980)[44], but they ignored quadratic effects. These studies may also suffer from omitted variable bias by ignoring variable such as wealth and financial stability.

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[43] See Bekkers and Wiepking (2011) for a review of the literature.

[44] Feldstein and Cotfelter (1976) used a national survey of the income, assets, and savings conducted in 1963 and 1964 to estimate how charitable giving correlated with income, age, children, and savings among other things; their results found a positive but statistically insignificant relationship between age and giving. Feldstein and Taylor

One of the first studies to estimate a quadratic relationship found that charitable giving of alumni increased with age but begins to level off and decline as the donor approaches 65 years old (Okunade, Wunnava, and Walsh 1994). A more recent study by Wu, Huang, and Kao (2004) used data from the Survey on Family Income and Expenditures in Taiwan and found that households in metropolitan areas with heads over the age of 65 were less likely to give after controlling for income, marital status, education, and household size. Andreoni (2006) found that the propensity to donate and average conditional donations begin to decline for individuals over 75 years old using U.S. data. A number of other studies have confirmed the quadratic relationship between age and giving with observational data including Belfield and Beney (2000), Simmons and Emanuele (2004), and Wiepking and James (2013).

A potential remedy for the omitted variable bias mentioned above is to allow for randomization in a lab or field experiment. One of the earliest of such studies used a field experiment to examine how giving varies with age; it found that the elderly donated more frequently to a cause, but their donations tended to be lower than middle-aged adults (Midlarsky and Hannah 1989). A more recent paper used three different field experiments[45] to study the link between aging and pro-social preferences[46] where one of the experiments allows for partially

(1976) used the 1970 Treasury Tax File and found that taxpayers over 65 years old gave 56 % more than younger tax payers with the same income and wealth.

[45] The first experiment used one-shot and multiple-shot public goods games and found that people over the age of 49 gave more than subjects in younger cohorts, and a higher percent (over 35%) of those over 49 contributed the social optimal amount compared to of persons between 19 and 49 years old (17%) and under 19 (12%). Further, no members of the older cohort free rode completely or nearly completely. Finally, age remains a factor in contributing to the public good even after controlling for income, gender, education, trial, and individual unobserved heterogeneity. The second experiment used a university fundraiser that is more applicable to the realm of charitable giving than the public goods game described above and also allows for the opportunity to partially distinguish between age and cohort effects. A letter and brochure were sent to 2,000 heads of households in central Florida to raise money for a new university environmental policy center. The results suggest that men and women over 49 gave more often and higher amounts than men and women under 49, but the age effect was stronger for men. The third experiment used data from a gameshow that closely mimics the prisoner's dilemma game; the results show that more mature people choose to cooperate more often than their younger counterparts.

[46] Pro-social preferences are voluntary behavior that helps others. Charitable giving is a subset of pro-social behavior.

distinguishing between cohort and age effects (List 2004). The results of the aforementioned study found a direct link between age and both the probability of giving and the amount of gifts, but the oldest cohort was defined broadly as over 49 years old and quadratic effects were not included. Contrary to this finding, another study using a field experiment to investigate different contribution mechanisms found that people over 65 were less likely to give (Landry et al. 2006).

The evidence shows that age and charitable giving have a concave relationship, giving increases up till an age between 65 and 75 when it begins to decline (Wiepking and James 2013), and the most logical sequential question is why this is the case. Few studies directly address this question, but Bekkers and Wiepking (2011) suggest that religion, marital status, income, and other variables correlated with age may drive the relationship between age and giving. This could reconcile some of the differences between the observational and experimental results. The only study that directly tests why charitable giving falls at the oldest age is Wiepking and James (2013) who hypothesized that declining health or cognitive abilities may drive a disposition to charitable giving down. The proposed mechanisms through which declining health affects charitable giving are the increasing share of income going to health costs, decreasing religious services attendance, decreasing egocentric networks, giving through alternative means (e.g. charitable bequests), leaving assets to dependents or other family, and a loss of cognitive ability. The empirical results indicate the decreasing religious participation mediates the impact of age on giving significantly, and cognitive abilities has a small mediating factor as well suggesting that these are the mechanisms that age works through to reduce charitable giving at the oldest ages.

Two additional explanations for the quadratic relationship with aging are generational effects and life-cycle considerations (Meer and Rosen 2013). Meer and Rosen (2013) argue that the decline in giving at older ages is the result of nearing death instead of just aging. They find that the giving decline at the oldest ages may in reality be an increase in giving when taking the approach to death into account. Further, they find little decline in giving for individuals who die quickly from health conditions, and the elderly reduce giving more sharply than the younger prior to death. One could also argue that the age-giving profile is the artifact of generational differences. A long panel is necessary to completely separate generational and age effects. However, the age-giving profile has been relatively stable over decades and across generations which suggests that more than generational effects are at play here.

2.2. Motivations for Giving

As outlined above, the motivations for charitable giving can be broadly defined as either a benefit to self or a benefit to others. Benefits to others from charitable giving is caring about the benefactors of the good or service provided by the charity[47] (Becker 1974) or, in the public goods literature, the total amount of the public good provided (Hochman and Rodgers 1969; Kolm 1969)[48]. This pure altruism implies that an additional dollar from public funds, or other private donors, totally crowds out a dollar of private funds from another donor because individuals only care about the provision of the public good and not the source of funding. While literature does find evidence of some crowding out, the empirical evidence overwhelmingly rejects total crowd-out (Abrams and Schitz 1978; Kingma 1989; Khanna, Posnett, and Sandler

[47] Becker wrote the utility function for person i would be the following:

$$U_i = U_i\left(x_i, x_j\left(= \frac{I_j + h_i}{p_j}\right)\right),$$

where h_i is individual i's charitable giving and x_j is the well-being of the recipients of the charitable giving.

[48] The well-being of person i is described by the following:

$$U_i = U(x_i, G),$$

where x_i is the consumption of the private good and G is the total provision of the public good from all individuals.

1995; Okten and Weisbrod 2000; Payne 1998; Payne 2001; Ribar and Wilhelm 2002; Simmons and Emanuele 2004; James Andreoni 1993; James Andreoni and Payne 2011; Bolton and Katok 1998; Chan et al. 2002), and some literature even suggests a crowd-in effect where government grants can attract private donations through signaling (Heutel 2014; Okten and Weisbrod 2000). The lack of evidence supporting pure altruism (James Andreoni 1988; James Andreoni 2006) lead researchers to look for other reasons individuals donate to private charities.

The next logical explanation is that individuals receive a benefit to self from their individual contribution. These benefits to self can be as simple as receiving a direct benefit or gift for a donation such as better seats at a college football game or public recognition for their gift, but a more general explanation is needed because these direct benefits mostly go only to the largest donors (J. Andreoni 2001). While a number of alternative explanations[49] have been proposed, Andreoni's (1989; 1990) model of warm-glow giving, or impure altruism, has gained the most traction over the years. Warm glow occurs when individuals receive a direct benefit from their donation independent of the gift's effect on the charity's output[50]. That is, the act of giving makes a person feel good about themselves. In addition to the evidence contradicting total crowd-out, other studies support the idea of warm glow (Tonin and Vlassopoulos 2010; Crumpler and Grossman 2008; Harbaugh, Mayr, and Burghart 2007). One major flaw of most crowd-out studies is that they test the measure at a single giving level from others. Ottoni-Wilhelm et al (2014) run an experiment with a low and high level of giving-by-others and find 97 percent and 82 percent crowd-out for low and high level of giving-by-others, respectively.

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[49] These include religious duty, social pressure from friends or colleagues, or as a signal of social status or social identity (James Andreoni and Bernheim 2009).

[50] An individual's contribution to a public good enters their utility function:

$$\mathrm{U_i = U(x_i g_i, G), i = I, \dots, N}$$

where $\mathrm{x_i}$ is consumption of the private good, $\mathrm{g_i}$ is the i's contribution to the public good, and $\mathrm{G} = \sum_{\mathrm{i}} \mathrm{g_i}$.

Using the experimental results to drive a structural model, the authors find that altruism is more important than warm-glow. Therefore, it would seem that donors are motived by some combination of pure and impure altruism.

In this literature review, I have established two stylized facts. First, people give to charities to help someone, make themselves feel good, or a combination of these two motivations. Second, charitable giving seems to be directly or indirectly related to age. A logical question is then: do the motivations for giving change with age (or the life-cycle)? While I do not have a theoretical prediction, I believe a number of observations will help make the case. A number of implications arise because older households are either in retirement or nearing retirement. First, their incomes may become less flexible as they shift their primary source of income toward investment and pension income. Second, their social networks may change by shrinking or increasing social connections. A shrinking social network would decrease the likelihood of being asked to give, reduce the utility costs of shame for not giving, and lessen the need to build a positive social image through donating. On the contrary, a larger social network will have the opposite effect. Many people's social network is their work-place, and retiree with this tendency may become less connected to others upon retirement. Further, the decrease in attendance of religious services of older individuals, as Wiepking and James (2013) suggested for overall giving, could reduce social networks and, consequently, the benefits to self from giving. However, retirees often have more time on their hands which could open doors to building new social networks. If we believe people donate to charities to build their social image as some literature has suggested, this could have a major effect on charitable giving. The psychology literature also has theories that our lives follow stages. For example Erik Erikson's psychoanalytic theory has 8 psychosocial stages. In his theory, people between the ages of 40 and 64 are characterized as caring who ask questions such as “Is my life significant?” while older individuals are characterized by wisdom and ask questions such as “Am I happy with the life I lived?” (Crain 2011). Evidence also exists that older individuals risk profiles differ by age. For example, Harrison, Lau, and Rutström (2007) conducted a field experiment in Denmark to elicit how risk attitudes change over demographic differences and find support that risk aversion decreases as a person ages, particularly after 40 years old. Bellante and Green (2004) also find decreasing relative risk aversion among the elderly using survey data. With all this in mind, I believe that the question of how the main drivers of charitable giving differ by age is an empirical one.

3. Data and Methodology

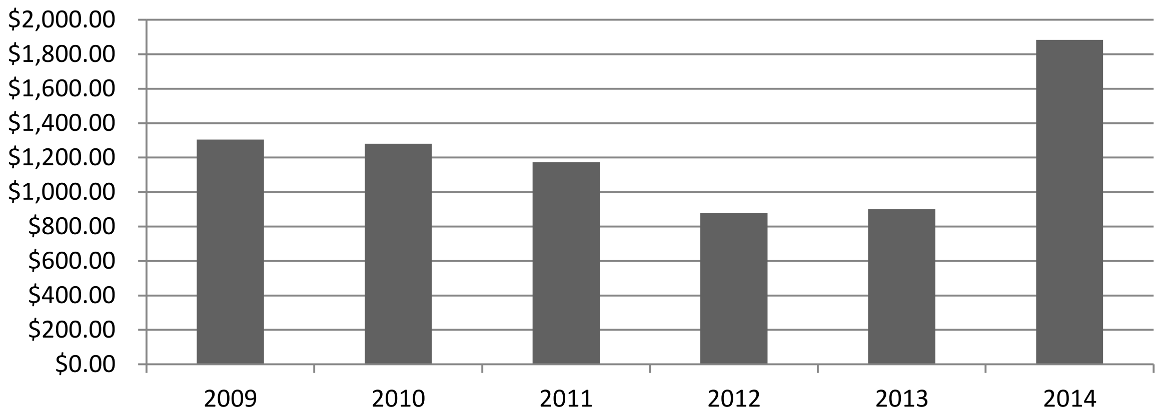
3.1 Alaska’s Permanent Fund and Pick, Click, Give

In 1976, Alaskan voters passed a constitutional amendment to establish a Permanent Fund[51] for the state that requires that no less than 25 percent of all mineral revenue be saved for future generations. As of June 29, 2015, the fund’s market value of over 53.5 billion dollars[52] was invested in a diverse portfolio managed by the Alaska Permanent Fund Corporation, an independent state agency. Only earnings in the reserve may be spent by the legislature, including distributions to the public, while the rest much be saved. After a two-year court battle, the Permanent Fund began distributing an annual dividend based on specific eligibility requirements; the first Permanent Fund Dividends (PFD) of $1,000 was sent to Alaskan residents in 1982. As it stands today, a resident qualifies for a Permanent Fund Dividend (PFD) if she or he files an application prior April 1, was a resident for the full prior calendar year (January 1 – December 31) and plans to remain in Alaska indefinitely. The dividends are distributed in early October.

[51] See http://www.apfc.org/home/Content/aboutFund/aboutPermFund.cfm.
[52] The market value can be found at http://www.apfc.org/home/Content/home/index.cfm.

The average dividend since 1982 has been $1,098, but the dividend has been an average of $1,237 since 2009. Figure 14 shows the dividend amounts for 2009 through 2014. In 2014, our analysis year, the dividend was $1,884.

Figure 14. Amount of Alaska's Permanent Fund Dividend



Source: Alaska Permanent Fund Corporation 2014
http://www.apfc.org/home/Content/dividend/dividendamounts.cfm

In 2009, the Charitable Contribution program, cleverly called "Pick.Click.Give[53]" was introduced to allow Alaskans to donate all or part of their PFD to eligible non-profit agencies of their choice. Only Alaskans who file for their PFD online are eligible to give through *Pick.Click.Give*. Table 1 illustrates the substantially growth of the Charitable Contribution program since its start. In 2009, only 5,046 of the 471,094 online applicants (1.07%) gave a total of $544,350 through the program. The average donation was just $1.16 for eligible applicant and $107.88 for those that gave any amount. By 2014, almost 27,000 people, a fivefold increase over 2009, donated a total of $3,131,800 or a 575 percent more than in 2009. The average donation and average conditional donation increased by 400 percent and 9 percent, respectively.

[53] See http://www.pickclickgive.org/ for more details.

Table 17. Summary of the *Pick.Click.Give* program

Year	Eligible Donors	Donors	% Eligible Gave	Total Donation ($)	Avg. Donation ($)	Avg. Cond. Gift ($)
2009	471,094	5,046	1.07%	544,350	1.16	107.88
2010	514,201	9,279	1.80%	902,625	1.76	97.28
2011	523,678	18,279	3.49%	1,558,725	2.98	85.27
2012	527,391	22,660	4.30%	2,399,050	4.55	105.87
2013	529,318	25,461	4.81%	2,502,700	4.73	98.30
2014	541,617	26,610	4.91%	3,131,800	5.78	117.69

Source: Users calculations based on data provided by *Pick.Click.Give.*
Notes: Residents are eligible to give only if they applied for their Permanent Fund Dividend electronically. The % Eligible that gave is simple the number of eligible donors divided by the number of donors. The Average Donation is Total Donations divided by Eligible Donors, and the Average Conditional Gift is Total Donations divided by the number of donors.

Figure 15. Postcard for the Others Treatment

3.2 Description of the Experiment

In conjunction with Alaska's Permanent Fund Dividend Charitable Giving Program, List, Murphy, and Price designed a natural field experiment to test the saliency of pure and impure altruism. As part of *Pick.Click,Give*'s annual marketing campaign, they randomly allocated households by zip code[54] into a control group or one of two treatment groups. One treatment group received a postcard the last week of December with a slogan “Make Alaska better for everyone: Share your PFD” designed to emphasize benefits to others while the second treatment group received a postcard with a message reading “Warm your heart: Share your PFD” to accentuate benefits to self. Figures 15 above and Figure 16 below show the postcard for the Others treatment and Self treatment, respectively.

Figure 16. Postcard for the Self Treatment

The 2014 data from *Pick.Click.Give* is summarized in table 18. Table 18 is divided into 4 panels. Panel A summarizes the full sample while Panels B, C, and D show summaries for the control, the Others treatment, and the Self treatment, respectively. The first column of each panel represents all ages while the remaining columns are split into the following age cohorts: Young (Under 19 year old), Middle Aged (19 to 49 years old), Mature (50 to 64 years old), and Older (65 years old and older). We will focus on panel A first. Overall, the program raised 3,131,800 dollars for non-profits in Alaska with 158,700 dollars (5.07%) from individuals under 19 years

[54] The designers were forced to randomize at the zip code level due to privacy laws that prevented the state from disclosing finer geographic information.

old, 1,267,250 dollars (40.46%) from individuals 19 to 49 years old, 1,167,600 dollars from individuals 50 to 64 years old, and 538,250 dollars (17.19%) from individuals 65 years old and older. Of the 541,617 individuals who applied for their Permanent Fund Dividend online, 26,610 individuals, or 4.91 percent, gave an average charitable gift of $117.29 which means that the average donation for all eligible individuals was $5.78[55].

The propensity to donate, the average gift, and the average conditional gift were almost always higher for older age cohorts[56]. The lone exception is that older individuals were about 5% less likely (6.965% vs. 7.335%) to give then those in the Mature cohort. Young individuals compared to all the other age cohorts were significantly less likely to give, gave less per individual, and donated smaller amounts when they did give confirming the results from List (2004) that the young are more selfish than their elders. Individuals in the Middle Aged cohort were twice as likely to donate as an individual in the Young cohort (4.941% vs. 2.343%) while individuals in the Mature and Older cohorts are about three times more likely to give than an individual in the Young cohort (7.335% and 6.965% vs 2.342%). The Mature and Older cohorts are almost 48 and 41 percent more likely to give than the Middle Aged cohort (7.335% and 6.695% vs. 4.941%), respectively.

[55] The $117.29 is the average donation conditional on the individual giving while the $5.78 is the average donation taking into account all individuals whether they gave or not.

[56] The level of significance comparing age cohorts to each other for the Propensity to Donate, the Average Donation, and the Average Conditional Donation is at 1% using Wilcoxon-Mann-Whitney rank sum tests (Wilcoxon 1945; Mann and Whitney 1947) except the significance level for average donation between the Mature and Older cohorts was at the 5% level.

Table 18. Summary statistics of the *Pick.Click.Give* data

Variables	All Ages	Young	Middle	Mature	Older
	Panel A: Full Sample				
Registered Individuals	541,617	145,637	236,944	112,029	47,007
# of Donors	26,610	3,412	11,707	8,217	3,274
Propensity to Donate (%)	4.91	2.34	4.94	7.33	6.96
Total Donations ($1,000s)	3,131.8	158.7	1,267.3	1,167.6	538.3
Average Donation ($)	5.78	1.09	5.35	10.42	11.45
Std Dev. ($)	(54.282)	(10.167)	(50.335)	(75.917)	(83.490)
Avg. Conditional Donation ($)	117.69	46.51	108.25	142.10	164.40
Std Dev. ($)	(216.342)	(47.960)	(200.361)	(244.691)	(273.782)
% Gave in 2013	4.49	1.82	4.34	7.15	7.11
% Gave any prior year	6.32	2.61	6.17	9.94	9.83
Avg Age	35.131	9.302	33.519	56.619	72.075
% Female	49.66942	48.58518067	50.19709159	49.95759862	49.68196206
Med. HH Income in Zip ($1,000s)	74.79	74.48	74.75	75.86	73.42
	Panel B: Control				
Registered Individuals	171,001	46,907	73,304	35,850	14,940
# of Donors	7,552	971	3,240	2,382	959
Propensity to Donate (%)	4.42	2.07	4.42	6.64	6.42
Total Donations ($1,000s)	807.4	41.1	321.8	291.8	152.7
Average Donation ($)	4.72	0.88	4.39	8.14	10.22
Std Dev. ($)	(46.292)	(7.624)	(44.203)	(61.406)	(74.871)
Avg. Conditional Donation ($)	106.91	42.28	99.31	122.50	159.25
Std Dev. ($)	(193.917)	(32.540)	(186.520)	(206.777)	(252.301)
% Gave in 2013	4.15	1.66	3.98	6.67	6.74
% Gave any prior year	5.80	2.33	5.64	9.22	9.32
Avg Age	35.142	9.413	33.586	56.620	72.014
% Female	49.40	48.45	50.01	49.43	49.34
Med. HH Income in Zip ($1,000s)	70.97	71.07	71.16	70.94	69.84

Variables	All Ages	Young	Middle	Mature	Older
	Panel C: "Make Alaska Better for Everyone"/Others treatment				
Registered Individuals	187,433	52,208	82,563	36,573	16,089
# of Donors	8,498	1,140	3,779	2,510	1,069
Propensity to Donate (%)	4.53	2.18	4.58	6.86	6.64
Total Donations ($1,000s)	976.5	53.9	414.2	337.8	170.6
Average Donation ($)	5.21	1.03	5.02	9.24	10.60
Std Dev. ($)	(51.063)	(9.283)	(48.744)	(70.581)	(80.3611)
Avg. Conditional Donation ($)	114.91	47.28	109.61	134.58	159.57
Std Dev. ($)	(211.920)	(41.973)	(201.134)	(236.088)	(271.087)
% Gave in 2013	4.04	1.64	3.91	6.58	6.77
% Gave any prior year	5.76	2.42	5.64	9.14	9.30
Avg Age	34.403	9.122	33.176	56.646	72.170
% Female	49.84	48.75	50.27	50.31	50.05
Med. HH Income in Zip ($1,000s)	66.47	66.29	66.59	66.83	65.55
	Panel D: "Warm Your Heart"/Self Treatment				
Registered Individuals	183,183	46,522	81,077	39,606	15,978
# of Donors	10,560	1,301	4,688	3,325	1,246
Propensity to Donate (%)	5.76	2.80	5.78	8.40	7.80
Total Donations ($1,000s)	1,348.0	63.8	531.2	538.0	215.0
Average Donation ($)	7.36	1.37	6.55	13.58	13.45
Std Dev. ($)	(63.559)	(12.967)	(56.710)	(90.958)	(93.583)
Avg. Conditional Donation ($)	127.65	49.00	113.32	161.80	172.51
Std Dev. ($)	(193.917)	(60.677)	(208.636)	(273.105)	(291.422)
% Gave in 2013	5.25	2.18	5.11	8.13	7.79
% Gave any prior year	7.36	3.11	7.18	11.33	10.83
Avg Age	35.867	9.392	33.807	56.592	72.036
% Female	49.75	48.53	50.29	50.11	49.63
Med. HH Income in Zip ($1,000s)	86.09	86.09	85.56	87.94	84.21

The average donation is almost five times and ten times higher for the Middle Aged and Mature cohorts compared to the Young cohort ($5.35 and $10.42 vs. $1.09), and the Older cohort's average donation is over ten times higher than the Young cohort ($11.45 vs. $1.09). Further, the Mature cohort donates almost twice as much on average than the Middle Aged cohort ($10.42 vs. $5.35), and the Older cohort donates approximately 114 percent and 9.8 percent more than the Middle and Mature cohorts ($11.45 vs. $5.35 and $10.42), respectively.

As expected, the average conditional donations follow a very similar pattern as the average donation. The donors in the Middle Aged cohort donate about 133 percent more than the donors in the Young cohort ($46.51 vs. $108.25). The average conditional gift of the Mature is approximately 32 percent higher than the average conditional gift of the Middle Aged ($142.10 vs. $108.25). Members of the Older cohort who donated gave approximately 253 and 52 percent more than the Younger and Middle cohorts ($164.50 vs. $46.51 and $108.25). Finally, the average conditional donations for the Mature and Older cohorts are $142.10 and $164.40, respectively, or almost 16% higher for the Older cohort.

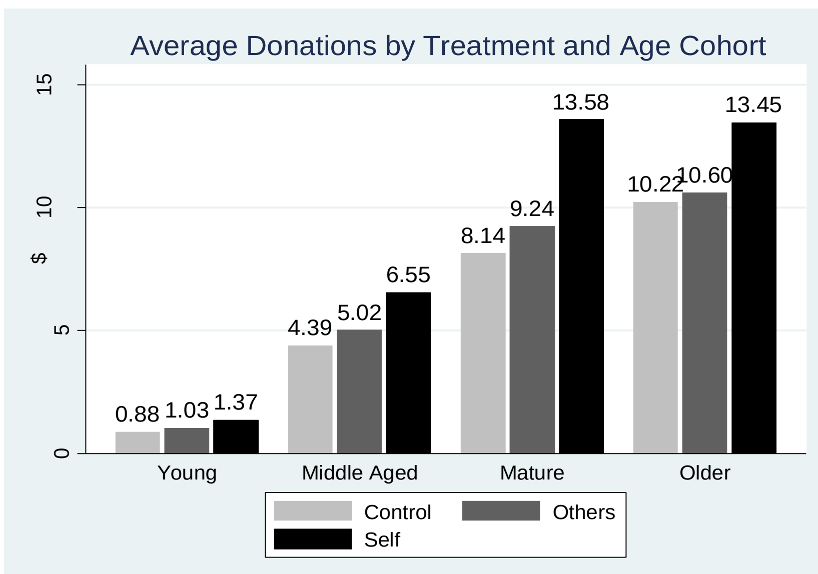
The raw data largely agrees with the literature that giving increases with age, but I do not find that the average gift falls at higher ages. Older individuals that donated gave more on average than their younger counterparts. However, they were less likely to give then those aged 50 to 64 years old. Therefore, the higher average gifts of the Older cohort are the result of larger gifts from fewer people when compared to the Mature cohort.

The summary statistics for the full sample and each age cohort are given in panels B, C, and D of table 18 for the control, Others treatment, and Self treatment. In addition to Table 1, Figures 17, 18, and 19 also show the average donation, propensity to donate, and the average conditional donation for each treatment-age-cohort pair. First, I will briefly discuss the results from the original experiment by comparing treatments effects for all ages using the first column of table 18. The average donation for all ages were $4.72, $5.21, and $7.36 for the control groups, Others treatment (10% more than control), and Self treatment (56% more than control and 41% more than the others treatment), respectively[57]. When I break the treatment effects into the intensive (average conditional gift) and extensive margins (propensity to give), I find that the

[57] The statistical significance are the following: Control vs. Others, $p < .1$; Control vs. Self, $p < .01$; and Others vs. Self, $p < .01$.

differences between the others treatment and the control is mostly driven by 7.5 percent larger average conditional gifts from the others group (\$114.91 vs. \$106.91), but the extensive margin also plays a role as the Others treatment gave approximately 2.7 percent more often than the controls (4.5% vs. 4.4%)[58]. In contrast, both the extensive and intensive margin drives the differences between the Self treatment and both the Others treatment and the control. Individuals who received the "Warm your heart" message gave almost 31 and 27 percent (5.8% vs. 4.4% and 4.5%) more often and 19 and 11 percent more (\$127.65 vs \$106.91 and \$114.91) than the control and the others treatment group[59].

Figure 17. Average Donations by Treatment and Age Cohort



[58] The difference between the others treatment and control is significant at the $p < 0.1$ level for the propensity to give and $p < .01$ for the average conditional gift.
[59] Both differences are significant at the $p < .01$ level.

Figure 18. Propensity to Donate by Treatment and Age Cohort

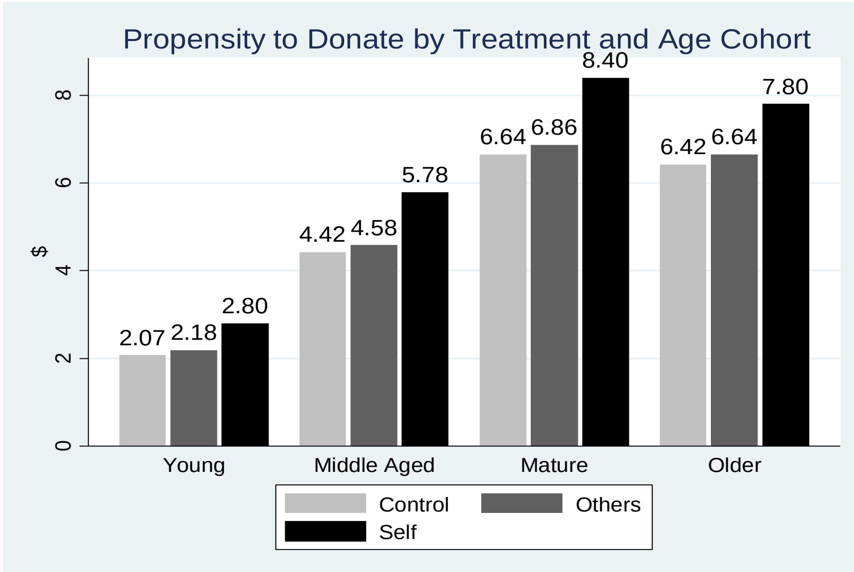
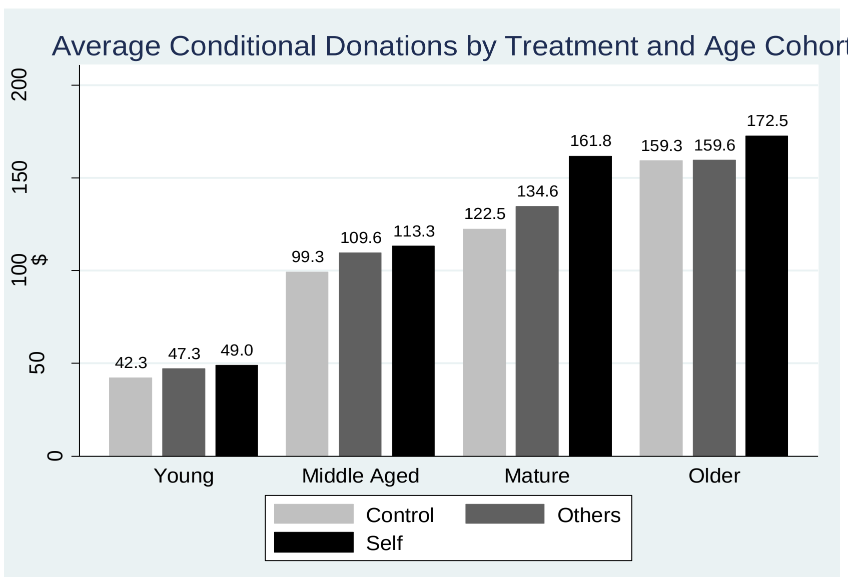


Figure 19. Average Conditional Donations by Treatment and Age Cohort



Panel A of table 18 establishes that the propensity to donate and the donation amounts increases with age and suggests that the treatments increase donations, but this paper is about whether age cohorts have heterogeneous treatment effects from the messaging. While randomization was not specifically designed to test for heterogeneous treatment effects by age, the mailing zip code randomization should be sufficient as the size of each cell is large. Further, the number of registered individuals, average ages, and the percentage that is female are fairly balanced for age cohorts across treatment assignment. One significant caveat must be given here. These simple tests in differences in means cannot tease out the effect of age and the treatment from the effect of the interaction of age and treatment. When looking within a treatment across age cohorts, I cannot distinguish between the effect of age alone and the interaction of age and the treatment. I also cannot distinguish between the effect of the treatment alone and the interaction of treatment and age when I am comparing within age cohort across treatments. In essence, any differences in means could be driven by age, the treatment, the interaction, or a combination of these factors.

While the non-parametric tests[60] of the raw data show some evidence of heterogeneous treatment effects, their results are largely uninformative as they don't allow the inclusion of additional explanatory variables and do not explicitly separate the effects of age, treatment, and the interaction of treatment and age. Further, the Wilcoxon-Mann-Whitney rank sum tests (Wilcoxon 1945; Mann and Whitney 1947) tests mean little with large data sets as many tests will return as statistically significant merely due to the size of the data set. The next section describes the main regression methodology designed to separate the effect of age, the treatments, and their interaction.

3.3 Methodology

Since the treatments were randomized according to an individual's mailing zip code in 2013, treatment assignment is close to exogenous. Therefore, cross sectional linear regressions similar to those found in Landry et al. (2006; 2010) are sufficient to estimate the heterogeneous

[60] The results from the non-parametric tests are available from the author.

treatment effects[61]. The basic setup to estimate the heterogeneous treatment effects on average donations is the following:

$$L_{ij} = Z_{ij}\delta + (Age_{ij} \times Z_{ij})\alpha_{Age} + Age_{ij}\sigma_{Age} + X_{ij}\beta + \varepsilon_{ij} \tag{26}$$

where L_{ij} is the contribution amount from the i^{th} individual in the j^{th} zip code, Z_{ij} is a vector of treatment indicators (control is excluded category), and X_{ij} is a vector of other covariates that may include observable characteristics of potential donors (age, gender, whether the individual gave the prior year). In particular, Z_{ij} and can be represented the following way:

$$Z_{ij} = \begin{cases} 0 \; if \; Control \\ 1 \; if \; Others \; Treatment \\ 2 \; if \; Self \; Treatment \; . \end{cases} \tag{27}$$

Age_{ij} is a vector indicating the age cohort that an individual belongs using the middle aged (20 to 49 years) as a reference age cohort. It can be represented by the following:

$$Age_{ij} = \begin{cases} 1 \; if \; under \; 19 \; years \; old \; (Young) \\ 2 \; if \; 19 \; to \; 49 \; years \; old \; (Middle \; Aged) \\ 3 \; if \; 50 \; to \; 64 \; years \; old \; (Mature) \\ 4 \; if \; over \; 64 \; years \; old \; (Older) \end{cases} \tag{28}$$

The overall treatment effect for a cohort is represented by adding the average treatment effect, δ, to the coefficient on the interaction between treatment and age cohort, α_{Age}. For example, the full treatment effect for those 65 and older is $\delta + \alpha_4$.

Further, I can divide the effect on average donations into an extensive (propensity to give) and extensive (average gift conditional on giving) margin. The intensive margin uses equation (29) but limits the sample to only individuals who gave something. The extensive

[61] Although the data is a panel, panel methods may not be appropriate for this analysis. Since a fixed effects model would be the appropriate panel method, we would be unlikely to find any significant effects. The heterogeneous effects would be identified by individuals that changed age categories between 2013 and 2014, and we would not expect to see a significant change in individual behavior after aging one year. A long panel with treatment interventions occurring at different points in time would be most appropriate, but such data collection would be prohibitively costly.

margin can be estimated by only changing the dependent variable of equation (30) to an indicator for giving any amount. This linear probability model is the following:

$$C_{ij} = Z_{ij}\delta + \left(Age_{ij} \times Z_{ij}\right)\alpha_{Age} + Age_{ij}\sigma_{Age} + X_{ij}\beta + \varepsilon_{ij} \qquad (31)$$

where C_{ij} equals 1 if the household gave and 0 otherwise.

I run five different specifications for each model. First, I simply estimate the treatment effects without including any additional controls, and then I add the indicators for each age cohort to model 2. Model 3 adds the treatment-age-cohort interactions to test for heterogeneous treatment effects. Finally, I add an indicator for whether a household gave in 2013 to Model 4 and the same indicator along with an indicator for whether the individual was female in Model 5. The standard errors are clustered at the zip code level to account for unobservable heterogeneity at the zip code level in all models and specifications. I then use Wald tests to assess the significance of heterogeneous treatment effects.

4. Results

The results for the regressions on the average donation are reported in table 19[62]. They largely confirm List, Murphy, and Price (2015) result that individuals who were mailed the "Warm Your Heart" message gave more, on average, than the control group and individuals who were sent the "Make Alaska Better for Everyone" message. In particular, average donations increased by $2.64 (72 percent) for the Self treatment group compared to the control group's average donation of $4.72 under specification (1). This result holds, albeit at smaller differences as control variables[63] are added to the regression. While the coefficient on the Others treatment is

[62] Note that if I do not discuss the results of the Wald tests of significance between coefficients directly in my comparisons below you can assume that significance level is $p < .05$.
[63] Control variables include age, the interaction of the treatment with age, whether a household gave in the previous year, and gender depending on the specification.

not statistically significant from zero, the difference between it and the Self treatment coefficient is significant at the $p < 0.05$ level for specifications one and two.

Table 19. Regression results on average donations

VARIABLES	(1) donation	(2) donation	(3) donation	(4) donation	(5) donation
Others Treatment	0.4885	0.5892	0.6275	0.6956	0.6957
	(0.873)	(0.844)	(0.929)	(0.572)	(0.572)
Self Treatment	2.6372***	2.5193***	2.1628**	1.1560**	1.1561**
	(0.779)	(0.737)	(0.859)	(0.563)	(0.563)
Young		-4.2072***	-3.5145***	-1.4356***	-1.4363***
		(0.371)	(0.483)	(0.327)	(0.327)
Mature		5.0583***	3.7499***	1.3528***	1.3523***
		(0.439)	(0.411)	(0.413)	(0.413)
Older		6.1115***	5.8330***	3.3727***	3.3721***
		(0.535)	(0.689)	(0.591)	(0.592)
Others*Young			-0.4702	-0.5198	-0.5198
			(0.855)	(0.622)	(0.622)
Others*Mature			0.4694	0.4848	0.4852
			(0.732)	(0.615)	(0.615)
Others*Older			-0.2481	-0.3470	-0.3467
			(1.081)	(0.953)	(0.953)
Self*Young			-1.6676**	-1.1317*	-1.1318
			(0.762)	(0.578)	(0.578)
Self*Mature			3.2815***	2.9887***	2.9889***
			(0.784)	(0.735)	(0.735)
Self*Older			1.0675	1.1353	1.1353
			(1.295)	(1.218)	(1.218)
Gave in 2013				89.2856***	89.2933***
				(3.662)	(3.670)
Female					-0.0557
					(0.116)
Constant	4.7213***	4.2810***	4.3896***	0.8318***	0.8593***
	(0.459)	(0.475)	(0.509)	(0.298)	(0.305)
Observations	541,617	541,617	541,617	541,617	541,617
R-squared	0.000	0.005	0.005	0.120	0.120

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

I find no statistical evidence that the “Make Alaska Better for Everyone” message increases average donations as a whole or within each age cohort. However, the results show limited heterogeneity for the “Warm Your Heart” message. When I include the treatment-age-cohort interactions (columns 3, 4, and 5 of table 19), the average treatment effect for the Self treatment falls from $2.52 in the second specification to between $1.16 and $2.17 depending on the control variables included. The decrease in the average treatment effect may be attributed to the inclusion of age-cohort-treatment interactions. I can test for heterogeneity in treatment effects between age groups directly by comparing the coefficients on the interaction between treatment group and age cohort in table 19. That is, I test for whether one age group is impacted more by one treatment compared to the other age groups.

Each age cohort receives a marginal increase or decrease in average donations as a result of the “Warm Your Heart” message, but many of changes are statistically insignificant. I use the last specification in table 19 for interpreting the marginal effect of each treatment by age group on average donations. The interaction coefficients of treatment and age cohort (α_{Age}) in equation (23) are reported in table 20[64]. This analysis will focus on the differences between the Mature cohort and the other three cohorts since the Mature cohort includes most of the aging Baby Boomer generation; figure 20 also provides a visualization of the interaction comparisons for the Mature cohort. Comparing the Self treatment to the control, the Mature cohort gives $4.12, $2.99, and $1.85 more on average than the Young, Middle Aged, and Older cohorts,

[64] The results from Table 20 can be used for any cohort comparison. For example, I could compute how the Self treatment effect differs for the Middle Aged and Older cohorts by subtracting $1.8536 from $2.9889 to find that the Mature cohort gives $1.1353 more than the Older cohort, on average. These results along with their statistical tests are available upon request from the author.

respectively[65]. Table 20 also reports the results of Wald tests for statistical significance. The heterogeneous response to the Self treatment for the Young and Middle Aged compared to the Mature are statistically significant at the 1% level, but the treatment heterogeneity between the Mature and Older cohorts is not quite statistically significant at the 10% level[66]. In addition to these findings, the Young cohort (< 19) gives significantly less than the Middle Aged and Older cohorts under the Self treatment. The Wald tests in Table 20 also clearly show no significant treatment effect heterogeneity by age group for the Others treatment when compared to the control. Finally, the differences in donations between the Self treatment and Others treatment are \$3.12 ($p < 0.01$), \$2.50 ($p < 0.01$), and \$1.02 (insignificant) higher for the Mature compared to the Young, Middle Aged, and Older cohorts, respectively.

