Essays in Identity and Urban Economics

by

Bert Lue

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Economics)
in the University of Michigan
2015

Doctoral Committee:

Professor Charles Brown, Co-Chair
Associate Professor David Albouy, University of Illinois, Co-Chair
Professor Mary Corcoran
Professor Melvin Stephens, Jr

TABLE OF CONTENTS

LIST OF FIGURES

Figure

LIST OF TABLES

Table

LIST OF APPENDICES

Appendix

ABSTRACT

This dissertation explores aspects of identity choice and change in an economic context, and how choice of location can help predict "quality of life".

The first chapter studies the malleability of race for those that are mixed-race. Many modern surveys that collect demographic information now allow one or more racial categories to be chosen for one person. I construct a simple model of racial identity choice which implies that cultural and socioeconomic factors will influence the racial choices of those with multiracial ancestry. I then use nationally representative data on Americans from the Census and the American Community Survey (ACS) to show supportive evidence that factors such as region, year, age, employment, and wages are associated with race selection among this population. I claim that these findings will be increasingly important as the mixed-race population grows, since measuring socioeconomic outcomes of multiracial groups may be complicated if these same socioeconomic outcomes influence self-reported race.

The second chapter examines relative group size, or whether a group is in the minority, an aspect of social identity that is changeable. We study how laboratory-created majorities and minorities interact, and how changing relative group size affects behavior. Our novel design allows us to examine whether two groups of unequal size exhibit differences in levels of trust and of trustworthiness and test whether causing the majority group to become the minority group, and vice-versa, changes behavior. We find that real-world majority race interacts with laboratory-created minority identity. In a trust game, where two individuals are partnered

and pass tokens with real money value back and forth once, White subjects in lab minorities pass and return more when compared to White subjects in lab majorities while the behavior of non-White subjects does not differ by relative group size. We also find that subjects do not change their behavior when their relative group sizes change; behavior is driven by initial group size differences.

In the third chapter we examine variation in local rents, wage levels, commuting costs, household characteristics, and amenities for 2071 areas covering the United States, within metropolitan areas, by density and central-city status. We demonstrate the sensibility of estimating wage levels by workplace, not residence, and recover decentralized rent gradients that fall with commuting costs. We construct and map a willingness-to-pay index, which indicates the "quality of life" typical households receive from local amenities, when households are similar, mobile, and informed. This index varies considerably within metros, and is typically high in areas that are dense, suburban, sunny, mild, safe, entertaining, and have elevated school-funding.

CHAPTER I

Mark one or more: Identity choice among multiracial individuals

1.1 Introduction

The growing non-white populations and increasing prevalence of interracial marriage[1] have led to changes in how race is viewed and categorized in the Unites States. These demographic shifts have even changed how the government recognizes race. Starting with the 2000 Census, in a change from previous years, individuals have been allowed to select more than one major race category to report how they identify their race.[2] Other government surveys and documents, such as the Current Population Survey (CPS) and the US standard birth certificate, now use this "check all that apply" method to measure race.[3] Comparisons of outcomes and characteristics across racial groups are complicated by these new, but more informative, additional race combinations.

While there are many alternative ways to define the mixed-race population, all of the various measures used in this paper support the fact that the mixed-race population is growing in the US.[4] Data from the 2000 census and the 2001-2013 American Community

[1] See Fryer, Jr. (2007) for a detailed exploration.

[2] Racial identity, how an individual views her own race, does differ from reported race, how an individual declares that race, but for this work I follow convention and assume individuals intend to truthfully report racial identity as there are no clear incentives to misreport race on informational surveys such as the Census.

[3] The CPS reflected this change starting in January 2003 and the US Standard Certificate of Live Birth was updated that same year, although the new standard certificate is only as of 2015 being utilized in all 50 states.

[4] These alternative measures are defined and discussed in Section 1.3.

Survey (ACS) show that the population of non-Hispanic individuals who self-report as two or more races has increased over the past decade.[5] Figure 1.1 illustrates this by showing the population of non-Hispanic individuals in the US who self-identify as biracial.[6] The size of this group is growing, in both relative and absolute size. A Pew Research Center report (Wang, 2012), also using ACS data, shows that in 2010 "9% of Whites, 17% of Blacks, ... and 28% of Asians married out [of their race]" so it is reasonable to expect the growth in this population to continue.

This growing population presents a challenge beyond just augmenting existing race related analysis to include additional mixed-race categories. A further complication arises as individuals with ancestors of different races may not choose to identify with or report all their racial ancestries. Parents with races different from their partners may declare their biological children to be the race of the mother, father, or a combination of both (Brunsma, 2005 and Xie and Goyette, 1997). Adults with ancestors from different racial groups have also been shown to choose among all permutations of their racial ancestry when declaring race (Goldstein and Morning, 2000). One particularly prominent example of this in America is President Barack Obama, the son of an Black African immigrant and a White American from Kansas. Obama publicly identifies as Black; his spokesman famously announced that the President had checked only "Black" in response to the race question on the census (Roberts and Baker, 2010).

While race is generally viewed in the economics literature as an immutable trait, there is some flexibility in this characteristic as race, through self-report, appears to vary among individuals with multiracial ancestry. This study uses nationally representative data and finds that cultural climate and socioeconomic status are strongly correlated with race selection among mixed-ancestry Americans. I construct a model to explain how these factors

[5]I use the term "self-report" here even though responses may have been given by the head of household or anther person filling out the survey on behalf of a household member. This is because the race question is worded to elicit the self-identified race of the person being documented on the survey: "indicate what [race] this person considers himself/herself to be." See Figure 1.2.

[6]Latinos are not addressed in this work due to Hispanic identity being captured by a question separate to racial identity. Bureau of the Census (2001) reports that an overwhelming majority of people who self-reported as "some other race" in the 2000 Census also self-reported as Hispanic; this is believed to have occurred because of the lack of a Hispanic race option. Of the 15.4 million individuals who declared "some other race," 97% of those also declared as Hispanic (Perez and Hirschman, 2009). 48% percent of Hispanics self-reported as white alone while 42% percent self-reported as "some other race" alone.

may influence race selection and show empirical evidence that is consistent with this model. Finally, I discuss limitations of the data and alternative explanations that could also be driving these results.

1.2 Literature

Akerlof and Kranton (2000) brought social identity to prominence within the economics literature. Their general model brings identity choice into the utility function through norms; utility increases when an individual's actions and characteristics more closely match with the norms of the identity she chooses. Work like that of Darity, Jr. et al. (2006) elaborates on how racial identities may be formed, recognizing that there are norms associated with race.

The study of mixed-race identity is relatively new to economics, but has had a presence in the sociology literature for some time. Goldstein and Morning (2000) point out many of the difficulties in measuring the mixed-race population. They argue that the set of self-reported multiracial individuals is a subset of individuals who are aware of their mixed-race ancestry, and that this set of people that are aware of their mixed-race ancestry is itself a subset of the entire mixed-race population. Continuing in this vein, Gullickson and Morning (2011) go beyond self-report and attempt to identify a more complete sample of the mixed-race population by looking at ancestry responses on the 2000 Census. The authors categorize heads of households by mapping ancestry to "biological" race and then examine how different mixed-ancestry household heads report their race, finding that a larger proportion of individuals with Black/White ancestry declare as Black rather than Black/White or White. I follow their technique of mapping ancestry to race and use this mixed-ancestry population as a proxy for the mixed-race population in the US.

Recent economic work has examined how ethnic identity and economic factors are related. Work on identity choice among ethnic minorities and immigrants finds that identity choice is correlated with experiences. Constant (2014) provides an overview of the economic research on the relationship between immigrant ethnic identity and labor market outcomes. She summarizes some theoretical and empirical work that hypothesizes that ethnic identity choice has an effect on labor market outcomes through choice of job, choice of career, and job networking opportunities. Battu and Zenou (2010) find that "oppositional identities," identities that reject the local dominant culture, and employment are negatively correlated for ethnic minorities. Constant et al. (2009) describe a one dimensional "ethnosizer," a constructed measure of five elements that describes an individual's ethnic identity. At one end is commitment to an immigrant's host country and at the other is commitment to country of origin. This setup is similar to the model I use here, but I replace differing ethnic identities with differing racial identities.

Beyond general economic factors, significant life events can also shape racial perceptions. Saperstein and Penner (2010) provide evidence that incarceration strongly shapes the answers to self-reported identity questions, and also how an individuals' race is perceived by others. They use data from the 1979 National Longitudinal Survey of Youth (NLSY) and find that respondents who have been incarcerated are both more likely to be seen by others as Black as well as self-identify as Black. Although spending time in prison is quite a significant life event, this work provides strong evidence that self-reported race, and even race as perceived by others, is malleable.

Changes in culture and policy outside of an individual's direct control have also been shown to influence self-identification of race. Mason and Matella (2014) find that individuals of Arab ancestry in the US were less likely to self-report as White after 9/11. Antman and Duncan (2014) find evidence that self-identified race can be affected by changes in state-level affirmative action policies for education and employment.

The wage and skin tone literature also relates to this study, as phenotype is one factor that may plausibly influence mixed-race and monoracial identity choice as well as economic outcomes. The literature is quite consistent in the finding that darker skin color does lead to lower wages, both among African-Americans (Goldsmith et al., 2007) and immigrants of all races (Hersch, 2008 and Hersch, 2011).

However, Francis and Tannuri-Pianto (2013) use data from college students in Brazil and find that conditional on skin tone, socioeconomic status does have an influence on racial self identification, particularly for those on the skin tone continuum near racial boundaries. Brazil's standard race question, used by Brazil's Census equivalent, includes five categories:

Branco (White), *Pardo* (Brown), *Preto* (Black), *Amarelo* (Yellow or Asian), and Indigenous. The largest two race categories in 2010 were Whites and Browns. While the Brazilian racial climate may differ significantly from that of the US, this work shows that racial self-categorization depends on more than phenotype and skin tone. This work also finds an effect of affirmative action on racial self-categorization, with darker skinned Brazilians more likely to declare as Black after the implementation of Affirmative-action racial quotas.

There are also some works in the economics literature examining how the endogeneity of self-reported race and ethnicity and may affect measures of outcomes in certain groups. Duncan and Trejo (2011a) examine this issue in the US, focusing on Mexican identity and education. They use Current Population Survey (CPS) data which has information about parents' country of birth, and use this to identify "true" race and ethnicity, rather than relying on self-report of race and ethnicity. They examine the intergenerational transmission of ethnic identity among Mexican Americans, coming to the conclusion that selective intermarriage causes the achievement gap between Mexicans and Whites to be overstated, as highly educated Mexicans are less likely to maintain their Mexican ethnic identity. For their purposes they treat all individuals with some Mexican ancestry as fitting into the Mexican-American group, which certainly makes sense in the context of assimilation (where different groups intermarry and assimilate into American society). However, there is an implicit assumption in this work that having some Mexican ancestry defines an individual as Mexican. I take a different approach and recognize that some individuals may specifically choose a mixed categorization.

Duncan and Trejo (2012) apply their previous methodology for looking at ethnic attrition among Mexicans to racial attrition among Asians. The authors report that after the after the 2003 change to the CPS race question, allowing for selection of more than one category for race, Asian racial attrition decreased. Like the work on Mexican ethnic attrition, their definition of racial attrition is different from the idea of race mixture we look at here. The authors characterize the choice of individuals with any degree of Asian ancestry to not self-report as Asian race as attrition, but do not apply the same thinking to the majority White group.

Biracial Black/Whites adolescents have received particular attention in recent economic work. Fryer, Jr. et al. (2012) use a "strict" definition of biracial identity[7] and find that biracial children engage in more risky behaviors in order to fit in with monoracial groups. Ruebeck et al. (2009) recognize the potential endogeneity of biracial identity, and use a definition of mixed-race based on racial ancestry. They find that biracial adolescents take actions that fit with both White and Black groups, and that the variance in their behavior is greater than that of either monoracial group.

Fairlie (2009) is one of the first economics papers to examine wage gaps for biracial people in the United States. Using data from the 2000 Census, the author finds that wages for biracial Blacks and monoracial Blacks are roughly 12% and 14% lower, respectively, than those of Whites. Although the gap between biracial Blacks and monoracial Blacks is statistically significant, biracial Black wages are lower than the average of monoracial Black and monoracial White wages. Fairlie presents this finding as evidence for the "one-drop" rule. However, this study uses only self-reported race from the Census and results may be affected by selection into or out of biracial Black identity.

Economics work on factors that may influence identity choice and affect measures of labor market outcomes of mixed-race individuals is relatively new; this population is young and individuals are hard to identify without large data sets. While there is one paper, Fairlie (2009), that explicitly looks at mixed-race wages, much of the other work deals solely with the endogeneity of identity choices. This paper attempts to bridge between the two together, but first it is necessary to discuss how new category choices may change how we speak about race.

1.3 Defining Race

The change of Census racial categorization, such as this recent change in the 2000 Census to accommodate mixed-race groups, is not without precedent. Hochschild and Powell (2008) document the volatility of Census racial categorization from 1890 to 1930. During this period, race categorization changed often. There were once measures of racial mixture on the Census based on antiquated terminology like Mulatto, Quadroon, and Octoroon. A

[7] The authors use panel data and their "strict" measure defines an individual as multiracial if she identifies as such each time she is observed in the data.

particularly interesting case is that of South Asians, who started out being classified as White, then as a separate category, "Hindus,"[8] and finally grouped with Asians as they are today. This volatility in race categorization lasted until the 1930 Census, where the major racial categories that we now use (White, Black, Native American, as well as various Asian nationalities) were implemented. Prior to 2000, respondents were asked to choose only one race category, making it difficult to record self-reported racial mixture.