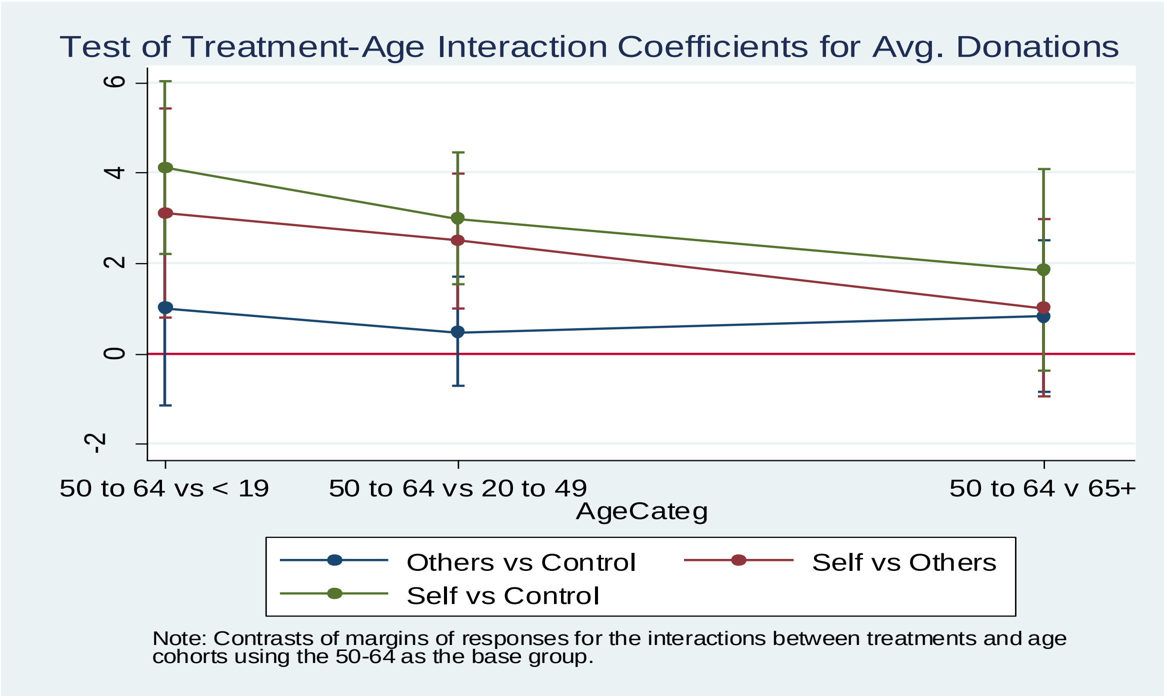
Table 20: Wald Tests of Interaction Coefficients (α_{Age}) for average donations

Comparison	Others vs Control	Self vs Control	Self vs Others
<19 vs 20 to 49	-0.5198	-1.1318*	-0.612*
<19 vs 50 to 64	-1.005	-4.1207***	-3.1157*
<19 vs 65+	-0.1731	-2.2671*	2.4402
20 to 49 vs < 19	0.5198	1.1318*	0.612
20 to 49 vs 50 to 64	-0.4852	-2.9889***	-2.5037
20 to 49 vs 65+	0.3467	-1.1353	-1.482
50 to 64 vs < 19	1.005	4.1207***	3.1158***
50 to 64 vs 20 to 49	0.4852	2.9889***	2.5037***
50 to 64 vs 65+	0.8319	1.8536	1.0217
65+ vs <19	0.1731	2.2671*	2.094
65+ vs 20 to 49	-0.3467	1.1353	1.4821
65+ vs 50 to 64	-0.8319	-1.8536	-1.0217

Note: This table presents the marginal effects of the interaction between treatments and age cohort and was calculated using column 5 of table 19. The significance level was calculated using Wald tests.
*** p<0.01, ** p<0.05, * p<0.1

[65] Prior to controlling for giving in 2013, the results in table 19, column 3 show that the Mature cohort increases average donations by \$4.95 ($p < 0.01$), \$3.28 ($p < 0.01$), and \$2.21 ($p < 0.1$) when compared to the Young, Middle Aged, and Older cohorts in response to the "Warm Your Heart" message.
[66] The difference has a p-value of 0.1011.

Figure 20: The Heterogeneous Treatment Effects on Average Donation by Age



For illustration purposes I assume that the point estimates are all statistically significant. I can then calculate the marginal effect of each treatment by age cohort[67]; the results are summarized in table 21 and figure 21. The most striking result is that the marginal effect of the "Warm Your Heart" message is 80, 250, and 20,600 percent higher for the Mature cohort ($4.14) than the Older ($2.29), Middle Aged ($1.16), and Young ($0.02) cohorts[68]. The heterogeneity within the Others treatment is much less pronounced and statistically insignificant in all comparisons. In conclusion, the results further show limited heterogeneity within the Self treatment but no heterogeneity for the Others treatment when compared to the control. The next logical question to ask is how much the two treatments differ overall from each other.

[67] For example the marginal effect of the "Warm Your Heart" message on the Mature cohort is the sum of the coefficient on the Self treatment and the coefficient on "Self*Mature":

$$1.1561 + 2.9889 = 4.145$$

[68] Only the difference between the Mature and Older cohorts is statistically insignificant with a p-value of 0.1011.

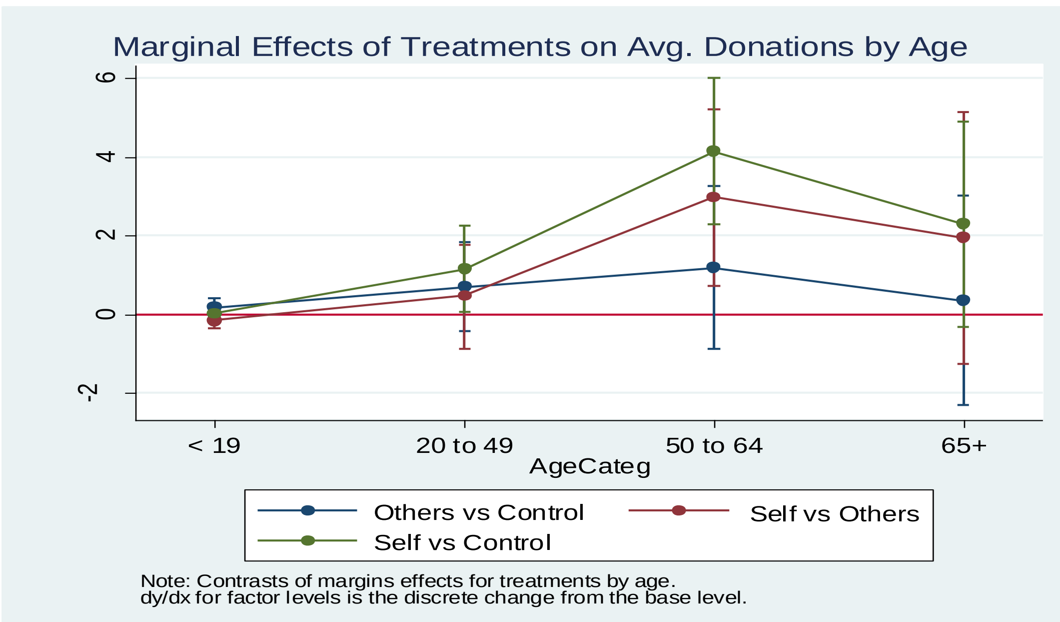
Table 21: Marginal Effects of Treatment on Average Donations by Age

Comparison	Others vs Control	Self vs Control	Self vs Others
< 19	0.1759	0.0243	-0.1517
20 to 49	0.6957	1.1561**	0.4603
50 to 64	1.1809	4.145***	2.9641***
65+	0.349	2.2914*	1.9424

Note: The marginal effects are calculated by adding δ and α_{age} coefficients in table 19 for each age cohort. The statistical significance was determined using Wald Tests.

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

Figure 21: The Marginal Effect of treatments on the Average Donation by Age



Again table 19 tells us that Mature individuals that received the "Warm Your Heart" message donated statistically significant larger amounts, on average, than Mature individuals that received the "Make Alaska Better for Everyone" postcard, and the difference is statistically significant at the $p < 0.01$ level for all the relevant specifications[69]. While the coefficient on the interaction between the Others treatment and the Mature cohort is imprecisely estimated, the

[69] In fact, the Mature cohort who received the Self treatment donate statistically significantly more on average than all other cohorts that received the Others treatment.

average donation of mature individuals that received the Self treatment was $2.50[70] higher than the similarly aged individuals who received the Others treatment. The marginal effect of each treatment for Mature individuals under both treatments can be found in table 21 and figure 21. Mature individuals give 250 percent more on average under the Self treatment ($4.14) compared to the Others treatment ($1.18). Assuming that every Mature individual that did not receive the Self treatment actually did (72,423 people), the amount given to charities through *Pick.Click.Give* would have increased by approximately $250,000[71]. Another glance at figure 21 might make you wonder about the difference between treatments for the Older cohort because the marginal effect for the "Warm Your Heart" message is $2.29 and $0.35 for the "Make Alaska Better for Everyone" treatment. Surprisingly, this difference is statistically insignificant, but it suggests that Older individuals may respond more to giving incentives geared toward benefits to self. Since we found some evidence for treatment heterogeneity for the "Warm Your Heart" message, the next section examines if the differences occur on the extensive or intensive margin.

4.2 Extensive vs. Intensive Margin

Tables 22 and 23 present the results for the propensity to donate (extensive margin) and the average gift conditional on giving (intensive margin), respectively. Overall, the "Warm Your Heart" message increases the probability of giving but has mixed effects on the average conditional gift. The results in table 22 clearly show that the Self treatment increases the probability of giving. Without any additional controls, individuals who receive this treatment are approximately 1.35 percentage points more likely (or 30.5 percent) to donate. Table 23 shows a consistent positive impact from the Self treatment on the average conditional gift, but the impact

[70] $2.99- $0.49

[71] 35,850 additional people from the Control group would donate $4.15 ($1.1561+$2.9889) more on average plus 36,573 more people from the Others group who donate $2.96 ($1.1561+$2.9889-$0.6957-$0.4852) more on average for a total of over $250,000 more.

turns statistically insignificant when I add the age-treatment interactions. The first specification of table 23 implies a $20.74 (19.3 percent) increase in the average conditional donation for the "Warm Your Heart" message over the control. The "Make Alaska Better for Everyone" message was statistically indistinguishable from the control in both the intensive and extensive margin.

Table 22. Regression results on propensity to donate

VARIABLES	(1) donor	(2) donor	(3) donor	(4) donor	(5) donor
Others Treatment	0.0012	0.0017	0.0016	0.0021	0.0021
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)
Self Treatment	0.0135***	0.0128***	0.0136***	0.0061***	0.0061***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Young		-0.0257***	-0.0235***	-0.0080***	-0.0079***
		(0.002)	(0.002)	(0.001)	(0.001)
Mature		0.0238***	0.0222***	0.0044***	0.0044***
		(0.001)	(0.002)	(0.001)	(0.001)
Older		0.0203***	0.0200***	0.0016	0.0017
		(0.002)	(0.003)	(0.001)	(0.001)
Others*Young			-0.0004	-0.0008	-0.0008
			(0.004)	(0.002)	(0.002)
Others*Mature			0.0006	0.0007	0.0007
			(0.003)	(0.002)	(0.002)
Others*Older			0.0007	-0.0001	-0.0001
			(0.004)	(0.002)	(0.002)
Self*Young			-0.0064**	-0.0024	-0.0024
			(0.003)	(0.002)	(0.002)
Self*Mature			0.0039	0.0017	0.0017
			(0.003)	(0.002)	(0.002)
Self*Older			0.0002	0.0007	0.0007
			(0.005)	(0.003)	(0.003)
Constant	0.0442***	0.0444***	0.0442***	0.0177***	0.0141***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Gave in 2013				Yes	Yes
Female					Yes
R-squared	0.001	0.008	0.008	0.411	0.411

Robust standard errors in parentheses

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

Table 23. Regression results on the average conditional donation

VARIABLES	(1) donation	(2) donation	(3) donation	(4) donation	(5) donation
Others Treatment	8.0039	9.0938	10.2991	10.5781	10.6221
	(10.412)	(10.161)	(10.746)	(10.359)	(10.258)
Self Treatment	20.7413**	20.9381**	14.0080	13.0214	13.0287
	(8.515)	(8.200)	(9.983)	(9.695)	(9.704)
Young		-61.4370***	-57.0373***	-53.6044***	-56.2795
		(3.943)	(6.693)	(6.755)	(6.869)
Mature		33.9180***	23.1888***	18.7583***	18.5269***
		(4.506)	(6.479)	(6.559)	(6.576)
Older		56.5364***	59.9412***	54.7054***	54.0426***
		(7.029)	(8.281)	(8.280)	(8.219)
Others*Young			-5.2944	-6.0301	-5.9805
			(9.947)	(10.060)	(9.924)
Others*Mature			1.7805	2.6890	2.7339
			(7.630)	(7.637)	(7.650)
Others*Older			-9.9885	-10.1410	-10.4235
			(11.092)	(11.086)	(11.089)
Self*Young			-7.2832	-7.8027	-7.5628
			(8.870)	(8.879)	(8.956)
Self*Mature			25.2944**	26.6706***	26.5754***
			(9.893)	(9.812)	(9.856)
Self*Older			-0.7504	0.2782	-0.0034
			(17.650)	(17.449)	(17.469)
Constant	106.9055***	96.9272***	99.3133***	80.1996***	92.0359***
	(6.248)	(6.414)	(6.928)	(6.598)	(7.174)
Gave in 2013				Yes	Yes
Female					Yes
R-squared	0.002	0.026	0.027	0.032	0.034

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Prior to controlling for past gifts and treatment heterogeneity (Model 2), the results in table 22 suggest that the Older individuals were 4.6 and 2 percentage points more likely to give than the Younger or Middle Aged but 0.35 percentage points less likely to give than the individuals aged 50 to 64 years old. While the direction of these results largely hold as I add more controls, the magnitude of the age effects diminishes. Using the fifth specification, I find that the Mature cohort are the most likely to donate, and Young individuals are the least likely. The Older cohort is more likely to give than the Young, less likely to give than the Mature, and just as likely to give as the Middle Aged. All differences are statistically significant at the $p < .01$ level except for the difference between the Mature and Older groups. Unfortunately, these differences are not very economically significant as most result in a less than 1 percentage point increase in donors.

The average donation for those who gave increased with age in all relevant specifications. Using the final specification, the Middle Aged, Mature, and Older donors increased their average donation size by $56.28, $74.81, and $110.32 compared to the Young cohort, respectively. Tables 22[72] and 23 together show that the propensity to give increases with age until individuals reach the Older cohort, but the average conditional donation monotonically increases with age. The former statement confirms the findings in previous literature, but the latter does not.

Finally, the heterogeneous treatment effects for the "Warm Your Heart" message are solely driven by individuals donating larger amounts and not by more individuals donating. The treatment effects on the probability of giving do not systematically differ by age cohorts for either treatment compared to the control or between the two treatments. The results presented in table 22, columns 3, 4, and 5 show little evidence that for heterogeneous treatment effects for the Mature cohort, or any other age cohort for that matter, on the extensive margin. The Wald tests comparing the coefficients do find significant differences ($p < .05$) between the Young cohort

[72]The results also suggest that an individual that gave in 2013 is 66 percentage points more likely to donate again in 2014 than those that did not. Finally, females are also more likely to give than males, but the effect is less than 1 percentage points.

and Middle Aged cohort as well as the Young and Mature cohorts, but these differences largely disappear when I add additional controls. Further, I find no statistical differences within any age cohorts between the two treatments. Therefore, the heterogeneous treatment effects for the "Warm your heart" message must be coming through on the intensive margin.

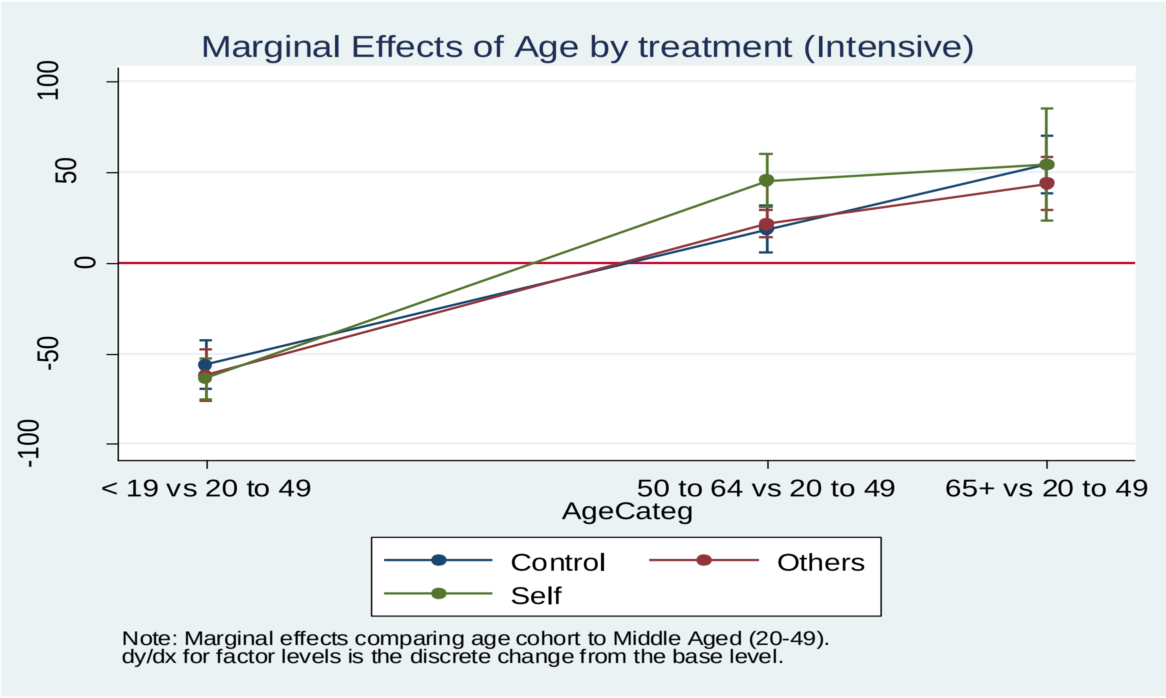
Table 24 and figure 22 highlight the differences in the intensive margin for the Self treatment. Donors in the Mature cohort gave \$34.14 (624%), \$26.58 (204%), and \$26.57 (204%) more, on average, than Young ($p < 0.01$), Middle Aged ($p < 0.01$), and Older donors ($p < 0.1$), respectively, when they lived in a zip code that was mailed the "Warm Your Heart" postcard. As expected, the donors living in zip codes that received the "Make Alaska Better for Everyone" did not have statistically significant difference in donation amounts overall or within age cohorts. Finally, Mature donors in the Self treatment gave \$23.84 higher amounts, on average, than Mature donors in the Others treatment which is the only significant difference between the two treatments within a single age cohort.

Table 24: Wald Tests of Interaction Coefficients (α_{Age}) for average conditional donations

Comparison	Others vs Control	Self vs Control	Self vs Others
50 to 64 vs < 19	8.7144	34.1382***	25.4238**
50 to 64 vs 20 to 49	2.7339	26.5754***	23.8416***
50 to 64 vs 65+	13.1574	26.5788*	13.4214

Note: This table presents the marginal effects of the interaction between treatments and age cohort and was calculated using column 5 of table 23. The significance level was calculated using Wald tests. These are only the results for comparing the Mature cohort to the other cohorts. The results for the comparison between all age cohorts are available by request to the author.
*** p<0.01, ** p<0.05, * p<0.1

Figure 22: The Heterogeneous Treatment Effects on Average Conditional Donation by Age



4.3 Giving Simulation

In order to gain a deeper understanding of the potential impact of the treatments and the changing demographics, I calculate several back of the envelope simulations with the caveat that these are for descriptive purposes only. For this illustration, I ignore statistical significance and take the point estimates as precise. First, I calculated the proportion of the population in each age cohort and treatment pair that applied for their PFD online using the *Pick.Click.Give* data and population estimates from the Census Bureau (2014). I then used state population projections by age and treatment from the Department of Labor and Workforce Development (2014) for Alaska and calculated an estimated number of people that will apply for their PFD online using the ratio in the first step[73]. The final step used the coefficient estimates in table 19, column 3 to predict total giving for each age cohort under 4 simulations using the years 2014 and 2032[74].

The first simulation estimates total donations under the normal treatments using the 2014 treatment exposure ratios for each age-treatment cell, and the second predicts the amount in the absence of any treatment. The final two simulations are designed to show the overall impact of the “Warm Your Heart” message. The third simulation predicts total donations if the “Warm Your Heart” message was given to all Mature individuals to measure the heterogeneous treatment effect for this group. Last, I estimate total giving if the “Warm Your Heart” message was sent to all individuals in Alaska. Table 25 summarizes the results of total donations under each scenario. Panel A of table 25 lists the results for 2014, and panel B shows the 2032 results. While I list the relative effects for each cohort in columns 2 through 5 of table 25, I will focus the discussion on the overall effect in the first column.

Unsurprisingly, total donations under normal treatments (Simulation 1) almost perfectly predict total giving in the raw data in 2014. In the absence of the treatments (Simulation 2), total donations fall by about 571 thousand dollars (18 percent) in 2014. By simply sending all individuals in the mature cohort who applied for their PFD online (an additional 72,423 people) the “Warm Your Heart” postcard, total donations increased by over 350 thousand dollars (11 percent) or an additional $4.89 per individual when compared to the first simulation. Finally, sending every household in the sample (358,434 people) the “Warm Your Heart” postcard increased total donations by over 24 percent (774 thousand dollars) compared to simulation 1. This is an additional $2.16 per additional person receiving the Self postcard. Overall, the results of these simulations for 2014 tell us that charities in Alaska would have raised significantly more

[73] This method more than likely under predicts the number of households that will sign-up online as this number has been rising steadily each year.
[74] The year 2032 was the closets Alaskan population projection available for around 20 years from 2014.

money had the “Warm Your Heart” message been sent to all households, but it may have been more cost effective to only send the postcard to individuals in the Mature cohort.

Table 25. Summary of giving simulations ($1,000s dollars)

Variables	All Ages	Young	Middle	Mature	Older
	Panel A: 2014				
1 - Normal Treatments	3,131.80	158.70	1,267.25	1,167.60	538.25
2 - No Treatments	2,559.93	127.45	1,040.09	911.86	480.53
3 - Treatments - All Mature receive "Warm" message	3,485.98	158.70	1,267.25	1,521.78	538.25
4 - All Ages get "Warm" message	3,906.28	199.57	1,552.55	1,521.78	632.38
	Panel B: 2032				
1 - Normal Treatments	5,094.16	272.89	1,869.14	1,296.12	1,656.00
2 - No Treatments	4,243.90	219.16	1,534.09	1,012.23	1,478.42
3 - Treatments - All Mature receive "Warm" message	5,487.32	272.89	1,869.14	1,689.28	1,656.00
4 - All Ages get "Warm" message	6,268.00	343.17	2,289.95	1,689.28	1,945.60

Sources: The simulations were calculated using the *Pick.Click.Give* data, data from the U.S. Census Bureau 2014, and data from Alaska's Department of Labor and Workforce Development (2014).

Comparing the simulations between 2014 and 2032 suggests that total donations should be expected to increase simply from a larger population that is also aging. If the experiment were repeated in 2032, total donations would be almost 2 million dollars more (62 percent increase over 2014). Even in the absence of intervention total giving would increase by over 1.6 million dollars by 2032 compared to the second simulation results from 2014. In 2032, the “Warm Your Heart” message increases donations by even more than in 2014 because of the larger and older population. Repeating the same experiment in 2032 would have raised an additional 850 thousand dollars compared to about 572 thousand dollars in 2014. Because of the smaller relative size of the Mature cohort, sending the message emphasizing benefits to self to every household in the Mature cohort would raise 393 thousand dollars more, but this is only 9 percent more than merely repeating the same 2014 experiment which is smaller than the 11 percent increase in total donations in 2014 under the same simulation. The difference between sending all households the "Warm Your Heart" message also conforms to a similar pattern. In conclusion, the simulations show that the "Warm Your Heart" message increases total donations in both 2014 and 2032. In absolute terms, much more money is raised in 2032 than 2014 under every scenario as the result of a larger, older population; however, the simulation results also suggest that the aging population dampens the effects of the Self treatment on total donations in 2032.

The results above show that Mature cohort are the only age cohort who were heterogeneously affected by the Self treatment while no heterogeneity existed for the Others message. The Baby Boomer generation makes up the Mature cohort. Historically, Baby Boomers have been very generous with their money and time. Moving forward the most important question is if the Mature cohort has a greater response to the Self message because of their age or their identity as a generation. One argument against generational effects is that the relationship with age and giving has been relatively stable through time which would suggest that actual age and life experience drives given patterns more so then generational effects. Unfortunately, I cannot completely rule out generational effects without a long panel of data with treatments that varied through time.

5. Conclusion

This study combines the literature on the relationship between charitable giving and age with the literature examining the motivations for giving. To my knowledge, it is the first to test whether the drivers of giving differ by age. I use the results from a randomized field trial designed to distinguish between pure and impure altruism (List, Murphy, and Price 2015). The field experiment randomly assigned households by zip code into a control or one of two treatments. The first treatment was mailed a post card with the message “Make Alaska Better for Everyone” to elicit the benefits to others motivation for giving, and the second treatment group was sent a postcard that emphasized the benefits to self with a message reading “Warm Your Heart.” I then divided the individuals into four age cohorts: Young (under 19 years old), Middle Aged (19 to 49 years old), Mature (50 to 64 years old), and Older (65 years old and older) and used regression analysis to explore any treatment heterogeneity. That is, are people of different ages motivated to give for different reasons?

The results found only some evidence that the drivers of charitable giving differ by age when the individual was sent the “Warm Your Heart” message and no evidence of heterogeneity for individuals sent the “Make Alaska Better for Everyone” message. In particular, people between 50 and 64 years old gave between \$4.12 and \$4.94 more on average in response to the benefits to Self treatment than the Young and between \$2.99 and \$3.28 more than Middle Aged cohorts under the same treatment. I also find that individuals 65 and older donate between \$1.85 and \$2.21 less when receiving the “Warm Your Heart” message than Mature individuals, but the difference of \$1.85 is not statistically significant. In addition, these results are entirely driven by larger donations (intensive margin) as opposed to more people donating (extensive margin). I find no evidence of heterogeneous treatment effects for the message emphasizing benefits to others. Finally, the Mature cohort responds more positively to the “Warm Your Heart” message compared to the “Make Alaska Better for Everyone” postcard. Overall, the results suggest that the benefits to self is the primary motivator for charitable giving, and the Mature cohort, who are from the Baby Boomer generation, are driven to donate more by benefits to self than other age cohorts.

As I mentioned in the text, these results cannot definitively distinguish between age and generational effects. If the results for the Mature cohort are actual driven by being part of the Baby Boom generation, the implications of my results may change dramatically. Therefore, this should be a fruitful area for future research. Further, my analysis only examined the two most basic drivers of charitable giving, but these drivers have many components that I am unable to examine. For instance, the benefits to self could be driven by social pressures (e.g. DellaVigna, List, and Malmendier 2012; Knutsson, Martinsson, and Wollbrant 2012), social identity (e.g. Kessler and Milkman 2014), or social image (e.g. Ariely, Bracha, and Meier 2009; Lacetera and Macis 2010). Finally, the charitable giving literature has also shown that various mechanisms such as seed money (e.g. James Andreoni 1998; A. List and Lucking-Reiley 2002), charitable auction-s (e.g. Goeree et al. 2005; Engers and McManus 2007), lotteries (e.g. Morgan 2000; Morgan and Sefton 2000; Apinunmahakul and Devlin 2004; Landry et al. 2006; Lange, List, and Price 2007), and matching grants (e.g. Eckel and Grossman 2003; Karlan and List 2007) tend to increase the probability and amount of giving. Another future area of research is measuring how age interacts with these mechanisms that charities use in practice.

Chapter III

Consequences of Local Homestead Exemptions in Georgia: A Proposal[75]

1. Introduction

In recent years, Cobb County has made headlines for its generous homestead exemption from the education property tax for seniors over the age of 62, at a time when schools budgets have been severely squeezed[76]. However, Cobb's exemption is only the most generous exemption on a continuum of Georgia's counties. While Cobb offers a 100% exemption for all seniors over the age of 62, other counties offer exemptions at higher ages, or with income tests, or for only a portion of the assessed value. Other districts have no exemptions at all.

We will explore the impact of these homestead exemptions on the demographic makeup of each jurisdiction. Seniors living even in modest homes receive a subsidy, relative to younger households, of $1,000 or more annually in a jurisdiction such as Cobb. We would expect this subsidy to attract seniors to such jurisdictions, or prevent them from leaving, relative to control jurisdictions. Using school-district-level Census data since 1970 along with the history of such exemptions, we will test for such demographic "sorting."

Second, but more speculatively, we will consider the impact of these laws on the levels of housing capital. According to the "new view" of the property tax, the incidence of the tax falls in part on capital (Zodrow 2001). The national average level of the property tax lowers the returns to capital, while above-average property taxes in a particular jurisdiction will lead to lower equilibrium levels of housing capital and be capitalized into lower land values, ceteris paribus. Since the education exemption shrinks the tax base, we would expect it to have such effects.

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[75] Much of this chapter was adapted from Mickey, Banzhaf, and Patrick (2015).
[76] See, e.g., Downey (2013) and Davis (2010).

More broadly, we would expect the equilibrium ratio of housing consumption for seniors to younger households to be higher in jurisdictions with such exemptions compared to control counties. We will test for sorting effects and heterogeneous housing consumption by age using a difference-in-difference-in-differences model previously used in demographic transition (Banzhaf and Walsh 2008; Card, Mas, and Rothstein 2008) and property tax (Banzhaf and Lavery 2010) contexts.

2. Related Literature

2.1 The Tiebout Hypothesis and Older Households

Charles Tiebout's (1956) seminal article suggesting that people "vote with their feet" by moving to communities with their optimal mix of taxes and public goods created a whole literature on sorting behavior of households. Researchers have examined sorting in the context of income (e.g. Epple and Sieg 1999; de Bartolome and Ross 2003; Finney, Goetzke, and Yoon 2011), race (e. g. Card, Mas, and Rothstein 2008; Banzhaf and Walsh 2013) environmental quality (e.g. Banzhaf and Walsh 2008; Cameron and McConnaha 2006; Greenstone and Gallagher 2008; Kahn 2009; Been and Gupta 1997), and other local public goods.

A branch of this "sorting" literature examines how location decisions change through the life-cycle of households, particularly at older ages and in retirement. That is, households often move when they experience a major life change such as a new job, marriage, the birth of a child, retirement, increasing health care needs, or the death of a spouse. Further, these same life changes influence where they move. Older households typically have the most freedom in their location decisions because they are less compelled to seek higher wages. One of the earliest applications of the Tiebout model to retiree location decisions was by Graves and Waldman

(1991b) who found the retirees are more likely to move to areas where local public goods are capitalized more into lower wages than higher land prices which confirms an earlier theoretical model developed by Graves and Knapp (1988).

Much of the existing literature on retiree location preferences is in the context of migration[77], and it attempts to answer question such as where do elderly households move, why they moved, and the reasons why they choose particular destinations. These questions, particularly the where they move and why they move there, fit nicely into Tiebout's "voting with your feet" framework. Conventional wisdom is that retirees seek places with mild weather (e.g. D. E. Clark, Knapp, and White 1996; Conway and Houtenville 1998; Conway and Houtenville 2003; Whisler et al. 2008; Karner and Dorfman 2012), more sunlight, and a relatively low cost of living (e.g. Fournier, Rasmussen, and Serow 1988; Cebula 1993), but people of all ages prefer to live in low cost of living areas with nice weather (e. g. Rappaport 2007). In addition to weather, retirees may be more likely to prefer to live in places with other natural amenities (e.g. Poudyal, Hodges, and Cordell 2008), low crime (e.g. Conway and Houtenville 1998; Duncombe, Robbins, and Wolf 2000; Whisler et al. 2008); access to quality health care (D. E. Clark, Knapp, and White 1996; Karner and Dorfman 2012); and cleaner air. Finally, local tax and expenditure policies may also play an important role in the location decision of older households. A number of studies examine various local tax and spending policies including state death, estate, and inheritance taxes (Duncombe, Robbins, and Wolf 2000; Conway and Houtenville 2003; Conway and Rork 2004; Conway and Rork 2006), property taxes (Shan 2010), elderly-specific tax exemptions (Conway and Houtenville 2003; Conway and Rork 2008a; Conway and Rork 2008b; Onder and Schlunk 2010; Conway and Rork 2012), and other local spending considerations (Conway and Houtenville 2003; Farnham and Sevak 2006). No consensus has been reached in

[77] See Walters (2002) for a review.

the literature about the sorting effects of such policies. Since this paper examines property tax exemptions for the elderly, I will focus on articles that specifically examine property taxes as well as older-specific tax exemptions for older households.

An early study by Conway and Houtenville (1998) looked at the effect of the share of total state and local taxes raised by property taxes, among others things, on in-migration and out-migration of older households and found that higher shares of property taxes were associated with higher out-migration They also unexpectedly found a positively correlation between the property tax variable and in-migration[78]. Gale and Heath (2000) amend Conway and Houtenville's model to allow for the endogeneity of elderly migration and state fiscal policy. Their results suggest that the higher property taxes reduce net in-migration when the endogeneity is explicitly modeled. One major flaw in these studies is the use of migration variables at the state level[79] whereas much of the property tax variation happens within a state in local jurisdictions. Further, sorting tends to occur more at geographic level smaller than states.

Three recent studies used Health and Retirement Survey (HRS), albeit from different time periods, to analyze questions regarding sorting as a result of property taxes. Farnham and Sevak (2006) were the first to use the household-level panel data to test for Tiebout sorting. They restricted the analysis to households that recently became empty-nesters and found that cross-state movers lowered their exposure to property taxes but local movers do not because of within state fiscal constraints on local jurisdictions. Seslen (2005) examined the effect of property taxes on the decision of older households to downsize using a panel of households and found little evidence of property taxes influencing the decision to move or liquidate their housing. Unfortunately, the two prior studies failed to account for the potential endogeneity problem of

[78] Two similar study by Houtenville and Conaway (2001; 2003) found similar results for property taxes.
[79] Duncombe, Robbins, and Wolf (2000) are an exception as they use county-to-county.

both property taxes and mobility decisions being driven by some unobserved factor. Shan (2010) used more recent data from the HRS than Farnham and Sevak (2006) and Seslen (2005) that allowed her to address the endogeneity issue by instrumenting for property tax payments with variation in state-provided property tax relief programs. She finds that higher property taxes raise mobility of older households. In particular, the results suggest that a 100 dollar increase in property taxes increases the mobility rate by 9 percent for elderly.

While the above studies examine the impact of property tax levels on older household mobility, we are the first, to our knowledge, to examine how property tax exemptions for older households at the local level affect the location decisions. However, we are not the first to study the effects of elderly tax breaks on location decisions. Older households have typically received the most tax relief from income taxes[80]. Conway and Houtenville (2003) find that the effect of an income tax exemption for pension income is sensitive to the progressivity of the state tax code: the less progressive a state's income tax code is the more likely it discourages out-migration and encourages in-migration. Some states also exempt certain items from sales tax which older households buy a more than younger households, on average; Onder and Schlunk (2010) found that older households are more likely to move to states with such exemptions. Finally, Conway and Rork (2012) provide the most careful and complete analysis of state tax breaks for older households and their location decisions; they find little evidence that older households move or leave a state as the result of such tax breaks.

2.2 Housing Consumption

Basic economic theory predicts that when the price of a good falls the quantity demanded for the good increase. While housing is unlike other goods in many ways, the housing market is not immune to the law of supply and demand. The cost of housing is the largest purchase that

[80] See Conway and Rork (2008a; 2008b) for a brief history.

most households make, and it is also that most subsidized. Implicitly, the imputed rent of an owner-occupied home is not taxable. Explicitly, mortgage interest is deductible from income taxes at the federal level and in many states. These tax preferences for home-owners effectively lower the user cost of owning a home. This could lead to an increase on the extensive margin in the number of households owning a home and on the intensive margin in the size of the house, or amount of housing capital.

The impact of tax preferences for home ownership has been studied extensively. The closets line of literature to our study asks what the impact of the mortgage interest deduction has on the number of homes bought and the size of those homes[81]. Overall, Mills (1987) and Poterba (1992) find that both the mortgage interest deduction (MID) and property tax deduction increase housing consumption by 12 to 24 percent. The impact of the MID on home ownership rates (extensive margin) is somewhat mixed. Older studies find that the MID increases homeownership rates by 4 percent (Rosen and Rosen 1980) to 6.5 percent (Hendershott and Shilling 1980), but more recent studies find little or no evidence of the MID affecting homeownership rates (Glaeser and Shapiro 2003; Hanson 2012; Bourassa et al. 2013). With the exception of Hanson (2012), these studies do not consider the impact of the MID on the size of house. In this respect, Hanson (2012) finds a 10.9 to 18.4[82] percent increase in the size of the home purchased in response to the MID; this puts the increase in square footage of the average house as a result of the MID at 250 to 1,000 square feet, depending on the city (Hanson, Brannon, and Hawley 2014).

[81] There is also a small literature on the impact of the MID on the demand for mortgage debt. See Follain and Dunsky (1997), Ling and McGill (1998), and Hanson and Martin (2013).

[82] The range of results depends on the method used by Hanson. He utilized ordinary least squares, instrumental variables, regression discontinuity, and sample selection estimation techniques.

With this in mind, local homestead exemptions can also have an impact, albeit small, on the user cost of home ownership. The key insight in this analysis is that different types of home owners may have heterogeneous user costs for the same house because of targeted local homestead exemptions. When the local homestead exemption is targeted toward a specific population (e.g. older households), the user cost of owning a home falls for this population relative to the population ineligible. The population benefitting from lower user costs of housing may respond by buying larger home just as homeowners buy larger houses as a result of the MID. In addition to analyzing a different policy variable, our study will examine the impact on a smaller geographic scale as most of the MID literature uses differences between state tax policies.

3. Local Homestead Exemptions in Georgia[83]

The State of Georgia provides homestead exemptions of property taxes based on a number of criteria and also allows local jurisdictions to implement their own homestead property tax exemptions. To become binding, these local exemptions must be approved by the state legislature, signed by the governor of Georgia, and then passed by a local referendum. While local jurisdictions can propose any exemption, many of the local homestead exemptions follow what the state government provides relatively closely. Therefore, it is important to understand both the state and local exemptions and how they interact.

The data are organized around the following conceptual framework. If there were no exemptions, the total ad valorem property tax for a household type *i* living in jurisdiction *j* would be:

$$T_{i,j} = \left(\tau_j^{MO} + \tau_j^{B}\right)\beta_j V \qquad (32)$$

[83] This information comes from Mickey, Banzhaf, and Patrick (2015).

In this expression, V is the fair market value, β is the assessment ratio (generally 0.4 in Georgia), and the total tax rate, τ, can be divided into two rates, a tax rate for bonds, τ^B, and a tax rate on maintenance and operations, τ^{MO}. Incorporating various exemptions into Equation (1), the ad valorem tax for a household type *i* living in jurisdiction *j* is the following:

$$T_{i,j} = \theta_{i,j}^{MO}\tau_j^{MO}\left(\phi_{i,j}^{MO}\beta_j V - \left(\delta_{S,i,j}^{MO} + \delta_{L,i,j}^{MO}\right)\right) + \theta_{i,j}^{B}\tau_j^{B}\left(\phi_{i,j}^{B}\beta_j V - \left(\delta_{S,i,j}^{B} + \delta_{L,i,j}^{B}\right)\right) \quad (33)$$

This expression uses the following notation:

$\theta \in [0,1]$ is the amount the millage rate is prorated (0 being a full exemption),

ϕ is a proportionate adjustment to the assessment ratio,

δ_S is the dollar amount of the state exemption, which in some cases may differ by jurisdiction and individual,

δ_L is the dollar amount of an applicable local exemption.

Using these definitions, $\beta_j V$ is the assessed value, and $\phi_{i,j}^{MO}\beta_j V - \left(\delta_S^{MO} + \delta_{L,i,j}^{MO}\right)$ is the net assessed value.