For the purposes of this paper, I treat race as a social construct. While an individuals' continent of ancestry can be identified with some degree of accuracy from genetic markers (Jorde and Wooding, 2004), socially accepted categorizations of race can change often, as illustrated above, and do not align perfectly with genetic differences. Bamshad et al. (2004) find that when grouping a diverse sample of individuals into the five race categories used by the Office of Management and Budget (OMB)[9], a person will be genetically more similar to a randomly chosen person from the same race group than to a randomly chosen person from a different race group only two-thirds of the time, and that this chance would likely have been lower had they used more genetically admixed populations like African-Americans and South Asians in their sample.

Although not precisely categorized according to genetic differences, racial groups are still important as people actively use these groups to define themselves and others. In addition, questions about how these categorizations may relate to labor market outcomes has lead to an important literature in economics on discrimination.[10] When I speak about race mixture I speak about individuals crossing over these socially constructed boundaries that are passed on by birth. An individual's race categorization is a complex product of societal attitudes, life experiences, and phenotype, and it is important to understand how the growing population of multiracial individuals, or individuals who are born of two (or more) racial groups, exist within or outside of these boundaries. This work sheds some light onto the complexities

[8]Hochschild and Powell point out that the majority of the South Asians in the United States at this time were actually Sikhs.

[9]This categorization guides the collection of data on race and ethnicity for all Federal data. While OMB encourages the collection of greater detail, the minimum five race categories are: American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or Other Pacific Islander, and White (Office of Management and Budget (1997))

[10]Please refer to the seminal work of Becker (1971) or a more recent overview by (Charles and Guryan, 2011)

of the taxonomical challenges that economics work on discrimination, Charles and Guryan (2011), is beginning to seriously consider.

In order to discuss these issues I need to be clear about the terminology I will be using in this study. First, I will define different distinct monoracial groups. Similar to the current Census classification, these categories will be White, Black, Native American, Asian, and Other.[11] I recognize that race is a social construct, and one that changes in definition over time. For this study I use these aforementioned accepted modern American definitions to classify race. Starting with these distinct monoracial groups, it is possible to construct various definitions of multiracial individuals.

One way to define an American as multiracial is to rely solely on their self-reported race and classify individuals as multiracial only if they choose to self-identify as such.[12] As race is a subjective identity category, I make no claim about how individuals of mixed-ancestry should identify, only that this population is one where racial classification seems to be more flexible (Khanna, 2011). This definition is the easiest to measure, especially with recent changes to the Census and other surveys that allow for more than one racial category to be chosen simultaneously. The main issue with reporting group characteristic differences based on this definition of multiracial is that individuals may select into multiracial identity because of plausibly mutable factors like racial climate or labor market outcomes. In other words, this potential endogeneity of race complicates how outcomes by race may be measured.

Alternatively, multiracial individuals can be defined as those who have ancestors that would be considered to be from at least two different monoracial groups. This definition seems useful when thinking about individuals with monoracial parents from different races, but this definition also captures individuals with some distant racial ancestry that may not relate to the person's current racial identity at all. From genetic studies, many African-Americans are found to have some European ancestry,[13] but it may not make sense to think

[11] I collapse the various specific Asian and Pacific Islander nationalities into one category, Asian. Everything that doesn't fit into White, Black, Native American, and Asian is put into the Other category; this includes write-in values that cannot easily be mapped to a race category using the method described in Appendix B

[12] The way questions are constructed may greatly influence responses that are collected. Surveys that allow for multiracial self-identification can be worded in different ways. Voluntary self-identification through an "other" or write-in category, as in the 1990 Census, may result in lower counts of multiracials than self-identification through a "mark one or more" method, used by the 2000 Census.

[13] Tishkoff (2009) sample different urban African-American populations and find that the average percent

of this group as multiracial in the same way we think of an individual with parents of two different races as multiracial. Being African-American implies Black race in the US and the two terms are used interchangeably, even on the Census. This definition of multiracial based on racial ancestry is of course difficult to use, as it requires having information on the races of all of an individual's ancestors.

For this study, I use a definition of mixed-race based on who it would be currently socially acceptable to identify as mixed-race in America. A person with solely European racial ancestry would not be thought of as Black by today's American definition of race. Likewise, a person with only Chinese ancestors would be viewed as monoracial Asian. However, an individual with one Asian and one White parent could be considered by others in America as Asian, White/Asian, or White (Xie and Goyette, 1997). While socially acceptable seems like an ill-defined criteria, the entire concept of race is really defined in this way.[14] The time component of this definition is particularly important, as evidenced by changes in the Census categorization of race over the past 100 years.

1.4 Data and Measuring Race

For the main analysis I use data from the 2001-2013 American Community Survey (ACS) compiled by Ruggles et al. (2010). This survey represents approximately 0.4% of the population from 2001-2004 and 1% of the population from 2005 and on. The large sample size and high response rate on ancestry[15] make this data ideal for my research method. The large sample size is needed to pick up enough mixed-race respondents for analysis, smaller surveys tend not to have many mixed-race subjects because of the relatively small size of the population, and the ancestry question is key to my strategy of counting additional mixed-race individuals. For the bulk of the analysis, I restrict the sample to non-Hispanic, native-born

of European ancestry is 14% among these groups.

[14]Modern humans originated in Africa around 200,000 years ago and began to spread out over the globe about 70,000 years ago (Klein, 2009). Current racial definitions could be described as groupings based on where the majority of ones' ancestors lived after this migration, and as research on historical Census categorizations of race show, these groupings have changed within the United States over time (Hochschild and Powell, 2008).

[15]There is am 89.1% response rate to the ancestry question for these years of the ACS compared to 78.4% on the 2000 Census.

adults, ages 25-54.[16]

With my definition of mixed-race, it is clear that relying on self-reported race alone will not provide the multiracial population I wish to study. The Census and ACS measure race by asking "What is this person's race? Mark one or more races to indicate what this person considers himself/herself to be"(Figure 1.2). Individuals may choose to select into and out of multiracial identity based on many different factors, so the population that self-identifies and self-reports as multiracial is only a subset of the population of those for whom it would be socially acceptable to classify as mixed-race.

While race is a potentially subjective category for certain groups, ancestry, particularly as it is collected on the Census and ACS, can be viewed as a more objective measure. The question in these surveys is "What is this person's ancestry or ethnic origin?" (Figure 1.3). This question asks for an objective answer, rather than the race question which uses the subjective language "considers himself/herself to be." I follow the ideas set forth in the sociology literature by Gullickson and Morning (2011) and use ancestry data as a way to capture a larger mixed-race population.

An important note on the ancestry data is that prior to 2010, the Census Bureau only accepted race and ethnicity related responses, such as "White/Caucasian," as ancestry responses if these were the only ancestry answers provided. This means that an individual who responded with two ancestries such as "Chinese" and "White/Caucasian" would only have "Chinese" recorded for their ancestry. In order to make the data comparable across all years of the 2001-2013 sample, I continue to censor "White/Caucasian" when used in combination with other ancestry responses for 2010-2013. This is discussed in detail in Appendix B.

In order to translate ancestry answers into measures of racial background, I classify ancestry in the same way that the Census classifies write-in answers to the race question. The major difficulty comes from responses like "American" which are not strongly associated with any one race. Answers that cannot be mapped cleanly to a certain race are categorized as "Other" when calculating racial ancestry.

One concern with this technique is that ancestry may not be strongly associated with

[16] As discussed earlier, Hispanic status is elicited separately from race, see Figure 1.4. Immigrants may have different norms attached to race than native born Americans.

race in each individual case. For example, a Black American, with two Black parents who emigrated from Ireland, may be incorrectly identified using ancestry as a proxy for race. This individual may self-report race as Black while listing "Irish" and "African" ancestries. According to the ancestry coding method used here, this individual would be classified as self-identified Black race with Black/White mixed-ancestry even if her parents also self-identified as Black. This should not be a significant problem because the question about ancestry is worded so that the answer is an objective measure, and there is a strong tie between the ancestry categories used here and race.

To illustrate this connection between declared ancestry and race, Table 1.1 shows the race categorizations of individuals in three monoracial ancestry categories, White, Black, and Asian, and the two combinations of White with Black and Asian ancestries.[17] For individuals who declare solely White ancestry, 99.5% declare their race to be White; among those who declare solely Black ancestry, 98.6% declare their race to be Black; and finally 83.7% of individuals that self-report solely Asian ancestry also declare Asian race. This is strong evidence that the mapping of ancestry categories to race that I use is accurate. For the biracial ancestry categories of Asian/White and Black/White there is great variation in race responses, but this is expected as self-reported race is flexible for the multiracial population.

Additionally, to address concerns that that particular ancestry responses may be driving self-reported race among the mixed-ancestry population, Table 1.2 shows the top ten ancestry responses of those with Black/White ancestry, split by racial category.[18] The table shows that combinations of responses for Black/White ancestry are quite similar across these three major race responses. "African-American" in combination with "English," "French," German," "Irish," and "Italian," are the five most frequent ancestry combinations for each race category. Furthermore, across the native-born, non-Hispanic sample of adults from the 2001-2013 ACS, close to 100% of those that declare only "English," "French," "Italian," "German," or "Irish" ancestry declare their race as White and only slightly less of those that declare only "African-American" or "African" ancestry declare their race as Black.

[17] Appendix Table F.1 provides some further comparisons of race with Hispanic ethnicity, "Other" ancestry, and those who do not declare any ancestry.

[18] Recall that ancestry is adjusted for 2010-2013 to make the data comparable across all years.

Table 1.3 repeats the exercise for those that declare Asian/White ancestry. Although there is more diversity in these responses, five of the ten most common ancestry combinations for each race are the same: "Filipino and German," "Filipino and Irish," "German and Japanese," "Hawaiian and Portuguese," and "Irish and Japanese."

Using ancestry to capture a larger set of multiracial individuals by separating self-identified race from socially-acceptable race, I can explore how cultural and socioeconomic factors may be associated with racial choice. I next describe a model to illustrate how these factors may actually influence racial choice.

1.5 Modeling Multiracial Choice

Work by Akerlof and Kranton (2000) has led to a class of models where utility depends on actions and a chosen identity. For the general identity model, utility is given by

$$U_j = U_j(\mathbf{a}_j, \mathbf{a}_{-j}, I_j). \tag{1.1}$$

Here the utility of individual j depends on self-image, I_j, a vector of j's actions, $\mathbf{a}_j$, and a vector of others' actions, $\mathbf{a}_{-j}$. Self-image, I_j, is defined as

$$I_j = I_j(\mathbf{a}_j, \mathbf{a}_{-j}; c_j, \epsilon_j, \mathbf{P}).$$

Identity depends on the actions of the individual, j, and others, $-j$, as before, as well as on j's social categories (assigned or chosen), c_j, and how individual j's own characteristics, ϵ_j, match with the ideals of the social categories, $\mathbf{P}$. For our purposes, the social categories c_j can be thought of as different racial categories, including combinations of two racial categories. The prescriptions, $\mathbf{P}$, would then have to do with traits that "fit" with being a member of a specific racial group. Utility increases with how well individuals' characteristics match with the prescriptions of their chosen identity, so there are costs to not fitting prescriptions. Individuals choose actions, a_j, and identity, c_j, to maximize their utility.

1.5.1 A Specific Multiracial Choice Model

I apply some structure to Akerlof and Kranton's general identity model (AK) and apply it to explain how individuals with multiracial ancestry may choose a multiracial identity. I split utility into the sum of an action payoff, G, an identity payoff, Q, and an action/identity interaction payoff, H, as follows:

$$U_j(a_j, c_j; s_j, v_j, p_L, p_R, \mathbf{C_X}) = G_j(a_j; v_j) + Q_j(c_j; s_j, p_L, p_R) - H_j(a_j, c_j; \mathbf{C_X}). \tag{1.2}$$

In this setup, similar to AK, individuals choose an action and an identity to maximize utility. There are two possible actions, $a_j \in (1, 0)$. Although there are two races, L and R, an individual can choose one of these two or a combination of the two, making her identity choice set $c_j \in (L, R, LR)$. The individual's endowed characteristics (ϵ_j in AK) are ability, $v_j \geq 0$, and skin tone/phenotype, $0 < s_j < 1$. The prescriptions, $\mathbf{P}$, or norms for how traits "fit" with being a member of a specific racial group, are characterized in this setup through p_L and p_R, skin tone norms, and $\mathbf{C_X}$, behavior norms.