We use equation (34) to build[84] a database that provides unique information about state and local property tax data as it affects households. Until now, the only data available has been that from the Georgia Tax Digest[85]. The digest provides aggregate data on property tax revenues, number of assessed properties, and aggregate assessed values by jurisdiction. Default millage rates are also available since 1990. However, those data provide only a partial picture of the property tax landscape in Georgia. In particular, they do not provide data on the variability in homestead exemptions across local jurisdictions, nor do they provide data on such exemptions as they vary within a jurisdiction by individual characteristics include age, disability status, veteran status, and income.

[84] See Mickey, Banzhaf, and Patrick (2015) for a description of how the data set was built.
[85] The digest can be found at http://dor.georgia.gov/county-ad-valorem-tax-digest-consolidated-summaries.

This unique data set provides this information for the state and for local jurisdictions from 1938 to 2013; however, the first local homestead exemption didn't appear on the books until 1948 in Muscogee County. In practice, it covers an even longer period, as we verified that there were no state or local exemptions before 1938, at least back to 1913. Merged with data on millage rates, this database allow one to simulate how much property tax an individual household of a given demographic category would pay in property taxes in a given jurisdiction in a given year in a property with a specified assessed value (assuming the household takes advantage of all exemptions available). The local homestead exemptions data by jurisdiction, includes all counties, all school districts, and a select number of municipalities. A municipality was automatically included if it had an independent school district for at least one year after 1990, was one of the 30 most populated cities in Georgia, or was one of the top 100 most populated cities and had no local homestead exemptions[86]. A small number of additional cities were also included. Appendix C contains a table 34 that shows the top 100 most populated cities in Georgia and indicates whether the city has ever had an exemption and whether it is coded in the database.

The local homestead exemptions in Georgia vary across space and time. The state of Georgia does not limit the type, amount, or eligibility requirements of local homestead exemptions which lead to a wide variety of exemptions. The exemptions range from an exemption from the full value of the assessed value which can save thousands of dollars to a few thousand dollars off of the assessed value of a homestead which saves homeowners a few hundred dollars. For example, Cobb County exempts homeowners who are over 62 years old from all school property taxes. In 2013, the millage rate in Cobb County for school purposes was

[86] The laws for other cities have been gathered, but they have not been coded into the data. They are available from the authors upon request.

18.9 mills. A homeowner who is over 62 years old with an assessed value of 100,000 dollars[87] would save approximately 1,890 dollars from the exemption. In contrast, Coweta County exempts homeowners who are 65 and older from 8,000 dollars of their assessed value for school purposes; with the 2013 millage rate of 18.59 they only save 148.72 dollars[88]. While tax jurisdictions often copy the state or each other, they adopt the jurisdictions at different points in time as well.

4. Data and Methodology

The basic methodology follows the empirical strategy outlined in Banzhaf and Lavery (2010) and also closely follows Banzhaf and Walsh (2008) and Card, Mas, and Rothstein (2008). In particular, we will estimate the following difference-in-difference-in-differences model which identifies the effect of property tax exemptions for the elderly off of differences from pre-existing trends relative to control jurisdictions:

$$\Delta D_{jt,t-T} = \delta AE_{jt} + \alpha_j + \beta_t + \gamma X_{jt-T} + \varepsilon_{ijt} \tag{35}$$

where $\Delta D_{jt,t-1}$ is the change between t and $t - T$ in dependent variable of interest[89], AE is the

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[87] The home is valued at \$250,000. In the absence of the full exemption and ignoring other exemptions the household may be eligible, the homeowner would pay the following:

$$\mathrm{T}_{\mathrm{i,j}} = \tau_{\mathrm{j}}^{\mathrm{MO}}\left(\beta_{\mathrm{j}}\mathrm{V} - \left(\delta_{\mathrm{S,i,j}}^{\mathrm{MO}} + \delta_{\mathrm{L,i,j}}^{\mathrm{MO}}\right)\right) + \tau_{\mathrm{j}}^{\mathrm{B}}\left(\beta_{\mathrm{j}}\mathrm{V} - \left(\delta_{\mathrm{S,i,j}}^{\mathrm{B}} + \delta_{\mathrm{L,i,j}}^{\mathrm{B}}\right)\right)$$
$$\mathrm{T}_{\mathrm{i,j}} = 0.0189(.4 * 250{,}000) = \$1{,}890$$

[88] With the \$8,000 exemption, a homeowner 65 and older would pay the following property tax for school purposes in Coweta County:

$$\mathrm{T}_{\mathrm{i,j}} = \tau_{\mathrm{j}}^{\mathrm{MO}}\left(\beta_{\mathrm{j}}\mathrm{V} - \left(\delta_{\mathrm{S,i,j}}^{\mathrm{MO}} + \delta_{\mathrm{L,i,j}}^{\mathrm{MO}}\right)\right) + \tau_{\mathrm{j}}^{\mathrm{B}}\left(\beta_{\mathrm{j}}\mathrm{V} - \left(\delta_{\mathrm{S,i,j}}^{\mathrm{B}} + \delta_{\mathrm{L,i,j}}^{\mathrm{B}}\right)\right)$$
$$\mathrm{T}_{\mathrm{i,j}} = 0.01859(.4 * 250{,}000 - 8{,}000) = \$1{,}710.28$$

Without the exemption and ignoring other exemptions the household could be eligible, the same household would pay the following in Coweta County:

$$\mathrm{T}_{\mathrm{i,j}} = \tau_{\mathrm{j}}^{\mathrm{MO}}\left(\beta_{\mathrm{j}}\mathrm{V} - \left(\delta_{\mathrm{S,i,j}}^{\mathrm{MO}} + \delta_{\mathrm{L,i,j}}^{\mathrm{MO}}\right)\right) + \tau_{\mathrm{j}}^{\mathrm{B}}\left(\beta_{\mathrm{j}}\mathrm{V} - \left(\delta_{\mathrm{S,i,j}}^{\mathrm{B}} + \delta_{\mathrm{L,i,j}}^{\mathrm{B}}\right)\right)$$
$$\mathrm{T}_{\mathrm{i,j}} = 0.01859(.4 * 250{,}000) = \$1{,}859$$

[89] *T* is ten years for the data using the decennial Censuses (1970, 1980, 1990, and 2000). Beginning in 2005, the Census Bureau discontinued the decennial long-form in favor of a yearly survey called the American Community

treatment variable, α_j is a jurisdiction fixed effect, β_t is a time trend, $\boldsymbol{X}_{jt-1}$ is a vector of lagged demographic and location controls, and ε_{jt} is a normally distributed error. We will cluster the standard errors at the school district level to account for within school district correlation of the error and estimate each model with and without population weighting.

We will use at least two different dependent variables for the sorting results, and one dependent variable to estimate the effect on housing consumption by older households. The ideal variable to estimate the sorting effects is the change (and percentage change) in the number of home-owning households with heads 65 years old and older (older households). We are also interested in how the proportion of older households[90] changes in levels and percentage terms in a jurisdiction as the results of an older-household exemption. While this ratio may seem redundant to using the number of older households, it could give us at least two additional insights. First, it will help us distinguish between a school district being relatively attractive to just older households from being attractive to all household types. Second, it could be possible that a school district is losing households, but older households are leaving at a slower rate than younger households because of a tax exemption. Changes in population levels would not capture this subtle effect, but the proportion of older households may.

We can also adjust the definitions of the dependent variables two different ways. The first adjustment we can make is to the demographic variable used in the dependent variable. Since owner-occupied houses are the target group of these local homestead exemptions, our ideal variable is owner-occupied households with heads 65 and older. As a robustness check, we will use the total population number of individuals 65 and over living in owner-occupied houses.

Survey. The American Community Survey accounts for roughly 1% of the population. Therefore, we may need to use either a 3-year or 5-year release. I used T to reflect that the time period may not always be 1 years.

[90] $Proportion\ of\ Older\ Households = \frac{Older\ Houseolds}{Total\ Households}$

Finally, the total population 65 and older regardless of tenure will be used to look at the effect on the whole population. Second, we will want to test for the sensitivity of using different age cutoffs. Sixty-five seems to be the ideal cutoff because the majority of age-targeted exemptions begin at that age, but many jurisdictions also have exemptions beginning at 62 years old while other exemptions begin at 70 years old. We also need to be concerned about households moving to a jurisdiction prior to being eligible for a local homestead exemption in anticipation of eligibility which makes using younger age cutoffs important. We will explore these differences; unfortunately, the actual cutoffs we use will be limited by the demographic data available.

The second question that this paper addresses is essentially whether older households will consume more housing than younger households as a result of local age-related homestead exemptions. Therefore, the natural dependent variable to use is changes (and percentage changes) in a ratio of housing consumption by age, or a proxy for housing consumption for older households to younger households. Reported house values may be a logical proxy for housing consumption, but this could be misleading if the two household types report house value differently. Another proxy candidate is the number of rooms or the number of bedrooms in a house.

Note that we haven't said much about the policy variable of interest; this is because the nature of local homestead exemptions complicates things. Recall that no two exemptions are exactly alike since Georgia allows its jurisdictions to create their own homestead exemptions with little oversight or stipulation. The intensity of the exemption can vary widely from a few thousand dollars off the assessed value to a complete property tax exemption, and the eligibility requirements for income differ significantly between school districts. In addition to the variability in the intensity of the actual exemption, the total amount of the exemption also depends on the millage rate applied by that jurisdiction. A complete exemption is worth more in a jurisdiction with a high property tax rate opposed to a jurisdiction with a much lower property tax rate. In light of these issues, we will use three separate treatment variables. First, we will use a simple binary indicator that equals unity if the jurisdiction has a local homestead exemption for older households and 0 otherwise. Second, we will calculate an index for the typical millage rate paid by residents of a school district to estimate the typical savings amount for residents resulting from homestead exemptions, and the final treatment will use the actual millage rates for each jurisdiction from the Georgia tax digest to find typical savings from the relevant exemptions. We will have to restrict the analysis to 1990 to 2013 for the final treatment variable because of data constraints.

The unit of analysis will be at the school district level. Conveniently, a constitutional amendment was passed in Georgia in 1945 that effectively limited the number of school districts. It prohibited the creation of new municipal-controlled school districts except through the consolidations of county school districts and grand-fathered municipal districts or other county systems. Therefore, we do not have to worry about school districts splitting in the sample. Unfortunately, this did not prevent school district boundaries from expanding or contracting through annexation and consolidations, and we will need to account for these changes in the analysis.

Finally, we need to control for a how the population and districts changed economically and socially through time by adding controls. We will want to control for the characteristics of the population living in each district by controlling for the average education levels, race, employment, marriage outcomes, tenure decisions, home values, and average rent depending on the specification and dependent variable of interest. We will also want to control for improvements in school quality, crime rates, pollution, and other location characteristics at the school district even though the school district fixed effect will control for any unobserved spatial amenities that are time invariant.

One major concern of estimating models of this kind is reverse causality. Our story is that the generous property tax exemptions attracted older households to the places that have them. In contrast, it is plausible that older households lobby the government for local homestead exemptions after moving to a certain community because of some other idiosyncratic reason. We may want to estimate to use lagged treatment effects to make sure that location decisions are happening after new local homestead exemptions.

We will use aggregate decennial Census for the years 1970, 1980, 1990, and 2000 and data from American Community Survey for years starting in 2005 for our analysis. The National Historical Geographic Information System (Minnesota Population Center 2011) possess most, if not all the variables, that we desire from the Census Bureau. I am in the process of gathering the necessary data.

5. Next Steps

While much of the heavy lifting of creating the homestead exemption database has been completed, this project is still in its infancy. The next steps are to gather demographic and location data from the Census Bureau and the National Historical Geographic Information System. The most difficult part will be keeping the geographic units constant by accounting for boundary changes. The Census Bureau releases Geographic Change Notes for Georgia[91] and the Boundary and Annexation Survey[92] that will help with this task, but I'm afraid that we will need to manually reconcile the boundaries for the relevant years in ArcGIS.

[91] This can be found at https://www.census.gov/geo/reference/bndrychange/changenotedisplay.php.
[92] The Boundary and Annexation Survey can be found at http://www.census.gov/geo/partnerships/bas.html.

In addition to tweaking our econometric model to fit the available data, we need to finalize the measurement of our treatment variables. Our data will span the years 1970, 1980, 1990, 2000, and 2010, but the homestead exemptions change between these years as well. We will need to find the best way to represent such changes along with the intensity and heterogeneity of eligibility requirements (i.e. the type of income relevant to the exemption). Once our data, model, and treatment effects are finalized, we will be ready to begin the analysis. As with any project in the early stages, this work is preliminary and subject to change significantly in the next coming months as we delve deeper into the data and methodology.

Conclusion

This work examines the heterogeneity between older and younger persons in the context of location choice and charitable giving. The first essay explores the heterogeneity in location preferences for older and younger households and uses these differences to simulate how the age distribution of the population across cities will change as the total number of older adults rises overall. The results suggest that MSAs on the west coast, particularly in California, and upstate New York will age more than other areas of the United States. MSAs in Florida have mostly modest gains in the number of older households, and their relative importance may diminish in the future. The highest net migration of older households were from MSAs in the western portion of the Northeast, smaller MSAs in the Carolinas, MSAs in Florida, smaller MSAs in Texas, MSAs in southern Arizona, and most MSAs in California. I see a number of areas for future research. The most obvious is to add to the literature exploring why older households choose different locations than the younger household by regressing the mean utility on local amenities. One amenity that I would be particularly interested in is air quality. Second, this study focuses on location choices between cities, but sorting within cities may be even more important. I can extend the current model to allow for some within city estimation.

The second essay examines how the motivations for giving vary for different ages. While my results show that individuals of all ages respond the same if the benefits to others are emphasized, I find limited treatment heterogeneity by age group when benefits to self are highlighted. The results indicate that individuals between the ages of 50 and 64 years old increase average donations more than any other age cohort in response to the "Warm Your Heart" message, but the result isn't robust to all specifications. Further, the heterogeneity that I do find comes through the intensive margin exclusively. The results from back-of-the-envelope calculations suggest that charities in Alaska would have raised significantly more money had they reminded more people about how good it feels to donate to a good cause. One major weakness of the analysis in this essay is the inability to distinguish between age and generation effect, and I see a bright future for this question.

The final essay is joint work with H. Spencer Banzhaf and Carlianne Patrick and is still in the development phase. Local homestead exemptions in Georgia vary by generosity and eligibility, and many are targeted to older households. We will explore the impact of these exemptions, particularly exemptions targeting older households, on the demographic makeup of each jurisdiction. We would expect these subsidies to attract seniors to such jurisdictions (or prevent them from leaving), relative to control jurisdictions. Second, we will consider the impact of these laws on the levels of housing capital by testing whether the equilibrium ratio of housing consumption for seniors to younger households is higher in jurisdictions with such exemptions compared to control districts. We will test for such demographic "sorting" and heterogeneous housing consumption by age with a difference-in-difference-in-differences model. As part of this project, we created a historical database of local homestead exemptions in Georgia that cover from 1913 to 2013 and contains all school districts and counties along with the state's largest municipalities. To our knowledge, this is the first of its kind, and we hope it opens the door to additional research in addition to the questions we propose here.

Overall, this work illustrates that the heterogeneity between the older and younger persons is significant in many instances, and these heterogeneities should play an important role in policy-making. Understanding of different household types respond to policy is important for policymakers to avoid many of the unintended consequences that economists discuss.

Appendix A

Full Results for MSAs in Chapter I

Table 26. List of MSAs used in the analysis of Chapter 1

Code	MSA Name	Region	Division
40	Abilene, TX	South	WSC
120	Albany, GA	South	SATL
160	Albany-Schenectady-Troy, NY	Northeast	MATL
200	Albuquerque, NM	West	MNT
220	Alexandria, LA	South	WSC
240	Allentown-Bethlehem-Easton, PA	Northeast	MATL
280	Altoona, PA	Northeast	MATL
320	Amarillo, TX	South	WSC
380	Anchorage, AK	West	PAC
450	Anniston, AL	South	ESC
460	Appleton-Oshkosh-Neenah, WI	Midwest	ENC
480	Asheville, NC	South	SATL
500	Athens, GA	South	SATL
520	Atlanta, GA	South	SATL
580	Auburn-Opelika, AL	South	ESC
600	Augusta-Aiken, GA-SC	South	SATL
640	Austin-San Marcos, TX	South	WSC
680	Bakersfield, CA	West	PAC
740	Barnstable-Yarmouth, MA	Northeast	NE
760	Baton Rouge, LA	South	WSC
840	Beaumont-Port Arthur, TX	South	WSC
860	Bellingham, WA	West	PAC
870	Benton Harbor, MI	Midwest	ENC
880	Billings, MT	West	MNT
920	Biloxi-Gulfport-Pascagoula, MS	South	ESC
960	Binghamton, NY	Northeast	MATL
1000	Birmingham, AL	South	ESC
1020	Bloomington, IN	Midwest	ENC
1040	Bloomington-Normal, IL	Midwest	ENC
1080	Boise City, ID	West	MNT
1122	Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	Northeast	NE
1240	Brownsville-Harlingen-San Benito, TX	South	WSC
1260	Bryan-College Station, TX	South	WSC
1280	Buffalo-Niagara Falls, NY	Northeast	MATL
1320	Canton-Massillon, OH	Midwest	ENC
1360	Cedar Rapids, IA	Midwest	WNC
1400	Champaign-Urbana, IL	Midwest	ENC

Code	MSA Name	Region	Division
1440	Charleston-North Charleston, SC	South	SATL
1520	Charlotte-Gastonia-Rock Hill, NC-SC	South	SATL
1540	Charlottesville, VA	South	SATL
1560	Chattanooga, TN-GA	South	SATL
1602	Chicago-Gary-Kenosha, IL-IN-WI (C)	Midwest	ENC
1620	Chico-Paradise, CA	West	PAC
1642	Cincinnati-Hamilton, OH-KY-IN (C)	Midwest	ENC
1660	Clarksville-Hopkinsville, TN-KY	South	ESC
1692	Cleveland-Akron, OH (C)	Midwest	ENC
1720	Colorado Springs, CO	West	MNT
1740	Columbia, MO	Midwest	WNC
1760	Columbia, SC	South	SATL
1800	Columbus, GA-AL	South	ESC
1840	Columbus, OH	Midwest	ENC
1880	Corpus Christi, TX	South	WSC
1922	Dallas-Fort Worth, TX (C)	South	WSC
1950	Danville, VA	South	SATL
1960	Davenport-Moline-Rock Island, IA-IL	Midwest	ENC
2000	Dayton-Springfield, OH	Midwest	ENC
2020	Daytona Beach, FL	South	SATL
2030	Decatur, AL	South	ESC
2040	Decatur, IL	Midwest	ENC
2082	Denver-Boulder-Greeley, CO (C)	West	MNT
2120	Des Moines, IA	Midwest	WNC
2162	Detroit-Ann Arbor-Flint, MI (C)	Midwest	ENC
2180	Dothan, AL	South	ESC
2190	Dover, DE	South	SATL
2240	Duluth-Superior, MN-WI	Midwest	WNC
2290	Eau Claire, WI	Midwest	ENC
2320	El Paso, TX	South	WSC
2330	Elkhart-Goshen, IN	Midwest	ENC
2360	Erie, PA	Northeast	MATL
2400	Eugene-Springfield, OR	West	PAC
2440	Evansville-Henderson, IN-KY	Midwest	ENC
2520	Fargo-Moorhead, ND-MN	Midwest	WNC
2560	Fayetteville, NC	South	SATL
2580	Fayetteville-Springdale-Rogers, AR	South	WSC
2620	Flagstaff, AZ-UT	West	MNT
2650	Florence, AL	South	ESC
2670	Fort Collins-Loveland, CO	West	MNT
2700	Fort Myers-Cape Coral, FL	South	SATL
2710	Fort Pierce-Port St. Lucie, FL	South	SATL
2720	Fort Smith, AR-OK	South	WSC

Code	MSA Name	Region	Division
2750	Fort Walton Beach, FL	South	SATL
2760	Fort Wayne, IN	Midwest	ENC
2840	Fresno, CA	West	PAC
2880	Gadsden, AL	South	ESC
2900	Gainesville, FL	South	SATL
2975	Glens Falls, NY	Northeast	MATL
2980	Goldsboro, NC	South	SATL
2995	Grand Junction, CO	West	MNT
3000	Grand Rapids-Muskegon-Holland, MI	Midwest	ENC
3080	Green Bay, WI	Midwest	ENC
3120	Greensboro--Winston Salem--High Point, NC	South	SATL
3150	Greenville, NC	South	SATL
3160	Greenville-Spartanburg-Anderson, SC	South	SATL
3240	Harrisburg-Lebanon-Carlisle, PA	Northeast	MATL
3280	Hartford, CT	Northeast	NE
3285	Hattiesburg, MS	South	ESC
3290	Hickory-Morganton-Lenoir, NC	South	SATL
3320	Honolulu, HI	West	PAC
3350	Houma, LA	South	WSC
3362	Houston-Galveston-Brazoria, TX (C)	South	WSC
3440	Huntsville, AL	South	ESC
3480	Indianapolis, IN	Midwest	ENC
3500	Iowa City, IA	Midwest	WNC
3520	Jackson, MI	Midwest	ENC
3560	Jackson, MS	South	ESC
3580	Jackson, TN	South	ESC
3600	Jacksonville, FL	South	SATL
3605	Jacksonville, NC	South	SATL
3610	Jamestown, NY	Northeast	MATL
3620	Janesville-Beloit, WI	Midwest	ENC
3660	Johnson City-Kingsport-Bristol, TN-VA	South	ESC
3680	Johnstown, PA	Northeast	MATL
3710	Joplin, MO	Midwest	WNC
3720	Kalamazoo-Battle Creek, MI	Midwest	ENC
3760	Kansas City, MO-KS	Midwest	WNC
3810	Killeen-Temple, TX	South	WSC
3840	Knoxville, TN	South	ESC
3850	Kokomo, IN	Midwest	ENC
3870	La Crosse, WI-MN	Midwest	WNC
3880	Lafayette, LA	South	WSC
3920	Lafayette, IN	Midwest	ENC
3960	Lake Charles, LA	South	WSC
3980	Lakeland-Winter Haven, FL	South	SATL

Code	MSA Name	Region	Division
4000	Lancaster, PA	Northeast	MATL
4040	Lansing-East Lansing, MI	Midwest	ENC
4080	Laredo, TX	South	WSC
4100	Las Cruces, NM	West	MNT
4120	Las Vegas, NV-AZ	West	MNT
4280	Lexington, KY	South	ESC
4320	Lima, OH	Midwest	ENC
4360	Lincoln, NE	Midwest	WNC
4400	Little Rock-North Little Rock, AR	South	WSC
4420	Longview-Marshall, TX	South	WSC
4472	Los Angeles-Riverside-Orange County, CA (C)	West	PAC
4520	Louisville, KY-IN	Midwest	ENC
4600	Lubbock, TX	South	WSC
4640	Lynchburg, VA	South	SATL
4680	Macon, GA	South	SATL
4720	Madison, WI	Midwest	ENC
4800	Mansfield, OH	Midwest	ENC
4880	McAllen-Edinburg-Mission, TX	South	WSC
4890	Medford-Ashland, OR	West	PAC
4900	Melbourne-Titusville-Palm Bay, FL	South	SATL
4920	Memphis, TN-AR-MS	South	WSC
4940	Merced, CA	West	PAC
4992	Miami-Fort Lauderdale, FL (C)	South	SATL
5082	Milwaukee-Racine, WI (C)	Midwest	ENC
5120	Minneapolis-St. Paul, MN-WI	Midwest	WNC
5160	Mobile, AL	South	ESC
5170	Modesto, CA	West	PAC
5200	Monroe, LA	South	WSC
5240	Montgomery, AL	South	ESC
5280	Muncie, IN	Midwest	ENC
5330	Myrtle Beach, SC	South	SATL
5345	Naples, FL	South	SATL
5360	Nashville, TN	South	ESC
5560	New Orleans, LA	South	WSC
5602	New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	Northeast	NE
5720	Norfolk-Virginia Beach-Newport News, VA-	South	SATL
5790	Ocala, FL	South	SATL
5800	Odessa-Midland, TX	South	WSC
5880	Oklahoma City, OK	South	WSC
5920	Omaha, NE-IA	Midwest	WNC
5960	Orlando, FL	South	SATL
6015	Panama City, FL	South	SATL
6080	Pensacola, FL	South	SATL

Code	MSA Name	Region	Division
6120	Peoria-Pekin, IL	Midwest	ENC
6162	Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	South	SATL
6200	Phoenix-Mesa, AZ	West	MNT
6280	Pittsburgh, PA	Northeast	MATL
6400	Portland, ME	Northeast	NE
6442	Portland-Salem, OR-WA (C)	West	PAC
6480	Providence-Fall River-Warwick, RI-MA	Northeast	NE
6520	Provo-Orem, UT	West	MNT
6560	Pueblo, CO	West	MNT
6580	Punta Gorda, FL	South	SATL
6640	Raleigh-Durham-Chapel Hill, NC	South	SATL
6680	Reading, PA	Northeast	MATL
6690	Redding, CA	West	PAC
6720	Reno, NV	West	MNT
6740	Richland-Kennewick-Pasco, WA	West	PAC
6760	Richmond-Petersburg, VA	South	SATL
6800	Roanoke, VA	South	SATL
6820	Rochester, MN	Midwest	WNC
6840	Rochester, NY	Northeast	MATL
6880	Rockford, IL	Midwest	ENC
6895	Rocky Mount, NC	South	SATL
6922	Sacramento-Yolo, CA (C)	West	PAC
6960	Saginaw-Bay City-Midland, MI	Midwest	ENC
6980	St. Cloud, MN	Midwest	WNC
7000	St. Joseph, MO	Midwest	WNC
7040	St. Louis, MO-IL	Midwest	ENC
7120	Salinas, CA	West	PAC
7160	Salt Lake City-Ogden, UT	West	MNT
7240	San Antonio, TX	South	WSC
7320	San Diego, CA	West	PAC
7362	San Francisco-Oakland-San Jose, CA (C)	West	PAC
7460	San Luis Obispo-Atascadero-Paso Robles, CA	West	PAC
7480	Santa Barbara-Santa Maria-Lompoc, CA	West	PAC
7490	Santa Fe, NM	West	MNT
7510	Sarasota-Bradenton, FL	South	SATL
7520	Savannah, GA	South	SATL
7560	Scranton--Wilkes-Barre--Hazleton, PA	Northeast	MATL
7602	Seattle-Tacoma-Bremerton, WA (C)	West	PAC
7610	Sharon, PA	Northeast	MATL
7620	Sheboygan, WI	Midwest	ENC
7680	Shreveport-Bossier City, LA	South	WSC
7720	Sioux City, IA-NE	Midwest	WNC
7760	Sioux Falls, SD	Midwest	WNC

Code	MSA Name	Region	Division
7800	South Bend, IN	Midwest	ENC
7840	Spokane, WA	West	PAC
7880	Springfield, IL	Midwest	ENC
7920	Springfield, MO	Midwest	WNC
8000	Springfield, MA	Northeast	NE
8050	State College, PA	Northeast	MATL
8120	Stockton-Lodi, CA	West	PAC
8140	Sumter, SC	South	SATL
8160	Syracuse, NY	Northeast	MATL
8240	Tallahassee, FL	South	SATL
8280	Tampa-St. Petersburg-Clearwater, FL	South	SATL
8320	Terre Haute, IN	Midwest	ENC
8400	Toledo, OH	Midwest	ENC
8440	Topeka, KS	Midwest	WNC
8520	Tucson, AZ	West	MNT
8560	Tulsa, OK	South	WSC
8600	Tuscaloosa, AL	South	ESC
8640	Tyler, TX	South	WSC
8680	Utica-Rome, NY	Northeast	MATL
8780	Visalia-Tulare-Porterville, CA	West	PAC
8800	Waco, TX	South	WSC
8872	Washington-Baltimore, DC-MD-VA-WV (C)	South	SATL
8920	Waterloo-Cedar Falls, IA	Midwest	WNC
8940	Wausau, WI	Midwest	ENC
8960	West Palm Beach-Boca Raton, FL	South	SATL
9040	Wichita, KS	Midwest	WNC
9080	Wichita Falls, TX	South	WSC
9140	Williamsport, PA	Northeast	MATL
9200	Wilmington, NC	South	SATL
9260	Yakima, WA	West	PAC
9280	York, PA	Northeast	MATL
9320	Youngstown-Warren, OH	Midwest	ENC
9340	Yuba City, CA	West	PAC
9360	Yuma, AZ	West	MNT

Abbreviations: East North Central (ENC); East South Central (ESC); Middle Atlantic (MATL); Mountain (MNT); New England (NE); Pacific (PAC); South Atlantic (SATL); West North Central (WNC); West South Central (WSC)

Table 27. MSAs rankings by mean utility for the young and old and the difference in rank

MSA	MU for Older	Rank for Older	MU for Younger	Rank for Young	Rank Diff.
Abilene, TX	-0.2251	151	0.1563	167	-16
Albany, GA	-1.2765	230	-0.2230	206	24
Albany-Schenectady-Troy, NY	0.1627	103	0.8783	96	7
Albuquerque, NM	1.1887	37	1.8828	37	0
Alexandria, LA	-0.9869	220	-0.2339	208	12
Allentown-Bethlehem-Easton, PA	-0.0425	130	0.4257	136	-6
Altoona, PA	-1.4893	238	-0.8945	241	-3
Amarillo, TX	-0.0941	136	0.4911	129	7
Anchorage, AK	-0.9018	213	-0.1887	203	10
Anniston, AL	-0.7963	201	-0.0558	192	9
Appleton-Oshkosh-Neenah, WI	0.1957	101	0.6324	118	-17
Asheville, NC	0.1341	109	1.0442	82	27
Athens, GA	-0.3401	158	0.4413	134	24
Atlanta, GA	2.0556	15	2.9763	5	10
Auburn-Opelika, AL	-1.0948	226	0.2382	156	70
Augusta-Aiken, GA-SC	0.4247	78	1.1610	74	4
Austin-San Marcos, TX	0.7006	63	1.7068	41	22
Bakersfield, CA	0.3892	83	0.7016	109	-26
Barnstable-Yarmouth, MA	-0.4345	168	-0.5858	233	-65
Baton Rouge, LA	0.4859	76	1.0424	83	-7
Beaumont-Port Arthur, TX	0.3486	89	0.6828	112	-23
Bellingham, WA	-0.2344	152	0.2247	158	-6
Benton Harbor, MI	-0.7269	197	-0.3725	222	-25
Billings, MT	-0.2054	148	0.0232	186	-38
Biloxi-Gulfport-Pascagoula, MS	-0.3696	162	0.6646	115	47
Binghamton, NY	-0.6805	194	-0.0998	198	-4
Birmingham, AL	0.7125	61	1.4865	53	8
Bloomington, IN	-1.1079	227	-0.2113	204	23
Bloomington-Normal, IL	-0.9010	212	-0.3949	224	-12
Boise City, ID	0.9838	44	1.5721	50	-6
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	2.3892	9	2.7141	13	-4
Brownsville-Harlingen-San Benito, TX	-0.2613	154	0.4177	137	17
Bryan-College Station, TX	-1.5000	239	-0.4138	225	14
Buffalo-Niagara Falls, NY	0.5008	74	1.1198	77	-3
Canton-Massillon, OH	0.1523	106	0.7421	108	-2
Cedar Rapids, IA	-0.6073	187	-0.0051	190	-3
Champaign-Urbana, IL	-1.3435	233	-0.3672	219	14
Charleston-North Charleston, SC	0.1464	107	1.0809	80	27
Charlotte-Gastonia-Rock Hill, NC-SC	1.4959	28	2.3812	19	9
Charlottesville, VA	-0.5315	180	0.2368	157	23
Chattanooga, TN-GA	0.4860	75	1.1595	75	0

MSA	MU for Older	Rank for Older	MU for Younger	Rank for Young	Rank Diff.
Chicago-Gary-Kenosha, IL-IN-WI (C)	2.1789	11	2.8456	9	2
Chico-Paradise, CA	0.2193	99	0.1725	165	-66
Cincinnati-Hamilton, OH-KY-IN (C)	1.3634	33	2.0082	33	0
Clarksville-Hopkinsville, TN-KY	-1.0807	225	0.2079	161	64
Cleveland-Akron, OH (C)	1.8454	18	2.4252	17	1
Colorado Springs, CO	0.8392	55	1.6829	44	11
Columbia, MO	-1.3871	235	-0.1258	200	35
Columbia, SC	0.6458	66	1.4507	54	12
Columbus, GA-AL	-0.5161	178	0.5078	126	52
Columbus, OH	0.8320	58	1.6922	42	16
Corpus Christi, TX	-0.5075	174	-0.0872	195	-21
Dallas-Fort Worth, TX (C)	2.2531	10	2.9328	7	3
Danville, VA	0.2732	95	0.6287	120	-25
Davenport-Moline-Rock Island, IA-IL	-0.4993	173	-0.1309	201	-28
Dayton-Springfield, OH	0.8848	51	1.5893	48	3
Daytona Beach, FL	0.8523	54	1.2058	72	-18
Decatur, AL	-0.5735	183	0.2578	155	28
Decatur, IL	-0.8394	206	-0.3580	218	-12
Denver-Boulder-Greeley, CO (C)	2.1649	13	2.6479	14	-1
Des Moines, IA	-0.3611	161	0.4429	133	28
Detroit-Ann Arbor-Flint, MI (C)	2.0977	14	2.8067	11	3
Dothan, AL	0.3900	81	1.1503	76	5
Dover, DE	-0.9102	214	-0.0878	196	18
Duluth-Superior, MN-WI	0.0051	126	0.4005	139	-13
Eau Claire, WI	-0.6376	190	0.0467	179	11
El Paso, TX	-0.0653	132	0.9832	87	45
Elkhart-Goshen, IN	-0.3535	160	0.1418	169	-9
Erie, PA	-0.4499	169	0.2946	151	18
Eugene-Springfield, OR	0.9008	50	1.3840	59	-9
Evansville-Henderson, IN-KY	-0.4926	172	0.1203	173	-1
Fargo-Moorhead, ND-MN	-1.5425	240	-0.5721	232	8
Fayetteville, NC	-0.8198	203	0.3613	143	60
Fayetteville-Springdale-Rogers, AR	0.1536	105	0.7649	105	0
Flagstaff, AZ-UT	-0.6081	188	0.1864	163	25
Florence, AL	-0.1775	144	0.6642	116	28
Fort Collins-Loveland, CO	0.2985	92	0.7831	104	-12
Fort Myers-Cape Coral, FL	1.1971	36	1.2888	65	-29
Fort Pierce-Port St. Lucie, FL	0.2021	100	0.4283	135	-35
Fort Smith, AR-OK	-0.7774	199	0.0564	177	22
Fort Walton Beach, FL	-0.6233	189	0.0645	176	13
Fort Wayne, IN	0.5403	72	1.2452	69	3
Fresno, CA	0.8357	56	1.1098	78	-22

MSA	MU for Older	Rank for Older	MU for Younger	Rank for Young	Rank Diff.
Gadsden, AL	-0.7895	200	-0.2187	205	-5
Gainesville, FL	0.0139	124	0.8896	93	31
Glens Falls, NY	-1.2832	232	-0.8992	242	-10
Goldsboro, NC	-0.4768	171	0.1977	162	9
Grand Junction, CO	-0.1683	142	-0.0588	193	-51
Grand Rapids-Muskegon-Holland, MI	0.5744	70	1.4212	55	15
Green Bay, WI	-1.0493	223	-0.4470	227	-4
Greensboro--Winston Salem--High Point, NC	1.5988	25	2.3842	18	7
Greenville, NC	-0.7049	196	0.1802	164	32
Greenville-Spartanburg-Anderson, SC	1.1061	43	1.8046	39	4
Harrisburg-Lebanon-Carlisle, PA	0.0518	119	0.7452	107	12
Hartford, CT	0.2751	94	0.6919	110	-16
Hattiesburg, MS	-0.9961	221	0.0091	187	34
Hickory-Morganton-Lenoir, NC	0.2493	97	0.8911	92	5
Honolulu, HI	0.3975	80	0.9706	88	-8
Houma, LA	-1.4323	237	-0.7506	239	-2
Houston-Galveston-Brazoria, TX (C)	1.9186	17	2.5904	15	2
Huntsville, AL	0.0175	123	0.8406	99	24
Indianapolis, IN	1.1715	40	1.9597	35	5
Iowa City, IA	-1.5691	241	-0.5103	229	12
Jackson, MI	-1.1527	228	-0.3190	214	14
Jackson, MS	0.2656	96	1.2247	71	25
Jackson, TN	-1.0737	224	-0.2359	209	15
Jacksonville, FL	1.2413	35	2.0354	30	5
Jacksonville, NC	-1.3720	234	-0.0792	194	40
Jamestown, NY	-0.6572	192	-0.3705	221	-29
Janesville-Beloit, WI	-0.8780	209	-0.3685	220	-11
Johnson City-Kingsport-Bristol, TN-VA	0.5492	71	1.2500	68	3
Johnstown, PA	0.0572	116	0.6855	111	5
Joplin, MO	-0.1275	140	0.5931	122	18
Kalamazoo-Battle Creek, MI	0.1809	102	0.9630	89	13
Kansas City, MO-KS	1.4497	31	2.2098	25	6
Killeen-Temple, TX	-0.3430	159	0.4936	128	31
Knoxville, TN	0.8355	57	1.6424	47	10
Kokomo, IN	-1.1537	229	-0.3560	217	12
La Crosse, WI-MN	-0.9643	218	-0.3828	223	-5
Lafayette, LA	-0.0838	134	0.5949	121	13
Lafayette, IN	-0.5567	182	0.0363	184	-2
Lake Charles, LA	-0.1980	147	0.3831	141	6
Lakeland-Winter Haven, FL	0.9725	46	1.2359	70	-24
Lancaster, PA	-0.4641	170	0.1531	168	2
Lansing-East Lansing, MI	-0.0425	129	0.8535	97	32

MSA	MU for Older	Rank for Older	MU for Younger	Rank for Young	Rank Diff.
Laredo, TX	-1.8584	243	-0.6011	234	9
Las Cruces, NM	-0.1011	139	0.5495	123	16
Las Vegas, NV-AZ	1.8248	19	2.2226	24	-5
Lexington, KY	-0.1860	145	0.6699	114	31
Lima, OH	-0.6870	195	-0.2526	210	-15
Lincoln, NE	-0.5157	177	0.4635	131	46
Little Rock-North Little Rock, AR	0.7441	59	1.5834	49	10
Longview-Marshall, TX	-0.3953	165	0.0413	182	-17
Los Angeles-Riverside-Orange County, CA (C)	3.3210	1	3.4039	2	-1
Louisville, KY-IN	0.9092	49	1.6593	45	4
Lubbock, TX	-0.2509	153	0.5044	127	26
Lynchburg, VA	0.0407	120	0.4837	130	-10
Macon, GA	-0.1647	141	0.7896	103	38
Madison, WI	-0.6452	191	0.3591	144	47
Mansfield, OH	-0.8060	202	-0.3381	216	-14
McAllen-Edinburg-Mission, TX	0.2751	93	0.8991	91	2
Medford-Ashland, OR	0.0564	117	0.2920	152	-35
Melbourne-Titusville-Palm Bay, FL	1.1075	42	1.3493	61	-19
Memphis, TN-AR-MS	0.6770	64	1.5486	51	13
Merced, CA	-0.3895	164	-0.0886	197	-33
Miami-Fort Lauderdale, FL (C)	1.7287	22	2.1745	28	-6
Milwaukee-Racine, WI (C)	0.9129	48	1.5015	52	-4
Minneapolis-St. Paul, MN-WI	1.4954	29	2.1961	26	3
Mobile, AL	0.6389	68	1.3736	60	8
Modesto, CA	0.3143	90	0.3378	147	-57
Monroe, LA	-0.5884	184	0.2644	153	31
Montgomery, AL	-0.0882	135	0.8186	100	35
Muncie, IN	-0.7472	198	-0.1083	199	-1
Myrtle Beach, SC	0.3110	91	0.7951	102	-11
Naples, FL	0.0356	121	-0.0384	191	-70
Nashville, TN	1.2696	34	2.2795	21	13
New Orleans, LA	0.9796	45	1.7406	40	5
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	3.3159	2	3.7355	1	1
Norfolk-Virginia Beach-Newport News, VA-	1.1809	39	2.0340	31	8
Ocala, FL	0.7067	62	0.6316	119	-57
Odessa-Midland, TX	-0.6023	186	-0.2267	207	-21
Oklahoma City, OK	0.8804	52	1.6881	43	9
Omaha, NE-IA	0.1055	113	1.0264	85	28
Orlando, FL	1.7767	21	2.3635	20	1
Panama City, FL	-0.3712	163	0.2628	154	9
Pensacola, FL	0.7313	60	1.3089	64	-4