The action payoff, G_j, depends on the individual's endowed ability and choice of action. If the individual chooses action 1, she receives an action payoff equal to her endowed ability, v_j. If the individual chooses action 0, she receives no action payoff. In other words, endowed ability determines how large the payoff from action 1 is, and this varies by individual. These action choices of 1 and 0 can be thought about as the decision between working in a high paying industry or a lower paying one, or investing in education leading to a more lucrative career or a less monetarily rewarding one, and individual differences in ability vary the returns to this action. This return to an education or labor market decision is independent of skin tone or choice of race in the current setup. The payoff from action choice can thus be written as

$$G_j(a_j; v_j) = \begin{cases} v_j & \text{if } a_j = 1 \\ 0 & \text{if } a_j = 0. \end{cases}$$

The self-image component of utility, I_j from AK, is replaced here by the sum of an identity payoff, Q_j, and an action/identity interaction payoff, H_j. The identity payoff, Q_j, comes from how well chosen identity, c_j, fits with endowed skin tone/phenotype, s_j. The value of s_j where an individual has equal identity payoff between L and LR (LR and R) is denoted as p_L (p_R), with $0 < p_L \leq p_R < 1$. Together, p_L and p_R, are the exogenous skin tone/phenotype norms that drive how physical characteristics affect self-image. The identity payoff is then as follows:

$$Q_j(c_j; s_j, p_L, p_R) = \begin{cases} -s_j/(4 * p_L) & \text{if } c_j = L \\ -\frac{1}{4} & \text{if } c_j = LR \\ (s_j - 1)/(4 * (1 - p_R)) & \text{if } c_j = R. \end{cases} \tag{1.3}$$

We can think of the three racial identities, L, LR, and R, as existing at the endpoints and a middle range of the s number line, see Figure 1.5. The identity payoff can be thought of as the psychic cost of deviating from the prescribed skin tone/phenotype norm for each identity. These norms driven "ideal" values of s for identities L and R are 0 and 1 respectively, and for identity LR are within the interval $[p_L, p_R]$.

For example, in a location where skin tone is not strongly tied to race categories, we might have $p_L \approx 0$ and $p_R \approx 1$ so that the identity payoff would be equal for all s_j and c_j combinations. Alternatively, in a location governed by the "one-drop" rule,[19] we might expect $p_L = p_R \approx 1$ so that any skin tone $s_j < 1$ is best associated with L identity, and that there is essentially no value of s_j that leads to an optimal LR, or mixed-race, identity choice.

I also allow for there to be an interaction between identity and action. Whereas the identity payoff, Q_j, captures the self-image component of utility driven by physical appearance, this interaction payoff, H_j, captures the self-image component of utility driven by behavioral norms associated with different identities. Modeling the association of particular actions with racial identity is a sensitive issue. The intention here is not to validate stereotypes, but rather to acknowledge these associations exist and may affect an individual's choice of identity. Papers such as Fryer, Jr. and Torelli (2010) address similar issues with Black and White adolescents and the concept of "acting White," where certain behaviors and human capital investments come with additional costs, such as social exclusion, for this population.

[19] This refers to the historically prominent view of race in the United States where a person with one ancestor of Black ancestry was considered Black.

Creating this interaction payoff allows us to model cases where actions are positively or negatively associated with certain identity choices. Let $\mathbf{C_X} \in (C_L, C_{LR}, C_R)$, where each of these terms represents an identity, labeled by the subscript, and association with action 1. A value of zero for C_X would indicate no interaction between the action 1 and the identity X. A positive value would indicate that the individual must pay a utility cost to choose associated identity X and the action 1 simultaneously. The interaction payoff between identity and action can then be written as

$$H_j(a_j, c_j; \mathbf{C_X}) = \begin{cases} a_j * C_L & \text{if } c_j = L \\ a_j * C_{LR} & \text{if } c_j = LR \\ a_j * C_R & \text{if } c_j = R. \end{cases} \tag{1.4}$$

To take this model to data, I first restrict to the set of individuals with mixed-ancestry. I assume that the distribution of endowed phenotype, s_j, is uniform across $(0, 1)$, and that endowed ability, v_j, is independent of phenotype. I restrict $C_L \geq C_{LR} \geq C_R$ making L the identity most negatively associated with action 1.

This model describes choices of action and identity and illustrates how utility-maximizing individuals with the same endowed phenotype may choose different identities based on endowed ability and racial climate. From equation 1.2, we can simplify the payoffs to the combinations of different actions (a_j) and identity choices (c_j), conditional on exogenous characteristics (s_j and v_j) and exogenous cultural factors (p_L, p_R, and C_X), written in short-hand as $U_j(a_j, c_j)$ for individual j below:

$$\begin{aligned} U_j(0,L) &= \frac{-s_j}{4(p_L)} && (1.5a)\\ U_j(1,L) &= \frac{-s_j}{4(p_L)} + v_j - C_L && (1.5b)\\ U_j(0,LR) &= \frac{-1}{4} && (1.5c)\\ U_j(1,LR) &= \frac{-1}{4} + v_j - C_{LR} && (1.5d)\\ U_j(0,R) &= \frac{-(1-s_j)}{4(1-p_R)} && (1.5e)\\ U_j(1,R) &= \frac{-(1-s_j)}{4(1-p_R)} + v_j - C_R. && (1.5f) \end{aligned}$$

First, individuals may compare identities L and LR in combination with actions 1 and 0. For a given identity choice, c_j, and skin tone, s_j, the choice between action 1 and 0 depends on the relationship between v_j, C_L, C_{LR}, and C_R. With $C_L \geq C_{LR} \geq C_R$, I can consider how ability, v_j, varies relative to these values to determine an individuals' utility maximizing action and identity.

In the scenario where $C_{LR} > v_j$, an individual who chooses identity LR should certainly choose action 0 rather than 1, as $v_j - C_{LR} < 0$, and if the individual chooses identity L she should also choose action 0 rather than 1, as $v_j - C_L < 0$. This individual then chooses identity LR rather than L if $U_j(0, LR) > U_j(0, L)$, which reduces to $s_j > p_L$.

In the scenario where $C_L > v_j > C_{LR}$, if the individual chooses identity LR she chooses action 1, as $v_j - C_{LR} > 0$, but if the individual chooses identity L she should choose 0, again since $v_j - C_L < 0$. This individual will then choose identity LR rather than L if $U_j(1, LR) > U_j(0, L)$, which reduces to $s_j > p_L - 4(v_j - C_{LR}) * p_L$.

Finally, in the scenario where $v_j > C_L > C_{LR}$, no matter which identity the individual chooses, she will choose action 1, since $v_j - C_{LR} > v_j - C_L > 0$. The individual will choose identity LR rather than L if $U_j(1, LR) > U_j(1, L)$, which reduces to $s_j > p_L - 4(C_L - C_{LR}) * p_L$.

I can thus summarize the information for an individual given an endowed phenotype (s_j) and ability (v_j), in an environment with racial climate parameters (C_L, C_{LR}, p_L), making a choice of identity between L and LR as follows. This individual will choose identity LR

rather than L when:

$$s_j > p_L \qquad \text{if } C_{LR} > v_j \tag{1.6a}$$

$$s_j > p_L - 4(v_j - C_{LR}) * p_L \qquad \text{if } C_L > v_j > C_{LR} \tag{1.6b}$$

$$s_j > p_L - 4(C_L - C_{LR}) * p_L \qquad \text{if } v_j > C_L > C_{LR} \tag{1.6c}$$

I can complete a similar exercise for comparing choices between the identities of LR and R again using comparisons of 1.5a through 1.5f. To summarize, an individual with an endowed phenotype (s_j) and ability (v_j), in an area with racial climate parameters (C_{LR}, C_R, p_R), will choose identity R rather than LR when:

$$s_j > p_R \qquad \text{if } C_R > v_j \tag{1.7a}$$

$$s_j > p_R - 4(v_j - C_R)(1 - p_R) \qquad \text{if } C_{LR} > v_j > C_R \tag{1.7b}$$

$$s_j > p_R - 4(C_{LR} - C_R)(1 - p_R) \qquad \text{if } v_j > C_{LR} > C_R \tag{1.7c}$$

Thus, given parameter values of racial climate regarding behavior (C_L, C_{LR}, C_R) and skin tone (p_R, p_L), for any given combination of s_j and v_j, I can determine which identity and action this individual will choose. When I plug some values in for the parameters and provide a range for v_j, I can clearly illustrate identity and action choices graphically.

1.5.2 Example 1

First, I consider a location where racial identity and actions are not tied and mixed-race identity is common. This can be parameterized by setting $C_L = C_{LR} = C_R = 0$ and $(p_L, p_R) = (.25, .75)$ in this location k. Further, let us assume that ability, v_j, is uniformly distributed $(0, .25)$ across each value of skin tone, s_j, which itself is uniformly distributed $(0, 1)$ for mixed race individuals. For simplicity, if individuals are indifferent between actions 1 and 0, I assume they choose action 1.

For an individual with $v_j = 0$, I can illustrate utility from all combinations of identity and action choice succinctly in Figure 1.6. Utils are on the y-axis and range from 0 to $-.25$, and skin tone is on the x-axis and ranges from 0 to 1. The dotted line pointing down from zero maps the utility when choosing identity L for each value of s, the dashed horizontal line illustrates the utility when choosing identity LR, and the dotted and dashed line pointing down from one reflects the utility when choosing identity R. The utility maximizing identity choice for every value of s is then shown from the upper envelop of these lines. Between $0 < s_j < .25$ the individual should choose L, for $.25 < s_j < .75$ the individual should choose LR, and for $s_j > .75$ the individual should choose R. This individual with $v_j = 0$, is indifferent between actions 1 and 0 for all identity choices as the action payoff will be 0 regardless of the action chosen.

In this example, everyone with $v_j > 0$, would choose action 1, but the ranges of s that are associated with each identity would not change regardless of the individual value of v_j. The upper envelop from choosing action 1 would simply shift all utility lines up by v_j, since in this case, action and identity are not associated. Figure 1.7 shows the combination of identity and action choices (c_j, a_j) mapped over possible values of ability, on the y-axis, and skin tone, on the x-axis. With ranges of s tied to identity as described above, this results in 25% of mixed race individuals choosing identity L, 50% choosing identity LR, and 25% choosing identity R.

1.5.3 Example 2

Next, I consider a location where the racial bias can be captured through a strong negative association between certain identities and actions, but where mixed-race identity is still common. I parametrize this situation by having both L and LR negatively associated with action 1; let $C_L = .2 > C_{LR} = .1 > C_R = 0$. As in the previous example, I set the phenotype range for mixed-race identity as $(p_L, p_R) = (.25, .75)$ and allow ability, v_j, to be uniformly distributed (0,.25).

Plugging these values into equations 1.6a-1.6c and 1.7a-1.7c, I can illustrate the combinations of skin tone and ability that lead to different race and action combinations in Figure 1.8. Once again, the y-axis shows endowed ability and the x-axis shows endowed phenotype. Within each identity type, L, LR, and R, it is the value of C_X which determines what proportion of individuals choose action 1 instead of action 0. The negative association of action 1 and identity L, means that ability, v_j, must be greater than the interaction cost of $C_L = .2$ in order to choose action 1, for those that select identity L. The same is true for identity LR, although a larger set of ability values allow for action choice 1 in this case, since $C_{LR} = .1$. For race R where there is no interaction cost, all ability types can choose 1.

There is flexibility for identity choice in the boundary range of phenotype where $.15 < s_j < .25$. Conditional on a particular phenotype value within this range, individuals with higher relative values of v_j choose identity LR and those with lower relative values choose identity L. This can be interpreted as positive ability selection into identity LR. In this range, as the phenotype value, s_j, increases, the cost of "switching" to identity LR decreases meaning that lower ability types can pay this cost, increasing the range of ability, v_j, that an individual can possess where utility maximizing behavior will be to switch from L to LR.

Contrasting this with example 1, individuals with high ability and phenotypes close to $p_L = .25$ are "switching" from identity L into identity LR. This is driven by the larger negative association of identity L with action 1, relative to the negative association of identity LR with action 1. In other words, an individual taking action 1 has an incentive to change identity to LR from L since the interaction cost is lower for LR. Therefore, close to this phenotype border, the ability payoff and decreased interaction cost outweigh the identity cost to switching, causing positive selection into LR. In other words, this describes a situation where an individual's behavior fits better with one identity while skin tone fits better with another, and high ability types are more likely to choose an identity that fits better with chosen behavior.

A similar situation occurs over the range of phenotype $.65 < s_j < .75$ where individuals now choose between identity R and LR. As with the boundary cases between L and LR, it is the interplay of the reduced interaction costs, identity "switching" costs, and varying payoff from taking action 1, that drives the decisions within this range of phenotype values.

This model makes several strong predictions for situations where actions are associated differentially with identity. The first is that near the phenotype boundary between racial groups, conditional on *phenotype*, higher ability types will choose a different identity than lower ability types. The second is that holding *identity* constant, darker skinned individuals should have higher ability than lighter skinned individuals on average. Third, when calculating average ability by identity group, identities where there is a greater negative association of identity and action will have lower average ability due to positive selection away from that identity. This means that in the above example with $C_L > C_{LR} > C_R$, I can now show that ability averaged by identity choice, denoted $\bar{v_X}$, where $X \in (L, LR, R)$, will follow this ordering: $\bar{v_L} < \bar{v_{LR}} < \bar{v_R}$.[20] Finally, the proportion of individuals who choose action 0 for each identity increases with the value of C_X for that identity. Therefore, the fraction of individuals choosing action 1 is lowest for identity L, higher for identity LR, and highest for identity R.

Figure 1.9 illustrates how selection into different identities leads to the overall ordering in average ability by identity type. Trapezoid A shows the group with relatively high ability, v_j, that "switch" from identity L to identity LR, compared to example 1 in which there is no tie between identity and action. This leads average ability of L to be lower than average ability of LR. Likewise, Trapezoid B shows the group with relatively high ability that "switch" from identity LR to identity R, leading the average ability of LR to be lower than that of R.