MSA	MU for Older	Rank for Older	MU for Younger	Rank for Young	Rank Diff.
Peoria-Pekin, IL	0.1551	104	0.7617	106	-2
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	2.5739	4	3.0481	4	0
Phoenix-Mesa, AZ	2.8797	3	3.1460	3	0
Pittsburgh, PA	1.4663	30	1.9276	36	-6
Portland, ME	-0.5306	179	0.1218	172	7
Portland-Salem, OR-WA (C)	2.4557	7	2.9484	6	1
Providence-Fall River-Warwick, RI-MA	0.8595	53	1.3282	63	-10
Provo-Orem, UT	0.1249	112	0.9534	90	22
Pueblo, CO	0.1272	110	0.3521	145	-35
Punta Gorda, FL	0.3706	86	0.3156	150	-64
Raleigh-Durham-Chapel Hill, NC	1.1689	41	2.1950	27	14
Reading, PA	-0.5077	175	-0.0015	189	-14
Redding, CA	0.0822	115	0.1278	171	-56
Reno, NV	0.3895	82	1.1020	79	3
Richland-Kennewick-Pasco, WA	-0.5149	176	-0.1413	202	-26
Richmond-Petersburg, VA	0.6321	69	1.3349	62	7
Roanoke, VA	-0.0944	137	0.3258	149	-12
Rochester, MN	-1.4046	236	-0.5591	231	5
Rochester, NY	0.4740	77	1.0308	84	-7
Rockford, IL	0.0539	118	0.5258	125	-7
Rocky Mount, NC	-0.3207	156	0.0923	175	-19
Sacramento-Yolo, CA (C)	1.6724	23	1.8220	38	-15
Saginaw-Bay City-Midland, MI	-0.0555	131	0.6443	117	14
St. Cloud, MN	-0.3378	157	0.3323	148	9
St. Joseph, MO	-0.9435	217	-0.5194	230	-13
St. Louis, MO-IL	1.5819	26	2.2756	22	4
Salinas, CA	-0.8349	205	-0.6940	237	-32
Salt Lake City-Ogden, UT	1.4244	32	2.1661	29	3
San Antonio, TX	1.1837	38	1.9631	34	4
San Diego, CA	1.7829	20	2.0189	32	-12
San Francisco-Oakland-San Jose, CA (C)	2.4902	6	2.4496	16	-10
San Luis Obispo-Atascadero-Paso Robles, CA	0.1432	108	0.0498	178	-70
Santa Barbara-Santa Maria-Lompoc, CA	0.1268	111	0.0979	174	-63
Santa Fe, NM	-0.0114	128	0.3446	146	-18
Sarasota-Bradenton, FL	1.5434	27	1.3997	58	-31
Savannah, GA	-0.4332	167	0.6719	113	54
Scranton--Wilkes-Barre--Hazleton, PA	0.3744	84	0.8886	94	-10
Seattle-Tacoma-Bremerton, WA (C)	2.4491	8	2.9166	8	0
Sharon, PA	-0.8783	210	-0.4307	226	-16
Sheboygan, WI	-0.9395	216	-0.8089	240	-24
Shreveport-Bossier City, LA	0.2326	98	0.8501	98	0
Sioux City, IA-NE	-0.5923	185	0.0400	183	2

MSA	MU for Older	Rank for Older	MU for Younger	Rank for Young	Rank Diff.
Sioux Falls, SD	-1.0244	222	-0.6987	238	-16
South Bend, IN	-0.0686	133	0.3997	140	-7
Spokane, WA	0.9497	47	1.4102	57	-10
Springfield, IL	-1.2821	231	-0.4765	228	3
Springfield, MO	0.3636	88	0.9987	86	2
Springfield, MA	0.3701	87	0.8151	101	-14
State College, PA	-1.6461	242	-0.9229	243	-1
Stockton-Lodi, CA	0.0889	114	0.2158	159	-45
Sumter, SC	-0.9767	219	-0.2609	211	8
Syracuse, NY	0.4054	79	1.0472	81	-2
Tallahassee, FL	-0.1922	146	0.8846	95	51
Tampa-St. Petersburg-Clearwater, FL	2.5342	5	2.8180	10	-5
Terre Haute, IN	-0.8453	207	-0.3352	215	-8
Toledo, OH	0.3719	85	1.2635	66	19
Topeka, KS	-0.6763	193	0.2098	160	33
Tucson, AZ	1.9644	16	2.2434	23	-7
Tulsa, OK	0.6431	67	1.4185	56	11
Tuscaloosa, AL	-0.4287	166	0.4581	132	34
Tyler, TX	-0.2072	150	0.1721	166	-16
Utica-Rome, NY	-0.3090	155	0.0359	185	-30
Visalia-Tulare-Porterville, CA	-0.0997	138	0.4040	138	0
Waco, TX	0.0083	125	0.3756	142	-17
Washington-Baltimore, DC-MD-VA-WV (C)	2.1771	12	2.7502	12	0
Waterloo-Cedar Falls, IA	-0.9148	215	0.0442	181	34
Wausau, WI	-0.1747	143	0.1415	170	-27
West Palm Beach-Boca Raton, FL	1.6053	24	1.6563	46	-22
Wichita, KS	0.5212	73	1.1891	73	0
Wichita Falls, TX	-0.8826	211	-0.6048	235	-24
Williamsport, PA	-0.8274	204	-0.2729	212	-8
Wilmington, NC	0.0309	122	0.5273	124	-2
Yakima, WA	-0.2057	149	-0.2822	213	-64
York, PA	-0.5529	181	0.0454	180	1
Youngstown-Warren, OH	0.6762	65	1.2629	67	-2
Yuba City, CA	-0.8748	208	-0.6848	236	-28
Yuma, AZ	0.0000	127	0.0000	188	-61

Note: This table reports the mean utility for each MSA by age cohort estimated with the residential sorting model. It also reports the difference in rank between the two age cohorts by subtracting the rank by the younger from the rank of the older. A negative value means that older households preferred the MSA more relative to younger households while younger households prefer MSAs with a positive value.

Table 28. Number of younger, older, and all ages in 2010

MSA	Younger HH in 2010	Older HH in 2010	Total HH in 2010
Abilene, TX	27,511	10,890	38,401
Albany, GA	31,301	9,375	40,676
Albany-Schenectady-Troy, NY	221,233	68,063	289,296
Albuquerque, NM	215,035	61,161	276,196
Alexandria, LA	30,685	12,006	42,691
Allentown-Bethlehem-Easton, PA	166,776	62,296	229,072
Altoona, PA	35,174	13,760	48,934
Amarillo, TX	58,731	15,948	74,679
Anchorage, AK	74,947	10,501	85,448
Anniston, AL	30,420	11,039	41,459
Appleton-Oshkosh-Neenah, WI	107,223	31,808	139,031
Asheville, NC	72,443	24,971	97,414
Athens, GA	35,578	9,865	45,443
Atlanta, GA	1,153,963	234,606	1,388,569
Auburn-Opelika, AL	31,922	8,367	40,289
Augusta-Aiken, GA-SC	126,389	36,718	163,107
Austin-San Marcos, TX	376,479	71,157	447,636
Bakersfield, CA	131,089	38,159	169,248
Barnstable-Yarmouth, MA	32,369	19,927	52,296
Baton Rouge, LA	177,720	45,105	222,825
Beaumont-Port Arthur, TX	88,535	32,720	121,255
Bellingham, WA	48,151	14,299	62,450
Benton Harbor, MI	38,894	15,973	54,867
Billings, MT	40,968	14,276	55,244
Biloxi-Gulfport-Pascagoula, MS	82,173	23,694	105,867
Binghamton, NY	64,782	23,960	88,742
Birmingham, AL	228,347	66,685	295,032
Bloomington, IN	32,094	8,857	40,951
Bloomington-Normal, IL	42,182	10,105	52,287
Boise City, ID	142,965	35,883	178,848
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	1,182,840	374,892	1,557,732
Brownsville-Harlingen-San Benito, TX	53,571	17,274	70,845
Bryan-College Station, TX	35,183	7,355	42,538
Buffalo-Niagara Falls, NY	299,597	105,730	405,327
Canton-Massillon, OH	108,439	40,218	148,657
Cedar Rapids, IA	58,813	17,971	76,784
Champaign-Urbana, IL	46,327	12,696	59,023
Charleston-North Charleston, SC	130,223	38,697	168,920
Charlotte-Gastonia-Rock Hill, NC-SC	499,104	120,906	620,010
Charlottesville, VA	44,321	13,928	58,249
Chattanooga, TN-GA	118,814	44,139	162,953
Chicago-Gary-Kenosha, IL-IN-WI (C)	1,991,169	556,853	2,548,022
Chico-Paradise, CA	49,456	20,128	69,584
Cincinnati-Hamilton, OH-KY-IN (C)	505,095	141,044	646,139
Clarksville-Hopkinsville, TN-KY	42,011	7,720	49,731

MSA	Younger HH in 2010	Older HH in 2010	Total HH in 2010
Cleveland-Akron, OH (C)	770,923	253,899	1,024,822
Colorado Springs, CO	155,950	34,662	190,612
Columbia, MO	38,731	9,880	48,611
Columbia, SC	166,329	41,785	208,114
Columbus, GA-AL	45,585	13,578	59,163
Columbus, OH	436,104	105,437	541,541
Corpus Christi, TX	59,465	18,594	78,059
Dallas-Fort Worth, TX (C)	1,331,631	296,884	1,628,515
Danville, VA	27,999	13,349	41,348
Davenport-Moline-Rock Island, IA-IL	67,931	23,292	91,223
Dayton-Springfield, OH	253,181	90,841	344,022
Daytona Beach, FL	107,605	56,889	164,494
Decatur, AL	38,917	14,989	53,906
Decatur, IL	30,015	11,908	41,923
Denver-Boulder-Greeley, CO (C)	651,406	164,121	815,527
Des Moines, IA	113,268	27,560	140,828
Detroit-Ann Arbor-Flint, MI (C)	1,265,807	384,361	1,650,168
Dothan, AL	40,041	13,601	53,642
Dover, DE	36,527	11,932	48,459
Duluth-Superior, MN-WI	56,924	20,068	76,992
Eau Claire, WI	43,541	14,083	57,624
El Paso, TX	107,274	27,225	134,499
Elkhart-Goshen, IN	44,651	13,899	58,550
Erie, PA	72,009	24,791	96,800
Eugene-Springfield, OR	90,136	30,426	120,562
Evansville-Henderson, IN-KY	75,323	23,276	98,599
Fargo-Moorhead, ND-MN	40,295	9,531	49,826
Fayetteville, NC	72,658	18,547	91,205
Fayetteville-Springdale-Rogers, AR	94,449	27,482	121,931
Flagstaff, AZ-UT	28,637	6,493	35,130
Florence, AL	39,800	16,226	56,026
Fort Collins-Loveland, CO	64,651	18,691	83,342
Fort Myers-Cape Coral, FL	115,332	72,324	187,656
Fort Pierce-Port St. Lucie, FL	83,863	50,053	133,916
Fort Smith, AR-OK	45,930	15,223	61,153
Fort Walton Beach, FL	44,640	14,536	59,176
Fort Wayne, IN	128,806	37,712	166,518
Fresno, CA	169,178	52,303	221,481
Gadsden, AL	26,604	10,735	37,339
Gainesville, FL	51,760	15,350	67,110
Glens Falls, NY	35,755	12,428	48,183
Goldsboro, NC	31,315	10,145	41,460
Grand Junction, CO	31,853	12,146	43,999
Grand Rapids-Muskegon-Holland, MI	259,747	71,987	331,734
Green Bay, WI	69,689	17,565	87,254
Greensboro--Winston Salem--High Point, NC	368,460	116,963	485,423
Greenville, NC	40,506	11,351	51,857

MSA	Younger HH in 2010	Older HH in 2010	Total HH in 2010
Greenville-Spartanburg-Anderson, SC	232,870	76,665	309,535
Harrisburg-Lebanon-Carlisle, PA	179,026	63,207	242,233
Hartford, CT	151,427	54,456	205,883
Hattiesburg, MS	33,946	8,244	42,190
Hickory-Morganton-Lenoir, NC	93,382	32,796	126,178
Honolulu, HI	156,090	61,806	217,896
Houma, LA	24,465	8,723	33,188
Houston-Galveston-Brazoria, TX (C)	1,106,434	250,330	1,356,764
Huntsville, AL	107,742	31,946	139,688
Indianapolis, IN	484,697	128,746	613,443
Iowa City, IA	30,314	7,042	37,356
Jackson, MI	40,704	14,389	55,093
Jackson, MS	127,773	33,876	161,649
Jackson, TN	27,317	8,554	35,871
Jacksonville, FL	323,765	87,723	411,488
Jacksonville, NC	34,223	7,624	41,847
Jamestown, NY	35,877	13,522	49,399
Janesville-Beloit, WI	42,460	13,755	56,215
Johnson City-Kingsport-Bristol, TN-VA	92,500	35,391	127,891
Johnstown, PA	57,750	26,545	84,295
Joplin, MO	45,094	14,276	59,370
Kalamazoo-Battle Creek, MI	119,413	37,684	157,097
Kansas City, MO-KS	491,340	138,380	629,720
Killeen-Temple, TX	72,801	16,357	89,158
Knoxville, TN	179,928	56,436	236,364
Kokomo, IN	26,787	10,519	37,306
La Crosse, WI-MN	29,106	9,372	38,478
Lafayette, LA	75,506	17,740	93,246
Lafayette, IN	42,823	13,254	56,077
Lake Charles, LA	50,609	15,356	65,965
Lakeland-Winter Haven, FL	117,912	57,600	175,512
Lancaster, PA	124,665	42,726	167,391
Lansing-East Lansing, MI	121,380	31,672	153,052
Laredo, TX	27,067	5,785	32,852
Las Cruces, NM	36,196	12,098	48,294
Las Vegas, NV-AZ	372,884	107,173	480,057
Lexington, KY	75,458	19,142	94,600
Lima, OH	40,264	14,544	54,808
Lincoln, NE	71,943	18,972	90,915
Little Rock-North Little Rock, AR	178,810	48,242	227,052
Longview-Marshall, TX	41,580	16,624	58,204
Los Angeles-Riverside-Orange County, CA (C)	2,533,034	780,789	3,313,823
Louisville, KY-IN	274,576	80,220	354,796
Lubbock, TX	64,469	19,069	83,538
Lynchburg, VA	59,927	23,368	83,295
Macon, GA	89,528	24,873	114,401
Madison, WI	134,198	30,136	164,334

MSA	Younger HH in 2010	Older HH in 2010	Total HH in 2010
Mansfield, OH	31,652	12,208	43,860
McAllen-Edinburg-Mission, TX	86,434	25,364	111,798
Medford-Ashland, OR	50,384	21,534	71,918
Melbourne-Titusville-Palm Bay, FL	126,764	59,727	186,491
Memphis, TN-AR-MS	274,426	67,981	342,407
Merced, CA	34,722	10,194	44,916
Miami-Fort Lauderdale, FL (C)	447,056	150,522	597,578
Milwaukee-Racine, WI (C)	458,508	138,587	597,095
Minneapolis-St. Paul, MN-WI	821,474	201,951	1,023,425
Mobile, AL	149,544	50,266	199,810
Modesto, CA	89,341	25,172	114,513
Monroe, LA	40,463	11,925	52,388
Montgomery, AL	92,868	28,838	121,706
Muncie, IN	28,729	11,477	40,206
Myrtle Beach, SC	68,022	27,745	95,767
Naples, FL	47,414	42,647	90,061
Nashville, TN	387,731	96,611	484,342
New Orleans, LA	276,001	77,683	353,684
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	3,698,630	1,203,082	4,901,712
Norfolk-Virginia Beach-Newport News, VA-	396,964	111,598	508,562
Ocala, FL	66,463	47,193	113,656
Odessa-Midland, TX	58,825	16,100	74,925
Oklahoma City, OK	212,520	69,597	282,117
Omaha, NE-IA	170,409	43,603	214,012
Orlando, FL	395,423	118,943	514,366
Panama City, FL	40,239	14,705	54,944
Pensacola, FL	104,408	38,253	142,661
Peoria-Pekin, IL	98,686	31,715	130,401
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	1,493,510	487,202	1,980,712
Phoenix-Mesa, AZ	804,391	249,248	1,053,639
Pittsburgh, PA	598,518	239,250	837,768
Portland, ME	72,854	19,230	92,084
Portland-Salem, OR-WA (C)	620,951	166,909	787,860
Providence-Fall River-Warwick, RI-MA	228,218	76,027	304,245
Provo-Orem, UT	89,223	19,765	108,988
Pueblo, CO	33,026	14,865	47,891
Punta Gorda, FL	31,152	29,196	60,348
Raleigh-Durham-Chapel Hill, NC	394,608	90,714	485,322
Reading, PA	95,030	35,055	130,085
Redding, CA	42,596	18,436	61,032
Reno, NV	96,660	28,114	124,774
Richland-Kennewick-Pasco, WA	51,409	15,053	66,462
Richmond-Petersburg, VA	287,877	82,041	369,918
Roanoke, VA	68,074	24,661	92,735
Rochester, MN	36,889	10,851	47,740
Rochester, NY	267,769	83,423	351,192
Rockford, IL	85,526	27,871	113,397

MSA	Younger HH in 2010	Older HH in 2010	Total HH in 2010
Rocky Mount, NC	40,604	14,344	54,948
Sacramento-Yolo, CA (C)	454,462	133,906	588,368
Saginaw-Bay City-Midland, MI	101,957	38,817	140,774
St. Cloud, MN	49,192	13,250	62,442
St. Joseph, MO	27,010	9,764	36,774
St. Louis, MO-IL	739,681	224,459	964,140
Salinas, CA	34,021	13,517	47,538
Salt Lake City-Ogden, UT	331,437	80,782	412,219
San Antonio, TX	411,414	114,639	526,053
San Diego, CA	545,336	153,509	698,845
San Francisco-Oakland-San Jose, CA (C)	1,286,527	397,991	1,684,518
San Luis Obispo-Atascadero-Paso Robles, CA	56,826	23,939	80,765
Santa Barbara-Santa Maria-Lompoc, CA	69,964	26,928	96,892
Santa Fe, NM	41,600	14,922	56,522
Sarasota-Bradenton, FL	137,954	107,962	245,916
Savannah, GA	66,702	18,920	85,622
Scranton--Wilkes-Barre--Hazleton, PA	162,272	66,884	229,156
Seattle-Tacoma-Bremerton, WA (C)	945,318	231,010	1,176,328
Sharon, PA	30,376	13,809	44,185
Sheboygan, WI	30,319	10,769	41,088
Shreveport-Bossier City, LA	108,682	34,710	143,392
Sioux City, IA-NE	24,545	8,523	33,068
Sioux Falls, SD	30,352	9,967	40,319
South Bend, IN	66,029	21,997	88,026
Spokane, WA	121,846	37,105	158,951
Springfield, IL	31,412	10,960	42,372
Springfield, MO	103,945	34,515	138,460
Springfield, MA	133,249	45,609	178,858
State College, PA	31,150	10,901	42,051
Stockton-Lodi, CA	113,166	31,330	144,496
Sumter, SC	25,963	8,828	34,791
Syracuse, NY	189,964	62,212	252,176
Tallahassee, FL	76,960	21,299	98,259
Tampa-St. Petersburg-Clearwater, FL	623,739	254,674	878,413
Terre Haute, IN	37,004	13,670	50,674
Toledo, OH	162,751	50,241	212,992
Topeka, KS	47,027	16,010	63,037
Tucson, AZ	209,323	82,577	291,900
Tulsa, OK	176,862	58,239	235,101
Tuscaloosa, AL	42,805	12,606	55,411
Tyler, TX	46,718	18,594	65,312
Utica-Rome, NY	72,966	30,468	103,434
Visalia-Tulare-Porterville, CA	67,495	19,801	87,296
Waco, TX	50,580	16,682	67,262
Washington-Baltimore, DC-MD-VA-WV (C)	1,837,862	481,714	2,319,576
Waterloo-Cedar Falls, IA	31,700	11,758	43,458
Wausau, WI	37,387	10,521	47,908

MSA	Younger HH in 2010	Older HH in 2010	Total HH in 2010
West Palm Beach-Boca Raton, FL	228,387	148,226	376,613
Wichita, KS	146,141	44,062	190,203
Wichita Falls, TX	28,037	10,731	38,768
Williamsport, PA	29,829	11,599	41,428
Wilmington, NC	84,899	30,701	115,600
Yakima, WA	42,884	15,493	58,377
York, PA	115,318	38,032	153,350
Youngstown-Warren, OH	148,657	60,349	209,006
Yuba City, CA	27,952	10,880	38,832
Yuma, AZ	28,160	13,668	41,828

Note: Data based on Ruggles et al. (2010)

Table 29. Proportion of MSA's HHs that are older and proportion of all older HHs in the MSA in 2010

MSA	% of MSA that is older in 2010	% of all older HH in the MSA in 2010
Abilene, TX	28.36%	0.07%
Albany, GA	23.05%	0.06%
Albany-Schenectady-Troy, NY	23.53%	0.44%
Albuquerque, NM	22.14%	0.39%
Alexandria, LA	28.12%	0.08%
Allentown-Bethlehem-Easton, PA	27.19%	0.40%
Altoona, PA	28.12%	0.09%
Amarillo, TX	21.36%	0.10%
Anchorage, AK	12.29%	0.07%
Anniston, AL	26.63%	0.07%
Appleton-Oshkosh-Neenah, WI	22.88%	0.20%
Asheville, NC	25.63%	0.16%
Athens, GA	21.71%	0.06%
Atlanta, GA	16.90%	1.51%
Auburn-Opelika, AL	20.77%	0.05%
Augusta-Aiken, GA-SC	22.51%	0.24%
Austin-San Marcos, TX	15.90%	0.46%
Bakersfield, CA	22.55%	0.25%
Barnstable-Yarmouth, MA	38.10%	0.13%
Baton Rouge, LA	20.24%	0.29%
Beaumont-Port Arthur, TX	26.98%	0.21%
Bellingham, WA	22.90%	0.09%
Benton Harbor, MI	29.11%	0.10%
Billings, MT	25.84%	0.09%
Biloxi-Gulfport-Pascagoula, MS	22.38%	0.15%
Binghamton, NY	27.00%	0.15%
Birmingham, AL	22.60%	0.43%
Bloomington, IN	21.63%	0.06%
Bloomington-Normal, IL	19.33%	0.07%
Boise City, ID	20.06%	0.23%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	24.07%	2.41%
Brownsville-Harlingen-San Benito, TX	24.38%	0.11%
Bryan-College Station, TX	17.29%	0.05%
Buffalo-Niagara Falls, NY	26.09%	0.68%
Canton-Massillon, OH	27.05%	0.26%
Cedar Rapids, IA	23.40%	0.12%
Champaign-Urbana, IL	21.51%	0.08%
Charleston-North Charleston, SC	22.91%	0.25%
Charlotte-Gastonia-Rock Hill, NC-SC	19.50%	0.78%
Charlottesville, VA	23.91%	0.09%
Chattanooga, TN-GA	27.09%	0.28%
Chicago-Gary-Kenosha, IL-IN-WI (C)	21.85%	3.59%

MSA	% of MSA that is older in 2010	% of all older HH in the MSA in 2010
Chico-Paradise, CA	28.93%	0.13%
Cincinnati-Hamilton, OH-KY-IN (C)	21.83%	0.91%
Clarksville-Hopkinsville, TN-KY	15.52%	0.05%
Cleveland-Akron, OH (C)	24.77%	1.63%
Colorado Springs, CO	18.18%	0.22%
Columbia, MO	20.32%	0.06%
Columbia, SC	20.08%	0.27%
Columbus, GA-AL	22.95%	0.09%
Columbus, OH	19.47%	0.68%
Corpus Christi, TX	23.82%	0.12%
Dallas-Fort Worth, TX (C)	18.23%	1.91%
Danville, VA	32.28%	0.09%
Davenport-Moline-Rock Island, IA-IL	25.53%	0.15%
Dayton-Springfield, OH	26.41%	0.58%
Daytona Beach, FL	34.58%	0.37%
Decatur, AL	27.81%	0.10%
Decatur, IL	28.40%	0.08%
Denver-Boulder-Greeley, CO (C)	20.12%	1.06%
Des Moines, IA	19.57%	0.18%
Detroit-Ann Arbor-Flint, MI (C)	23.29%	2.47%
Dothan, AL	25.36%	0.09%
Dover, DE	24.62%	0.08%
Duluth-Superior, MN-WI	26.07%	0.13%
Eau Claire, WI	24.44%	0.09%
El Paso, TX	20.24%	0.18%
Elkhart-Goshen, IN	23.74%	0.09%
Erie, PA	25.61%	0.16%
Eugene-Springfield, OR	25.24%	0.20%
Evansville-Henderson, IN-KY	23.61%	0.15%
Fargo-Moorhead, ND-MN	19.13%	0.06%
Fayetteville, NC	20.34%	0.12%
Fayetteville-Springdale-Rogers, AR	22.54%	0.18%
Flagstaff, AZ-UT	18.48%	0.04%
Florence, AL	28.96%	0.10%
Fort Collins-Loveland, CO	22.43%	0.12%
Fort Myers-Cape Coral, FL	38.54%	0.47%
Fort Pierce-Port St. Lucie, FL	37.38%	0.32%
Fort Smith, AR-OK	24.89%	0.10%
Fort Walton Beach, FL	24.56%	0.09%
Fort Wayne, IN	22.65%	0.24%
Fresno, CA	23.62%	0.34%
Gadsden, AL	28.75%	0.07%
Gainesville, FL	22.87%	0.10%
Glens Falls, NY	25.79%	0.08%
Goldsboro, NC	24.47%	0.07%

MSA	% of MSA that is older in 2010	% of all older HH in the MSA in 2010
Grand Junction, CO	27.61%	0.08%
Grand Rapids-Muskegon-Holland, MI	21.70%	0.46%
Green Bay, WI	20.13%	0.11%
Greensboro--Winston Salem--High Point, NC	24.10%	0.75%
Greenville, NC	21.89%	0.07%
Greenville-Spartanburg-Anderson, SC	24.77%	0.49%
Harrisburg-Lebanon-Carlisle, PA	26.09%	0.41%
Hartford, CT	26.45%	0.35%
Hattiesburg, MS	19.54%	0.05%
Hickory-Morganton-Lenoir, NC	25.99%	0.21%
Honolulu, HI	28.36%	0.40%
Houma, LA	26.28%	0.06%
Houston-Galveston-Brazoria, TX (C)	18.45%	1.61%
Huntsville, AL	22.87%	0.21%
Indianapolis, IN	20.99%	0.83%
Iowa City, IA	18.85%	0.05%
Jackson, MI	26.12%	0.09%
Jackson, MS	20.96%	0.22%
Jackson, TN	23.85%	0.06%
Jacksonville, FL	21.32%	0.56%
Jacksonville, NC	18.22%	0.05%
Jamestown, NY	27.37%	0.09%
Janesville-Beloit, WI	24.47%	0.09%
Johnson City-Kingsport-Bristol, TN-VA	27.67%	0.23%
Johnstown, PA	31.49%	0.17%
Joplin, MO	24.05%	0.09%
Kalamazoo-Battle Creek, MI	23.99%	0.24%
Kansas City, MO-KS	21.97%	0.89%
Killeen-Temple, TX	18.35%	0.11%
Knoxville, TN	23.88%	0.36%
Kokomo, IN	28.20%	0.07%
La Crosse, WI-MN	24.36%	0.06%
Lafayette, LA	19.02%	0.11%
Lafayette, IN	23.64%	0.09%
Lake Charles, LA	23.28%	0.10%
Lakeland-Winter Haven, FL	32.82%	0.37%
Lancaster, PA	25.52%	0.28%
Lansing-East Lansing, MI	20.69%	0.20%
Laredo, TX	17.61%	0.04%
Las Cruces, NM	25.05%	0.08%
Las Vegas, NV-AZ	22.33%	0.69%
Lexington, KY	20.23%	0.12%
Lima, OH	26.54%	0.09%
Lincoln, NE	20.87%	0.12%
Little Rock-North Little Rock, AR	21.25%	0.31%

MSA	% of MSA that is older in 2010	% of all older HH in the MSA in 2010
Longview-Marshall, TX	28.56%	0.11%
Los Angeles-Riverside-Orange County, CA (C)	23.56%	5.03%
Louisville, KY-IN	22.61%	0.52%
Lubbock, TX	22.83%	0.12%
Lynchburg, VA	28.05%	0.15%
Macon, GA	21.74%	0.16%
Madison, WI	18.34%	0.19%
Mansfield, OH	27.83%	0.08%
McAllen-Edinburg-Mission, TX	22.69%	0.16%
Medford-Ashland, OR	29.94%	0.14%
Melbourne-Titusville-Palm Bay, FL	32.03%	0.38%
Memphis, TN-AR-MS	19.85%	0.44%
Merced, CA	22.70%	0.07%
Miami-Fort Lauderdale, FL (C)	25.19%	0.97%
Milwaukee-Racine, WI (C)	23.21%	0.89%
Minneapolis-St. Paul, MN-WI	19.73%	1.30%
Mobile, AL	25.16%	0.32%
Modesto, CA	21.98%	0.16%
Monroe, LA	22.76%	0.08%
Montgomery, AL	23.69%	0.19%
Muncie, IN	28.55%	0.07%
Myrtle Beach, SC	28.97%	0.18%
Naples, FL	47.35%	0.27%
Nashville, TN	19.95%	0.62%
New Orleans, LA	21.96%	0.50%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	24.54%	7.75%
Norfolk-Virginia Beach-Newport News, VA-	21.94%	0.72%
Ocala, FL	41.52%	0.30%
Odessa-Midland, TX	21.49%	0.10%
Oklahoma City, OK	24.67%	0.45%
Omaha, NE-IA	20.37%	0.28%
Orlando, FL	23.12%	0.77%
Panama City, FL	26.76%	0.09%
Pensacola, FL	26.81%	0.25%
Peoria-Pekin, IL	24.32%	0.20%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	24.60%	3.14%
Phoenix-Mesa, AZ	23.66%	1.60%
Pittsburgh, PA	28.56%	1.54%
Portland, ME	20.88%	0.12%
Portland-Salem, OR-WA (C)	21.19%	1.07%
Providence-Fall River-Warwick, RI-MA	24.99%	0.49%
Provo-Orem, UT	18.14%	0.13%
Pueblo, CO	31.04%	0.10%
Punta Gorda, FL	48.38%	0.19%
Raleigh-Durham-Chapel Hill, NC	18.69%	0.58%

MSA	% of MSA that is older in 2010	% of all older HH in the MSA in 2010
Reading, PA	26.95%	0.23%
Redding, CA	30.21%	0.12%
Reno, NV	22.53%	0.18%
Richland-Kennewick-Pasco, WA	22.65%	0.10%
Richmond-Petersburg, VA	22.18%	0.53%
Roanoke, VA	26.59%	0.16%
Rochester, MN	22.73%	0.07%
Rochester, NY	23.75%	0.54%
Rockford, IL	24.58%	0.18%
Rocky Mount, NC	26.10%	0.09%
Sacramento-Yolo, CA (C)	22.76%	0.86%
Saginaw-Bay City-Midland, MI	27.57%	0.25%
St. Cloud, MN	21.22%	0.09%
St. Joseph, MO	26.55%	0.06%
St. Louis, MO-IL	23.28%	1.45%
Salinas, CA	28.43%	0.09%
Salt Lake City-Ogden, UT	19.60%	0.52%
San Antonio, TX	21.79%	0.74%
San Diego, CA	21.97%	0.99%
San Francisco-Oakland-San Jose, CA (C)	23.63%	2.56%
San Luis Obispo-Atascadero-Paso Robles, CA	29.64%	0.15%
Santa Barbara-Santa Maria-Lompoc, CA	27.79%	0.17%
Santa Fe, NM	26.40%	0.10%
Sarasota-Bradenton, FL	43.90%	0.70%
Savannah, GA	22.10%	0.12%
Scranton--Wilkes-Barre--Hazleton, PA	29.19%	0.43%
Seattle-Tacoma-Bremerton, WA (C)	19.64%	1.49%
Sharon, PA	31.25%	0.09%
Sheboygan, WI	26.21%	0.07%
Shreveport-Bossier City, LA	24.21%	0.22%
Sioux City, IA-NE	25.77%	0.05%
Sioux Falls, SD	24.72%	0.06%
South Bend, IN	24.99%	0.14%
Spokane, WA	23.34%	0.24%
Springfield, IL	25.87%	0.07%
Springfield, MO	24.93%	0.22%
Springfield, MA	25.50%	0.29%
State College, PA	25.92%	0.07%
Stockton-Lodi, CA	21.68%	0.20%
Sumter, SC	25.37%	0.06%
Syracuse, NY	24.67%	0.40%
Tallahassee, FL	21.68%	0.14%
Tampa-St. Petersburg-Clearwater, FL	28.99%	1.64%
Terre Haute, IN	26.98%	0.09%
Toledo, OH	23.59%	0.32%

MSA	% of MSA that is older in 2010	% of all older HH in the MSA in 2010
Topeka, KS	25.40%	0.10%
Tucson, AZ	28.29%	0.53%
Tulsa, OK	24.77%	0.37%
Tuscaloosa, AL	22.75%	0.08%
Tyler, TX	28.47%	0.12%
Utica-Rome, NY	29.46%	0.20%
Visalia-Tulare-Porterville, CA	22.68%	0.13%
Waco, TX	24.80%	0.11%
Washington-Baltimore, DC-MD-VA-WV (C)	20.77%	3.10%
Waterloo-Cedar Falls, IA	27.06%	0.08%
Wausau, WI	21.96%	0.07%
West Palm Beach-Boca Raton, FL	39.36%	0.95%
Wichita, KS	23.17%	0.28%
Wichita Falls, TX	27.68%	0.07%
Williamsport, PA	28.00%	0.07%
Wilmington, NC	26.56%	0.20%
Yakima, WA	26.54%	0.10%
York, PA	24.80%	0.24%
Youngstown-Warren, OH	28.87%	0.39%
Yuba City, CA	28.02%	0.07%
Yuma, AZ	32.68%	0.09%

Note: Data based on Ruggles et al. (2010)

Table 30. Number of younger, older, and all ages in 2030 under the sorting simulation

MSA	Younger HH in 2030	Older HH in 2030	Total HH in 2030
Abilene, TX	31,513	18,640	50,153
Albany, GA	27,316	14,530	41,846
Albany-Schenectady-Troy, NY	269,009	164,245	433,254
Albuquerque, NM	168,584	95,977	264,561
Alexandria, LA	26,773	23,908	50,681
Allentown-Bethlehem-Easton, PA	134,600	93,226	227,826
Altoona, PA	34,037	24,574	58,611
Amarillo, TX	63,455	29,024	92,479
Anchorage, AK	31,075	7,527	38,602
Anniston, AL	21,228	19,421	40,649
Appleton-Oshkosh-Neenah, WI	79,945	38,550	118,495
Asheville, NC	54,677	31,224	85,901
Athens, GA	32,485	20,265	52,750
Atlanta, GA	945,160	371,074	1,316,234
Auburn-Opelika, AL	33,481	16,763	50,244
Augusta-Aiken, GA-SC	108,594	66,605	175,199
Austin-San Marcos, TX	384,701	119,504	504,205
Bakersfield, CA	149,224	71,697	220,921
Barnstable-Yarmouth, MA	37,963	39,289	77,252
Baton Rouge, LA	146,687	67,328	214,015
Beaumont-Port Arthur, TX	104,267	67,996	172,263
Bellingham, WA	40,777	22,888	63,665
Benton Harbor, MI	43,412	29,837	73,249
Billings, MT	24,511	17,238	41,749
Biloxi-Gulfport-Pascagoula, MS	59,920	33,660	93,580
Binghamton, NY	100,094	65,503	165,597
Birmingham, AL	185,230	103,858	289,088
Bloomington, IN	24,127	15,111	39,238
Bloomington-Normal, IL	46,329	23,240	69,569
Boise City, ID	93,601	43,812	137,413
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	810,464	453,350	1,263,814
Brownsville-Harlingen-San Benito, TX	62,887	36,511	99,398
Bryan-College Station, TX	33,408	9,967	43,375
Buffalo-Niagara Falls, NY	357,445	232,787	590,232
Canton-Massillon, OH	109,539	71,883	181,422
Cedar Rapids, IA	36,070	18,873	54,943
Champaign-Urbana, IL	43,277	24,940	68,217
Charleston-North Charleston, SC	106,744	64,386	171,130
Charlotte-Gastonia-Rock Hill, NC-SC	399,215	172,339	571,554
Charlottesville, VA	44,699	27,020	71,719
Chattanooga, TN-GA	101,137	59,326	160,463
Chicago-Gary-Kenosha, IL-IN-WI (C)	1,662,251	848,847	2,511,098
Chico-Paradise, CA	57,046	41,735	98,781
Cincinnati-Hamilton, OH-KY-IN (C)	401,078	195,086	596,164
Clarksville-Hopkinsville, TN-KY	34,694	12,554	47,248

MSA	Younger HH in 2030	Older HH in 2030	Total HH in 2030
Cleveland-Akron, OH (C)	783,442	468,625	1,252,067
Colorado Springs, CO	126,998	49,201	176,199
Columbia, MO	42,305	12,995	55,300
Columbia, SC	130,183	71,343	201,526
Columbus, GA-AL	45,876	21,068	66,944
Columbus, OH	398,117	190,489	588,606
Corpus Christi, TX	58,254	34,235	92,489
Dallas-Fort Worth, TX (C)	1,396,015	546,742	1,942,757
Danville, VA	29,232	22,542	51,774
Davenport-Moline-Rock Island, IA-IL	59,835	40,819	100,654
Dayton-Springfield, OH	258,140	161,282	419,422
Daytona Beach, FL	92,154	74,285	166,439
Decatur, AL	34,069	17,761	51,830
Decatur, IL	29,730	22,982	52,712
Denver-Boulder-Greeley, CO (C)	597,532	266,708	864,240
Des Moines, IA	60,932	25,559	86,491
Detroit-Ann Arbor-Flint, MI (C)	1,006,735	583,516	1,590,251
Dothan, AL	77,696	54,778	132,474
Dover, DE	28,784	12,890	41,674
Duluth-Superior, MN-WI	57,138	32,372	89,510
Eau Claire, WI	39,119	19,913	59,032
El Paso, TX	106,357	50,651	157,008
Elkhart-Goshen, IN	27,850	19,482	47,332
Erie, PA	69,562	44,434	113,996
Eugene-Springfield, OR	73,594	46,333	119,927
Evansville-Henderson, IN-KY	64,096	34,378	98,474
Fargo-Moorhead, ND-MN	23,169	8,356	31,525
Fayetteville, NC	55,536	23,530	79,066
Fayetteville-Springdale-Rogers, AR	70,596	34,493	105,089
Flagstaff, AZ-UT	28,592	13,950	42,542
Florence, AL	31,258	28,391	59,649
Fort Collins-Loveland, CO	51,050	30,327	81,377
Fort Myers-Cape Coral, FL	109,400	106,471	215,871
Fort Pierce-Port St. Lucie, FL	72,070	68,662	140,732
Fort Smith, AR-OK	28,946	18,350	47,296
Fort Walton Beach, FL	39,203	24,164	63,367
Fort Wayne, IN	111,669	52,574	164,243
Fresno, CA	175,341	112,471	287,812
Gadsden, AL	22,867	20,016	42,883
Gainesville, FL	48,737	21,575	70,312
Glens Falls, NY	69,754	42,009	111,763
Goldsboro, NC	42,916	29,351	72,267
Grand Junction, CO	28,504	18,978	47,482
Grand Rapids-Muskegon-Holland, MI	232,209	100,295	332,504
Green Bay, WI	53,486	19,346	72,832
Greensboro--Winston Salem--High Point, NC	292,265	186,288	478,553
Greenville, NC	31,507	19,358	50,865