In this setup, discrimination does not directly affect returns to the action but instead operates through measures of local culture (p_L, p_R, and $\mathbf{C_I}$) which can reduce utility from self-image (Q_j and H_j of the utility function) of certain endowed skin tone levels and race choices. The model could be could be modified so that the action payoff is directly affected by discrimination by adding a multiplier, $0 < d(s_j) < 1$, to v_j to dampen returns to the action, so that the action payoff for action 1 is $d(s_j) * v_j$. Here function d would be decreasing in skin tone, s_j. In such a case, returns to higher education or working in certain industries would be directly affected by skin tone.

The model illuminates the central insight that when certain identities impose costs for taking otherwise utility enhancing actions, only high ability types able to pay this self-image cost will choose these actions. Furthermore, conditional on skin tone and other factors, high ability types may find it beneficial to also change their identity to avoid self-image costs that stem from the negative association of utility enhancing actions and certain identities.

This model provides a framework for thinking about how identity selection may be broadly affected by endowed circumstance and the association of identity and chosen ac-

[20]See Appendix A for details.

tions. From this model, if certain characteristics are more strongly tied to one race than another, this will influence how a multiracial individual chooses her race, and more broadly, will influence the total count of multiracial individuals based on self-declared race.

1.6 Results

Without available data for skin tone of a large set of multiracial individuals, some of the strongest predictions of the model cannot be tested. However, I can use the large population of mixed-ancestry Americans to show that cultural and socioeconomic factors are associated with the choice of race as the model suggests. The limitations of this evidence and alternative explanations that could be driving these results are discussed after the empirical results are presented.

I begin the empirical analysis by examining cultural and socioeconomic factors associated with the choice of race by individuals with self-reported Black/White ancestry. The sample is first restricted to native-born, non-Hispanic adults, ages 25-54. Recall that individuals respond to ancestry on these surveys with write-in answers, up to two of which I can code to racial categories. As the population of individuals who declare Black and White ancestry is still relatively small, I first pool across 2001-2013. I examine the choice of race among this population, limited to Black, Black and White, and White.[21] Table 1.4 shows summary statistics for this population by self-reported race. Overall, those that choose Black/White race appear to be more educated and younger than their Black and White counterparts.

I run a multinomial logistic regression of these three race categories on census division, year, age, and education, categories, as well as on employment fraction and gender. The employment fraction measure is calculated by multiplying the usual hours reported having worked each week last year by the number of weeks worked. The most common answer for usual hours of work is 40 each week, and the most common answer for weeks worked per year is the 50-52 week category, so I normalize the employment fraction measure by dividing each value by $2,040$ hours. Standard errors are clustered by state (including Washington DC) to address concerns that errors may be correlated by geography.

[21] 4% of individuals with Black/White ancestry declare race in some other way and are ignored in this analysis.

From the model presented above, I expect that factors such as education, local racial climate, and labor market participation all may have systematic associations with race. Column (1) of Table 1.5 shows the relative risk ratios for Black race, where the comparison group is mixed Black/White race; column (2) has the relevant standard errors. Column (3) of Table 1.5 shows this same information for White race compared again to Black/White race with the relevant standard errors in column (4).

First, we see evidence that culture, or racial climate, is associated with racial self-identification from the relative risk ratios on the three southern census divisions, South Atlantic, East South Central, and West South Central, and from the relative risk ratios on the year categories. Looking at Column (1), comparing Black to mixed Black/White in the three southern divisions, these values and subsequent Wald tests reveal that individuals with Black/White ancestry are significantly more likely to declare as Black compared to biracial in these areas, when compared to any other division, including the omitted New England division. This result fits with the history of Blacks in the south, where anti-miscegenation laws and the "one-drop rule" have had a lasting effect on the concept of race so that those with mixed ancestry are still much more likely to declare as Black only.

Also in Column (1), we see significantly decreasing odds of identifying as Black compared to mixed Black/White as the year category increases.[22] I cannot reject the hypothesis that year category effects are the same from 2001-2002 through 2005-2006, but the odds of declaring Black race drop precipitously after that and through the most recent period of 2011-2013. These year effects operate separately from age, as I control for this to by including 10-year age categories. The age effect works in the opposite direction, where older individuals are more likely to declare as Black than mixed. These results indicate both a time and cohort effect for cultural attitudes towards race; I interpret this result as evidence of an increase in the social acceptability to declare as mixed for younger generations and generally over time as well.

Education and employment are used here as indicators of socioeconomic status. I break education down into six categories; the omitted category is bachelor's degree. Wald tests

[22] I use combined 2-year periods here (the last category includes 2011, 2012, and 2013) to deal with degrees of freedom and the limited 51 geographic clusters. Results are similar using a single linear coefficient for year.

indicate that while we see no differences between those with Bachelor's or Master's degrees, individuals with those levels of education are significantly more likely to declare as Black than those with a professional degree, but less likely to declare as Black compared those with only a high school degree. This is evidence that more education, in general, is associated with a higher likelihood of identifying as mixed-race.[23] The employment fraction is also associated with a lower likelihood of identifying as Black compared to mixed. With both these pieces of evidence I claim that higher socioeconomic status is associated with mixed race compared to Black race identification.

Column (3) presents the relative risk ratios of declaring race as White compared to Black/White. Cultural factors as proxied by division, year, and age exhibit strong trends, but socioeconomic status, as proxied by eduction and employment status, do not appear to. There are differences in race declarations when comparing the southern divisions to the Mid Atlantic, East North Central, and Mountain Divisions, and similar time and age patterns to the Black and Black/White comparison. This shows that it has become increasingly likely to declare as multiracial in recent years, with younger individuals exhibiting a more flexible view of race, more often choosing multiracial rather than White identity.

Additional measures with finer geographic location, metropolitan resident status, and method of interview (mail, telephone, or in person) are only available in the public use data beginning in 2005. Starting with the 2012 ACS, geographic areas of residence were switched over to 2010 Census area definitions, causing PUMAs and metropolitan areas to have different boundaries in the 2005-2011 ACS compared to the 2012-2013 ACS. In light of this, I restrict the sample to 2005-2011 to take advantage of these extra variables and finer geographic data.[24] In addition, as I can now identify the Public Use Microdata Area (PUMA) of residence, I can construct measures of % Black and % Black/White in the local area for each individual.[25]

[23]Individuals with doctorates seem to be a counter example here, but the observations are too few and the error terms too large to draw any concrete conclusions.

[24]Running the initial specification while restricting years does not substantially affect the magnitudes of relative risk ratios, however, notably I can no longer reject the null that the 0.878 relative risk ratio between Blacks and Black/Whites for employment fraction is equal to 1 (p=0.106) for the 2005-2011 sample.

[25]Here the standardized measure of proportion Black (Black/White) is the percent of population in a PUMA that is Black (Black/White) divided by the standard deviation of this proportion across all PUMAs. This allows us to interpret a one unit change in standardized proportion Black as the effect of a one standard deviation change in proportion Black and make a simpler comparison between standardized proportion Black

I expect that the proportion Black and proportion Black/White in a person's PUMA of residence will influence her choice of race. Areas with more Blacks or more biracial Black/Whites may have different racial climates due to increased minority presence. Likewise, metropolitan areas may also have different racial climates than more racially homogenous, rural areas. I also expect method of interview, or whether the data was collected by survey or computer assisted telephone interview/computer assisted in-person interview (CATI/CAPI) to matter. As detailed in Appendix D, the latter two interview types are only pursued when a person does not respond to the initial mailing. This behavior may be associated with groups that are not as trusting of the government.

Table 1.6 shows the results of a multinomial logistic model again using Black, Black/White, and White race as outcomes on employment fraction and an expanded set of division, year, age, and education variables with additional controls for metropolitan resident status, local percent Black, local percent Black/White, and phone/personal interview (CATI/CAPI). Standard errors are clustered by metropolitan area for this sample.[26]

To further examine results of this specification, I offer graphs of the predicted probabilities of declaring race according to various categories while holding all other variables at their means. I begin with census division; in Figure 1.10 the probabilities of Black, Black/White, and White race by census division are shown in the three plots from left to right. The increased likelihood of declaring monoracial in the southern divisions compared to others can be seen.[27] The year dummies indicate an increasing likelihood to declare as multiracial vs Black in recent years, but the difference levels off after 2008, as illustrated by predicted probabilities in Figure 1.11. With extended age categories, now 5-year instead of 10-year groups, the same pattern of older individuals being more likely to declare as monoracial, either Black or White, compared to multiracial still holds. This is perhaps the most striking example, as shown in Figure 1.12, with very strong trends towards more mixed-race identification among

and standardized proportion Black/White as these actual proportions are very different in magnitude.

[26] When clustered at the PUMA level, standard errors are roughly the same size as non-clustered standard errors, perhaps indicating that there are too many PUMAs relative to observations. I choose to cluster standard errors by metropolitan area as the size of the standard errors increases substantially when doing so, suggesting that there is some within metropolitan area correlation of errors.

[27] While I can no longer claim individuals in East South Central or South Atlantic are more likely to declare Black rather than Black/White in New England, there are still statistically significant differences between the odds of declaring Black in the East South Central and South Atlantic with the Mid Atlantic.

younger cohorts. Together these proxies for cultural climate indicate significant differences in the likelihood of identifying as Black or mixed race.

In this specification I also expand education categories and break out "High School Degree" into "High School Degree", "Some College", and "Associate's Degree." "No HS Degree" is broken out into "Some High School" and "Less than High School." Predicted probabilities of race by expanded education categories are shown in Figure 1.13. From the leftmost panel we see the major trend is the decreasing likelihood of declaring Black race with increasing education above a HS Degree. The reverse pattern can be seen in the middle panel for the probability of declaring Black/White race. The coefficients on expanded education categories in Table 1.6 quantify these differences and Wald tests verify that there are differences between the odds of declaring Black among those with less than a Bachelor's Degree and those with a Professional Degree.

The addition of controls for being a metropolitan resident, proportion Black and proportion Black/White, interview type (CATI/CAPI), and expanded categories, increase the pseudo r^2 to .171 compared to .066 in the previous 2001-2013 specification. Notably, the coefficient on employment fraction is no longer statistically significant. The additional controls are strongly significant for the comparison between Black and Black/White racial identification. The addition of metropolitan resident, proportion Black, and proportion Black/White greatly reduce the magnitude of the geographic division effects, but still do not pull the south in line with other areas of the country.

The broad patterns found in the original specification still hold for this second specification, indicating that the cultural differences through location, time, and age are associated with racial selection among those with mixed Black/White ancestry. The evidence is more mixed for socioeconomic factors, as educational attainment differences still hold but employment fraction is no longer associated with choice of race for this group.

In order to look at another socioeconomic factor, wages, I repeat the above analysis but use a sample of full-time (30+ hours a week, 27+ weeks per year) working adults rather than the entire universe of adults with Black and White ancestry. Table 1.7 shows the relative risk ratios of Black and White racial identification with Black/White racial identification as the omitted category. The patterns for cultural factors, division, year category, and age on workers are the same as on adults. In the three southern divisions, individuals are more likely to declare as Black compared to mixed-race. In more recent years the probability of declaring mixed-race compared to either Black or White monoracial increases, and younger individuals are also more likely to declare a mixed-race rather than either monoracial category.

With the restricted full-time workers sample, education shows slightly weaker differences but individuals in the "High School Degree" education category are still more likely to declare Black race than Black/White race relative to those in the "Bachelor's Degree" education category ($p = 0.041$). Log hourly wages are strongly significant comparing Blacks to Black/Whites. Together this evidence shows that shows that individuals with more education and higher wages are less likely to declare as Black and more likely to declare as Black/White, as the model would suggest.

Again, to examine additional categories and controls we restrict our sample of full time working adults to the years 2005-2011. This allows us to add proportion Black and Black/White, metropolitan status, response type (survey or CATI/CAPI) and expand our year, age, and education categories. The broad patterns of differences in predicted probability by race and division, year, age, and education are plotted in Figures 1.14, 1.15, 1.16, and 1.17,respectively.

Again, patterns that hold in other specifications for differences by division also hold here, with individuals more likely to choose a monoracial identity in the southern divisions rather than a multiracial one. Individuals with higher levels of education are still less likely to declare Black compared to Black/White. Table 1.8 shows the relative risk ratios, and Wald tests reveal that those with Professional degrees and Master's degrees are significantly less likely to declare Black than those with just a "High School Degree" or "Some College". These education relative risk ratios are quite similar between the sample of adults compared to the sample of full-time workers.

There continues to be a strong year effect, where it appears to have become more acceptable to choose a multiracial identity as the likelihood of those choosing Black compared to Black/White has decreased in later years, but leveled off around 2008. Interestingly, the pattern is weaker for the likelihood of declaring White race compared to multiracial. However, even for Whites I still can reject the joint hypothesis that the year coefficients should not be included in the model.

Differences in educational attainment remain significant although log hourly wages is now marginally significant ($p = 0.073$). Thus, even with these detailed controls, socioeconomic status is still somewhat associated with the choice of race between Black and Black/White. The controls for metropolitan resident status, proportion Black, and proportion Black/White are all significant here in the expected direction. In comparing Black racial identification to Black/White racial identification, column (1), those that live in cities and are around more monoracial Blacks are more likely to identify as Black, and those that are around more multiracial Black/Whites are more likely to declare as multiracial.

Repeating the analysis but splitting by gender leads to some interesting results, particularly with employment and wage measures. Table 1.9 repeats the analysis on the 2001-2013 sample of adults with Black/White ancestry, split by gender. For the choice between Black and Black/White Race, columns (1) and (5) show similar significant differences by location, year, and age in the expected directions, consistent with earlier results. However, employment fraction is only significant for males, and shows that males are much less likely to report their race as Black as employment fraction increases (0.748 RRR compared to Black/White). This same pattern holds with wages between males and females, as seen in Table 1.10. Again, the results from columns (1) and (5) show that males are less likely to declare their race as Black as their wages increase, relative to Black/White, but females don't show this same significant difference. This is an interesting finding that warrants more exploration. There could perhaps be a tie between utility from gender identity and labor market attachment since women, at least traditionally, have had less labor market attachment than men. This could be interacting with the tie between labor market attachment and racial identity.

The population of individuals with Asian/White ancestry is also of interest as there are potentially different associations between socioeconomic and cultural factors with this population, relative to the population of individuals with Black/White ancestry. I therefore repeat some analysis with the sample of native-born, non-Hispanic adults, ages 25-54 that report Asian/White ancestry. Table 1.11 shows results using data from 2001-2013. Interestingly, factors appear to affect the choice between Asian/White and White as much as between Asian/White and Asian. Differences in racial identification by geographic location are concentrated in the Mountain and Pacific divisions where individuals are much more likely to identify as mixed-race than monoracial White. The time trend towards multi-racial self-identification is also stronger comparing Whites to White/Asians, and this trend moves in the same direction as it does for those of Black/White ancestry. Younger individuals are again less likely to declare as monoracial. Higher levels of educational attainment move racial identification towards Asian/White from both monoracial categories. The employment fraction is marginally significant ($p = 0.078$) with individuals more likely to declare race as monoracial Asian compared to mixed-race Asian/White as employment fraction increases.

As with Black/Whites, I further extend with additional categories and controls, but must subsequently restrict years to 2005-2011. Table 1.12 shows the results of this specification. All the patterns for the 2001-2013 sample hold, including that the employment fraction remains marginally significant ($p = 0.053$) with the likelihood of declaring monoracial Asian increasing in employment fraction relative to mixed-race Asian/White.

Table 1.13 shows the analysis for a sample of full-time working adults with Asian and White ancestry. Patterns are similar to the analysis of adults over the same 2001-2013 time period; Asian/White race self-identification is much more likely in the Pacific division compared to White race, year and age relative risk ratios show that youth and more recent time periods increase the likelihood of declared mixed-race, and higher education is more associated with Asian/White race than either monoracial category. I cannot reject the hypothesis that the relative risk ratio of log hourly wages is equal across race categorization, meaning that wages do not seem to be differentially associated with Asian, Asian/White, and White race categorization among this population.

Extending to additional categories and controls, but restricting years to 2005-2011, the results presented in Table 1.14 show that changes from the preceding full-time working adults specification do not alter the broad patterns on year, age, education, or even wages. Metropolitan residency and increased proportions of Asian/Whites in the PUMA of residence make it more likely for an individual to declare as Asian/White.

Analysis on individuals with mixed Asian/White ancestry shows some similar patterns to that on individuals with Black/White ancestry. The probability of identifying as mixed-race compared to monoracial increases with year and decreases with age. Living in the south increases the likelihood of declaring as monoracial, although much less so for Asian/Whites. However, there are also significant differences between Asian/White ancestry and Black/White ancestry. While the coefficients on education seem to suggest higher levels of education are more associated with mixed race identification for Black/Whites only compared to Blacks, these coefficients show higher education being associated with mixed race identification for Asian/Whites compared to both Asian and White monoracial groups. Other socioeconomic factors such as employment fraction and wages seem to be less influential on the choice of race for those with Asian/White ancestry than for those with Black/White ancestry.

The distribution of minority monoracial and biracial adults across the continental United States helps to illustrate some of these findings. Figure 1.18 displays the percent of adults in each PUMA by race and ancestry for Asians and Blacks. Each map has a separate quantile scale with darker shades indicating higher concentrations of the applicable categoric population. Subfigures 1.18a and 1.18b show the dispersion of individuals declaring only Asian race and only Asian ancestry respectively. These populations are spread throughout the county, but concentrated around metropolitan areas. Asian race and ancestry also strongly overlap and that is reflected in the similarity in appearance between these two Subfigures.

Subfigures 1.18c and 1.18d show the dispersion of individuals declaring only Black race and only Black ancestry respectively. Blacks reach a higher relative concentration in single PUMAs than Asians do, and Black populations are concentrated in the South East. As with Asians, Black race and Black ancestry concentrations overlap to a high degree.

Figure 1.19 repeats this exercise but with the biracial and biancestral population of Asian/Whites and Black/Whites. For Asian/White race and ancestry, the maps look remarkably similar to each other and also to those for Asian race and ancestry. This indicates that PUMAs with higher concentrations of Asians also tend to have higher concentrations of mixed-race and mixed-ancestry Asian/whites.

There is an interesting contrast between maps of Black/White race, Subfigure 1.19c, and Black/White ancestry, Subfigure 1.19d. The south eastern area of the United States appears much lighter for race than for ancestry, illustrating the difference in attitudes towards race in the south. The darker shades in this area for Black/White ancestry compared to Black/White race indicate that it is relatively more common to declare Black/White ancestry than it is to declare Black/White race. This difference is also reflected in the regression results where individuals with Black/White ancestry are much more likely to report race as Black than as Black/White in the southern census divisions. A comparison of the maps of Black/White race and ancestry, Subfigures 1.19c and 1.19d, to maps of Black race and ancestry, Subfigures 1.18c and 1.18d, also shows an interesting difference with Black/White race and ancestry being relatively less geographically concentrated than Black race and ancestry.

1.7 Specification Checks

Recall that due to how the Census chose to censor ancestry pre-2010 I manually coded ancestry in the same way for data after 2009 so that the sample was comparable across years. However, this means that individuals with Black/White ancestry that declared one of their ancestries as "White/Caucasian" were recoded as Black Ancestry only. I cannot identify these individuals in the data before 2010, but I can in later years. In Table 1.15, I show summary characteristics of Black, Black/White, and White race individuals with "Excluded" Black/White ancestry, those with Black/White ancestry that declare one ancestry as "White/Caucasian," and "Adjusted" Black/White ancestry, those with Black/White ancestry that do not answer with "White/Caucasian." Those with "Adjusted" ancestry appear to be more educated, but no other differences between the samples stand out.

As a robustness check, I repeat regressions of choice of race on location, year, age, education, and employment fraction for individuals in 2011-2013 with Black/White ancestry. I choose this time frame because these are years where I can identify individuals who declared Black/White ancestry using "White/Caucasian" as and ancestry response. Table 1.16 shows the results for adults. Columns (1)-(4) display results for the "Excluded" sample, columns (5)-(8) display results for the "Adjusted" sample, and columns (9)-(12) display results for a "Combined" sample which includes everyone who declared Black/White ancestry in 2011-2013. The results from the "Combined" sample are most directly comparable to Table 1.5 since the specification is the same and only the years in the sample differ. Comparing the 2011-2013 results to the 2001-2013 results, the difference that stands out the most is that employed fraction is not significantly associated with race choice in the 2011-2013 sample, suggesting that the association is strongest in earlier years.

When comparing the "Excluded" and "Adjusted" samples for 2011-2013, relative risk ratios tend to point in the same direction although magnitude and significance levels do vary. Comparing column (1) to column (5), the education values indicate that, for both samples, less educated individuals are more likely to declare as Black race. Consistent with earlier findings, younger individuals are less likely to declare as monoracial Black only. Individuals in the three southern divisions are more likely to declare as Black. Strangely, there are strong opposing year effects. For the "Excluded" sample Wald tests indicate an increase in the likelihood of declaring black from 2011 and 2012, while the "Adjusted" sample shows the opposite. Perhaps these and other minor differences may be attributable to the relatively small sample. These comparisons show that between individuals who do and do not use "White/Caucasian" to report their Black/White ancestry do not differ greatly in which factors are associated with their choice of race.[28]

One can make the argument that individuals may migrate to areas that align with their racial declarations, meaning that attitude toward race may drive both division of residence and choice of race. To examine this possibility I reran the above specifications for those with Black/White ancestry using division of birth in place of division of residence. An individual certainly has no choice on location of birth, however it is still possible that family attitudes towards race could drive both an individual's choice of race and location of birth. Replacing place of residence with place of birth does not have a substantial effects on the estimates. As an example I repeat the specification of Table 1.5 with the 2001-2013 sample of adults but replace division of residence with division of birth. These results are shown in Appendix Table F.2. Southern division effects for both Black and White race are stronger when using division of birth rather than division of residence, in other words, both monoracial categories are more likely in the three southern divisions relative Black/White race. Employment fraction for Black compared to Black/White becomes marginally significant ($p = 0.092$) with the birth

[28] I also examined full time working adults in 2011-2013 with Black/White ancestry (not included here but available upon request). One significant difference when comparing these results to Table 1.7, the 2001-2013 "Adjusted" sample, is that higher log hourly wages do not lead to choosing Black/White race relative to Black in the "Excluded" 2011-2013 sample as it does in the "Adjusted" and "Combined" 2011-2013 samples. Other results are similar between the "Excluded" and "Adjusted" 2011-2013 samples and are very similar to results in Table 1.7.

division specification compared to the residence specification ($p = 0.038$) but the effect is still in the correct direction. In other regressions that repeat specifications shown in Tables 1.6 - 1.8, the stronger southern effects on division remain and significance levels on employment fraction and log hourly wages remain the same when comparing division of birth and division of residence.[29]

1.8 Conclusion

Race is typically viewed in the economics literature as an immutable trait. Recent work has shown that large policy changes, such as bans in affirmative action (Antman and Duncan, 2014), and seminal life events, such as incarceration (Saperstein and Penner, 2010), can change how individuals self-identify their race. However, other strong, but everyday factors may also influence race selection. I presented a model here that can explain just how certain cultural and economic factors could influence race and provided some empirical evidence that these factors are indeed associated with the racial self-identification of a nationally representative sample of mixed-ancestry Americans.

While these empirical results do establish a relationship between cultural and socioeconomic factors with racial choice among mixed-ancestry Americans, under the current set-up I cannot claim that a causal relationship exists with wages, educational attainment, or employment fraction influencing the choice of race. These associations are consistent with the model, but there are also plausible alternative explanations for these findings.

The literature on skin tone and wages (Hersch (2008), Hersch (2011), Goldsmith et al. (2007)) finds that skin tone and phenotype influence socioeconomic outcomes, as discrimination based on skin tone and phenotype can reduce wages. Skin tone and phenotype may also dictate the choice of race, meaning that skin tone could be an omitted factor that influences both socioeconomic outcomes and race. However, it is unlikely that skin tone drives all the associations attributed to culture found here. For example, the mixed-race population is probably not becoming light skinned as rapidly as the year effect differences between 2006 and 2011 would imply. Alternatively, both socioeconomic factors and racial choice could

[29] These tables not included here, but are available upon request.

influenced by family background, as more educated parents may influence their children by simultaneously passing along nuanced views of mixed-racial identity and encouraging human capital development.

This work still contributes to the budding literature on mixed-race identity in several ways. Previous work has shown that identifying the population of mixed-race individuals is difficult, depending on the measure of multiracial identity, as self-report may only provide a subset of the desired population. Using the technique utilized by Gullickson and Morning to identify a larger set mixed-ancestry Americans, I present evidence that certain cultural and socioeconomic factors are indeed associated with the choice of race. This shows how even counting the mixed-race population through self-report can be systematically biased. Individuals in the south will be undercounted, as well as older individuals. Metropolitan areas and areas with higher concentrations of Blacks will also have an undercount of multiracials by self-report. Mixed-race individuals with less education, lower wages, and less attachment to the work force are more likely to identify as monoracial. These selection problems may be larger for men than for women.

This evidence also shows that attempting to measure outcomes for multiracials is difficult using measures of self-report. For the reasons stated above, measuring educational attainment of multiracials may be biased up, as some lower educated multiracials may select out of multiracial identity. Likewise, measures of employment and wages could be biased in the same direction. As this mixed-ancestry population grows, these issues could even expand to biasing socioeconomic measures of monoracial groups, as mixed-ancestry individuals select into and out of monoracial identities in systematic ways.

This paper builds on ideas from Akerlof and Kranton's general social identity model to construct a framework that describes how selection into and out of multiracial identity might be driven by the identity tie between actions and racial categories. This framework describes how individuals near racial prescriptive boundaries may make their decisions, and shows how this decision process could lead to biased overall measures of socioeconomic outcomes for racial groups.

Future work could attempt to test the stronger predictions of the model with a large data set of multiracials containing measures of skin tone. The model predicts that among mixed-ancestry individuals who declare as mixed race, those with darker skin tone should, on-average, have more education and more labor force attachment than those with lighter skin tone. This finding would lend strong support to the model, as it would show an identity choice effect large enough to overcome the evidence of discrimination based on skin tone, where lighter skinned individuals have higher wages than darker skinned individuals. Such a data set could also test the prediction of the model that, holding skin tone and other factors constant, a mixed-ancestry individual's choice of race would vary with how her education, wages, or more labor force attachment fit with prescriptions of racial norms.