MSA	Younger HH in 2030	Older HH in 2030	Total HH in 2030
Greenville-Spartanburg-Anderson, SC	191,777	116,261	308,038
Harrisburg-Lebanon-Carlisle, PA	179,031	99,932	278,963
Hartford, CT	107,978	66,616	174,594
Hattiesburg, MS	24,131	12,494	36,625
Hickory-Morganton-Lenoir, NC	88,213	52,672	140,885
Honolulu, HI	123,146	85,889	209,035
Houma, LA	25,518	10,607	36,125
Houston-Galveston-Brazoria, TX (C)	1,067,442	431,165	1,498,607
Huntsville, AL	92,034	49,572	141,606
Indianapolis, IN	364,834	178,229	543,063
Iowa City, IA	19,066	5,995	25,061
Jackson, MI	35,528	18,453	53,981
Jackson, MS	104,116	48,700	152,816
Jackson, TN	25,987	17,288	43,275
Jacksonville, FL	285,501	123,772	409,273
Jacksonville, NC	31,182	12,167	43,349
Jamestown, NY	68,319	47,360	115,679
Janesville-Beloit, WI	30,459	14,926	45,385
Johnson City-Kingsport-Bristol, TN-VA	89,128	56,666	145,794
Johnstown, PA	87,631	57,199	144,830
Joplin, MO	58,475	33,910	92,385
Kalamazoo-Battle Creek, MI	126,916	63,908	190,824
Kansas City, MO-KS	337,770	163,255	501,025
Killeen-Temple, TX	86,302	39,634	125,936
Knoxville, TN	167,196	103,947	271,143
Kokomo, IN	21,460	14,719	36,179
La Crosse, WI-MN	22,769	10,550	33,319
Lafayette, LA	60,414	25,326	85,740
Lafayette, IN	30,770	20,020	50,790
Lake Charles, LA	51,654	26,378	78,032
Lakeland-Winter Haven, FL	114,184	84,673	198,857
Lancaster, PA	101,408	55,325	156,733
Lansing-East Lansing, MI	121,372	54,319	175,691
Laredo, TX	25,550	11,833	37,383
Las Cruces, NM	24,916	14,944	39,860
Las Vegas, NV-AZ	330,560	172,945	503,505
Lexington, KY	53,261	28,912	82,173
Lima, OH	48,694	31,779	80,473
Lincoln, NE	42,731	15,635	58,366
Little Rock-North Little Rock, AR	127,852	55,451	183,303
Longview-Marshall, TX	45,400	25,451	70,851
Los Angeles-Riverside-Orange County, CA (C)	2,773,696	1,578,813	4,352,509
Louisville, KY-IN	239,014	139,295	378,309
Lubbock, TX	67,579	35,824	103,403
Lynchburg, VA	57,384	39,610	96,994
Macon, GA	79,917	38,496	118,413
Madison, WI	92,566	36,771	129,337

MSA	Younger HH in 2030	Older HH in 2030	Total HH in 2030
Mansfield, OH	27,392	22,182	49,574
McAllen-Edinburg-Mission, TX	85,652	45,466	131,118
Medford-Ashland, OR	42,550	29,528	72,078
Melbourne-Titusville-Palm Bay, FL	117,978	83,298	201,276
Memphis, TN-AR-MS	180,745	90,530	271,275
Merced, CA	38,726	24,852	63,578
Miami-Fort Lauderdale, FL (C)	403,119	215,189	618,308
Milwaukee-Racine, WI (C)	275,864	137,440	413,304
Minneapolis-St. Paul, MN-WI	563,933	216,301	780,234
Mobile, AL	110,892	70,318	181,210
Modesto, CA	94,261	58,435	152,696
Monroe, LA	38,174	18,331	56,505
Montgomery, AL	74,051	43,109	117,160
Muncie, IN	27,548	15,923	43,471
Myrtle Beach, SC	53,220	39,324	92,544
Naples, FL	43,739	59,661	103,400
Nashville, TN	348,655	147,660	496,315
New Orleans, LA	243,792	125,219	369,011
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	2,363,028	1,430,803	3,793,831
Norfolk-Virginia Beach-Newport News, VA-	330,538	177,320	507,858
Ocala, FL	63,711	59,900	123,611
Odessa-Midland, TX	58,399	31,327	89,726
Oklahoma City, OK	150,478	84,945	235,423
Omaha, NE-IA	112,174	47,748	159,922
Orlando, FL	371,288	184,728	556,016
Panama City, FL	38,472	19,647	58,119
Pensacola, FL	105,092	51,570	156,662
Peoria-Pekin, IL	109,492	64,290	173,782
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	816,316	501,871	1,318,187
Phoenix-Mesa, AZ	694,079	376,158	1,070,237
Pittsburgh, PA	578,128	393,386	971,514
Portland, ME	37,771	13,541	51,312
Portland-Salem, OR-WA (C)	479,613	242,794	722,407
Providence-Fall River-Warwick, RI-MA	259,334	157,544	416,878
Provo-Orem, UT	77,082	28,792	105,874
Pueblo, CO	28,289	20,546	48,835
Punta Gorda, FL	27,583	36,839	64,422
Raleigh-Durham-Chapel Hill, NC	319,866	129,523	449,389
Reading, PA	90,800	56,508	147,308
Redding, CA	45,391	39,582	84,973
Reno, NV	82,215	38,230	120,445
Richland-Kennewick-Pasco, WA	42,799	21,886	64,685
Richmond-Petersburg, VA	282,746	147,175	429,921
Roanoke, VA	63,440	40,681	104,121
Rochester, MN	26,636	11,690	38,326
Rochester, NY	365,714	216,313	582,027
Rockford, IL	82,438	43,904	126,342

MSA	Younger HH in 2030	Older HH in 2030	Total HH in 2030
Rocky Mount, NC	37,187	23,547	60,734
Sacramento-Yolo, CA (C)	473,692	272,836	746,528
Saginaw-Bay City-Midland, MI	116,193	69,917	186,110
St. Cloud, MN	57,791	23,165	80,956
St. Joseph, MO	33,575	19,534	53,109
St. Louis, MO-IL	620,162	351,640	971,802
Salinas, CA	40,182	27,515	67,697
Salt Lake City-Ogden, UT	301,817	102,788	404,605
San Antonio, TX	423,794	194,215	618,009
San Diego, CA	620,120	313,967	934,087
San Francisco-Oakland-San Jose, CA (C)	1,433,947	757,172	2,191,119
San Luis Obispo-Atascadero-Paso Robles, CA	58,670	42,882	101,552
Santa Barbara-Santa Maria-Lompoc, CA	83,684	62,504	146,188
Santa Fe, NM	36,012	28,107	64,119
Sarasota-Bradenton, FL	121,455	154,155	275,610
Savannah, GA	54,669	34,360	89,029
Scranton--Wilkes-Barre--Hazleton, PA	178,038	134,645	312,683
Seattle-Tacoma-Bremerton, WA (C)	813,599	389,814	1,203,413
Sharon, PA	40,371	34,473	74,844
Sheboygan, WI	29,516	15,557	45,073
Shreveport-Bossier City, LA	94,452	59,298	153,750
Sioux City, IA-NE	12,935	11,702	24,637
Sioux Falls, SD	13,569	7,651	21,220
South Bend, IN	50,020	34,019	84,039
Spokane, WA	102,442	62,515	164,957
Springfield, IL	26,118	17,185	43,303
Springfield, MO	123,787	59,058	182,845
Springfield, MA	148,755	89,540	238,295
State College, PA	38,187	20,546	58,733
Stockton-Lodi, CA	119,667	68,554	188,221
Sumter, SC	24,484	13,443	37,927
Syracuse, NY	302,785	180,594	483,379
Tallahassee, FL	68,172	25,262	93,434
Tampa-St. Petersburg-Clearwater, FL	588,906	364,171	953,077
Terre Haute, IN	34,373	21,186	55,559
Toledo, OH	165,201	94,682	259,883
Topeka, KS	28,909	21,837	50,746
Tucson, AZ	195,585	133,421	329,006
Tulsa, OK	120,075	63,504	183,579
Tuscaloosa, AL	43,369	18,876	62,245
Tyler, TX	50,923	34,309	85,232
Utica-Rome, NY	127,031	88,049	215,080
Visalia-Tulare-Porterville, CA	86,135	49,602	135,737
Waco, TX	59,448	33,676	93,124
Washington-Baltimore, DC-MD-VA-WV (C)	1,279,974	654,073	1,934,047
Waterloo-Cedar Falls, IA	23,514	13,972	37,486
Wausau, WI	41,750	19,467	61,217

MSA	Younger HH in 2030	Older HH in 2030	Total HH in 2030
West Palm Beach-Boca Raton, FL	217,928	200,742	418,670
Wichita, KS	94,698	49,715	144,413
Wichita Falls, TX	27,139	20,303	47,442
Williamsport, PA	48,525	27,617	76,142
Wilmington, NC	67,768	47,979	115,747
Yakima, WA	30,389	24,200	54,589
York, PA	106,998	51,627	158,625
Youngstown-Warren, OH	151,520	110,960	262,480
Yuba City, CA	35,897	22,233	58,130
Yuma, AZ	18,983	19,260	38,243

Note: Data based on Ruggles et al. (2010) and the results from the Sorting simulation

Table 31. Number of older HH, Change in older HH, and % change in older HH under the sorting simulation

MSA	Older HH in 2010	Older HH in 2030	Change Older HH	% Change Older HH
Abilene, TX	10,890	18,640	7,750	71.17%
Albany, GA	9,375	14,530	5,155	54.99%
Albany-Schenectady-Troy, NY	68,063	164,245	96,182	141.31%
Albuquerque, NM	61,161	95,977	34,816	56.93%
Alexandria, LA	12,006	23,908	11,902	99.13%
Allentown-Bethlehem-Easton, PA	62,296	93,226	30,930	49.65%
Altoona, PA	13,760	24,574	10,814	78.59%
Amarillo, TX	15,948	29,024	13,076	81.99%
Anchorage, AK	10,501	7,527	-2,974	-28.32%
Anniston, AL	11,039	19,421	8,382	75.93%
Appleton-Oshkosh-Neenah, WI	31,808	38,550	6,742	21.20%
Asheville, NC	24,971	31,224	6,253	25.04%
Athens, GA	9,865	20,265	10,400	105.42%
Atlanta, GA	234,606	371,074	136,468	58.17%
Auburn-Opelika, AL	8,367	16,763	8,396	100.35%
Augusta-Aiken, GA-SC	36,718	66,605	29,887	81.40%
Austin-San Marcos, TX	71,157	119,504	48,347	67.94%
Bakersfield, CA	38,159	71,697	33,538	87.89%
Barnstable-Yarmouth, MA	19,927	39,289	19,362	97.16%
Baton Rouge, LA	45,105	67,328	22,223	49.27%
Beaumont-Port Arthur, TX	32,720	67,996	35,276	107.81%
Bellingham, WA	14,299	22,888	8,589	60.07%
Benton Harbor, MI	15,973	29,837	13,864	86.80%
Billings, MT	14,276	17,238	2,962	20.75%
Biloxi-Gulfport-Pascagoula, MS	23,694	33,660	9,966	42.06%
Binghamton, NY	23,960	65,503	41,543	173.38%
Birmingham, AL	66,685	103,858	37,173	55.74%
Bloomington, IN	8,857	15,111	6,254	70.61%
Bloomington-Normal, IL	10,105	23,240	13,135	129.99%
Boise City, ID	35,883	43,812	7,929	22.10%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	374,892	453,350	78,458	20.93%
Brownsville-Harlingen-San Benito, TX	17,274	36,511	19,237	111.36%
Bryan-College Station, TX	7,355	9,967	2,612	35.51%
Buffalo-Niagara Falls, NY	105,730	232,787	127,057	120.17%
Canton-Massillon, OH	40,218	71,883	31,665	78.73%
Cedar Rapids, IA	17,971	18,873	902	5.02%
Champaign-Urbana, IL	12,696	24,940	12,244	96.44%
Charleston-North Charleston, SC	38,697	64,386	25,689	66.38%
Charlotte-Gastonia-Rock Hill, NC-SC	120,906	172,339	51,433	42.54%
Charlottesville, VA	13,928	27,020	13,092	94.00%
Chattanooga, TN-GA	44,139	59,326	15,187	34.41%
Chicago-Gary-Kenosha, IL-IN-WI (C)	556,853	848,847	291,994	52.44%
Chico-Paradise, CA	20,128	41,735	21,607	107.35%
Cincinnati-Hamilton, OH-KY-IN (C)	141,044	195,086	54,042	38.32%

MSA	Older HH in 2010	Older HH in 2030	Change Older HH	% Change Older HH
Clarksville-Hopkinsville, TN-KY	7,720	12,554	4,834	62.62%
Cleveland-Akron, OH (C)	253,899	468,625	214,726	84.57%
Colorado Springs, CO	34,662	49,201	14,539	41.95%
Columbia, MO	9,880	12,995	3,115	31.53%
Columbia, SC	41,785	71,343	29,558	70.74%
Columbus, GA-AL	13,578	21,068	7,490	55.16%
Columbus, OH	105,437	190,489	85,052	80.67%
Corpus Christi, TX	18,594	34,235	15,641	84.12%
Dallas-Fort Worth, TX (C)	296,884	546,742	249,858	84.16%
Danville, VA	13,349	22,542	9,193	68.87%
Davenport-Moline-Rock Island, IA-IL	23,292	40,819	17,527	75.25%
Dayton-Springfield, OH	90,841	161,282	70,441	77.54%
Daytona Beach, FL	56,889	74,285	17,396	30.58%
Decatur, AL	14,989	17,761	2,772	18.49%
Decatur, IL	11,908	22,982	11,074	93.00%
Denver-Boulder-Greeley, CO (C)	164,121	266,708	102,587	62.51%
Des Moines, IA	27,560	25,559	-2,001	-7.26%
Detroit-Ann Arbor-Flint, MI (C)	384,361	583,516	199,155	51.81%
Dothan, AL	13,601	54,778	41,177	302.75%
Dover, DE	11,932	12,890	958	8.03%
Duluth-Superior, MN-WI	20,068	32,372	12,304	61.31%
Eau Claire, WI	14,083	19,913	5,830	41.40%
El Paso, TX	27,225	50,651	23,426	86.05%
Elkhart-Goshen, IN	13,899	19,482	5,583	40.17%
Erie, PA	24,791	44,434	19,643	79.23%
Eugene-Springfield, OR	30,426	46,333	15,907	52.28%
Evansville-Henderson, IN-KY	23,276	34,378	11,102	47.70%
Fargo-Moorhead, ND-MN	9,531	8,356	-1,175	-12.33%
Fayetteville, NC	18,547	23,530	4,983	26.87%
Fayetteville-Springdale-Rogers, AR	27,482	34,493	7,011	25.51%
Flagstaff, AZ-UT	6,493	13,950	7,457	114.85%
Florence, AL	16,226	28,391	12,165	74.97%
Fort Collins-Loveland, CO	18,691	30,327	11,636	62.25%
Fort Myers-Cape Coral, FL	72,324	106,471	34,147	47.21%
Fort Pierce-Port St. Lucie, FL	50,053	68,662	18,609	37.18%
Fort Smith, AR-OK	15,223	18,350	3,127	20.54%
Fort Walton Beach, FL	14,536	24,164	9,628	66.24%
Fort Wayne, IN	37,712	52,574	14,862	39.41%
Fresno, CA	52,303	112,471	60,168	115.04%
Gadsden, AL	10,735	20,016	9,281	86.46%
Gainesville, FL	15,350	21,575	6,225	40.55%
Glens Falls, NY	12,428	42,009	29,581	238.02%
Goldsboro, NC	10,145	29,351	19,206	189.31%
Grand Junction, CO	12,146	18,978	6,832	56.25%
Grand Rapids-Muskegon-Holland, MI	71,987	100,295	28,308	39.32%
Green Bay, WI	17,565	19,346	1,781	10.14%
Greensboro--Winston Salem--High Point, NC	116,963	186,288	69,325	59.27%

MSA	Older HH in 2010	Older HH in 2030	Change Older HH	% Change Older HH
Greenville, NC	11,351	19,358	8,007	70.54%
Greenville-Spartanburg-Anderson, SC	76,665	116,261	39,596	51.65%
Harrisburg-Lebanon-Carlisle, PA	63,207	99,932	36,725	58.10%
Hartford, CT	54,456	66,616	12,160	22.33%
Hattiesburg, MS	8,244	12,494	4,250	51.55%
Hickory-Morganton-Lenoir, NC	32,796	52,672	19,876	60.60%
Honolulu, HI	61,806	85,889	24,083	38.97%
Houma, LA	8,723	10,607	1,884	21.60%
Houston-Galveston-Brazoria, TX (C)	250,330	431,165	180,835	72.24%
Huntsville, AL	31,946	49,572	17,626	55.17%
Indianapolis, IN	128,746	178,229	49,483	38.43%
Iowa City, IA	7,042	5,995	-1,047	-14.87%
Jackson, MI	14,389	18,453	4,064	28.24%
Jackson, MS	33,876	48,700	14,824	43.76%
Jackson, TN	8,554	17,288	8,734	102.10%
Jacksonville, FL	87,723	123,772	36,049	41.09%
Jacksonville, NC	7,624	12,167	4,543	59.59%
Jamestown, NY	13,522	47,360	33,838	250.24%
Janesville-Beloit, WI	13,755	14,926	1,171	8.51%
Johnson City-Kingsport-Bristol, TN-VA	35,391	56,666	21,275	60.11%
Johnstown, PA	26,545	57,199	30,654	115.48%
Joplin, MO	14,276	33,910	19,634	137.53%
Kalamazoo-Battle Creek, MI	37,684	63,908	26,224	69.59%
Kansas City, MO-KS	138,380	163,255	24,875	17.98%
Killeen-Temple, TX	16,357	39,634	23,277	142.31%
Knoxville, TN	56,436	103,947	47,511	84.19%
Kokomo, IN	10,519	14,719	4,200	39.93%
La Crosse, WI-MN	9,372	10,550	1,178	12.57%
Lafayette, LA	17,740	25,326	7,586	42.76%
Lafayette, IN	13,254	20,020	6,766	51.05%
Lake Charles, LA	15,356	26,378	11,022	71.78%
Lakeland-Winter Haven, FL	57,600	84,673	27,073	47.00%
Lancaster, PA	42,726	55,325	12,599	29.49%
Lansing-East Lansing, MI	31,672	54,319	22,647	71.50%
Laredo, TX	5,785	11,833	6,048	104.55%
Las Cruces, NM	12,098	14,944	2,846	23.52%
Las Vegas, NV-AZ	107,173	172,945	65,772	61.37%
Lexington, KY	19,142	28,912	9,770	51.04%
Lima, OH	14,544	31,779	17,235	118.50%
Lincoln, NE	18,972	15,635	-3,337	-17.59%
Little Rock-North Little Rock, AR	48,242	55,451	7,209	14.94%
Longview-Marshall, TX	16,624	25,451	8,827	53.10%
Los Angeles-Riverside-Orange County, CA (C)	780,789	1,578,813	798,024	102.21%
Louisville, KY-IN	80,220	139,295	59,075	73.64%
Lubbock, TX	19,069	35,824	16,755	87.87%
Lynchburg, VA	23,368	39,610	16,242	69.51%
Macon, GA	24,873	38,496	13,623	54.77%

MSA	Older HH in 2010	Older HH in 2030	Change Older HH	% Change Older HH
Madison, WI	30,136	36,771	6,635	22.02%
Mansfield, OH	12,208	22,182	9,974	81.70%
McAllen-Edinburg-Mission, TX	25,364	45,466	20,102	79.25%
Medford-Ashland, OR	21,534	29,528	7,994	37.12%
Melbourne-Titusville-Palm Bay, FL	59,727	83,298	23,571	39.46%
Memphis, TN-AR-MS	67,981	90,530	22,549	33.17%
Merced, CA	10,194	24,852	14,658	143.79%
Miami-Fort Lauderdale, FL (C)	150,522	215,189	64,667	42.96%
Milwaukee-Racine, WI (C)	138,587	137,440	-1,147	-0.83%
Minneapolis-St. Paul, MN-WI	201,951	216,301	14,350	7.11%
Mobile, AL	50,266	70,318	20,052	39.89%
Modesto, CA	25,172	58,435	33,263	132.14%
Monroe, LA	11,925	18,331	6,406	53.72%
Montgomery, AL	28,838	43,109	14,271	49.49%
Muncie, IN	11,477	15,923	4,446	38.74%
Myrtle Beach, SC	27,745	39,324	11,579	41.73%
Naples, FL	42,647	59,661	17,014	39.89%
Nashville, TN	96,611	147,660	51,049	52.84%
New Orleans, LA	77,683	125,219	47,536	61.19%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	1,203,082	1,430,803	227,721	18.93%
Norfolk-Virginia Beach-Newport News, VA-	111,598	177,320	65,722	58.89%
Ocala, FL	47,193	59,900	12,707	26.93%
Odessa-Midland, TX	16,100	31,327	15,227	94.58%
Oklahoma City, OK	69,597	84,945	15,348	22.05%
Omaha, NE-IA	43,603	47,748	4,145	9.51%
Orlando, FL	118,943	184,728	65,785	55.31%
Panama City, FL	14,705	19,647	4,942	33.61%
Pensacola, FL	38,253	51,570	13,317	34.81%
Peoria-Pekin, IL	31,715	64,290	32,575	102.71%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	487,202	501,871	14,669	3.01%
Phoenix-Mesa, AZ	249,248	376,158	126,910	50.92%
Pittsburgh, PA	239,250	393,386	154,136	64.42%
Portland, ME	19,230	13,541	-5,689	-29.58%
Portland-Salem, OR-WA (C)	166,909	242,794	75,885	45.46%
Providence-Fall River-Warwick, RI-MA	76,027	157,544	81,517	107.22%
Provo-Orem, UT	19,765	28,792	9,027	45.67%
Pueblo, CO	14,865	20,546	5,681	38.22%
Punta Gorda, FL	29,196	36,839	7,643	26.18%
Raleigh-Durham-Chapel Hill, NC	90,714	129,523	38,809	42.78%
Reading, PA	35,055	56,508	21,453	61.20%
Redding, CA	18,436	39,582	21,146	114.70%
Reno, NV	28,114	38,230	10,116	35.98%
Richland-Kennewick-Pasco, WA	15,053	21,886	6,833	45.39%
Richmond-Petersburg, VA	82,041	147,175	65,134	79.39%
Roanoke, VA	24,661	40,681	16,020	64.96%

MSA	Older HH in 2010	Older HH in 2030	Change Older HH	% Change Older HH
Rochester, MN	10,851	11,690	839	7.73%
Rochester, NY	83,423	216,313	132,890	159.30%
Rockford, IL	27,871	43,904	16,033	57.53%
Rocky Mount, NC	14,344	23,547	9,203	64.16%
Sacramento-Yolo, CA (C)	133,906	272,836	138,930	103.75%
Saginaw-Bay City-Midland, MI	38,817	69,917	31,100	80.12%
St. Cloud, MN	13,250	23,165	9,915	74.83%
St. Joseph, MO	9,764	19,534	9,770	100.06%
St. Louis, MO-IL	224,459	351,640	127,181	56.66%
Salinas, CA	13,517	27,515	13,998	103.56%
Salt Lake City-Ogden, UT	80,782	102,788	22,006	27.24%
San Antonio, TX	114,639	194,215	79,576	69.41%
San Diego, CA	153,509	313,967	160,458	104.53%
San Francisco-Oakland-San Jose, CA (C)	397,991	757,172	359,181	90.25%
San Luis Obispo-Atascadero-Paso Robles, CA	23,939	42,882	18,943	79.13%
Santa Barbara-Santa Maria-Lompoc, CA	26,928	62,504	35,576	132.12%
Santa Fe, NM	14,922	28,107	13,185	88.36%
Sarasota-Bradenton, FL	107,962	154,155	46,193	42.79%
Savannah, GA	18,920	34,360	15,440	81.61%
Scranton--Wilkes-Barre--Hazleton, PA	66,884	134,645	67,761	101.31%
Seattle-Tacoma-Bremerton, WA (C)	231,010	389,814	158,804	68.74%
Sharon, PA	13,809	34,473	20,664	149.64%
Sheboygan, WI	10,769	15,557	4,788	44.46%
Shreveport-Bossier City, LA	34,710	59,298	24,588	70.84%
Sioux City, IA-NE	8,523	11,702	3,179	37.30%
Sioux Falls, SD	9,967	7,651	-2,316	-23.24%
South Bend, IN	21,997	34,019	12,022	54.65%
Spokane, WA	37,105	62,515	25,410	68.48%
Springfield, IL	10,960	17,185	6,225	56.80%
Springfield, MO	34,515	59,058	24,543	71.11%
Springfield, MA	45,609	89,540	43,931	96.32%
State College, PA	10,901	20,546	9,645	88.48%
Stockton-Lodi, CA	31,330	68,554	37,224	118.81%
Sumter, SC	8,828	13,443	4,615	52.28%
Syracuse, NY	62,212	180,594	118,382	190.29%
Tallahassee, FL	21,299	25,262	3,963	18.61%
Tampa-St. Petersburg-Clearwater, FL	254,674	364,171	109,497	42.99%
Terre Haute, IN	13,670	21,186	7,516	54.98%
Toledo, OH	50,241	94,682	44,441	88.46%
Topeka, KS	16,010	21,837	5,827	36.40%
Tucson, AZ	82,577	133,421	50,844	61.57%
Tulsa, OK	58,239	63,504	5,265	9.04%
Tuscaloosa, AL	12,606	18,876	6,270	49.74%
Tyler, TX	18,594	34,309	15,715	84.52%
Utica-Rome, NY	30,468	88,049	57,581	188.99%
Visalia-Tulare-Porterville, CA	19,801	49,602	29,801	150.50%
Waco, TX	16,682	33,676	16,994	101.87%

MSA	Older HH in 2010	Older HH in 2030	Change Older HH	% Change Older HH
Washington-Baltimore, DC-MD-VA-WV (C)	481,714	654,073	172,359	35.78%
Waterloo-Cedar Falls, IA	11,758	13,972	2,214	18.83%
Wausau, WI	10,521	19,467	8,946	85.03%
West Palm Beach-Boca Raton, FL	148,226	200,742	52,516	35.43%
Wichita, KS	44,062	49,715	5,653	12.83%
Wichita Falls, TX	10,731	20,303	9,572	89.20%
Williamsport, PA	11,599	27,617	16,018	138.10%
Wilmington, NC	30,701	47,979	17,278	56.28%
Yakima, WA	15,493	24,200	8,707	56.20%
York, PA	38,032	51,627	13,595	35.75%
Youngstown-Warren, OH	60,349	110,960	50,611	83.86%
Yuba City, CA	10,880	22,233	11,353	104.35%
Yuma, AZ	13,668	19,260	5,592	40.91%

Note: Data based on Ruggles et al. (2010) and the results from the Sorting simulation

Table 32. Proportion of MSA's HHs that are older (with change and % change) under the sorting simulation

MSA	% of MSA that is older in 2010	% of MSA that is older in 2030	Change in % of MSA that is older	% Change in % of MSA that is older
Abilene, TX	28.36%	37.17%	8.81%	31.06%
Albany, GA	23.05%	34.72%	11.67%	50.65%
Albany-Schenectady-Troy, NY	23.53%	37.91%	14.38%	61.13%
Albuquerque, NM	22.14%	36.28%	14.13%	63.83%
Alexandria, LA	28.12%	47.17%	19.05%	67.74%
Allentown-Bethlehem-Easton, PA	27.19%	40.92%	13.72%	50.47%
Altoona, PA	28.12%	41.93%	13.81%	49.10%
Amarillo, TX	21.36%	31.38%	10.03%	46.96%
Anchorage, AK	12.29%	19.50%	7.21%	58.67%
Anniston, AL	26.63%	47.78%	21.15%	79.44%
Appleton-Oshkosh-Neenah, WI	22.88%	32.53%	9.65%	42.20%
Asheville, NC	25.63%	36.35%	10.71%	41.80%
Athens, GA	21.71%	38.42%	16.71%	76.97%
Atlanta, GA	16.90%	28.19%	11.30%	66.86%
Auburn-Opelika, AL	20.77%	33.36%	12.60%	60.65%
Augusta-Aiken, GA-SC	22.51%	38.02%	15.51%	68.88%
Austin-San Marcos, TX	15.90%	23.70%	7.81%	49.10%
Bakersfield, CA	22.55%	32.45%	9.91%	43.94%
Barnstable-Yarmouth, MA	38.10%	50.86%	12.75%	33.47%
Baton Rouge, LA	20.24%	31.46%	11.22%	55.41%
Beaumont-Port Arthur, TX	26.98%	39.47%	12.49%	46.28%
Bellingham, WA	22.90%	35.95%	13.05%	57.01%
Benton Harbor, MI	29.11%	40.73%	11.62%	39.92%
Billings, MT	25.84%	41.29%	15.45%	59.78%
Biloxi-Gulfport-Pascagoula, MS	22.38%	35.97%	13.59%	60.71%
Binghamton, NY	27.00%	39.56%	12.56%	46.50%
Birmingham, AL	22.60%	35.93%	13.32%	58.95%
Bloomington, IN	21.63%	38.51%	16.88%	78.06%
Bloomington-Normal, IL	19.33%	33.41%	14.08%	72.85%
Boise City, ID	20.06%	31.88%	11.82%	58.91%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	24.07%	35.87%	11.81%	49.05%
Brownsville-Harlingen-San Benito, TX	24.38%	36.73%	12.35%	50.65%
Bryan-College Station, TX	17.29%	22.98%	5.69%	32.90%
Buffalo-Niagara Falls, NY	26.09%	39.44%	13.35%	51.20%
Canton-Massillon, OH	27.05%	39.62%	12.57%	46.45%
Cedar Rapids, IA	23.40%	34.35%	10.95%	46.77%
Champaign-Urbana, IL	21.51%	36.56%	15.05%	69.96%
Charleston-North Charleston, SC	22.91%	37.62%	14.72%	64.24%
Charlotte-Gastonia-Rock Hill, NC-SC	19.50%	30.15%	10.65%	54.62%
Charlottesville, VA	23.91%	37.67%	13.76%	57.56%
Chattanooga, TN-GA	27.09%	36.97%	9.88%	36.49%
Chicago-Gary-Kenosha, IL-IN-WI (C)	21.85%	33.80%	11.95%	54.68%
Chico-Paradise, CA	28.93%	42.25%	13.32%	46.06%

MSA	% of MSA that is older in 2010	% of MSA that is older in 2030	Change in % of MSA that is older	% Change in % of MSA that is older
Cincinnati-Hamilton, OH-KY-IN (C)	21.83%	32.72%	10.89%	49.91%
Clarksville-Hopkinsville, TN-KY	15.52%	26.57%	11.05%	71.16%
Cleveland-Akron, OH (C)	24.77%	37.43%	12.65%	51.07%
Colorado Springs, CO	18.18%	27.92%	9.74%	53.56%
Columbia, MO	20.32%	23.50%	3.17%	15.62%
Columbia, SC	20.08%	35.40%	15.32%	76.32%
Columbus, GA-AL	22.95%	31.47%	8.52%	37.13%
Columbus, OH	19.47%	32.36%	12.89%	66.22%
Corpus Christi, TX	23.82%	37.02%	13.19%	55.39%
Dallas-Fort Worth, TX (C)	18.23%	28.14%	9.91%	54.37%
Danville, VA	32.28%	43.54%	11.25%	34.86%
Davenport-Moline-Rock Island, IA-IL	25.53%	40.55%	15.02%	58.83%
Dayton-Springfield, OH	26.41%	38.45%	12.05%	45.63%
Daytona Beach, FL	34.58%	44.63%	10.05%	29.05%
Decatur, AL	27.81%	34.27%	6.46%	23.24%
Decatur, IL	28.40%	43.60%	15.19%	53.49%
Denver-Boulder-Greeley, CO (C)	20.12%	30.86%	10.74%	53.35%
Des Moines, IA	19.57%	29.55%	9.98%	51.00%
Detroit-Ann Arbor-Flint, MI (C)	23.29%	36.69%	13.40%	57.53%
Dothan, AL	25.36%	41.35%	15.99%	63.08%
Dover, DE	24.62%	30.93%	6.31%	25.62%
Duluth-Superior, MN-WI	26.07%	36.17%	10.10%	38.75%
Eau Claire, WI	24.44%	33.73%	9.29%	38.02%
El Paso, TX	20.24%	32.26%	12.02%	59.37%
Elkhart-Goshen, IN	23.74%	41.16%	17.42%	73.39%
Erie, PA	25.61%	38.98%	13.37%	52.20%
Eugene-Springfield, OR	25.24%	38.63%	13.40%	53.09%
Evansville-Henderson, IN-KY	23.61%	34.91%	11.30%	47.88%
Fargo-Moorhead, ND-MN	19.13%	26.51%	7.38%	38.57%
Fayetteville, NC	20.34%	29.76%	9.42%	46.34%
Fayetteville-Springdale-Rogers, AR	22.54%	32.82%	10.28%	45.63%
Flagstaff, AZ-UT	18.48%	32.79%	14.31%	77.41%
Florence, AL	28.96%	47.60%	18.64%	64.34%
Fort Collins-Loveland, CO	22.43%	37.27%	14.84%	66.17%
Fort Myers-Cape Coral, FL	38.54%	49.32%	10.78%	27.97%
Fort Pierce-Port St. Lucie, FL	37.38%	48.79%	11.41%	30.53%
Fort Smith, AR-OK	24.89%	38.80%	13.90%	55.86%
Fort Walton Beach, FL	24.56%	38.13%	13.57%	55.24%
Fort Wayne, IN	22.65%	32.01%	9.36%	41.34%
Fresno, CA	23.62%	39.08%	15.46%	65.48%
Gadsden, AL	28.75%	46.68%	17.93%	62.35%
Gainesville, FL	22.87%	30.68%	7.81%	34.15%
Glens Falls, NY	25.79%	37.59%	11.79%	45.73%
Goldsboro, NC	24.47%	40.61%	16.15%	65.98%
Grand Junction, CO	27.61%	39.97%	12.36%	44.79%

MSA	% of MSA that is older in 2010	% of MSA that is older in 2030	Change in % of MSA that is older	% Change in % of MSA that is older
Grand Rapids-Muskegon-Holland, MI	21.70%	30.16%	8.46%	39.00%
Green Bay, WI	20.13%	26.56%	6.43%	31.95%
Greensboro--Winston Salem--High Point, NC	24.10%	38.93%	14.83%	61.56%
Greenville, NC	21.89%	38.06%	16.17%	73.87%
Greenville-Spartanburg-Anderson, SC	24.77%	37.74%	12.97%	52.39%
Harrisburg-Lebanon-Carlisle, PA	26.09%	35.82%	9.73%	37.29%
Hartford, CT	26.45%	38.15%	11.70%	44.25%
Hattiesburg, MS	19.54%	34.11%	14.57%	74.58%
Hickory-Morganton-Lenoir, NC	25.99%	37.39%	11.39%	43.84%
Honolulu, HI	28.36%	41.09%	12.72%	44.86%
Houma, LA	26.28%	29.36%	3.08%	11.71%
Houston-Galveston-Brazoria, TX (C)	18.45%	28.77%	10.32%	55.94%
Huntsville, AL	22.87%	35.01%	12.14%	53.07%
Indianapolis, IN	20.99%	32.82%	11.83%	56.38%
Iowa City, IA	18.85%	23.92%	5.07%	26.90%
Jackson, MI	26.12%	34.18%	8.07%	30.89%
Jackson, MS	20.96%	31.87%	10.91%	52.07%
Jackson, TN	23.85%	39.95%	16.10%	67.53%
Jacksonville, FL	21.32%	30.24%	8.92%	41.86%
Jacksonville, NC	18.22%	28.07%	9.85%	54.06%
Jamestown, NY	27.37%	40.94%	13.57%	49.57%
Janesville-Beloit, WI	24.47%	32.89%	8.42%	34.41%
Johnson City-Kingsport-Bristol, TN-VA	27.67%	38.87%	11.19%	40.45%
Johnstown, PA	31.49%	39.49%	8.00%	25.41%
Joplin, MO	24.05%	36.71%	12.66%	52.65%
Kalamazoo-Battle Creek, MI	23.99%	33.49%	9.50%	39.62%
Kansas City, MO-KS	21.97%	32.58%	10.61%	48.28%
Killeen-Temple, TX	18.35%	31.47%	13.13%	71.54%
Knoxville, TN	23.88%	38.34%	14.46%	60.56%
Kokomo, IN	28.20%	40.68%	12.49%	44.29%
La Crosse, WI-MN	24.36%	31.66%	7.31%	30.00%
Lafayette, LA	19.02%	29.54%	10.51%	55.26%
Lafayette, IN	23.64%	39.42%	15.78%	66.77%
Lake Charles, LA	23.28%	33.80%	10.53%	45.21%
Lakeland-Winter Haven, FL	32.82%	42.58%	9.76%	29.74%
Lancaster, PA	25.52%	35.30%	9.77%	38.29%
Lansing-East Lansing, MI	20.69%	30.92%	10.22%	49.41%
Laredo, TX	17.61%	31.65%	14.04%	79.75%
Las Cruces, NM	25.05%	37.49%	12.44%	49.66%
Las Vegas, NV-AZ	22.33%	34.35%	12.02%	53.86%
Lexington, KY	20.23%	35.18%	14.95%	73.88%
Lima, OH	26.54%	39.49%	12.95%	48.82%
Lincoln, NE	20.87%	26.79%	5.92%	28.37%
Little Rock-North Little Rock, AR	21.25%	30.25%	9.00%	42.38%
Longview-Marshall, TX	28.56%	35.92%	7.36%	25.77%

MSA	% of MSA that is older in 2010	% of MSA that is older in 2030	Change in % of MSA that is older	% Change in % of MSA that is older
Los Angeles-Riverside-Orange County, CA (C)	23.56%	36.27%	12.71%	53.95%
Louisville, KY-IN	22.61%	36.82%	14.21%	62.85%
Lubbock, TX	22.83%	34.65%	11.82%	51.77%
Lynchburg, VA	28.05%	40.84%	12.78%	45.57%
Macon, GA	21.74%	32.51%	10.77%	49.53%
Madison, WI	18.34%	28.43%	10.09%	55.03%
Mansfield, OH	27.83%	44.75%	16.91%	60.76%
McAllen-Edinburg-Mission, TX	22.69%	34.68%	11.99%	52.84%
Medford-Ashland, OR	29.94%	40.97%	11.02%	36.82%
Melbourne-Titusville-Palm Bay, FL	32.03%	41.38%	9.36%	29.22%
Memphis, TN-AR-MS	19.85%	33.37%	13.52%	68.09%
Merced, CA	22.70%	39.09%	16.39%	72.23%
Miami-Fort Lauderdale, FL (C)	25.19%	34.80%	9.61%	38.17%
Milwaukee-Racine, WI (C)	23.21%	33.25%	10.04%	43.27%
Minneapolis-St. Paul, MN-WI	19.73%	27.72%	7.99%	40.49%
Mobile, AL	25.16%	38.80%	13.65%	54.25%
Modesto, CA	21.98%	38.27%	16.29%	74.09%
Monroe, LA	22.76%	32.44%	9.68%	42.52%
Montgomery, AL	23.69%	36.79%	13.10%	55.29%
Muncie, IN	28.55%	36.63%	8.08%	28.32%
Myrtle Beach, SC	28.97%	42.49%	13.52%	46.67%
Naples, FL	47.35%	57.70%	10.35%	21.85%
Nashville, TN	19.95%	29.75%	9.80%	49.15%
New Orleans, LA	21.96%	33.93%	11.97%	54.50%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	24.54%	37.71%	13.17%	53.66%
Norfolk-Virginia Beach-Newport News, VA-	21.94%	34.92%	12.97%	59.11%
Ocala, FL	41.52%	48.46%	6.94%	16.70%
Odessa-Midland, TX	21.49%	34.91%	13.43%	62.48%
Oklahoma City, OK	24.67%	36.08%	11.41%	46.26%
Omaha, NE-IA	20.37%	29.86%	9.48%	46.54%
Orlando, FL	23.12%	33.22%	10.10%	43.67%
Panama City, FL	26.76%	33.80%	7.04%	26.31%
Pensacola, FL	26.81%	32.92%	6.10%	22.76%
Peoria-Pekin, IL	24.32%	36.99%	12.67%	52.11%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	24.60%	38.07%	13.48%	54.78%
Phoenix-Mesa, AZ	23.66%	35.15%	11.49%	48.58%
Pittsburgh, PA	28.56%	40.49%	11.93%	41.79%
Portland, ME	20.88%	26.39%	5.51%	26.37%
Portland-Salem, OR-WA (C)	21.19%	33.61%	12.42%	58.64%
Providence-Fall River-Warwick, RI-MA	24.99%	37.79%	12.80%	51.23%
Provo-Orem, UT	18.14%	27.19%	9.06%	49.96%
Pueblo, CO	31.04%	42.07%	11.03%	35.55%
Punta Gorda, FL	48.38%	57.18%	8.80%	18.20%
Raleigh-Durham-Chapel Hill, NC	18.69%	28.82%	10.13%	54.20%

MSA	% of MSA that is older in 2010	% of MSA that is older in 2030	Change in % of MSA that is older	% Change in % of MSA that is older
Reading, PA	26.95%	38.36%	11.41%	42.35%
Redding, CA	30.21%	46.58%	16.37%	54.21%
Reno, NV	22.53%	31.74%	9.21%	40.87%
Richland-Kennewick-Pasco, WA	22.65%	33.83%	11.19%	49.39%
Richmond-Petersburg, VA	22.18%	34.23%	12.05%	54.35%
Roanoke, VA	26.59%	39.07%	12.48%	46.92%
Rochester, MN	22.73%	30.50%	7.77%	34.19%
Rochester, NY	23.75%	37.17%	13.41%	56.46%
Rockford, IL	24.58%	34.75%	10.17%	41.39%
Rocky Mount, NC	26.10%	38.77%	12.67%	48.52%
Sacramento-Yolo, CA (C)	22.76%	36.55%	13.79%	60.58%
Saginaw-Bay City-Midland, MI	27.57%	37.57%	9.99%	36.24%
St. Cloud, MN	21.22%	28.61%	7.39%	34.85%
St. Joseph, MO	26.55%	36.78%	10.23%	38.53%
St. Louis, MO-IL	23.28%	36.18%	12.90%	55.43%
Salinas, CA	28.43%	40.64%	12.21%	42.94%
Salt Lake City-Ogden, UT	19.60%	25.40%	5.81%	29.64%
San Antonio, TX	21.79%	31.43%	9.63%	44.21%
San Diego, CA	21.97%	33.61%	11.65%	53.02%
San Francisco-Oakland-San Jose, CA (C)	23.63%	34.56%	10.93%	46.26%
San Luis Obispo-Atascadero-Paso Robles, CA	29.64%	42.23%	12.59%	42.46%
Santa Barbara-Santa Maria-Lompoc, CA	27.79%	42.76%	14.96%	53.84%
Santa Fe, NM	26.40%	43.84%	17.44%	66.04%
Sarasota-Bradenton, FL	43.90%	55.93%	12.03%	27.40%
Savannah, GA	22.10%	38.59%	16.50%	74.66%
Scranton--Wilkes-Barre--Hazleton, PA	29.19%	43.06%	13.87%	47.53%
Seattle-Tacoma-Bremerton, WA (C)	19.64%	32.39%	12.75%	64.95%
Sharon, PA	31.25%	46.06%	14.81%	47.38%
Sheboygan, WI	26.21%	34.52%	8.31%	31.69%
Shreveport-Bossier City, LA	24.21%	38.57%	14.36%	59.33%
Sioux City, IA-NE	25.77%	47.50%	21.72%	84.28%
Sioux Falls, SD	24.72%	36.06%	11.34%	45.85%
South Bend, IN	24.99%	40.48%	15.49%	61.99%
Spokane, WA	23.34%	37.90%	14.55%	62.35%
Springfield, IL	25.87%	39.69%	13.82%	53.43%
Springfield, MO	24.93%	32.30%	7.37%	29.57%
Springfield, MA	25.50%	37.58%	12.08%	47.35%
State College, PA	25.92%	34.98%	9.06%	34.94%
Stockton-Lodi, CA	21.68%	36.42%	14.74%	67.98%
Sumter, SC	25.37%	35.44%	10.07%	39.69%
Syracuse, NY	24.67%	37.36%	12.69%	51.44%
Tallahassee, FL	21.68%	27.04%	5.36%	24.73%
Tampa-St. Petersburg-Clearwater, FL	28.99%	38.21%	9.22%	31.79%
Terre Haute, IN	26.98%	38.13%	11.16%	41.36%
Toledo, OH	23.59%	36.43%	12.84%	54.45%

MSA	% of MSA that is older in 2010	% of MSA that is older in 2030	Change in % of MSA that is older	% Change in % of MSA that is older
Topeka, KS	25.40%	43.03%	17.63%	69.43%
Tucson, AZ	28.29%	40.55%	12.26%	43.35%
Tulsa, OK	24.77%	34.59%	9.82%	39.64%
Tuscaloosa, AL	22.75%	30.33%	7.58%	33.30%
Tyler, TX	28.47%	40.25%	11.78%	41.39%
Utica-Rome, NY	29.46%	40.94%	11.48%	38.98%
Visalia-Tulare-Porterville, CA	22.68%	36.54%	13.86%	61.10%
Waco, TX	24.80%	36.16%	11.36%	45.81%
Washington-Baltimore, DC-MD-VA-WV (C)	20.77%	33.82%	13.05%	62.85%
Waterloo-Cedar Falls, IA	27.06%	37.27%	10.22%	37.76%
Wausau, WI	21.96%	31.80%	9.84%	44.80%
West Palm Beach-Boca Raton, FL	39.36%	47.95%	8.59%	21.83%
Wichita, KS	23.17%	34.43%	11.26%	48.61%
Wichita Falls, TX	27.68%	42.80%	15.12%	54.61%
Williamsport, PA	28.00%	36.27%	8.27%	29.55%
Wilmington, NC	26.56%	41.45%	14.89%	56.08%
Yakima, WA	26.54%	44.33%	17.79%	67.04%
York, PA	24.80%	32.55%	7.75%	31.23%
Youngstown-Warren, OH	28.87%	42.27%	13.40%	46.41%
Yuba City, CA	28.02%	38.25%	10.23%	36.51%
Yuma, AZ	32.68%	50.36%	17.69%	54.12%

Note: Data based on Ruggles et al. (2010) and the results from the Sorting simulation

Table 33. % of all older HH in the MSA (with change and % change) under the sorting simulation

MSA	% of all older HH in the MSA in 2010	% of all older HH in the MSA in 2030	Change in % of all older HH in the MSA in 2030	% Change in % of all older HH in the MSA in 2030
Abilene, TX	0.07%	0.08%	0.01%	9.14%
Albany, GA	0.06%	0.06%	0.00%	-1.18%
Albany-Schenectady-Troy, NY	0.44%	0.67%	0.24%	53.87%
Albuquerque, NM	0.39%	0.39%	0.00%	0.06%
Alexandria, LA	0.08%	0.10%	0.02%	26.97%
Allentown-Bethlehem-Easton, PA	0.40%	0.38%	-0.02%	-4.58%
Altoona, PA	0.09%	0.10%	0.01%	13.87%
Amarillo, TX	0.10%	0.12%	0.02%	16.04%
Anchorage, AK	0.07%	0.03%	-0.04%	-54.30%
Anniston, AL	0.07%	0.08%	0.01%	12.18%
Appleton-Oshkosh-Neenah, WI	0.20%	0.16%	-0.05%	-22.72%
Asheville, NC	0.16%	0.13%	-0.03%	-20.27%
Athens, GA	0.06%	0.08%	0.02%	30.98%
Atlanta, GA	1.51%	1.52%	0.01%	0.85%
Auburn-Opelika, AL	0.05%	0.07%	0.01%	27.75%
Augusta-Aiken, GA-SC	0.24%	0.27%	0.04%	15.66%
Austin-San Marcos, TX	0.46%	0.49%	0.03%	7.09%
Bakersfield, CA	0.25%	0.29%	0.05%	19.80%
Barnstable-Yarmouth, MA	0.13%	0.16%	0.03%	25.72%
Baton Rouge, LA	0.29%	0.28%	-0.01%	-4.82%
Beaumont-Port Arthur, TX	0.21%	0.28%	0.07%	32.51%
Bellingham, WA	0.09%	0.09%	0.00%	2.06%
Benton Harbor, MI	0.10%	0.12%	0.02%	19.11%
Billings, MT	0.09%	0.07%	-0.02%	-23.01%
Biloxi-Gulfport-Pascagoula, MS	0.15%	0.14%	-0.01%	-9.42%
Binghamton, NY	0.15%	0.27%	0.11%	74.32%
Birmingham, AL	0.43%	0.43%	0.00%	-0.69%
Bloomington, IN	0.06%	0.06%	0.01%	8.79%
Bloomington-Normal, IL	0.07%	0.10%	0.03%	46.64%
Boise City, ID	0.23%	0.18%	-0.05%	-22.15%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	2.41%	1.86%	-0.55%	-22.89%
Brownsville-Harlingen-San Benito, TX	0.11%	0.15%	0.04%	34.77%
Bryan-College Station, TX	0.05%	0.04%	-0.01%	-13.59%
Buffalo-Niagara Falls, NY	0.68%	0.96%	0.27%	40.39%
Canton-Massillon, OH	0.26%	0.30%	0.04%	13.96%
Cedar Rapids, IA	0.12%	0.08%	-0.04%	-33.04%
Champaign-Urbana, IL	0.08%	0.10%	0.02%	25.25%
Charleston-North Charleston, SC	0.25%	0.26%	0.02%	6.09%
Charlotte-Gastonia-Rock Hill, NC-SC	0.78%	0.71%	-0.07%	-9.11%
Charlottesville, VA	0.09%	0.11%	0.02%	23.70%
Chattanooga, TN-GA	0.28%	0.24%	-0.04%	-14.30%

MSA	% of all older HH in the MSA in 2010	% of all older HH in the MSA in 2030	Change in % of all older HH in the MSA in 2030	% Change in % of all older HH in the MSA in 2030
Chicago-Gary-Kenosha, IL-IN-WI (C)	3.59%	3.48%	-0.10%	-2.80%
Chico-Paradise, CA	0.13%	0.17%	0.04%	32.21%
Cincinnati-Hamilton, OH-KY-IN (C)	0.91%	0.80%	-0.11%	-11.81%
Clarksville-Hopkinsville, TN-KY	0.05%	0.05%	0.00%	3.69%
Cleveland-Akron, OH (C)	1.63%	1.92%	0.29%	17.69%
Colorado Springs, CO	0.22%	0.20%	-0.02%	-9.49%
Columbia, MO	0.06%	0.05%	-0.01%	-16.13%
Columbia, SC	0.27%	0.29%	0.02%	8.87%
Columbus, GA-AL	0.09%	0.09%	0.00%	-1.06%
Columbus, OH	0.68%	0.78%	0.10%	15.20%
Corpus Christi, TX	0.12%	0.14%	0.02%	17.40%
Dallas-Fort Worth, TX (C)	1.91%	2.24%	0.33%	17.42%
Danville, VA	0.09%	0.09%	0.01%	7.67%
Davenport-Moline-Rock Island, IA-IL	0.15%	0.17%	0.02%	11.74%
Dayton-Springfield, OH	0.58%	0.66%	0.08%	13.21%
Daytona Beach, FL	0.37%	0.30%	-0.06%	-16.74%
Decatur, AL	0.10%	0.07%	-0.02%	-24.45%
Decatur, IL	0.08%	0.09%	0.02%	23.06%
Denver-Boulder-Greeley, CO (C)	1.06%	1.09%	0.04%	3.62%
Des Moines, IA	0.18%	0.10%	-0.07%	-40.87%
Detroit-Ann Arbor-Flint, MI (C)	2.47%	2.40%	-0.08%	-3.20%
Dothan, AL	0.09%	0.22%	0.14%	156.80%
Dover, DE	0.08%	0.05%	-0.02%	-31.12%
Duluth-Superior, MN-WI	0.13%	0.13%	0.00%	2.86%
Eau Claire, WI	0.09%	0.08%	-0.01%	-9.84%
El Paso, TX	0.18%	0.21%	0.03%	18.63%
Elkhart-Goshen, IN	0.09%	0.08%	-0.01%	-10.63%
Erie, PA	0.16%	0.18%	0.02%	14.28%
Eugene-Springfield, OR	0.20%	0.19%	-0.01%	-2.90%
Evansville-Henderson, IN-KY	0.15%	0.14%	-0.01%	-5.82%
Fargo-Moorhead, ND-MN	0.06%	0.03%	-0.03%	-44.10%
Fayetteville, NC	0.12%	0.10%	-0.02%	-19.11%
Fayetteville-Springdale-Rogers, AR	0.18%	0.14%	-0.04%	-19.97%
Flagstaff, AZ-UT	0.04%	0.06%	0.02%	36.99%
Florence, AL	0.10%	0.12%	0.01%	11.57%
Fort Collins-Loveland, CO	0.12%	0.12%	0.00%	3.46%
Fort Myers-Cape Coral, FL	0.47%	0.44%	-0.03%	-6.13%
Fort Pierce-Port St. Lucie, FL	0.32%	0.28%	-0.04%	-12.53%
Fort Smith, AR-OK	0.10%	0.08%	-0.02%	-23.14%
Fort Walton Beach, FL	0.09%	0.10%	0.01%	6.00%
Fort Wayne, IN	0.24%	0.22%	-0.03%	-11.11%
Fresno, CA	0.34%	0.46%	0.12%	37.11%
Gadsden, AL	0.07%	0.08%	0.01%	18.89%

MSA	% of all older HH in the MSA in 2010	% of all older HH in the MSA in 2030	Change in % of all older HH in the MSA in 2030	% Change in % of all older HH in the MSA in 2030
Gainesville, FL	0.10%	0.09%	-0.01%	-10.38%
Glens Falls, NY	0.08%	0.17%	0.09%	115.53%
Goldsboro, NC	0.07%	0.12%	0.06%	84.47%
Grand Junction, CO	0.08%	0.08%	0.00%	-0.37%
Grand Rapids-Muskegon-Holland, MI	0.46%	0.41%	-0.05%	-11.16%
Green Bay, WI	0.11%	0.08%	-0.03%	-29.77%
Greensboro--Winston Salem--High Point, NC	0.75%	0.76%	0.01%	1.55%
Greenville, NC	0.07%	0.08%	0.01%	8.74%
Greenville-Spartanburg-Anderson, SC	0.49%	0.48%	-0.02%	-3.31%
Harrisburg-Lebanon-Carlisle, PA	0.41%	0.41%	0.00%	0.81%
Hartford, CT	0.35%	0.27%	-0.08%	-22.00%
Hattiesburg, MS	0.05%	0.05%	0.00%	-3.37%
Hickory-Morganton-Lenoir, NC	0.21%	0.22%	0.01%	2.41%
Honolulu, HI	0.40%	0.35%	-0.05%	-11.39%
Houma, LA	0.06%	0.04%	-0.01%	-22.47%
Houston-Galveston-Brazoria, TX (C)	1.61%	1.77%	0.16%	9.82%
Huntsville, AL	0.21%	0.20%	0.00%	-1.06%
Indianapolis, IN	0.83%	0.73%	-0.10%	-11.73%
Iowa City, IA	0.05%	0.02%	-0.02%	-45.72%
Jackson, MI	0.09%	0.08%	-0.02%	-18.23%
Jackson, MS	0.22%	0.20%	-0.02%	-8.34%
Jackson, TN	0.06%	0.07%	0.02%	28.87%
Jacksonville, FL	0.56%	0.51%	-0.06%	-10.04%
Jacksonville, NC	0.05%	0.05%	0.00%	1.76%
Jamestown, NY	0.09%	0.19%	0.11%	123.32%
Janesville-Beloit, WI	0.09%	0.06%	-0.03%	-30.81%
Johnson City-Kingsport-Bristol, TN-VA	0.23%	0.23%	0.00%	2.09%
Johnstown, PA	0.17%	0.23%	0.06%	37.39%
Joplin, MO	0.09%	0.14%	0.05%	51.46%
Kalamazoo-Battle Creek, MI	0.24%	0.26%	0.02%	8.13%
Kansas City, MO-KS	0.89%	0.67%	-0.22%	-24.78%
Killeen-Temple, TX	0.11%	0.16%	0.06%	54.50%
Knoxville, TN	0.36%	0.43%	0.06%	17.44%
Kokomo, IN	0.07%	0.06%	-0.01%	-10.78%
La Crosse, WI-MN	0.06%	0.04%	-0.02%	-28.22%
Lafayette, LA	0.11%	0.10%	-0.01%	-8.97%
Lafayette, IN	0.09%	0.08%	0.00%	-3.69%
Lake Charles, LA	0.10%	0.11%	0.01%	9.53%
Lakeland-Winter Haven, FL	0.37%	0.35%	-0.02%	-6.27%
Lancaster, PA	0.28%	0.23%	-0.05%	-17.44%
Lansing-East Lansing, MI	0.20%	0.22%	0.02%	9.36%
Laredo, TX	0.04%	0.05%	0.01%	30.42%
Las Cruces, NM	0.08%	0.06%	-0.02%	-21.24%

MSA	% of all older HH in the MSA in 2010	% of all older HH in the MSA in 2030	Change in % of all older HH in the MSA in 2030	% Change in % of all older HH in the MSA in 2030
Las Vegas, NV-AZ	0.69%	0.71%	0.02%	2.89%
Lexington, KY	0.12%	0.12%	0.00%	-3.69%
Lima, OH	0.09%	0.13%	0.04%	39.32%
Lincoln, NE	0.12%	0.06%	-0.06%	-47.45%
Little Rock-North Little Rock, AR	0.31%	0.23%	-0.08%	-26.71%
Longview-Marshall, TX	0.11%	0.10%	0.00%	-2.38%
Los Angeles-Riverside-Orange County, CA (C)	5.03%	6.48%	1.45%	28.93%
Louisville, KY-IN	0.52%	0.57%	0.06%	10.72%
Lubbock, TX	0.12%	0.15%	0.02%	19.79%
Lynchburg, VA	0.15%	0.16%	0.01%	8.08%
Macon, GA	0.16%	0.16%	0.00%	-1.31%
Madison, WI	0.19%	0.15%	-0.04%	-22.20%
Mansfield, OH	0.08%	0.09%	0.01%	15.86%
McAllen-Edinburg-Mission, TX	0.16%	0.19%	0.02%	14.30%
Medford-Ashland, OR	0.14%	0.12%	-0.02%	-12.57%
Melbourne-Titusville-Palm Bay, FL	0.38%	0.34%	-0.04%	-11.07%
Memphis, TN-AR-MS	0.44%	0.37%	-0.07%	-15.09%
Merced, CA	0.07%	0.10%	0.04%	55.45%
Miami-Fort Lauderdale, FL (C)	0.97%	0.88%	-0.09%	-8.84%
Milwaukee-Racine, WI (C)	0.89%	0.56%	-0.33%	-36.77%
Minneapolis-St. Paul, MN-WI	1.30%	0.89%	-0.41%	-31.71%
Mobile, AL	0.32%	0.29%	-0.03%	-10.80%
Modesto, CA	0.16%	0.24%	0.08%	48.02%
Monroe, LA	0.08%	0.08%	0.00%	-1.99%
Montgomery, AL	0.19%	0.18%	-0.01%	-4.68%
Muncie, IN	0.07%	0.07%	-0.01%	-11.54%
Myrtle Beach, SC	0.18%	0.16%	-0.02%	-9.63%
Naples, FL	0.27%	0.24%	-0.03%	-10.80%
Nashville, TN	0.62%	0.61%	-0.02%	-2.55%
New Orleans, LA	0.50%	0.51%	0.01%	2.78%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	7.75%	5.87%	-1.87%	-24.17%
Norfolk-Virginia Beach-Newport News, VA-	0.72%	0.73%	0.01%	1.31%
Ocala, FL	0.30%	0.25%	-0.06%	-19.07%
Odessa-Midland, TX	0.10%	0.13%	0.02%	24.07%
Oklahoma City, OK	0.45%	0.35%	-0.10%	-22.18%
Omaha, NE-IA	0.28%	0.20%	-0.08%	-30.18%
Orlando, FL	0.77%	0.76%	-0.01%	-0.97%
Panama City, FL	0.09%	0.08%	-0.01%	-14.81%
Pensacola, FL	0.25%	0.21%	-0.03%	-14.04%
Peoria-Pekin, IL	0.20%	0.26%	0.06%	29.25%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	3.14%	2.06%	-1.08%	-34.32%
Phoenix-Mesa, AZ	1.60%	1.54%	-0.06%	-3.77%
Pittsburgh, PA	1.54%	1.62%	0.07%	4.84%

MSA	% of all older HH in the MSA in 2010	% of all older HH in the MSA in 2030	Change in % of all older HH in the MSA in 2030	% Change in % of all older HH in the MSA in 2030
Portland, ME	0.12%	0.06%	-0.07%	-55.10%
Portland-Salem, OR-WA (C)	1.07%	1.00%	-0.08%	-7.25%
Providence-Fall River-Warwick, RI-MA	0.49%	0.65%	0.16%	32.13%
Provo-Orem, UT	0.13%	0.12%	-0.01%	-7.12%
Pueblo, CO	0.10%	0.08%	-0.01%	-11.87%
Punta Gorda, FL	0.19%	0.15%	-0.04%	-19.55%
Raleigh-Durham-Chapel Hill, NC	0.58%	0.53%	-0.05%	-8.96%
Reading, PA	0.23%	0.23%	0.01%	2.78%
Redding, CA	0.12%	0.16%	0.04%	36.90%
Reno, NV	0.18%	0.16%	-0.02%	-13.29%
Richland-Kennewick-Pasco, WA	0.10%	0.09%	-0.01%	-7.29%
Richmond-Petersburg, VA	0.53%	0.60%	0.08%	14.38%
Roanoke, VA	0.16%	0.17%	0.01%	5.18%
Rochester, MN	0.07%	0.05%	-0.02%	-31.31%
Rochester, NY	0.54%	0.89%	0.35%	65.33%
Rockford, IL	0.18%	0.18%	0.00%	0.44%
Rocky Mount, NC	0.09%	0.10%	0.00%	4.67%
Sacramento-Yolo, CA (C)	0.86%	1.12%	0.26%	29.92%
Saginaw-Bay City-Midland, MI	0.25%	0.29%	0.04%	14.85%
St. Cloud, MN	0.09%	0.10%	0.01%	11.48%
St. Joseph, MO	0.06%	0.08%	0.02%	27.56%
St. Louis, MO-IL	1.45%	1.44%	0.00%	-0.11%
Salinas, CA	0.09%	0.11%	0.03%	29.79%
Salt Lake City-Ogden, UT	0.52%	0.42%	-0.10%	-18.87%
San Antonio, TX	0.74%	0.80%	0.06%	8.02%
San Diego, CA	0.99%	1.29%	0.30%	30.41%
San Francisco-Oakland-San Jose, CA (C)	2.56%	3.11%	0.55%	21.31%
San Luis Obispo-Atascadero-Paso Robles, CA	0.15%	0.18%	0.02%	14.22%
Santa Barbara-Santa Maria-Lompoc, CA	0.17%	0.26%	0.08%	48.00%
Santa Fe, NM	0.10%	0.12%	0.02%	20.10%
Sarasota-Bradenton, FL	0.70%	0.63%	-0.06%	-8.96%
Savannah, GA	0.12%	0.14%	0.02%	15.80%
Scranton--Wilkes-Barre--Hazleton, PA	0.43%	0.55%	0.12%	28.36%
Seattle-Tacoma-Bremerton, WA (C)	1.49%	1.60%	0.11%	7.59%
Sharon, PA	0.09%	0.14%	0.05%	59.18%
Sheboygan, WI	0.07%	0.06%	-0.01%	-7.89%
Shreveport-Bossier City, LA	0.22%	0.24%	0.02%	8.93%
Sioux City, IA-NE	0.05%	0.05%	-0.01%	-12.45%
Sioux Falls, SD	0.06%	0.03%	-0.03%	-51.05%
South Bend, IN	0.14%	0.14%	0.00%	-1.39%
Spokane, WA	0.24%	0.26%	0.02%	7.43%
Springfield, IL	0.07%	0.07%	0.00%	-0.02%
Springfield, MO	0.22%	0.24%	0.02%	9.10%

MSA	% of all older HH in the MSA in 2010	% of all older HH in the MSA in 2030	Change in % of all older HH in the MSA in 2030	% Change in % of all older HH in the MSA in 2030
Springfield, MA	0.29%	0.37%	0.07%	25.18%
State College, PA	0.07%	0.08%	0.01%	20.18%
Stockton-Lodi, CA	0.20%	0.28%	0.08%	39.52%
Sumter, SC	0.06%	0.06%	0.00%	-2.90%
Syracuse, NY	0.40%	0.74%	0.34%	85.09%
Tallahassee, FL	0.14%	0.10%	-0.03%	-24.37%
Tampa-St. Petersburg-Clearwater, FL	1.64%	1.50%	-0.14%	-8.82%
Terre Haute, IN	0.09%	0.09%	0.00%	-1.18%
Toledo, OH	0.32%	0.39%	0.07%	20.16%
Topeka, KS	0.10%	0.09%	-0.01%	-13.03%
Tucson, AZ	0.53%	0.55%	0.02%	3.02%
Tulsa, OK	0.37%	0.26%	-0.11%	-30.47%
Tuscaloosa, AL	0.08%	0.08%	0.00%	-4.52%
Tyler, TX	0.12%	0.14%	0.02%	17.65%
Utica-Rome, NY	0.20%	0.36%	0.17%	84.27%
Visalia-Tulare-Porterville, CA	0.13%	0.20%	0.08%	59.73%
Waco, TX	0.11%	0.14%	0.03%	28.72%
Washington-Baltimore, DC-MD-VA-WV (C)	3.10%	2.69%	-0.42%	-13.42%
Waterloo-Cedar Falls, IA	0.08%	0.06%	-0.02%	-24.23%
Wausau, WI	0.07%	0.08%	0.01%	17.98%
West Palm Beach-Boca Raton, FL	0.95%	0.82%	-0.13%	-13.65%
Wichita, KS	0.28%	0.20%	-0.08%	-28.06%
Wichita Falls, TX	0.07%	0.08%	0.01%	20.64%
Williamsport, PA	0.07%	0.11%	0.04%	51.82%
Wilmington, NC	0.20%	0.20%	0.00%	-0.35%
Yakima, WA	0.10%	0.10%	0.00%	-0.40%
York, PA	0.24%	0.21%	-0.03%	-13.44%
Youngstown-Warren, OH	0.39%	0.46%	0.07%	17.24%
Yuba City, CA	0.07%	0.09%	0.02%	30.30%
Yuma, AZ	0.09%	0.08%	-0.01%	-10.15%

Note: Data based on Ruggles et al. (2010) and the results from the Sorting simulation

Table 34. Net migration of older HHs (with % change)

MSA	Net Migration of older	% Chng in older HHs due to migration
Abilene, TX	5,160	47.38%
Albany, GA	-1,342	-14.31%
Albany-Schenectady-Troy, NY	57,302	84.19%
Albuquerque, NM	-6,089	-9.96%
Alexandria, LA	9,167	76.35%
Allentown-Bethlehem-Easton, PA	9,634	15.46%
Altoona, PA	7,571	55.02%
Amarillo, TX	2,217	13.90%
Anchorage, AK	-25,767	-245.38%
Anniston, AL	3,865	35.01%
Appleton-Oshkosh-Neenah, WI	-11,841	-37.23%
Asheville, NC	-4,932	-19.75%
Athens, GA	3,928	39.82%
Atlanta, GA	-135,143	-57.60%
Auburn-Opelika, AL	2,870	34.30%
Augusta-Aiken, GA-SC	5,691	15.50%
Austin-San Marcos, TX	-29,074	-40.86%
Bakersfield, CA	9,848	25.81%
Barnstable-Yarmouth, MA	20,469	102.72%
Baton Rouge, LA	-14,003	-31.05%
Beaumont-Port Arthur, TX	23,007	70.31%
Bellingham, WA	4	0.03%
Benton Harbor, MI	8,822	55.23%
Billings, MT	-1,755	-12.29%
Biloxi-Gulfport-Pascagoula, MS	-4,431	-18.70%
Binghamton, NY	31,057	129.62%
Birmingham, AL	-3,480	-5.22%
Bloomington, IN	1,202	13.57%
Bloomington-Normal, IL	4,150	41.07%
Boise City, ID	-16,142	-44.99%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	-143,340	-38.24%
Brownsville-Harlingen-San Benito, TX	14,075	81.48%
Bryan-College Station, TX	-2,932	-39.86%
Buffalo-Niagara Falls, NY	80,748	76.37%
Canton-Massillon, OH	15,370	38.22%
Cedar Rapids, IA	-8,065	-44.88%
Champaign-Urbana, IL	5,059	39.85%
Charleston-North Charleston, SC	1,237	3.20%
Charlotte-Gastonia-Rock Hill, NC-SC	-47,232	-39.07%
Charlottesville, VA	5,995	43.04%
Chattanooga, TN-GA	-1,292	-2.93%
Chicago-Gary-Kenosha, IL-IN-WI (C)	-80,251	-14.41%
Chico-Paradise, CA	15,816	78.58%

MSA	Net Migration of older	% Chng in older HHs due to migration
Cincinnati-Hamilton, OH-KY-IN (C)	-46,028	-32.63%
Clarksville-Hopkinsville, TN-KY	-3,487	-45.17%
Cleveland-Akron, OH (C)	76,248	30.03%
Colorado Springs, CO	-21,150	-61.02%
Columbia, MO	-4,035	-40.84%
Columbia, SC	-7,431	-17.78%
Columbus, GA-AL	47	0.35%
Columbus, OH	-3,413	-3.24%
Corpus Christi, TX	5,064	27.23%
Dallas-Fort Worth, TX (C)	-41,213	-13.88%
Danville, VA	6,876	51.51%
Davenport-Moline-Rock Island, IA-IL	7,563	32.47%
Dayton-Springfield, OH	34,571	38.06%
Daytona Beach, FL	12,416	21.82%
Decatur, AL	-1,791	-11.95%
Decatur, IL	8,119	68.18%
Denver-Boulder-Greeley, CO (C)	-39,370	-23.99%
Des Moines, IA	-23,310	-84.58%
Detroit-Ann Arbor-Flint, MI (C)	-41,627	-10.83%
Dothan, AL	35,626	261.94%
Dover, DE	-5,842	-48.96%
Duluth-Superior, MN-WI	3,496	17.42%
Eau Claire, WI	-550	-3.91%
El Paso, TX	7,066	25.95%
Elkhart-Goshen, IN	-2,039	-14.67%
Erie, PA	8,111	32.72%
Eugene-Springfield, OR	1,993	6.55%
Evansville-Henderson, IN-KY	-1,786	-7.67%
Fargo-Moorhead, ND-MN	-8,279	-86.86%
Fayetteville, NC	-8,226	-44.35%
Fayetteville-Springdale-Rogers, AR	-8,916	-32.44%
Flagstaff, AZ-UT	-1,367	-21.05%
Florence, AL	7,975	49.15%
Fort Collins-Loveland, CO	-1,026	-5.49%
Fort Myers-Cape Coral, FL	37,226	51.47%
Fort Pierce-Port St. Lucie, FL	21,137	42.23%
Fort Smith, AR-OK	-2,859	-18.78%
Fort Walton Beach, FL	880	6.05%
Fort Wayne, IN	-6,041	-16.02%
Fresno, CA	32,481	62.10%
Gadsden, AL	5,395	50.26%
Gainesville, FL	-3,129	-20.38%
Glens Falls, NY	23,297	187.46%
Goldsboro, NC	14,630	144.21%
Grand Junction, CO	2,588	21.31%

MSA	Net Migration of older	% Chng in older HHs due to migration
Grand Rapids-Muskegon-Holland, MI	-20,249	-28.13%
Green Bay, WI	-11,721	-66.73%
Greensboro--Winston Salem--High Point, NC	4,819	4.12%
Greenville, NC	1,732	15.26%
Greenville-Spartanburg-Anderson, SC	2,905	3.79%
Harrisburg-Lebanon-Carlisle, PA	10,761	17.03%
Hartford, CT	-9,647	-17.72%
Hattiesburg, MS	-2,496	-30.28%
Hickory-Morganton-Lenoir, NC	5,213	15.90%
Honolulu, HI	11,105	17.97%
Houma, LA	-1,275	-14.62%
Houston-Galveston-Brazoria, TX (C)	-71,661	-28.63%
Huntsville, AL	-3,111	-9.74%
Indianapolis, IN	-41,900	-32.54%
Iowa City, IA	-6,914	-98.18%
Jackson, MI	-2,165	-15.05%
Jackson, MS	-10,794	-31.86%
Jackson, TN	3,415	39.92%
Jacksonville, FL	-33,421	-38.10%
Jacksonville, NC	-1,710	-22.43%
Jamestown, NY	27,551	203.75%
Janesville-Beloit, WI	-5,713	-41.53%
Johnson City-Kingsport-Bristol, TN-VA	9,835	27.79%
Johnstown, PA	26,063	98.18%
Joplin, MO	14,371	100.67%
Kalamazoo-Battle Creek, MI	6,205	16.47%
Kansas City, MO-KS	-61,334	-44.32%
Killeen-Temple, TX	9,130	55.82%
Knoxville, TN	17,440	30.90%
Kokomo, IN	158	1.50%
La Crosse, WI-MN	-3,372	-35.98%
Lafayette, LA	-9,983	-56.27%
Lafayette, IN	384	2.90%
Lake Charles, LA	994	6.47%
Lakeland-Winter Haven, FL	21,104	36.64%
Lancaster, PA	-5,252	-12.29%
Lansing-East Lansing, MI	-3,292	-10.39%
Laredo, TX	3,215	55.57%
Las Cruces, NM	-1,604	-13.26%
Las Vegas, NV-AZ	4,727	4.41%
Lexington, KY	-3,857	-20.15%
Lima, OH	12,181	83.75%
Lincoln, NE	-15,426	-81.31%
Little Rock-North Little Rock, AR	-27,130	-56.24%
Longview-Marshall, TX	3,624	21.80%

MSA	Net Migration of older	% Chng in older HHs due to migration
Los Angeles-Riverside-Orange County, CA (C)	394,922	50.58%
Louisville, KY-IN	8,407	10.48%
Lubbock, TX	6,668	34.97%
Lynchburg, VA	8,051	34.45%
Macon, GA	-4,168	-16.76%
Madison, WI	-20,538	-68.15%
Mansfield, OH	5,238	42.91%
McAllen-Edinburg-Mission, TX	11,691	46.09%
Medford-Ashland, OR	2,164	10.05%
Melbourne-Titusville-Palm Bay, FL	11,067	18.53%
Memphis, TN-AR-MS	-37,079	-54.54%
Merced, CA	8,438	82.77%
Miami-Fort Lauderdale, FL (C)	-400	-0.27%
Milwaukee-Racine, WI (C)	-79,821	-57.60%
Minneapolis-St. Paul, MN-WI	-162,528	-80.48%
Mobile, AL	-6,209	-12.35%
Modesto, CA	15,427	61.29%
Monroe, LA	-1,270	-10.65%
Montgomery, AL	-211	-0.73%
Muncie, IN	2,379	20.73%
Myrtle Beach, SC	2,689	9.69%
Naples, FL	27,808	65.21%
Nashville, TN	-25,650	-26.55%
New Orleans, LA	-10,159	-13.08%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	-360,655	-29.98%
Norfolk-Virginia Beach-Newport News, VA-	-9,854	-8.83%
Ocala, FL	20,795	44.06%
Odessa-Midland, TX	5,064	31.45%
Oklahoma City, OK	-18,637	-26.78%
Omaha, NE-IA	-25,995	-59.62%
Orlando, FL	-84	-0.07%
Panama City, FL	-374	-2.54%
Pensacola, FL	-2,547	-6.66%
Peoria-Pekin, IL	17,651	55.66%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	-246,967	-50.69%
Phoenix-Mesa, AZ	10,106	4.05%
Pittsburgh, PA	80,964	33.84%
Portland, ME	-20,568	-106.96%
Portland-Salem, OR-WA (C)	-39,992	-23.96%
Providence-Fall River-Warwick, RI-MA	44,076	57.97%
Provo-Orem, UT	-1,318	-6.67%
Pueblo, CO	2,788	18.76%
Punta Gorda, FL	16,010	54.84%
Raleigh-Durham-Chapel Hill, NC	-44,400	-48.95%
Reading, PA	6,814	19.44%

MSA	Net Migration of older	% Chng in older HHs due to migration
Redding, CA	16,027	86.93%
Reno, NV	-8,343	-29.68%
Richland-Kennewick-Pasco, WA	-2,720	-18.07%
Richmond-Petersburg, VA	8,415	10.26%
Roanoke, VA	6,012	24.38%
Rochester, MN	-5,187	-47.80%
Rochester, NY	82,437	98.82%
Rockford, IL	1,973	7.08%
Rocky Mount, NC	3,061	21.34%
Sacramento-Yolo, CA (C)	54,344	40.58%
Saginaw-Bay City-Midland, MI	18,657	48.06%
St. Cloud, MN	2,197	16.58%
St. Joseph, MO	6,428	65.83%
St. Louis, MO-IL	-2,736	-1.22%
Salinas, CA	10,047	74.33%
Salt Lake City-Ogden, UT	-34,543	-42.76%
San Antonio, TX	10,869	9.48%
San Diego, CA	66,755	43.49%
San Francisco-Oakland-San Jose, CA (C)	128,928	32.39%
San Luis Obispo-Atascadero-Paso Robles, CA	11,721	48.96%
Santa Barbara-Santa Maria-Lompoc, CA	27,433	101.88%
Santa Fe, NM	2,417	16.20%
Sarasota-Bradenton, FL	65,627	60.79%
Savannah, GA	2,794	14.77%
Scranton--Wilkes-Barre--Hazleton, PA	48,714	72.83%
Seattle-Tacoma-Bremerton, WA (C)	-50,815	-22.00%
Sharon, PA	18,540	134.26%
Sheboygan, WI	270	2.51%
Shreveport-Bossier City, LA	8,849	25.49%
Sioux City, IA-NE	-5	-0.06%
Sioux Falls, SD	-6,371	-63.92%
South Bend, IN	1,126	5.12%
Spokane, WA	5,260	14.18%
Springfield, IL	2,448	22.34%
Springfield, MO	9,902	28.69%
Springfield, MA	21,654	47.48%
State College, PA	5,371	49.27%
Stockton-Lodi, CA	14,755	47.10%
Sumter, SC	853	9.66%
Syracuse, NY	83,472	134.17%
Tallahassee, FL	-11,798	-55.39%
Tampa-St. Petersburg-Clearwater, FL	47,817	18.78%
Terre Haute, IN	2,638	19.30%
Toledo, OH	17,999	35.83%
Topeka, KS	-477	-2.98%