Table 1.1: Self-Identified Race by Ancestry

	ANCESTRY									
	White		Black		Black/White		Asian		Asian/White	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RACE										
White	6,031,333	99.45	4,652	0.48	1,487	8.99	6,050	5.20	8,206	31.51
Black	6,936	0.11	962,172	98.61	6,841	41.38	449	0.39	57	0.22
Native	2,201	0.04	464	0.05	9	0.05	88	0.08	15	0.06
Asian	1,411	0.02	239	0.02	16	0.10	97,376	83.66	2,850	10.94
Other	1,639	0.03	560	0.06	315	1.91	190	0.16	181	0.70
White/Black	2,680	0.04	4,363	0.45	6,510	39.38	23	0.02	11	0.04
White/Native	13,173	0.22	40	0.00	22	0.13	24	0.02	25	0.10
White/Asian	2,773	0.05	18	0.00	14	0.08	8,219	7.06	13,378	51.37
White/Other	1,240	0.02	15	0.00	50	0.30	13	0.01	21	0.08
Black/Native	77	0.00	1,779	0.18	119	0.72	6	0.01	1	0.00
Black/Asian	19	0.00	351	0.04	13	0.08	337	0.29	18	0.07
Black/Other	15	0.00	313	0.03	47	0.28	3	0.00	1	0.00
Asian/Native	9	0.00	2	0.00			97	0.08	13	0.05
Asian/Other	19	0.00	8	0.00	3	0.02	140	0.12	30	0.12
Other/Native	13	0.00	4	0.00	2	0.01	1	0.00		
Three or More	968	0.02	723	0.07	1085	6.56	3375	2.9	1234	4.74
Total	6,064,506	100	975,703	100	16,533	100	116,391	100	26,041	100

Source: Pooled 2001-2013 ACS

The sample consists of native-born, non-Hispanic adults, ages 25-54

Table 1.2: Top Black/White Ancestry Responses By Race, 2001-2013

	Ancestry (1)	Frequency (2)	Percent (3)	Cumulative (4)
Black/White Race				
	African-American and German	878	18.22	18.22
	African-American and Irish	776	16.10	34.32
	African-American and Italian	606	12.57	46.89
	African-American and English	286	5.93	52.82
	African-American and French	230	4.77	57.59
	African-American and Polish	171	3.55	61.14
	African-American and European, nec	149	3.09	64.23
	African-American and Dutch	108	2.24	66.47
	African and German	96	1.99	68.46
	African-American and Scottish	89	1.85	70.31
White Race				
	African-American and French	140	10.89	10.89
	African-American and German	108	8.40	19.28
	African-American and Irish	106	8.24	27.53
	African-American and Italian	72	5.60	33.13
	African-American and English	53	4.12	37.25
	African-American and Polish	21	1.63	38.88
	Acadian and African-American	20	1.56	40.44
	African and European, nec	20	1.56	41.99
	English and Jamaican	20	1.56	43.55
	African-American and Scottish	19	1.48	45.02
Black Race				
	African-American and Irish	1,026	18.68	18.68
	African-American and French	809	14.73	33.41
	African-American and German	588	10.70	44.11
	African-American and Italian	545	9.92	54.03
	African-American and English	368	6.70	60.73
	African and Irish	226	4.11	64.85
	African and French	142	2.59	67.43
	African-American and Portuguese	139	2.53	69.96
	African-American and European, nec	107	1.95	71.91
	African and European, nec	104	1.89	73.80

Ancestry adjusted for 2010-2013

Table 1.3: Top Asian/White Ancestry Responses By Race, 2001-2013

	Ancestry (1)	Frequency (2)	Percent (3)	Cumulative (4)
Asian/White Race				
	German and Japanese	779	6.85	6.85
	Filipino and German	597	5.25	12.10
	Irish and Japanese	566	4.98	17.08
	Filipino and Irish	505	4.44	21.52
	Hawaiian and Portuguese	433	3.81	25.32
	English and Japanese	390	3.43	28.75
	German and Korean	312	2.74	31.50
	Chinese and German	298	2.62	34.12
	Chinese and Irish	252	2.22	36.33
	Irish and Korean	237	2.08	38.42
White Race				
	German and Japanese	578	7.50	7.50
	Filipino and German	408	5.30	12.80
	Irish and Japanese	375	4.87	17.66
	Dutch and Indonesian	329	4.27	21.93
	Filipino and Irish	324	4.21	26.14
	English and Japanese	211	2.74	28.88
	Filipino and Italian	184	2.39	31.27
	Hawaiian and Portuguese	181	2.35	33.61
	German and Hawaiian	174	2.26	35.87
	Chinese and German	173	2.25	38.12
Asian Race				
	Hawaiian and Portuguese	265	10.12	10.12
	Dutch and Indonesian	137	5.23	15.35
	Filipino and German	136	5.19	20.54
	German and Japanese	122	4.66	25.20
	Filipino and Irish	110	4.20	29.40
	Irish and Japanese	109	4.16	33.56
	German and Hawaiian	90	3.44	37.00
	Filipino and Portuguese	76	2.90	39.90
	Filipino and Italian	57	2.18	42.08
	German and Korean	53	2.02	44.10

Ancestry adjusted for 2010-2013

Table 1.4: Demographics of Adults with Black/White Ancestry by Race, Ages 25-54, 2001-2013 Sample

	Black (1)	Black/White (2)	White (3)
Years of Schooling	14.06	14.22	14.04
Fraction College Graduates	0.27	0.33	0.32
Age	37.95	33.81	37.30
Potential Experience	17.89	13.59	17.26
Married	0.36	0.36	0.51
Own Children in Household	0.99	0.89	0.95
Female	0.55	0.52	0.53
Phone/Personal Interview	0.36	0.32	0.26
Employed Last Week	0.74	0.78	0.76
Employment Fraction	0.76	0.79	0.80
Log Hourly Wages*	2.54	2.59	2.62
Number of Observations	5,493	4,820	1,286

Ancestry adjusted for 2010-2013. Values are population weighted.
*Log Hourly Wages only for those with some employment

Table 1.5: Relative Risk Ratios of Race Compared to Black/White, Adults Aged 25-54, 2001-2013 Sample

	Black		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.955	(0.197)	0.630**	(0.141)
East North Central	1.331	(0.256)	0.627**	(0.137)
West North Central	1.037	(0.256)	0.854	(0.172)
South Atlantic	2.125***	(0.435)	1.273	(0.443)
East South Central	3.151***	(0.982)	1.498*	(0.327)
West South Central	3.302***	(1.017)	1.768	(0.642)
Mountain	1.082	(0.253)	1.101	(0.243)
Pacific	0.857	(0.176)	0.673**	(0.121)
Year Category (2001-2002 Excluded)				
2003-2004	1.044	(0.136)	0.829	(0.175)
2005-2006	0.958	(0.190)	0.707	(0.173)
2007-2008	0.655**	(0.124)	0.427***	(0.095)
2009-2010	0.516***	(0.084)	0.444***	(0.101)
2011, 2012, 2013	0.474***	(0.074)	0.391***	(0.085)
Age (35-44 Excluded)				
25-34	0.520***	(0.039)	0.658***	(0.065)
45-54	1.888***	(0.151)	2.089***	(0.202)
Education (Bachelor's Degree Excluded)				
No High School Degree	1.101	(0.203)	1.257	(0.200)
High School Degree	1.303***	(0.102)	0.965	(0.097)
Master's Degree	1.009	(0.159)	0.730	(0.174)
Professional Degree	0.695*	(0.134)	1.098	(0.318)
PhD	1.057	(0.228)	0.982	(0.365)
Employment Fraction	0.868**	(0.059)	1.029	(0.102)
Female	1.061	(0.074)	1.015	(0.095)
Observations	11,599			
Pseudo R2	0.0659			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level. Ancestry adjusted for 2010-2013.

Table 1.6: Relative Risk Ratios of Race Compared to Black/White, Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

	Black		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.752	(0.165)	0.912	(0.229)
East North Central	1.054	(0.222)	0.913	(0.245)
West North Central	1.123	(0.224)	1.128	(0.298)
South Atlantic	1.347*	(0.228)	2.062***	(0.553)
East South Central	1.379	(0.303)	0.915	(0.323)
West South Central	1.934***	(0.426)	2.141**	(0.748)
Mountain	1.157	(0.268)	1.120	(0.319)
Pacific	0.932	(0.174)	1.007	(0.292)
Year (2005 Excluded)				
2006	1.024	(0.145)	1.246	(0.248)
2007	0.744**	(0.093)	0.721	(0.145)
2008	0.646***	(0.081)	0.703*	(0.138)
2009	0.537***	(0.069)	0.807	(0.159)
2010	0.555***	(0.079)	0.716*	(0.142)
2011	0.602***	(0.085)	0.768	(0.147)
Age (35-39 Excluded)				
25-29	0.587***	(0.060)	0.758*	(0.125)
30-34	0.665***	(0.073)	0.801	(0.134)
40-44	1.375**	(0.184)	1.654**	(0.324)
45-49	1.716***	(0.253)	2.540***	(0.489)
49-54	2.992***	(0.429)	3.525***	(0.640)
Education (Bachelor's Degree Excluded)				
Less than High School	1.485	(0.635)	2.060	(0.908)
Some High School	1.298	(0.234)	1.490	(0.393)
High School Degree	1.361***	(0.161)	1.298	(0.255)
Some College	1.320***	(0.135)	0.887	(0.157)
Associate's Degree	1.233*	(0.156)	0.905	(0.183)
Master's Degree	0.977	(0.124)	0.695	(0.169)
Professional	0.718	(0.178)	0.846	(0.251)
Doctorate	1.186	(0.371)	1.002	(0.441)
Employment Fraction	0.910	(0.070)	1.078	(0.132)
Female	0.994	(0.066)	1.045	(0.101)
Metropolitan Resident	1.444***	(0.142)	0.835	(0.156)
Phone/Personal Interview	2.271***	(0.177)	1.206*	(0.117)
Proportion Black (Standardized)	1.507***	(0.067)	0.732***	(0.064)
Proportion Black/White (Standardized)	0.555***	(0.026)	0.380***	(0.030)
Observations	7,569			
Pseudo R2	0.171			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by metropolitan area. Ancestry adjusted for 2010-2011.

Table 1.7: Relative Risk Ratios of Race Compared to Black/White, Full Time Workers 25-54, 2001-2013 Sample

	Black		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.938	(0.178)	0.791	(0.266)
East North Central	1.381*	(0.266)	0.777	(0.205)
West North Central	0.977	(0.216)	1.146	(0.301)
South Atlantic	2.058***	(0.400)	1.533	(0.570)
East South Central	3.443***	(0.859)	1.662*	(0.464)
West South Central	3.248***	(1.120)	1.962*	(0.801)
Mountain	0.983	(0.238)	1.077	(0.350)
Pacific	0.821	(0.150)	0.678	(0.167)
Year Category (2001-2002 Excluded)				
2003-2004	1.241	(0.183)	0.925	(0.239)
2005-2006	1.126	(0.245)	0.866	(0.268)
2007-2008	0.704	(0.184)	0.475**	(0.155)
2009-2010	0.565***	(0.105)	0.529**	(0.140)
2011, 2012, 2013	0.520***	(0.094)	0.455***	(0.130)
Age (35-44 Excluded)				
25-34	0.497***	(0.042)	0.654***	(0.070)
45-54	2.062***	(0.166)	2.209***	(0.276)
Education (Bachelor's Degree Excluded)				
No High School Degree	0.857	(0.197)	0.969	(0.312)
High School Degree	1.264**	(0.145)	1.030	(0.119)
Master's Degree	1.132	(0.187)	0.855	(0.196)
Professional Degree	0.778	(0.177)	0.918	(0.273)
PhD	1.026	(0.235)	0.727	(0.347)
Log Hourly Wages	0.797***	(0.047)	0.994	(0.077)
Female	1.073	(0.096)	0.878	(0.119)
Observations	7,735			
Pseudo R2	0.0717			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level.
Ancestry adjusted for 2010-2013.

Table 1.8: Relative Risk Ratios of Race Compared to Black/White, Full Time Working Adults 25-54, 2005-2011 Sample, Expanded Categories

	Black		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.820	(0.249)	0.911	(0.264)
East North Central	1.091	(0.307)	0.877	(0.261)
West North Central	1.155	(0.315)	1.181	(0.408)
South Atlantic	1.395	(0.347)	1.931**	(0.557)
East South Central	1.678*	(0.516)	1.007	(0.427)
West South Central	2.143***	(0.604)	1.808*	(0.649)
Mountain	1.217	(0.364)	1.008	(0.368)
Pacific	0.951	(0.262)	0.890	(0.277)
Year (2005 Excluded)				
2006	1.045	(0.152)	1.224	(0.280)
2007	0.748*	(0.111)	0.670*	(0.161)
2008	0.593***	(0.088)	0.655*	(0.147)
2009	0.508***	(0.079)	0.799	(0.188)
2010	0.552***	(0.092)	0.741	(0.169)
2011	0.536***	(0.095)	0.692*	(0.145)
Age (35-39 Excluded)				
25-29	0.613***	(0.085)	0.731	(0.141)
30-34	0.703**	(0.101)	0.672*	(0.142)
40-44	1.435**	(0.247)	1.324	(0.297)
45-49	1.862***	(0.371)	2.211***	(0.537)
49-54	3.032***	(0.448)	3.075***	(0.708)
Education (Bachelor's Degree Excluded)				
Less than High School	2.917*	(1.791)	1.236	(0.731)
Some High School	1.174	(0.321)	1.945*	(0.684)
High School Degree	1.585***	(0.231)	1.553*	(0.366)
Some College	1.343**	(0.176)	1.014	(0.219)
Associate's Degree	1.253	(0.193)	1.183	(0.291)
Master's Degree	1.173	(0.173)	0.823	(0.212)
Professional	0.871	(0.228)	0.898	(0.309)
Doctorate	1.099	(0.348)	0.574	(0.308)
Log Hourly Wages	0.880*	(0.063)	1.045	(0.111)
Female	1.065	(0.091)	0.871	(0.109)
Metropolitan Resident	1.476***	(0.187)	0.834	(0.154)
Phone/Personal Interview	2.220***	(0.202)	1.002	(0.122)
Proportion Black (Standardized)	1.481***	(0.073)	0.766***	(0.077)
Proportion Black/White (Standardized)	0.571***	(0.036)	0.376***	(0.035)
Observations		5,052		
Pseudo R2		0.168		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by metropolitan area. Ancestry adjusted for 2010-2011.