MSA	Net Migration of older	% Chng in older HHs due to migration
Tucson, AZ	25,597	31.00%
Tulsa, OK	-22,449	-38.55%
Tuscaloosa, AL	-1,034	-8.20%
Tyler, TX	12,286	66.08%
Utica-Rome, NY	48,552	159.35%
Visalia-Tulare-Porterville, CA	20,773	104.91%
Waco, TX	9,428	56.52%
Washington-Baltimore, DC-MD-VA-WV (C)	-214,133	-44.45%
Waterloo-Cedar Falls, IA	-437	-3.72%
Wausau, WI	2,488	23.65%
West Palm Beach-Boca Raton, FL	69,178	46.67%
Wichita, KS	-20,857	-47.34%
Wichita Falls, TX	5,912	55.09%
Williamsport, PA	12,584	108.49%
Wilmington, NC	6,381	20.78%
Yakima, WA	3,583	23.13%
York, PA	-6,513	-17.13%
Youngstown-Warren, OH	31,645	52.44%
Yuba City, CA	8,002	73.55%
Yuma, AZ	6,458	47.25%

Note: Data based on Ruggles et al. (2010) and the results from difference between the Sorting simulation and the Aging-in-Place simulation

Table 35. Change (% change) in proportion of MSA's HHs that are older due to migration

MSA	Change in proportion of MSA's HHs that are older due to migration	% Change in proportion of MSA's HHs that are older due to migration
Abilene, TX	3.32%	11.72%
Albany, GA	-0.93%	-4.03%
Albany-Schenectady-Troy, NY	0.62%	2.63%
Albuquerque, NM	0.80%	3.62%
Alexandria, LA	13.10%	46.58%
Allentown-Bethlehem-Easton, PA	1.84%	6.78%
Altoona, PA	4.70%	16.70%
Amarillo, TX	-0.17%	-0.78%
Anchorage, AK	-13.47%	-109.58%
Anniston, AL	9.82%	36.88%
Appleton-Oshkosh-Neenah, WI	-2.31%	-10.08%
Asheville, NC	-2.09%	-8.16%
Athens, GA	4.79%	22.04%
Atlanta, GA	-4.09%	-24.23%
Auburn-Opelika, AL	1.21%	5.82%
Augusta-Aiken, GA-SC	1.14%	5.07%
Austin-San Marcos, TX	-2.74%	-17.24%
Bakersfield, CA	-1.16%	-5.16%
Barnstable-Yarmouth, MA	3.48%	9.13%
Baton Rouge, LA	-1.57%	-7.77%
Beaumont-Port Arthur, TX	2.19%	8.12%
Bellingham, WA	1.68%	7.36%
Benton Harbor, MI	-1.66%	-5.69%
Billings, MT	7.55%	29.22%
Biloxi-Gulfport-Pascagoula, MS	3.37%	15.07%
Binghamton, NY	-2.30%	-8.51%
Birmingham, AL	1.10%	4.89%
Bloomington, IN	10.71%	49.51%
Bloomington-Normal, IL	-0.22%	-1.16%
Boise City, ID	3.01%	15.02%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	-2.86%	-11.89%
Brownsville-Harlingen-San Benito, TX	6.99%	28.67%
Bryan-College Station, TX	-0.85%	-4.91%
Buffalo-Niagara Falls, NY	-0.12%	-0.45%
Canton-Massillon, OH	-0.92%	-3.41%
Cedar Rapids, IA	0.76%	3.26%
Champaign-Urbana, IL	7.26%	33.77%
Charleston-North Charleston, SC	3.38%	14.77%
Charlotte-Gastonia-Rock Hill, NC-SC	-1.68%	-8.64%
Charlottesville, VA	3.13%	13.08%
Chattanooga, TN-GA	-2.52%	-9.31%
Chicago-Gary-Kenosha, IL-IN-WI (C)	-0.46%	-2.09%
Chico-Paradise, CA	1.37%	4.72%
Cincinnati-Hamilton, OH-KY-IN (C)	-3.12%	-14.30%

MSA	Change in proportion of MSA's HHs that are older due to migration	% Change in proportion of MSA's HHs that are older due to migration
Clarksville-Hopkinsville, TN-KY	1.79%	11.52%
Cleveland-Akron, OH (C)	-2.22%	-8.95%
Colorado Springs, CO	-5.46%	-30.02%
Columbia, MO	-6.65%	-32.73%
Columbia, SC	0.50%	2.49%
Columbus, GA-AL	-2.17%	-9.46%
Columbus, OH	0.99%	5.09%
Corpus Christi, TX	0.53%	2.24%
Dallas-Fort Worth, TX (C)	-3.71%	-20.36%
Danville, VA	-4.09%	-12.66%
Davenport-Moline-Rock Island, IA-IL	3.43%	13.44%
Dayton-Springfield, OH	0.64%	2.44%
Daytona Beach, FL	-1.87%	-5.41%
Decatur, AL	-7.35%	-26.43%
Decatur, IL	7.16%	25.20%
Denver-Boulder-Greeley, CO (C)	-4.03%	-20.04%
Des Moines, IA	-0.98%	-5.02%
Detroit-Ann Arbor-Flint, MI (C)	-2.13%	-9.14%
Dothan, AL	6.83%	26.95%
Dover, DE	-8.31%	-33.76%
Duluth-Superior, MN-WI	-2.99%	-11.47%
Eau Claire, WI	0.78%	3.19%
El Paso, TX	4.19%	20.68%
Elkhart-Goshen, IN	2.18%	9.19%
Erie, PA	-0.08%	-0.32%
Eugene-Springfield, OR	2.66%	10.53%
Evansville-Henderson, IN-KY	-0.44%	-1.88%
Fargo-Moorhead, ND-MN	0.54%	2.80%
Fayetteville, NC	-0.76%	-3.76%
Fayetteville-Springdale-Rogers, AR	0.77%	3.43%
Flagstaff, AZ-UT	-8.53%	-46.17%
Florence, AL	9.21%	31.81%
Fort Collins-Loveland, CO	0.15%	0.65%
Fort Myers-Cape Coral, FL	1.41%	3.65%
Fort Pierce-Port St. Lucie, FL	4.20%	11.24%
Fort Smith, AR-OK	5.69%	22.87%
Fort Walton Beach, FL	-4.34%	-17.66%
Fort Wayne, IN	-0.57%	-2.52%
Fresno, CA	5.51%	23.32%
Gadsden, AL	2.72%	9.47%
Gainesville, FL	-2.20%	-9.61%
Glens Falls, NY	-4.51%	-17.50%
Goldsboro, NC	5.74%	23.45%
Grand Junction, CO	1.83%	6.62%
Grand Rapids-Muskegon-Holland, MI	-4.12%	-19.01%

MSA	Change in proportion of MSA's HHs that are older due to migration	% Change in proportion of MSA's HHs that are older due to migration
Green Bay, WI	-5.94%	-29.53%
Greensboro--Winston Salem--High Point, NC	1.16%	4.83%
Greenville, NC	9.73%	44.45%
Greenville-Spartanburg-Anderson, SC	1.42%	5.73%
Harrisburg-Lebanon-Carlisle, PA	-1.99%	-7.64%
Hartford, CT	-0.54%	-2.04%
Hattiesburg, MS	3.33%	17.04%
Hickory-Morganton-Lenoir, NC	-2.73%	-10.50%
Honolulu, HI	6.97%	24.58%
Houma, LA	-6.48%	-24.67%
Houston-Galveston-Brazoria, TX (C)	-4.15%	-22.48%
Huntsville, AL	-0.96%	-4.18%
Indianapolis, IN	-0.08%	-0.37%
Iowa City, IA	-2.91%	-15.45%
Jackson, MI	-7.02%	-26.88%
Jackson, MS	-1.28%	-6.10%
Jackson, TN	2.85%	11.95%
Jacksonville, FL	-6.46%	-30.31%
Jacksonville, NC	1.44%	7.91%
Jamestown, NY	-4.09%	-14.93%
Janesville-Beloit, WI	-5.41%	-22.13%
Johnson City-Kingsport-Bristol, TN-VA	0.32%	1.16%
Johnstown, PA	-3.06%	-9.72%
Joplin, MO	6.96%	28.93%
Kalamazoo-Battle Creek, MI	-1.56%	-6.52%
Kansas City, MO-KS	-0.33%	-1.50%
Killeen-Temple, TX	2.73%	14.86%
Knoxville, TN	2.38%	9.95%
Kokomo, IN	-2.30%	-8.17%
La Crosse, WI-MN	-5.66%	-23.23%
Lafayette, LA	-4.95%	-26.01%
Lafayette, IN	7.19%	30.43%
Lake Charles, LA	-4.38%	-18.83%
Lakeland-Winter Haven, FL	1.68%	5.11%
Lancaster, PA	-1.72%	-6.75%
Lansing-East Lansing, MI	-5.41%	-26.14%
Laredo, TX	12.08%	68.62%
Las Cruces, NM	4.16%	16.59%
Las Vegas, NV-AZ	2.79%	12.48%
Lexington, KY	5.52%	27.30%
Lima, OH	3.85%	14.51%
Lincoln, NE	-4.41%	-21.11%
Little Rock-North Little Rock, AR	-2.33%	-10.98%
Longview-Marshall, TX	-4.31%	-15.10%
Los Angeles-Riverside-Orange County, CA (C)	2.53%	10.75%

MSA	Change in proportion of MSA's HHs that are older due to migration	% Change in proportion of MSA's HHs that are older due to migration
Louisville, KY-IN	1.80%	7.98%
Lubbock, TX	2.97%	13.00%
Lynchburg, VA	-1.05%	-3.76%
Macon, GA	-5.13%	-23.58%
Madison, WI	-1.22%	-6.68%
Mansfield, OH	3.44%	12.35%
McAllen-Edinburg-Mission, TX	8.94%	39.42%
Medford-Ashland, OR	-0.77%	-2.58%
Melbourne-Titusville-Palm Bay, FL	-5.44%	-16.97%
Memphis, TN-AR-MS	-0.43%	-2.19%
Merced, CA	7.31%	32.23%
Miami-Fort Lauderdale, FL (C)	-1.31%	-5.22%
Milwaukee-Racine, WI (C)	-1.81%	-7.80%
Minneapolis-St. Paul, MN-WI	-6.55%	-33.17%
Mobile, AL	-0.12%	-0.48%
Modesto, CA	2.66%	12.12%
Monroe, LA	-2.30%	-10.10%
Montgomery, AL	3.08%	13.00%
Muncie, IN	4.36%	15.27%
Myrtle Beach, SC	-0.17%	-0.58%
Naples, FL	1.65%	3.48%
Nashville, TN	-2.29%	-11.49%
New Orleans, LA	-2.44%	-11.13%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	1.54%	6.26%
Norfolk-Virginia Beach-Newport News, VA-	-0.13%	-0.61%
Ocala, FL	2.32%	5.59%
Odessa-Midland, TX	4.26%	19.82%
Oklahoma City, OK	0.96%	3.90%
Omaha, NE-IA	-0.49%	-2.39%
Orlando, FL	-0.76%	-3.30%
Panama City, FL	-1.93%	-7.20%
Pensacola, FL	-5.74%	-21.40%
Peoria-Pekin, IL	1.67%	6.88%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	-0.36%	-1.45%
Phoenix-Mesa, AZ	2.74%	11.57%
Pittsburgh, PA	-0.41%	-1.45%
Portland, ME	-11.03%	-52.80%
Portland-Salem, OR-WA (C)	0.67%	3.17%
Providence-Fall River-Warwick, RI-MA	-0.86%	-3.44%
Provo-Orem, UT	6.83%	37.67%
Pueblo, CO	-1.03%	-3.33%
Punta Gorda, FL	1.10%	2.28%
Raleigh-Durham-Chapel Hill, NC	-2.92%	-15.62%
Reading, PA	-4.05%	-15.05%

MSA	Change in proportion of MSA's HHs that are older due to migration	% Change in proportion of MSA's HHs that are older due to migration
Redding, CA	3.32%	10.99%
Reno, NV	-3.69%	-16.37%
Richland-Kennewick-Pasco, WA	-2.34%	-10.33%
Richmond-Petersburg, VA	-2.34%	-10.56%
Roanoke, VA	-1.03%	-3.88%
Rochester, MN	-3.26%	-14.32%
Rochester, NY	-1.16%	-4.87%
Rockford, IL	-3.29%	-13.38%
Rocky Mount, NC	-0.73%	-2.81%
Sacramento-Yolo, CA (C)	0.98%	4.31%
Saginaw-Bay City-Midland, MI	-0.08%	-0.28%
St. Cloud, MN	-0.69%	-3.26%
St. Joseph, MO	2.19%	8.25%
St. Louis, MO-IL	0.81%	3.47%
Salinas, CA	1.96%	6.88%
Salt Lake City-Ogden, UT	-2.16%	-11.02%
San Antonio, TX	0.19%	0.86%
San Diego, CA	1.27%	5.78%
San Francisco-Oakland-San Jose, CA (C)	-2.20%	-9.33%
San Luis Obispo-Atascadero-Paso Robles, CA	-1.14%	-3.83%
Santa Barbara-Santa Maria-Lompoc, CA	6.06%	21.82%
Santa Fe, NM	-10.23%	-38.73%
Sarasota-Bradenton, FL	2.42%	5.51%
Savannah, GA	4.55%	20.60%
Scranton--Wilkes-Barre--Hazleton, PA	0.87%	2.98%
Seattle-Tacoma-Bremerton, WA (C)	-2.08%	-10.57%
Sharon, PA	4.64%	14.85%
Sheboygan, WI	-3.09%	-11.78%
Shreveport-Bossier City, LA	5.88%	24.27%
Sioux City, IA-NE	11.81%	45.83%
Sioux Falls, SD	5.22%	21.10%
South Bend, IN	3.96%	15.84%
Spokane, WA	3.86%	16.53%
Springfield, IL	6.43%	24.87%
Springfield, MO	-1.58%	-6.34%
Springfield, MA	-1.97%	-7.72%
State College, PA	-0.89%	-3.41%
Stockton-Lodi, CA	2.04%	9.42%
Sumter, SC	-0.10%	-0.40%
Syracuse, NY	-2.02%	-8.18%
Tallahassee, FL	-7.19%	-33.18%
Tampa-St. Petersburg-Clearwater, FL	-0.36%	-1.24%
Terre Haute, IN	0.65%	2.41%
Toledo, OH	2.43%	10.31%
Topeka, KS	8.14%	32.04%

MSA	Change in proportion of MSA's HHs that are older due to migration	% Change in proportion of MSA's HHs that are older due to migration
Tucson, AZ	1.61%	5.69%
Tulsa, OK	-1.75%	-7.06%
Tuscaloosa, AL	-3.27%	-14.39%
Tyler, TX	6.38%	22.42%
Utica-Rome, NY	-3.25%	-11.05%
Visalia-Tulare-Porterville, CA	7.34%	32.36%
Waco, TX	0.75%	3.01%
Washington-Baltimore, DC-MD-VA-WV (C)	-1.14%	-5.47%
Waterloo-Cedar Falls, IA	4.89%	18.08%
Wausau, WI	-1.01%	-4.60%
West Palm Beach-Boca Raton, FL	2.00%	5.08%
Wichita, KS	-0.61%	-2.64%
Wichita Falls, TX	4.15%	15.01%
Williamsport, PA	-3.62%	-12.93%
Wilmington, NC	6.11%	22.99%
Yakima, WA	10.36%	39.03%
York, PA	-6.34%	-25.56%
Youngstown-Warren, OH	-1.22%	-4.21%
Yuba City, CA	-0.50%	-1.78%
Yuma, AZ	20.57%	62.96%

Note: Data based on Ruggles et al. (2010) and the results from difference between the Sorting simulation and the Aging-in-Place simulation

Table 36. Change (% change) in % of all older HH in the MSA due to migration

MSA	Change in % of all older HH in the MSA due to migration	%Change in % of all older HH in the MSA due to migration
Abilene, TX	0.02%	30.21%
Albany, GA	-0.01%	-9.13%
Albany-Schenectady-Troy, NY	0.24%	53.68%
Albuquerque, NM	-0.02%	-6.35%
Alexandria, LA	0.04%	48.68%
Allentown-Bethlehem-Easton, PA	0.04%	9.86%
Altoona, PA	0.03%	35.08%
Amarillo, TX	0.01%	8.86%
Anchorage, AK	-0.11%	-156.46%
Anniston, AL	0.02%	22.32%
Appleton-Oshkosh-Neenah, WI	-0.05%	-23.74%
Asheville, NC	-0.02%	-12.59%
Athens, GA	0.02%	25.39%
Atlanta, GA	-0.55%	-36.73%
Auburn-Opelika, AL	0.01%	21.87%
Augusta-Aiken, GA-SC	0.02%	9.88%
Austin-San Marcos, TX	-0.12%	-26.05%
Bakersfield, CA	0.04%	16.46%
Barnstable-Yarmouth, MA	0.08%	65.50%
Baton Rouge, LA	-0.06%	-19.80%
Beaumont-Port Arthur, TX	0.09%	44.83%
Bellingham, WA	0.00%	0.02%
Benton Harbor, MI	0.04%	35.22%
Billings, MT	-0.01%	-7.84%
Biloxi-Gulfport-Pascagoula, MS	-0.02%	-11.92%
Binghamton, NY	0.13%	82.65%
Birmingham, AL	-0.01%	-3.33%
Bloomington, IN	0.00%	8.65%
Bloomington-Normal, IL	0.02%	26.19%
Boise City, ID	-0.07%	-28.68%
Boston-Worcester-Lawrence, MA-NH-ME-CT (C)	-0.59%	-24.38%
Brownsville-Harlingen-San Benito, TX	0.06%	51.95%
Bryan-College Station, TX	-0.01%	-25.42%
Buffalo-Niagara Falls, NY	0.33%	48.70%
Canton-Massillon, OH	0.06%	24.37%
Cedar Rapids, IA	-0.03%	-28.62%
Champaign-Urbana, IL	0.02%	25.41%
Charleston-North Charleston, SC	0.01%	2.04%
Charlotte-Gastonia-Rock Hill, NC-SC	-0.19%	-24.91%
Charlottesville, VA	0.02%	27.45%
Chattanooga, TN-GA	-0.01%	-1.87%
Chicago-Gary-Kenosha, IL-IN-WI (C)	-0.33%	-9.19%
Chico-Paradise, CA	0.06%	50.10%
Cincinnati-Hamilton, OH-KY-IN (C)	-0.19%	-20.81%

MSA	Change in % of all older HH in the MSA due to migration	%Change in % of all older HH in the MSA due to migration
Clarksville-Hopkinsville, TN-KY	-0.01%	-28.80%
Cleveland-Akron, OH (C)	0.31%	19.15%
Colorado Springs, CO	-0.09%	-38.91%
Columbia, MO	-0.02%	-26.04%
Columbia, SC	-0.03%	-11.34%
Columbus, GA-AL	0.00%	0.22%
Columbus, OH	-0.01%	-2.06%
Corpus Christi, TX	0.02%	17.37%
Dallas-Fort Worth, TX (C)	-0.17%	-8.85%
Danville, VA	0.03%	32.84%
Davenport-Moline-Rock Island, IA-IL	0.03%	20.70%
Dayton-Springfield, OH	0.14%	24.27%
Daytona Beach, FL	0.05%	13.92%
Decatur, AL	-0.01%	-7.62%
Decatur, IL	0.03%	43.47%
Denver-Boulder-Greeley, CO (C)	-0.16%	-15.30%
Des Moines, IA	-0.10%	-53.93%
Detroit-Ann Arbor-Flint, MI (C)	-0.17%	-6.91%
Dothan, AL	0.15%	167.02%
Dover, DE	-0.02%	-31.22%
Duluth-Superior, MN-WI	0.01%	11.11%
Eau Claire, WI	0.00%	-2.49%
El Paso, TX	0.03%	16.55%
Elkhart-Goshen, IN	-0.01%	-9.35%
Erie, PA	0.03%	20.86%
Eugene-Springfield, OR	0.01%	4.18%
Evansville-Henderson, IN-KY	-0.01%	-4.89%
Fargo-Moorhead, ND-MN	-0.03%	-55.39%
Fayetteville, NC	-0.03%	-28.28%
Fayetteville-Springdale-Rogers, AR	-0.04%	-20.69%
Flagstaff, AZ-UT	-0.01%	-13.42%
Florence, AL	0.03%	31.34%
Fort Collins-Loveland, CO	0.00%	-3.50%
Fort Myers-Cape Coral, FL	0.15%	32.82%
Fort Pierce-Port St. Lucie, FL	0.09%	26.93%
Fort Smith, AR-OK	-0.01%	-11.98%
Fort Walton Beach, FL	0.00%	3.86%
Fort Wayne, IN	-0.02%	-10.21%
Fresno, CA	0.13%	39.60%
Gadsden, AL	0.02%	32.04%
Gainesville, FL	-0.01%	-13.00%
Glens Falls, NY	0.10%	119.53%
Goldsboro, NC	0.06%	91.95%
Grand Junction, CO	0.01%	13.59%
Grand Rapids-Muskegon-Holland, MI	-0.08%	-17.94%

MSA	Change in % of all older HH in the MSA due to migration	%Change in % of all older HH in the MSA due to migration
Green Bay, WI	-0.05%	-42.55%
Greensboro--Winston Salem--High Point, NC	0.02%	2.63%
Greenville, NC	0.01%	9.73%
Greenville-Spartanburg-Anderson, SC	0.01%	2.42%
Harrisburg-Lebanon-Carlisle, PA	0.04%	10.86%
Hartford, CT	-0.04%	-11.30%
Hattiesburg, MS	-0.01%	-19.31%
Hickory-Morganton-Lenoir, NC	0.02%	10.14%
Honolulu, HI	0.05%	11.46%
Houma, LA	-0.01%	-9.32%
Houston-Galveston-Brazoria, TX (C)	-0.29%	-18.25%
Huntsville, AL	-0.01%	-6.21%
Indianapolis, IN	-0.17%	-20.75%
Iowa City, IA	-0.03%	-62.60%
Jackson, MI	-0.01%	-9.59%
Jackson, MS	-0.04%	-20.32%
Jackson, TN	0.01%	25.46%
Jacksonville, FL	-0.14%	-24.29%
Jacksonville, NC	-0.01%	-14.30%
Jamestown, NY	0.11%	129.92%
Janesville-Beloit, WI	-0.02%	-26.48%
Johnson City-Kingsport-Bristol, TN-VA	0.04%	17.72%
Johnstown, PA	0.11%	62.60%
Joplin, MO	0.06%	64.19%
Kalamazoo-Battle Creek, MI	0.03%	10.50%
Kansas City, MO-KS	-0.25%	-28.26%
Killeen-Temple, TX	0.04%	35.59%
Knoxville, TN	0.07%	19.70%
Kokomo, IN	0.00%	0.96%
La Crosse, WI-MN	-0.01%	-22.94%
Lafayette, LA	-0.04%	-35.88%
Lafayette, IN	0.00%	1.85%
Lake Charles, LA	0.00%	4.13%
Lakeland-Winter Haven, FL	0.09%	23.36%
Lancaster, PA	-0.02%	-7.84%
Lansing-East Lansing, MI	-0.01%	-6.63%
Laredo, TX	0.01%	35.44%
Las Cruces, NM	-0.01%	-8.45%
Las Vegas, NV-AZ	0.02%	2.81%
Lexington, KY	-0.02%	-12.85%
Lima, OH	0.05%	53.40%
Lincoln, NE	-0.06%	-51.84%
Little Rock-North Little Rock, AR	-0.11%	-35.86%
Longview-Marshall, TX	0.01%	13.90%
Los Angeles-Riverside-Orange County, CA (C)	1.62%	32.25%

MSA	Change in % of all older HH in the MSA due to migration	%Change in % of all older HH in the MSA due to migration
Louisville, KY-IN	0.03%	6.68%
Lubbock, TX	0.03%	22.30%
Lynchburg, VA	0.03%	21.97%
Macon, GA	-0.02%	-10.68%
Madison, WI	-0.08%	-43.45%
Mansfield, OH	0.02%	27.36%
McAllen-Edinburg-Mission, TX	0.05%	29.39%
Medford-Ashland, OR	0.01%	6.41%
Melbourne-Titusville-Palm Bay, FL	0.05%	11.81%
Memphis, TN-AR-MS	-0.15%	-34.78%
Merced, CA	0.03%	52.78%
Miami-Fort Lauderdale, FL (C)	0.00%	-0.17%
Milwaukee-Racine, WI (C)	-0.33%	-36.72%
Minneapolis-St. Paul, MN-WI	-0.67%	-51.32%
Mobile, AL	-0.03%	-7.88%
Modesto, CA	0.06%	39.08%
Monroe, LA	-0.01%	-6.79%
Montgomery, AL	0.00%	-0.47%
Muncie, IN	0.01%	13.22%
Myrtle Beach, SC	0.01%	6.18%
Naples, FL	0.11%	41.58%
Nashville, TN	-0.11%	-16.93%
New Orleans, LA	-0.04%	-8.34%
New York, Northern New Jersey, Long Island, NY-NJ-CT-PA (C)	-1.48%	-19.11%
Norfolk-Virginia Beach-Newport News, VA-	-0.04%	-5.63%
Ocala, FL	0.09%	28.10%
Odessa-Midland, TX	0.02%	20.06%
Oklahoma City, OK	-0.08%	-17.07%
Omaha, NE-IA	-0.11%	-38.01%
Orlando, FL	0.00%	-0.05%
Panama City, FL	0.00%	-1.62%
Pensacola, FL	-0.01%	-4.25%
Peoria-Pekin, IL	0.07%	35.49%
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD (C)	-1.01%	-32.32%
Phoenix-Mesa, AZ	0.04%	2.59%
Pittsburgh, PA	0.33%	21.58%
Portland, ME	-0.08%	-68.20%
Portland-Salem, OR-WA (C)	-0.16%	-15.28%
Providence-Fall River-Warwick, RI-MA	0.18%	36.97%
Provo-Orem, UT	-0.01%	-4.25%
Pueblo, CO	0.01%	11.96%
Punta Gorda, FL	0.07%	34.96%
Raleigh-Durham-Chapel Hill, NC	-0.18%	-31.21%
Reading, PA	0.03%	12.39%
Redding, CA	0.07%	55.43%

MSA	Change in % of all older HH in the MSA due to migration	%Change in % of all older HH in the MSA due to migration
Reno, NV	-0.03%	-18.92%
Richland-Kennewick-Pasco, WA	-0.01%	-11.52%
Richmond-Petersburg, VA	0.03%	6.54%
Roanoke, VA	0.02%	15.54%
Rochester, MN	-0.02%	-30.48%
Rochester, NY	0.34%	63.01%
Rockford, IL	0.01%	4.51%
Rocky Mount, NC	0.01%	13.61%
Sacramento-Yolo, CA (C)	0.22%	25.88%
Saginaw-Bay City-Midland, MI	0.08%	30.65%
St. Cloud, MN	0.01%	10.57%
St. Joseph, MO	0.03%	41.98%
St. Louis, MO-IL	-0.01%	-0.78%
Salinas, CA	0.04%	47.39%
Salt Lake City-Ogden, UT	-0.14%	-27.27%
San Antonio, TX	0.04%	6.05%
San Diego, CA	0.27%	27.73%
San Francisco-Oakland-San Jose, CA (C)	0.53%	20.66%
San Luis Obispo-Atascadero-Paso Robles, CA	0.05%	31.22%
Santa Barbara-Santa Maria-Lompoc, CA	0.11%	64.96%
Santa Fe, NM	0.01%	10.33%
Sarasota-Bradenton, FL	0.27%	38.76%
Savannah, GA	0.01%	9.42%
Scranton--Wilkes-Barre--Hazleton, PA	0.20%	46.44%
Seattle-Tacoma-Bremerton, WA (C)	-0.21%	-14.03%
Sharon, PA	0.08%	85.61%
Sheboygan, WI	0.00%	1.60%
Shreveport-Bossier City, LA	0.04%	16.26%
Sioux City, IA-NE	0.00%	-0.04%
Sioux Falls, SD	-0.03%	-40.76%
South Bend, IN	0.00%	3.26%
Spokane, WA	0.02%	9.04%
Springfield, IL	0.01%	14.24%
Springfield, MO	0.04%	18.29%
Springfield, MA	0.09%	30.27%
State College, PA	0.02%	31.42%
Stockton-Lodi, CA	0.06%	30.03%
Sumter, SC	0.00%	6.16%
Syracuse, NY	0.34%	85.55%
Tallahassee, FL	-0.05%	-35.32%
Tampa-St. Petersburg-Clearwater, FL	0.20%	11.97%
Terre Haute, IN	0.01%	12.30%
Toledo, OH	0.07%	22.84%
Topeka, KS	0.00%	-1.90%
Tucson, AZ	0.11%	19.76%

MSA	Change in % of all older HH in the MSA due to migration	%Change in % of all older HH in the MSA due to migration
Tulsa, OK	-0.09%	-24.58%
Tuscaloosa, AL	0.00%	-5.23%
Tyler, TX	0.05%	42.13%
Utica-Rome, NY	0.20%	101.61%
Visalia-Tulare-Porterville, CA	0.09%	66.89%
Waco, TX	0.04%	36.04%
Washington-Baltimore, DC-MD-VA-WV (C)	-0.88%	-28.34%
Waterloo-Cedar Falls, IA	0.00%	-2.37%
Wausau, WI	0.01%	15.08%
West Palm Beach-Boca Raton, FL	0.28%	29.76%
Wichita, KS	-0.09%	-30.18%
Wichita Falls, TX	0.02%	35.13%
Williamsport, PA	0.05%	69.18%
Wilmington, NC	0.03%	13.25%
Yakima, WA	0.01%	14.75%
York, PA	-0.03%	-10.92%
Youngstown-Warren, OH	0.13%	33.43%
Yuba City, CA	0.03%	46.90%
Yuma, AZ	0.03%	30.13%

Note: Data based on Ruggles et al. (2010) and the results from difference between the Sorting simulation and the Aging-in-Place simulation

Appendix B Chapter 1 Maps in Color

Figure 23. Difference in MSA rank between older and younger HHs (Color)

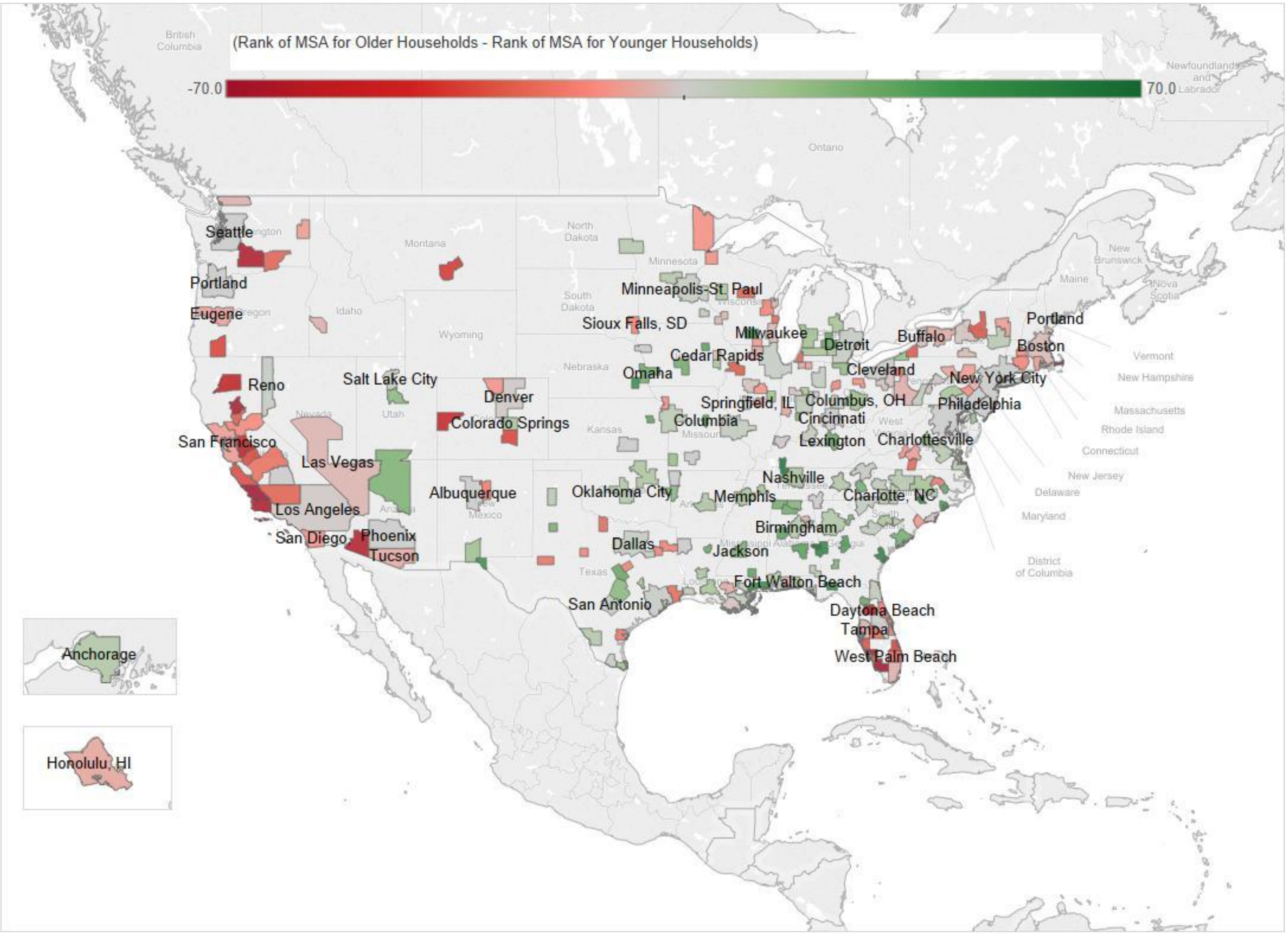


Figure 24. Number of Older HHs in 2010 (Color)

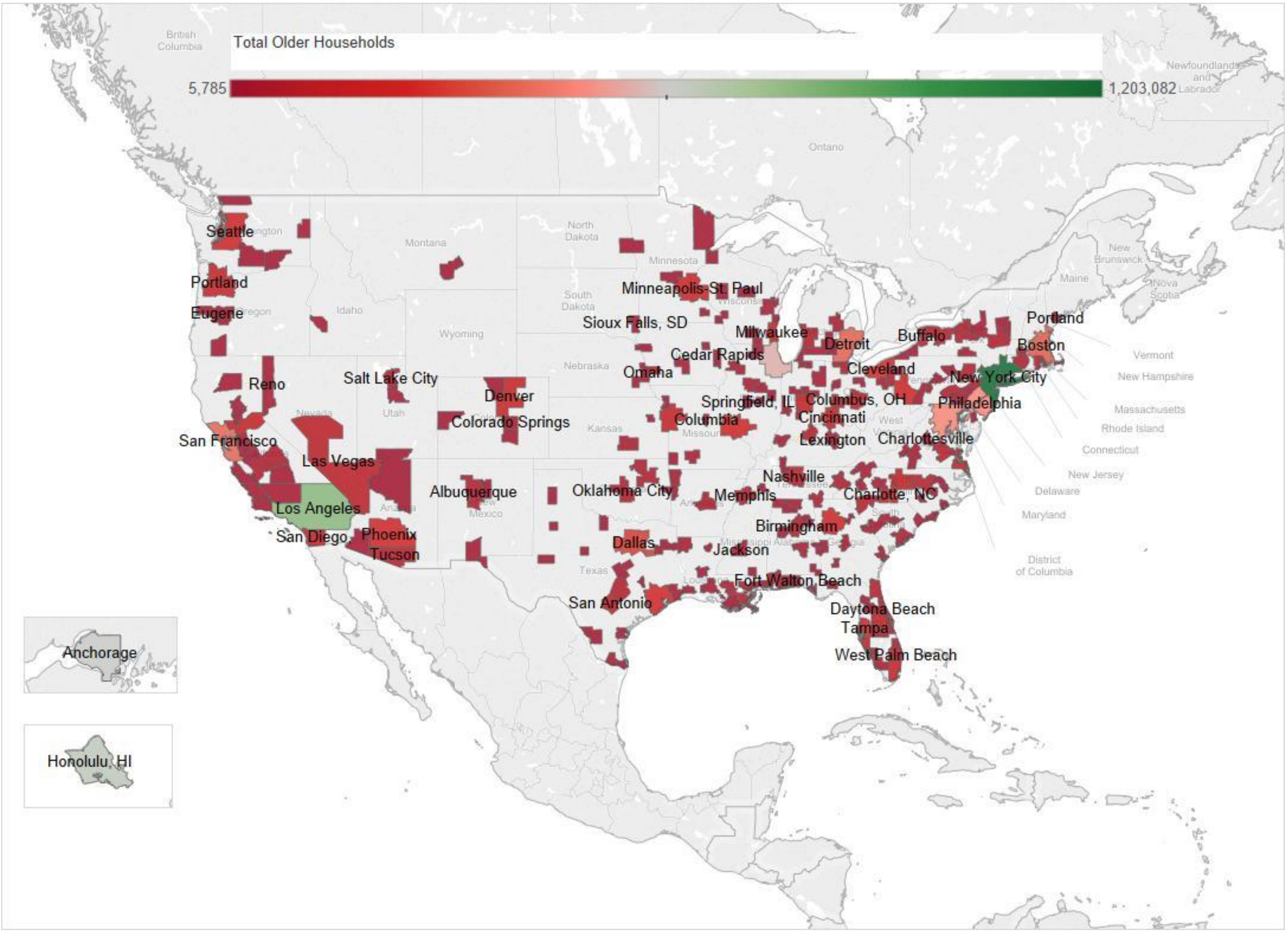


Figure 25. Proportion of MSA's HHs that are older in 2010 (Color)

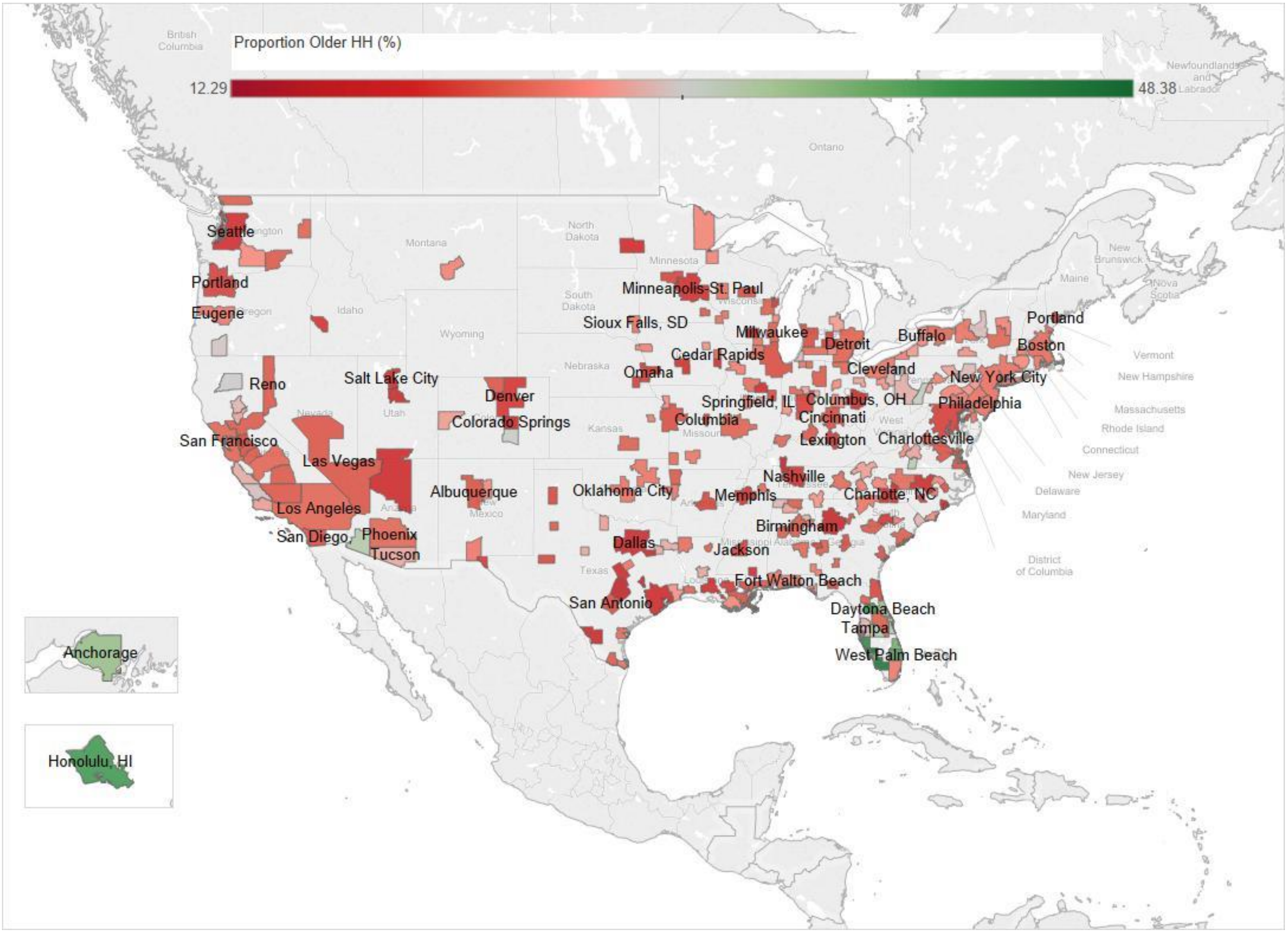
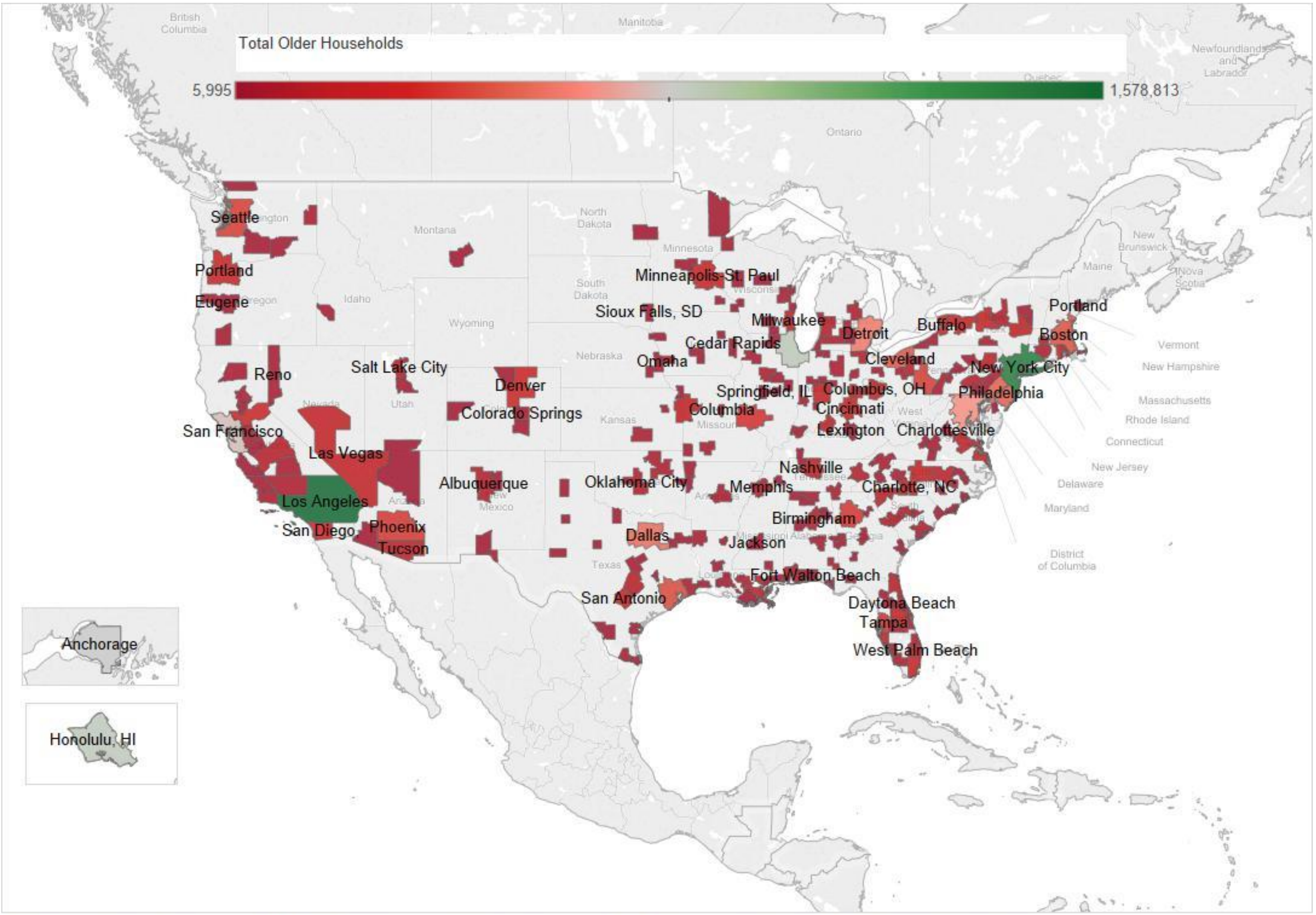
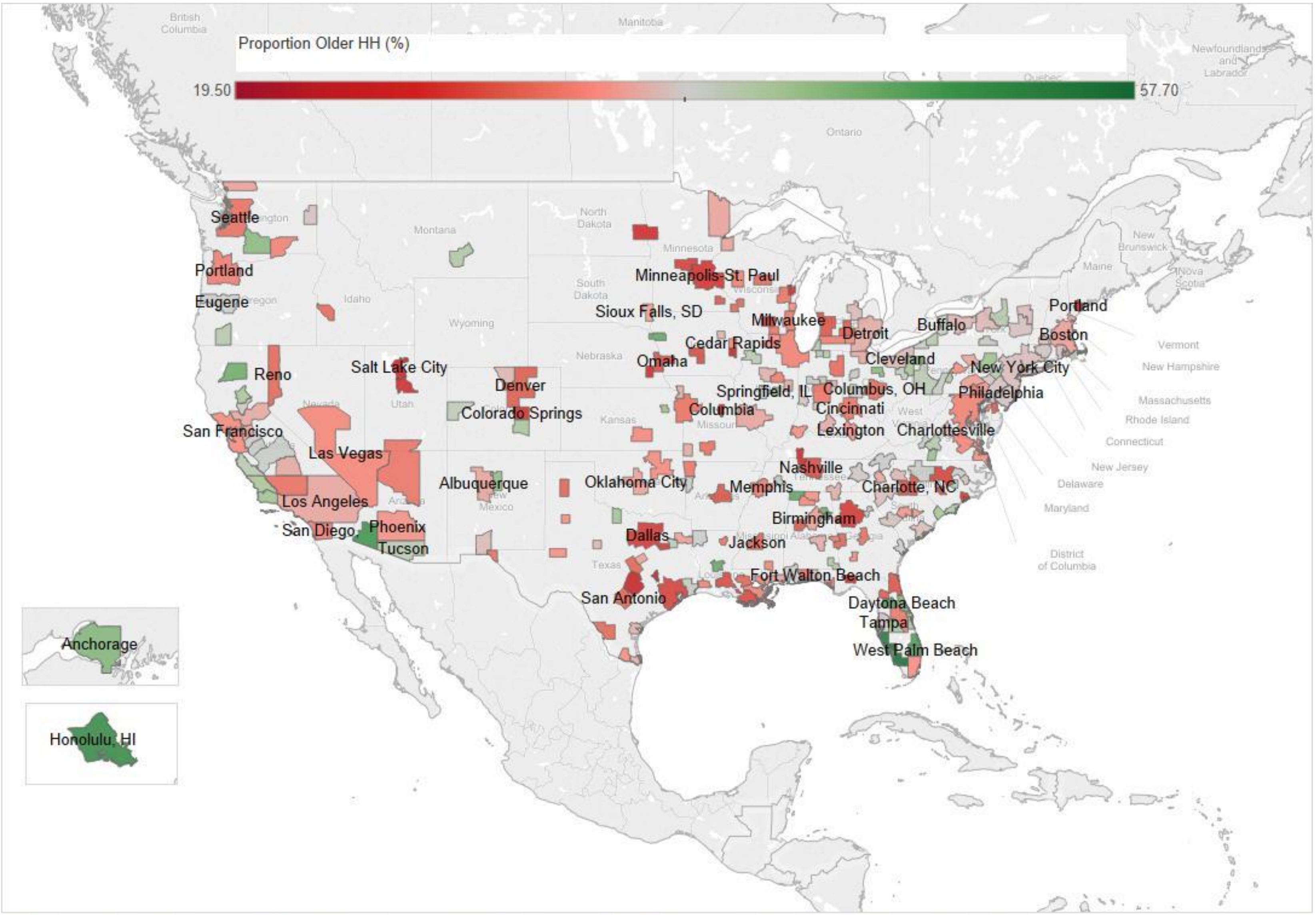


Figure 26. Number of older HHs in 2030 under the sorting simulation (Color)



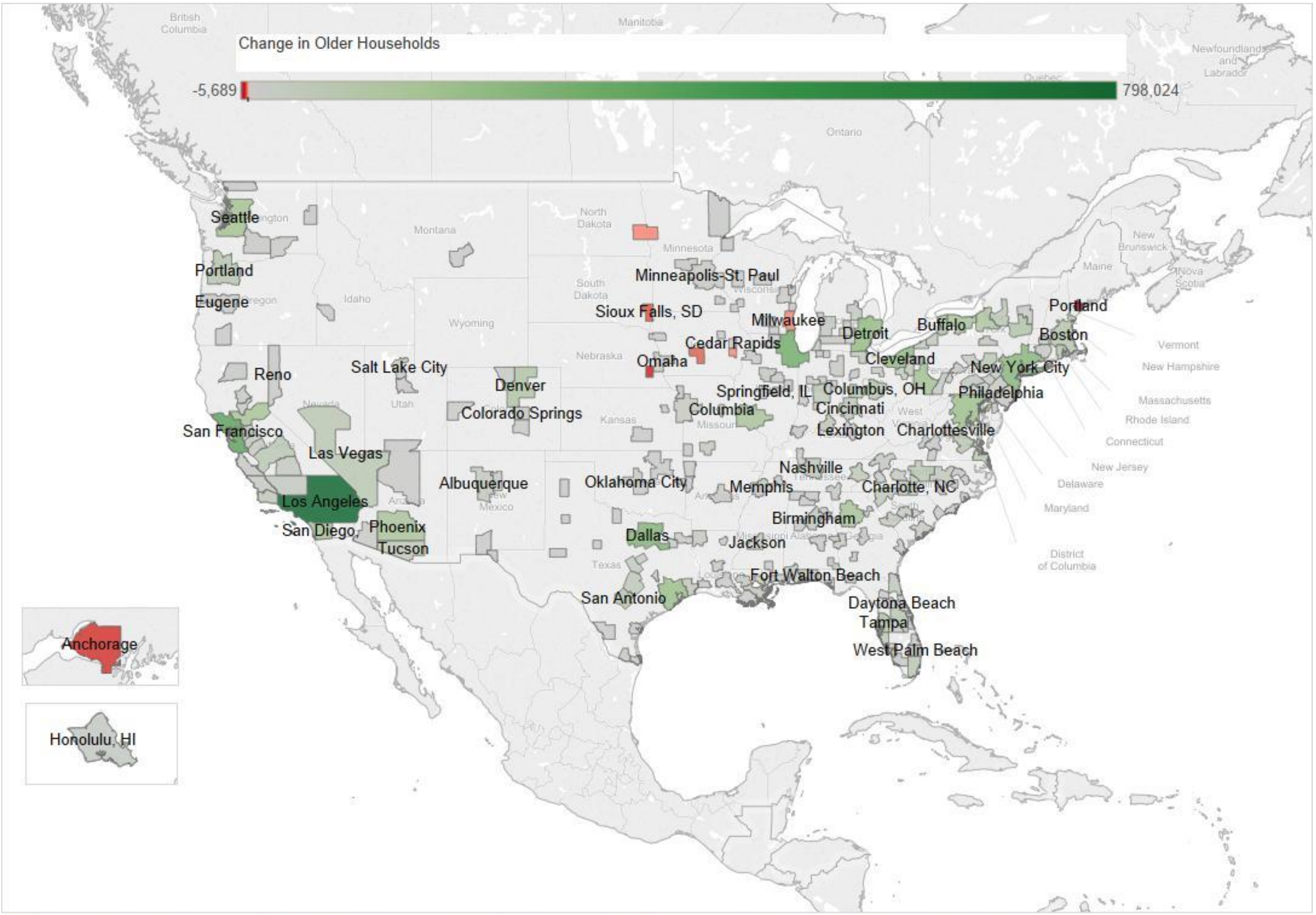
Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 27. Proportion of MSA's HHs that are older in 2030 under the sorting simulation (Color)



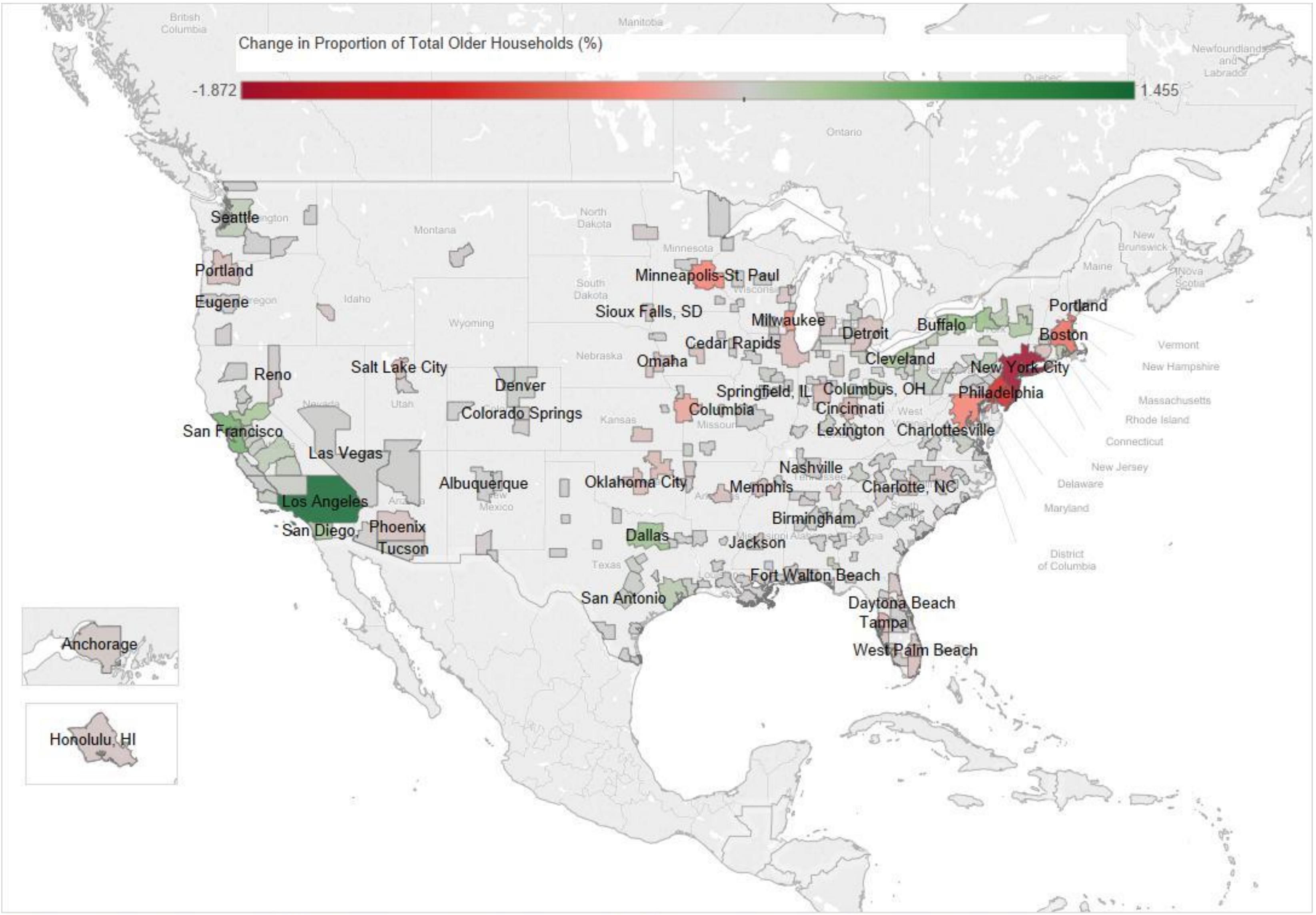
Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 28. Change in number of Older HHs under the sorting simulation (Color)



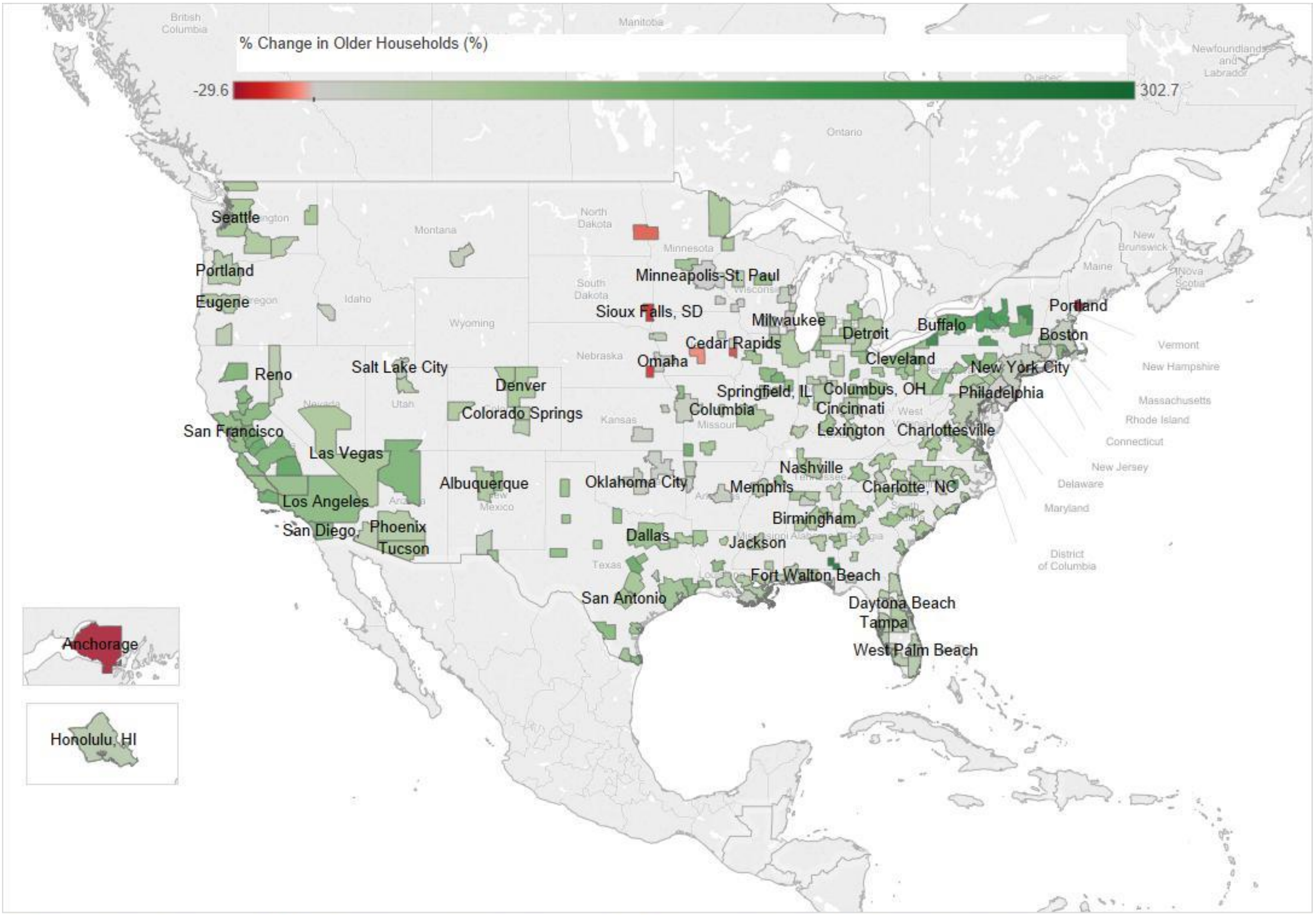
Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 29. Change in % of All US HHs that are Older under the sorting simulation (Color)



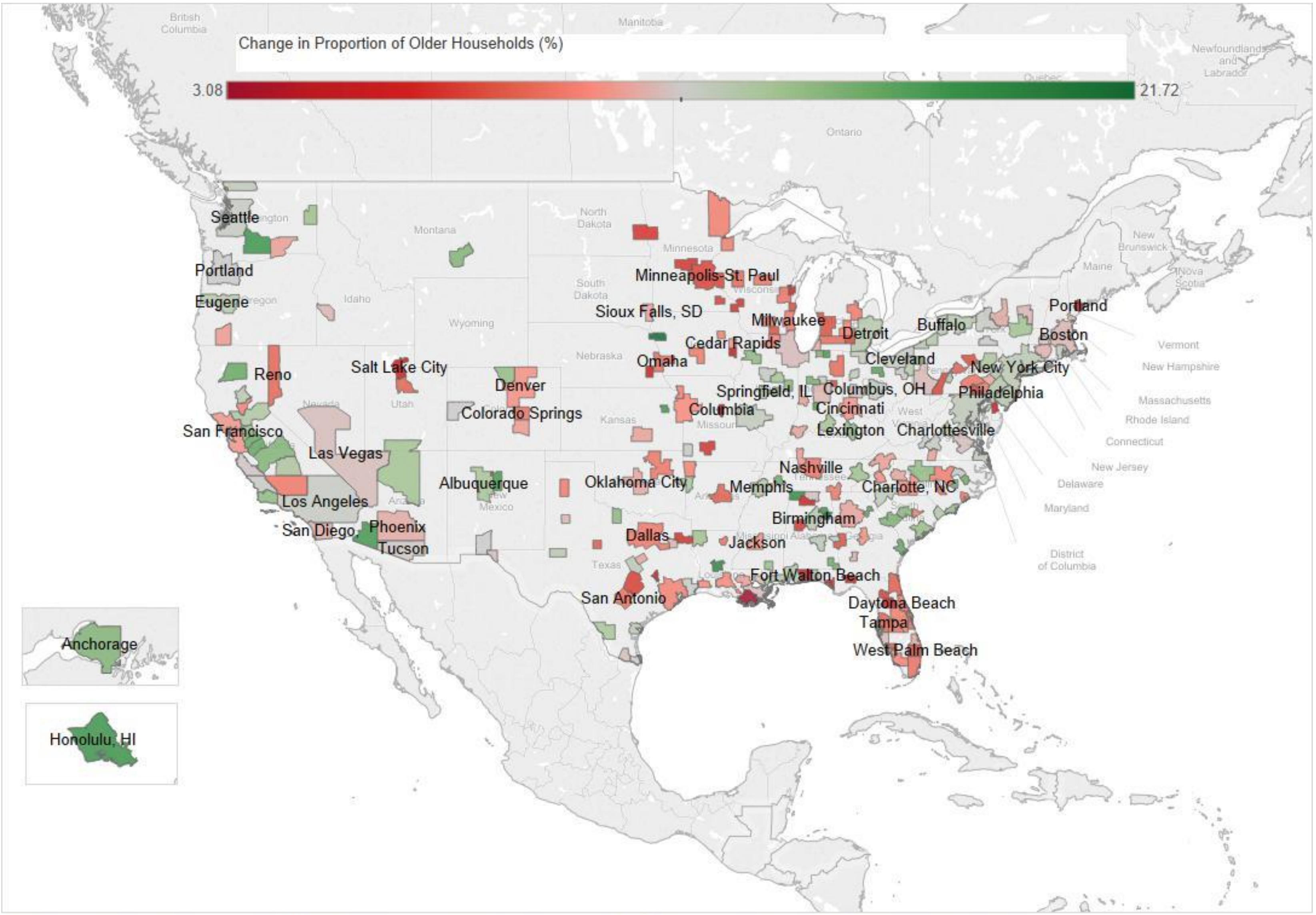
Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 30. % Change in Older HHs under the sorting simulation (Color)



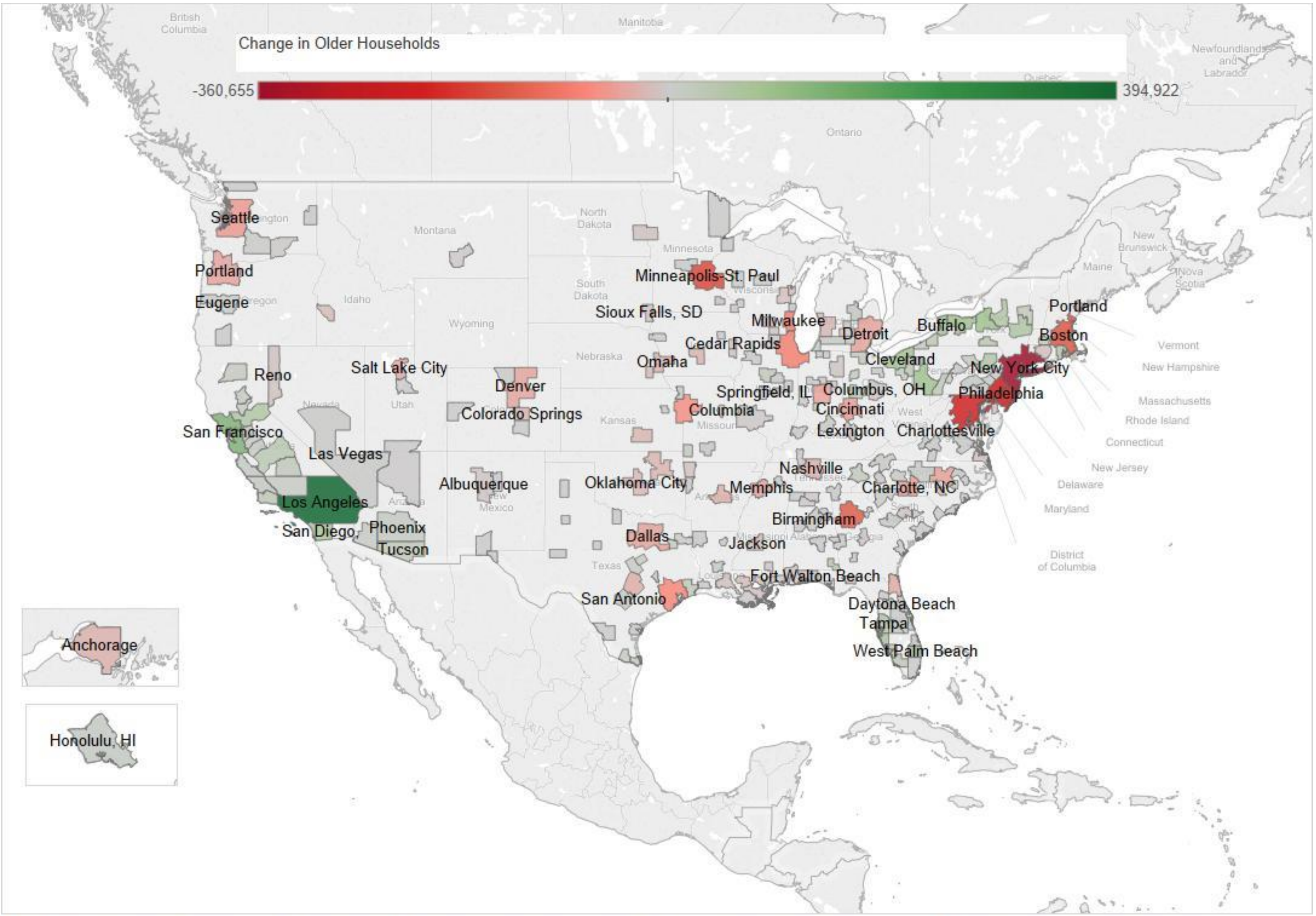
Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 31. Change in % of Older HHs under the sorting simulation (Color)



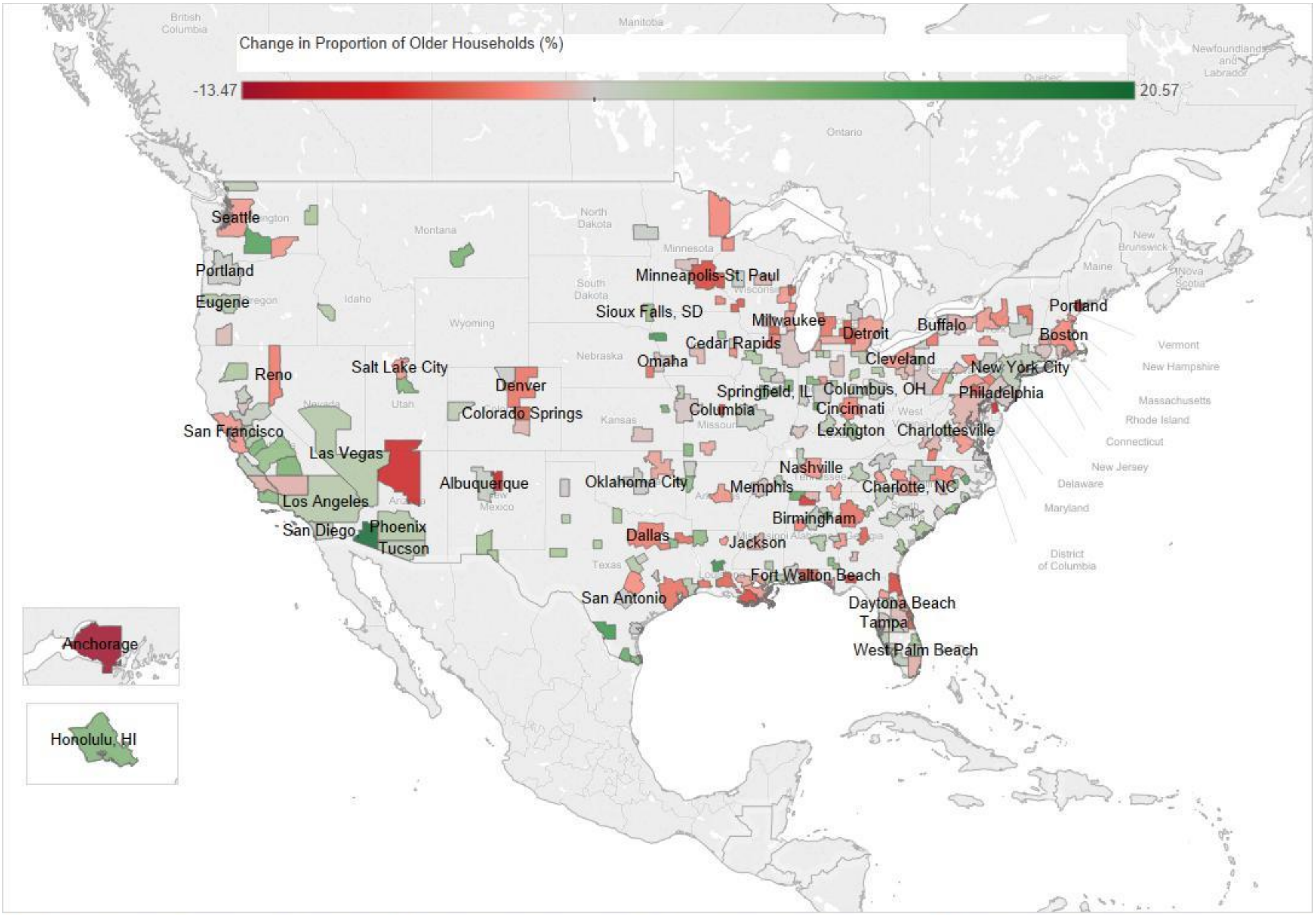
Sorting scenario: Changes to household composition as a result of aging in place and household migration.

Figure 32. Net migration of older HHs (Color)



Migration scenario: Changes to household composition as a result of household migration; total values measure Net Migration.

Figure 33. Change in % of Older HHs due to Net Migration (Color)



Migration scenario: Changes to household composition as a result of household migration; total values measure Net Migration.

Appendix C

Coverage Information for 100 Most Populated Georgia Cities for Chapter 3

Table 37. Coverage Information for 100 Most Populated Georgia Cities

Rank	Name	2012 Pop.	County	Has Exemptions?	Exemption Included in Database?
1	Atlanta	443,775	Fulton, DeKalb	Yes	Yes
2	Augusta	198,413	Richmond	Yes	Yes
3	Columbus	197,872	Muscogee	Yes (Joint)	Yes
4	Macon	155,369	Bibb	Yes	Yes
5	Savannah	142,022	Chatham	Yes	Yes
6	Athens	118,999	Clarke	No	Yes
7	Sandy Springs	99,419	Fulton	Yes	Yes
8	Roswell	93,692	Fulton	Yes	Yes
9	Johns Creek	82,306	Fulton	Yes	Yes
10	Albany	77,431	Dougherty	Yes	Yes
11	Warner Robins	70,712	Houston, Peach	Yes	Yes
12	Alpharetta	61,981	Fulton	Yes	Yes
13	Marietta	58,359	Cobb	Yes	Yes
14	Valdosta	57,597	Lowndes	Yes	Yes
15	Smyrna	52,650	Cobb	Yes	Yes
16	Dunwoody	47,224	DeKalb	Yes	Yes
17	Rome	36,159	Floyd	Yes	Yes
18	East Point	35,584	Fulton	Yes	Yes
19	Milton	35,015	Fulton	Yes	Yes
20	Gainesville	34,786	Hall	Yes	Yes
21	Hinesville	33,751	Liberty	Yes	Yes
22	Peachtree City	34,662	Fayette	Yes	Yes
23	Newnan	34,174	Coweta	No	Yes
24	Dalton	33,413	Whitfield	No	Yes
25	Douglasville	31,269	Douglas	Yes	Yes
26	Kennesaw	30,990	Cobb	Yes	Yes
27	LaGrange	30,478	Troup	No	Yes
28	Statesboro	29,779	Bulloch	No	Yes
29	Lawrenceville	29,481	Gwinnett	Yes	Yes
30	Duluth	27,926	Gwinnett	Yes	Yes
31	Stockbridge	26,281	Henry	No	Yes
32	Woodstock	25,135	Cherokee	Yes	No
33	Carrollton	24,958	Carroll	Yes	Yes
34	Canton	23,791	Cherokee	Yes	No
35	Griffin	23,389	Spalding	Yes	Yes
36	McDonough	22,599	Henry	No	Yes
37	Acworth	21,215	Cobb	Yes	Yes
38	Pooler	20,598	Chatham	Yes	No
39	Union City	20,501	Fulton	Yes	No
40	Decatur	19,853	DeKalb	Yes	Yes

Rank	Name	2012 Pop.	County	Has Exemptions?	Exemption Included in Database?
41	Cartersville	19,810	Bartow	Yes	Yes
42	Sugar Hill	19,681	Gwinnett	Yes	No
43	Milledgeville	19,401	Baldwin	No	Yes
44	Snellville	19,026	Gwinnett	Yes	No
45	Forest Park	18,874	Clayton	Yes	No
46	Thomasville	18,488	Thomas	No	Yes
47	St. Mary's	17,606	Camden	Yes	No
48	Tifton	16,672	Tift	Yes	No
49	Americus	16,393	Sumter	No	Yes
50	Kingsland	16,285	Camden	Yes	No
51	Suwanee	16,253	Gwinnett	Yes	No
52	Dublin	16,215	Laurens	No	Yes
53	Fayetteville	16,206	Fayette	No	Yes
54	Calhoun	15,812	Gordon	Yes	Yes
55	Chamblee	15,790	DeKalb	Yes	No
56	Brunswick	15,640	Glynn	No	Yes
57	Norcross	15,632	Gwinnett	Yes	No
58	Riverdale	15,493	Clayton	Yes	No
59	Conyers	15,408	Rockdale	Yes	No
60	Perry	14,730	Houston	Yes	No
61	College Park	14,649	Fulton, Clayton	Yes	No
62	Moultrie	14,506	Colquitt	No	Yes
63	Waycross	14,322	Ware	Yes	Yes
64	Winder	14,271	Barrow	No	Yes
65	Powder Springs	14,253	Cobb	Yes	No
66	Villa Rica	14,226	Carroll, Douglas	Yes	No
67	Fairburn	13,720	Fulton	Yes	No
68	Monroe	13,349	Walton	No	No
69	Covington	13,347	Newton	Yes	No
70	Cusseta	13,037	Chattahoochee	Yes	No
71	Buford	12,735	Gwinnett, Hall	Yes	Yes
72	Bainbridge	12,603	Decatur	No	Yes
73	Lilburn	12,266	Gwinnett	Yes	No
74	Grovetown	12,210	Columbia	No	Yes
75	Dallas	12,044	Paulding	No	Yes
76	Douglas	11,834	Coffee	Yes	No
77	Cordele	11,297	Crisp	No	Yes
78	Loganville	10,646	Walton, Gwinnett	No	Yes
79	Vidalia	10,609	Toombs, Montgomery	No	Yes
80	Richmond Hill	10,452	Bryan	Yes	No
81	Jesup	10,452	Wayne	No	Yes
82	Cairo	10,268	Grady	No	Yes
83	Cedartown	9,821	Polk	yes	No
84	Fort Valley	9,775	Peach	No	Yes
85	Holly Springs	9,721	Cherokee	Yes	No
86	Jefferson	9,667	Jackson	Yes	Yes

Rank	Name	2012 Pop.	County	Has Exemptions?	Exemption Included in Database?
87	Fort Oglethorpe	9,601	Catoosa	Yes	No
88	Rincon	9,446	Effingham	Yes	No
89	Thomaston	9,198	Upson	No	Yes
90	Fitzgerald	9,070	Ben Hill	Yes	No
91	Garden City	9,048	Chatham	Yes	No
92	Doraville	8,913	DeKalb	Yes	No
93	Toccoa	8,482	Stephens	No	Yes
94	Braselton	8,404	Jackson	No	Yes
95	Clarkston	7,875	DeKalb	Yes	No
96	Swainsboro	7,733	Emanuel	No	Yes
97	Centerville	7,599	Houston	Yes	Yes
98	Hampton	7,531	Henry	No	Yes
99	LaFayette	7,098	Walker	No	Yes
100	Auburn	7,076	Barrow	Yes	No

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Vita

Ryan Douglas Mickey was born on May 28, 1985 in Atlanta, GA. He graduated cumma sum laude with a B.A. in Economics from Georgia College & State University in 2008. As a senior, Ryan was chosen as the outstanding economics major at GCSU, and his senior thesis, "The Impact of a Seller's eBay Reputation on Price", won the Frank W. Taussig Article Award from Omicron Delta Epsilon and was published in *The American Economist* in 2010. Upon graduation, Ryan worked in financial planning and investment management in Charlotte, NC for almost a year and a half and then as an analyst in foreign exchange the sixth months prior to graduate school.

Ryan entered the doctoral program in economics in the Andrew Young School of Policy Studies at Georgia State University the fall of 2010. During his first two years at GSU, he held a number of assistantships including a year serving as an economics tutor and writing mentor to visiting Indonesian Master's students. In the Fall of 2012, Ryan was awarded a University Fellowship and began working with Dr. Michael K. Price on a project examining the impact of norm-based messaging on household adoption of energy efficient technology as well as several projects investigating the motivations for charitable giving. In his last year of graduate school, Ryan served as a graduate research assistant to Dr. H. Spencer Banzhaf on a project investigating the impact of local homestead exemptions targeting older households on the demographic makeup of tax jurisdictions and on the relative levels of housing capital consumed by older and younger households. During his graduate studies, Ryan presented his work at the Southern Economics Association's annual conference. Ryan also served as the Vice President of the Economics Graduate Student Association from Fall of 2013 to the Summer of 2014.

Georgia State University awarded Ryan a M.A. in Economics in 2013 and a Ph.D. in Economics in 2015. In August of 2015, Ryan began work as an Assistant Professor of Economics at Maryville College in Maryville, TN.