Table 1.9: Relative Risk Ratios of Race Compared to Black/White by Gender, Adults Aged 25-54, 2001-2013 Sample

	Males				Females			
	Black		White		Black		White	
	RRR	SE	RRR	SE	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Division (New England Excluded)								
Mid Atlantic	0.788	(0.249)	0.807	(0.106)	1.140	(0.219)	0.523*	(0.182)
East North Central	1.053	(0.250)	0.847	(0.161)	1.636**	(0.315)	0.491***	(0.129)
West North Central	0.883	(0.196)	0.902	(0.175)	1.210	(0.409)	0.829	(0.230)
South Atlantic	1.678**	(0.408)	1.602	(0.539)	2.638***	(0.535)	1.076	(0.394)
East South Central	2.096**	(0.638)	1.709***	(0.275)	4.544***	(1.622)	1.405	(0.429)
West South Central	3.157***	(0.856)	2.942***	(0.762)	3.564***	(1.360)	1.158	(0.574)
Mountain	0.987	(0.287)	0.859	(0.270)	1.145	(0.248)	1.319	(0.374)
Pacific	0.799	(0.172)	0.873	(0.112)	0.925	(0.223)	0.543**	(0.131)
Year Category (2001-2002 Excluded)								
2003-2004	1.242	(0.238)	0.652*	(0.147)	0.898	(0.164)	1.006	(0.288)
2005-2006	0.961	(0.245)	0.574**	(0.143)	0.980	(0.208)	0.821	(0.283)
2007-2008	0.687*	(0.156)	0.363***	(0.075)	0.646*	(0.149)	0.472**	(0.146)
2009-2010	0.519***	(0.096)	0.344***	(0.066)	0.523***	(0.121)	0.541*	(0.200)
2011, 2012, 2013	0.488***	(0.099)	0.305***	(0.065)	0.469***	(0.089)	0.474**	(0.141)
Age (35-44 Excluded)								
25-34	0.562***	(0.061)	0.602***	(0.080)	0.489***	(0.046)	0.697**	(0.103)
45-54	2.101***	(0.241)	2.092***	(0.383)	1.725***	(0.175)	2.110***	(0.269)
Education (Bachelor's Degree Excluded)								
No High School Degree	0.841	(0.172)	1.021	(0.224)	1.393	(0.305)	1.575**	(0.335)
High School Degree	1.103	(0.132)	0.794*	(0.096)	1.501***	(0.108)	1.129	(0.172)
Master's Degree	0.940	(0.232)	0.702	(0.224)	1.095	(0.150)	0.740	(0.229)
Professional Degree	0.406***	(0.090)	0.685	(0.274)	0.993	(0.235)	1.543	(0.551)
PhD	0.989	(0.430)	0.850	(0.452)	1.112	(0.286)	1.165	(0.476)
Employed Fraction	0.748***	(0.053)	1.326**	(0.169)	0.979	(0.100)	0.834	(0.126)
Observations	5,198				6,401			
Pseudo R2	0.0679				0.0729			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level. Ancestry adjusted for 2010-2013.

Table 1.10: Relative Risk Ratios of Race Compared to Black/White by Gender, Full-time Workers Aged 25-54, 2001-2013 Sample

	Males				Females			
	Black		White		Black		White	
	RRR	SE	RRR	SE	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Division (New England Excluded)								
Mid Atlantic	0.711	(0.217)	0.720*	(0.122)	1.298	(0.273)	0.852	(0.467)
East North Central	1.026	(0.225)	0.798	(0.188)	1.940***	(0.401)	0.725	(0.315)
West North Central	0.798	(0.151)	0.945	(0.215)	1.288	(0.411)	1.331	(0.550)
South Atlantic	1.565**	(0.334)	1.375	(0.435)	2.856***	(0.603)	1.670	(0.785)
East South Central	2.153***	(0.498)	1.452	(0.483)	5.958***	(1.692)	1.959	(0.953)
West South Central	3.401***	(0.963)	2.961***	(0.742)	3.554***	(1.503)	1.246	(0.866)
Mountain	0.805	(0.226)	0.643	(0.189)	1.257	(0.296)	1.785	(0.794)
Pacific	0.798	(0.144)	0.757*	(0.113)	0.899	(0.200)	0.576	(0.237)
Year Category (2001-2002 Excluded)								
2003-2004	1.489*	(0.352)	0.832	(0.222)	0.988	(0.255)	1.010	(0.430)
2005-2006	1.082	(0.279)	0.786	(0.235)	1.177	(0.319)	0.894	(0.399)
2007-2008	0.730	(0.207)	0.468**	(0.142)	0.693	(0.231)	0.451*	(0.187)
2009-2010	0.573***	(0.117)	0.442***	(0.081)	0.568**	(0.163)	0.597	(0.283)
2011, 2012, 2013	0.536***	(0.124)	0.397***	(0.110)	0.512***	(0.123)	0.495*	(0.190)
Age (35-44 Excluded)								
25-34	0.598***	(0.068)	0.575***	(0.095)	0.421***	(0.047)	0.763*	(0.122)
45-54	2.582***	(0.336)	2.346***	(0.498)	1.689***	(0.199)	2.190***	(0.374)
Education (Bachelor's Degree Excluded)								
No High School Degree	0.645	(0.188)	0.732	(0.314)	1.176	(0.300)	1.297	(0.472)
High School Degree	1.023	(0.164)	0.798	(0.129)	1.569***	(0.173)	1.341*	(0.212)
Master's Degree	1.016	(0.308)	0.727	(0.254)	1.268*	(0.174)	0.991	(0.264)
Professional Degree	0.505***	(0.132)	0.536	(0.230)	1.022	(0.310)	1.365	(0.630)
PhD	1.018	(0.462)	0.660	(0.441)	1.068	(0.290)	0.873	(0.447)
Log Hourly Wages	0.732***	(0.061)	1.050	(0.087)	0.892	(0.070)	0.916	(0.117)
Observations	3,686				4,049			
Pseudo R2	0.0714				0.0839			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level. Ancestry adjusted for 2010-2013.

Table 1.11: Relative Risk Ratios of Race Compared to Asian/White, Adults Aged 25-54, 2001-2013 Sample

	Asian		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.983	(0.273)	0.927	(0.089)
East North Central	1.026	(0.252)	0.788	(0.130)
West North Central	0.952	(0.270)	0.795	(0.158)
South Atlantic	0.950	(0.241)	1.010	(0.148)
East South Central	0.928	(0.257)	1.325	(0.249)
West South Central	1.095	(0.283)	1.043	(0.162)
Mountain	1.165	(0.307)	0.810**	(0.082)
Pacific	0.866	(0.212)	0.386***	(0.120)
Year Category (2001-2002 Excluded)				
2003-2004	1.343*	(0.225)	1.003	(0.095)
2005-2006	1.403***	(0.175)	0.951	(0.071)
2007-2008	1.070	(0.127)	0.709***	(0.074)
2009-2010	0.839	(0.094)	0.615***	(0.056)
2011-2012	0.819	(0.129)	0.578***	(0.064)
Age (35-44 Excluded)				
25-34	0.892*	(0.056)	0.811***	(0.040)
45-54	1.026	(0.076)	1.189***	(0.075)
Education (Bachelor's Degree Excluded)				
No High School Degree	1.661***	(0.264)	2.266***	(0.428)
High School Degree	1.434***	(0.086)	1.511***	(0.133)
Master's Degree	0.791**	(0.081)	0.812***	(0.063)
Professional Degree	0.876	(0.132)	0.643***	(0.097)
PhD	0.893	(0.189)	0.467***	(0.087)
Employment Fraction	1.148*	(0.090)	1.034	(0.036)
Female	0.887**	(0.054)	0.968	(0.032)
Observations	21,697			
Pseudo R2	0.0370			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level.
Ancestry adjusted for 2010-2013.

Table 1.12: Relative Risk Ratios of Race Compared to Asian/White, Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

	Asian		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.816	(0.146)	1.033	(0.094)
East North Central	1.003	(0.190)	0.750**	(0.099)
West North Central	0.708	(0.183)	0.638**	(0.119)
South Atlantic	0.805	(0.156)	1.101	(0.136)
East South Central	0.897	(0.204)	1.321*	(0.214)
West South Central	1.022	(0.225)	1.088	(0.146)
Mountain	1.061	(0.220)	0.928	(0.110)
Pacific	0.773	(0.140)	0.725**	(0.096)
Year (2005 Excluded)				
2006	1.167	(0.141)	0.970	(0.077)
2007	0.889	(0.107)	0.790**	(0.072)
2008	0.716***	(0.079)	0.661***	(0.060)
2009	0.591***	(0.068)	0.619***	(0.055)
2010	0.655***	(0.084)	0.631***	(0.067)
2011	0.637***	(0.075)	0.597***	(0.053)
Age (35-39 Excluded)				
25-29	0.871	(0.076)	0.958	(0.063)
30-34	0.739***	(0.067)	0.853**	(0.061)
40-44	1.104	(0.100)	1.231**	(0.110)
45-49	0.983	(0.106)	1.290***	(0.100)
49-54	1.421***	(0.177)	1.872***	(0.189)
Education (Bachelor's Degree Excluded)				
Less than High School	3.818**	(2.253)	3.312***	(0.998)
Some High School	1.430	(0.313)	2.037***	(0.256)
High School Degree	1.467***	(0.154)	1.819***	(0.156)
Some College	1.470***	(0.133)	1.325***	(0.090)
Associate's Degree	1.343**	(0.169)	1.347***	(0.130)
Master's Degree	0.916	(0.107)	0.804**	(0.081)
Professional	0.865	(0.152)	0.659***	(0.096)
Doctorate	1.152	(0.333)	0.551***	(0.119)
Employment Fraction	1.200*	(0.113)	1.032	(0.059)
Female	0.931	(0.063)	1.006	(0.044)
Metropolitan Resident	0.878	(0.110)	0.795**	(0.079)
Phone/Personal Interview	2.264***	(0.256)	1.819***	(0.160)
Proportion Asian (Standardized)	1.083**	(0.042)	0.962	(0.030)
Proportion Asian/White (Standardized)	0.907***	(0.033)	0.752**	(0.095)
Observations	14,164			
Pseudo R2	0.0846			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by metropolitan area. Ancestry adjusted for 2010-2011.

Table 1.13: Relative Risk Ratios of Race Compared to Asian/White, Full Time Workers 25-54, 2001-2013 Sample

	Asian		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	1.109	(0.287)	0.935	(0.119)
East North Central	1.231	(0.308)	0.852	(0.170)
West North Central	0.956	(0.324)	0.804	(0.179)
South Atlantic	1.153	(0.293)	1.106	(0.186)
East South Central	0.941	(0.306)	1.447**	(0.243)
West South Central	1.195	(0.310)	1.051	(0.193)
Mountain	1.357	(0.379)	0.847	(0.117)
Pacific	0.995	(0.257)	0.405***	(0.132)
Year Category (2001-2002 Excluded)				
2003-2004	1.191	(0.186)	1.022	(0.104)
2005-2006	1.329**	(0.171)	0.922	(0.069)
2007-2008	1.026	(0.094)	0.695***	(0.069)
2009-2010	0.767**	(0.088)	0.588***	(0.053)
2011, 2012, 2013	0.782	(0.130)	0.548***	(0.055)
Age (35-44 Excluded)				
25-34	0.870**	(0.060)	0.846**	(0.060)
45-54	1.030	(0.079)	1.253***	(0.091)
Education (Bachelor's Degree Excluded)				
No High School Degree	1.827***	(0.351)	2.292***	(0.513)
High School Degree	1.477***	(0.113)	1.515***	(0.146)
Master's Degree	0.787**	(0.079)	0.839**	(0.069)
Professional Degree	0.818	(0.163)	0.640***	(0.106)
PhD	0.968	(0.240)	0.500***	(0.084)
Log Hourly Wages	1.045	(0.053)	1.011	(0.058)
Female	0.927	(0.046)	0.942*	(0.034)
Observations	15,204			
Pseudo R2	0.0379			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level.
Ancestry adjusted for 2010-2013.

Table 1.14: Relative Risk Ratios of Race Compared to Asian/White, Full Time Working Adults 25-54, 2005-2011 Sample, Expanded Categories

	Asian		White	
	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)
Division (New England Excluded)				
Mid Atlantic	0.936	(0.144)	1.090	(0.153)
East North Central	1.051	(0.182)	0.805	(0.131)
West North Central	0.668	(0.173)	0.662*	(0.163)
South Atlantic	0.962	(0.155)	1.183	(0.182)
East South Central	0.837	(0.185)	1.370	(0.295)
West South Central	1.036	(0.200)	1.200	(0.198)
Mountain	1.081	(0.249)	0.951	(0.135)
Pacific	0.936	(0.137)	0.807	(0.139)
Year (2005 Excluded)				
2006	1.203	(0.188)	0.973	(0.107)
2007	0.889	(0.127)	0.816*	(0.100)
2008	0.728***	(0.088)	0.656***	(0.070)
2009	0.560***	(0.077)	0.598***	(0.066)
2010	0.640***	(0.088)	0.623***	(0.081)
2011	0.640***	(0.089)	0.552***	(0.062)
Age (35-39 Excluded)				
25-29	0.825*	(0.092)	0.991	(0.075)
30-34	0.750**	(0.087)	0.845**	(0.071)
40-44	1.193	(0.131)	1.283**	(0.133)
45-49	1.009	(0.133)	1.349***	(0.124)
49-54	1.482**	(0.232)	2.069***	(0.223)
Education (Bachelor's Degree Excluded)				
Less than High School	1.862	(0.965)	2.635*	(1.364)
Some High School	1.477	(0.374)	1.902***	(0.406)
High School Degree	1.350**	(0.168)	1.799***	(0.174)
Some College	1.447***	(0.136)	1.280***	(0.103)
Associate's Degree	1.256	(0.180)	1.381***	(0.155)
Master's Degree	0.929	(0.112)	0.828*	(0.093)
Professional	0.934	(0.196)	0.716**	(0.119)
Doctorate	1.166	(0.386)	0.644*	(0.145)
Log Hourly Wages	0.972	(0.073)	0.966	(0.038)
Female	0.970	(0.071)	0.984	(0.054)
Metropolitan Resident	0.777*	(0.104)	0.744***	(0.080)
Phone/Personal Interview	2.383***	(0.302)	1.817***	(0.179)
Proportion Asian (Standardized)	1.074**	(0.039)	0.961	(0.032)
Proportion Asian/White (Standardized)	0.891***	(0.032)	0.735**	(0.106)
Observations	9,978			
Pseudo R2	0.0880			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered by metropolitan area. Ancestry adjusted for 2010-2011.

Table 1.15: Demographics of Adults with Black/White Ancestry by Race and Excluded and Adjusted Status, Ages 25-54, 2011-2013 Sample

	Black		Black/White		White	
	Excl	Adj	Excl	Adj	Excl	Adj
	(1)	(2)	(3)	(4)	(5)	(6)
Years of Schooling	13.81	14.07	13.89	14.32	13.41	14.21
Fraction College Graduates	0.22	0.26	0.29	0.33	0.20	0.31
Age	38.08	37.75	34.16	34.52	36.73	37.56
Potential Experience	18.26	17.68	14.27	14.20	17.31	17.35
Married	0.37	0.34	0.36	0.34	0.34	0.48
Own Children in Household	1.07	0.99	0.93	0.88	0.76	0.86
Female	0.59	0.56	0.54	0.53	0.44	0.56
Phone/Computer Assisted	0.59	0.72	0.31	0.55	0.66	0.59
Employed Last Week	0.71	0.73	0.72	0.74	0.73	0.74
Employment Fraction	0.72	0.74	0.71	0.76	0.80	0.78
Log Hourly Wages*	2.51	2.46	2.48	2.56	2.41	2.52
Number of Observations	665	1,703	1,112	1,935	82	379

*Log Hourly Wages only for those with some employment
Excluded sample consists of individuals with Black/White ancestry, where one ancestry response is "White/Caucasian." Adjusted sample consists of all other individuals with Black/White ancestry that do not fit into the this category. Values are population weighted.

Table 1.16: Relative Risk Ratios of Race Comparing Excluded, Adjusted, and Combined Black/White Ancestry, Adults Aged 25-54, 2011-2013 Sample

	Excluded				Adjusted				Combined			
	Black		White		Black		White		Black		White	
	RRR	SE	RRR	SE	RRR	SE	RRR	SE	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Division (New England Excluded)												
Mid Atlantic	0.673	(0.186)	0.125***	(0.097)	1.022	(0.188)	0.413**	(0.167)	0.917	(0.171)	0.351***	(0.111)
East North Central	0.735	(0.183)	0.584	(0.391)	1.206	(0.161)	0.451*	(0.199)	0.997	(0.124)	0.447**	(0.150)
West North Central	0.969	(0.273)	0.499	(0.498)	0.758	(0.220)	0.412**	(0.178)	0.789	(0.204)	0.429**	(0.165)
South Atlantic	1.994***	(0.481)	0.389	(0.266)	2.144***	(0.301)	1.083	(0.528)	1.996***	(0.300)	0.828	(0.310)
East South Central	2.381*	(1.119)	0.266	(0.250)	2.607***	(0.853)	1.228	(0.523)	2.393**	(0.853)	0.791	(0.236)
West South Central	2.027***	(0.493)	1.330	(0.850)	3.161***	(0.967)	1.341	(0.517)	2.665***	(0.724)	1.254	(0.330)
Mountain	0.633	(0.182)	0.575	(0.406)	0.963	(0.184)	1.122	(0.517)	0.814	(0.138)	0.893	(0.301)
Pacific	0.624**	(0.120)	0.440	(0.279)	0.812	(0.172)	0.509	(0.226)	0.731**	(0.117)	0.456***	(0.137)
Year Category (2011 Excluded)												
2012	1.386**	(0.215)	0.739	(0.346)	0.813**	(0.081)	1.019	(0.212)	0.950	(0.060)	0.987	(0.163)
2013	1.220	(0.204)	0.943	(0.326)	0.719***	(0.065)	0.759*	(0.107)	0.852**	(0.053)	0.813	(0.105)
Age (35-44 Excluded)												
25-34	0.484***	(0.068)	0.616	(0.244)	0.670***	(0.076)	1.042	(0.168)	0.606***	(0.051)	0.924	(0.138)
45-54	1.448*	(0.274)	1.327	(0.488)	1.911***	(0.265)	2.941***	(0.572)	1.759***	(0.196)	2.540***	(0.453)
Education (Bachelor's Degree Excluded)												
No High School Degree	1.730**	(0.406)	1.796	(0.873)	1.225	(0.372)	1.362	(0.488)	1.345	(0.287)	1.414	(0.407)
High School Degree	1.413**	(0.210)	1.809	(0.657)	1.370**	(0.196)	1.102	(0.245)	1.358***	(0.151)	1.160	(0.218)
Master's Degree	0.787	(0.234)	1.243	(0.681)	1.088	(0.277)	0.770	(0.219)	0.989	(0.177)	0.831	(0.200)
Professional Degree	0.688	(0.423)	1.984	(1.586)	0.684	(0.204)	1.340	(0.766)	0.709	(0.228)	1.351	(0.664)
PhD	1.138	(0.797)	0.000***	(0.000)	0.449	(0.238)	1.518	(0.768)	0.567*	(0.181)	1.465	(0.776)
Employed Fraction	0.981	(0.139)	1.400	(0.392)	0.964	(0.086)	1.151	(0.161)	0.985	(0.073)	1.209	(0.165)
Female	1.201	(0.154)	0.701	(0.231)	1.066	(0.092)	1.140	(0.159)	1.100	(0.069)	1.035	(0.146)
Observations	1,859				4,017				5,876			
Pseudo R2	0.0866				0.0583				0.0578			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level.

Figure 1.1: US Biracial Population, 2000-2013

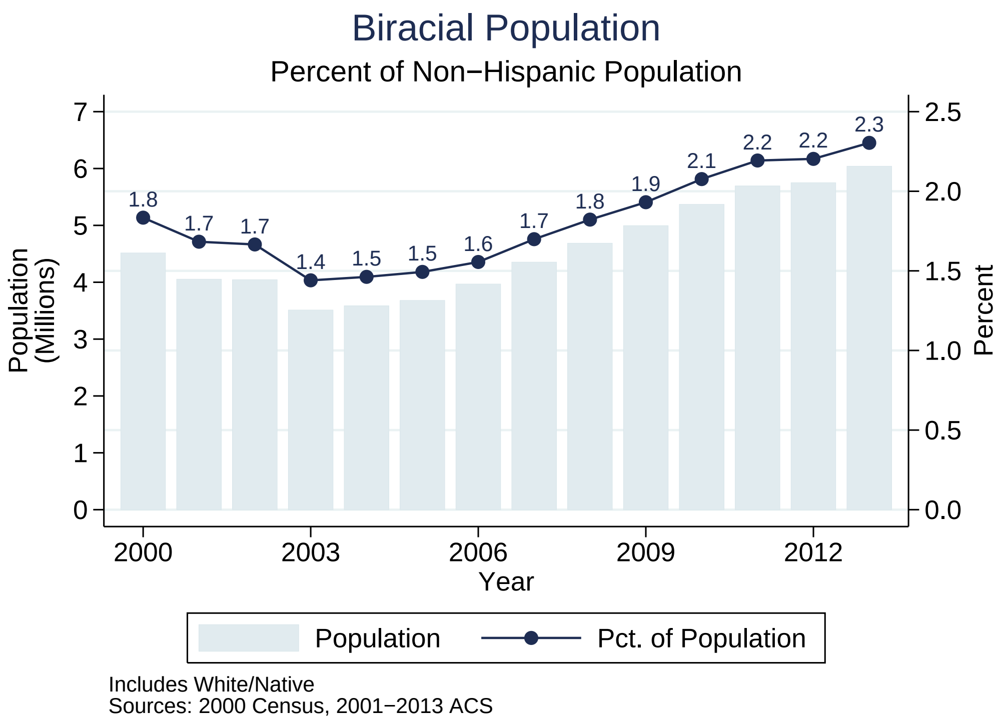
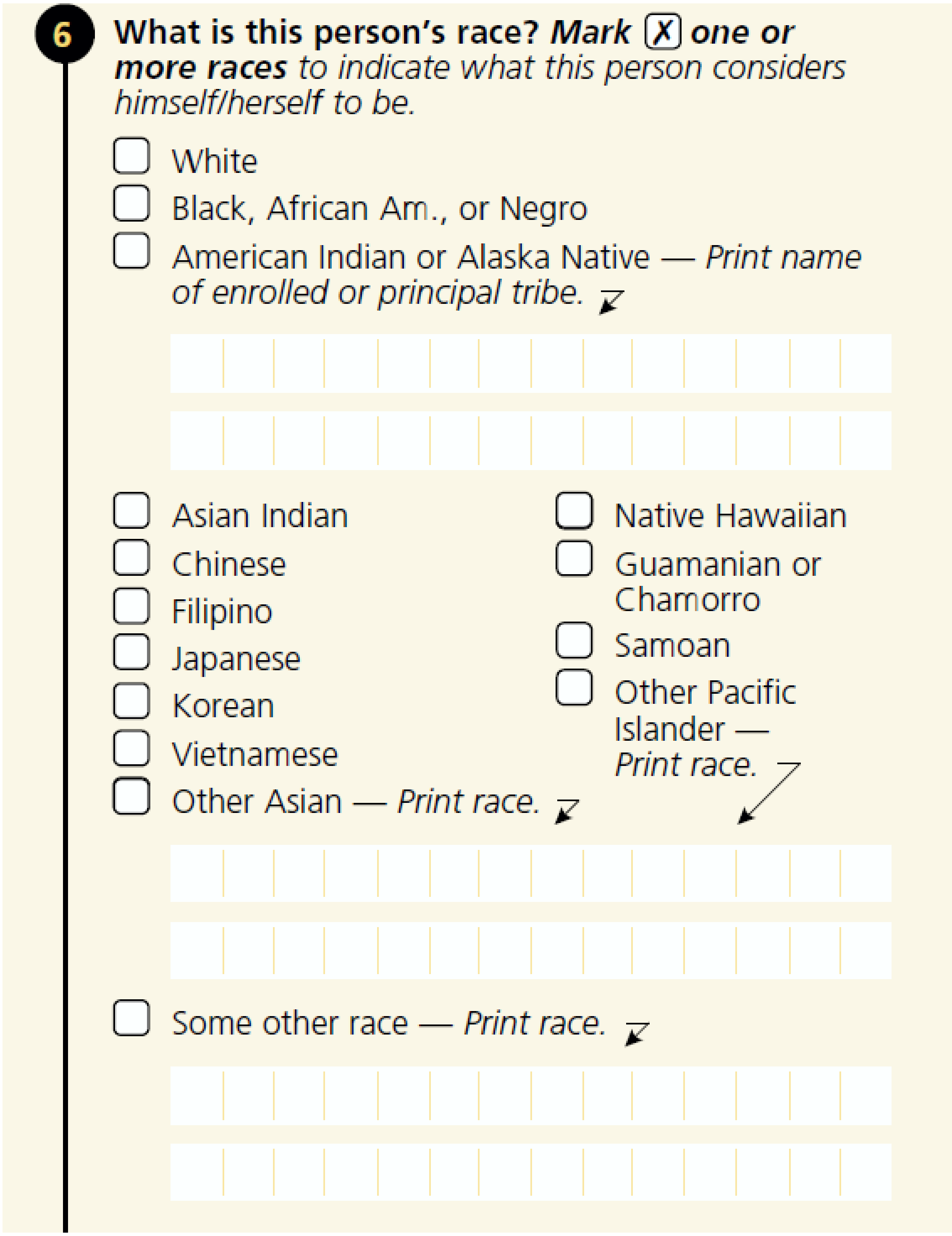
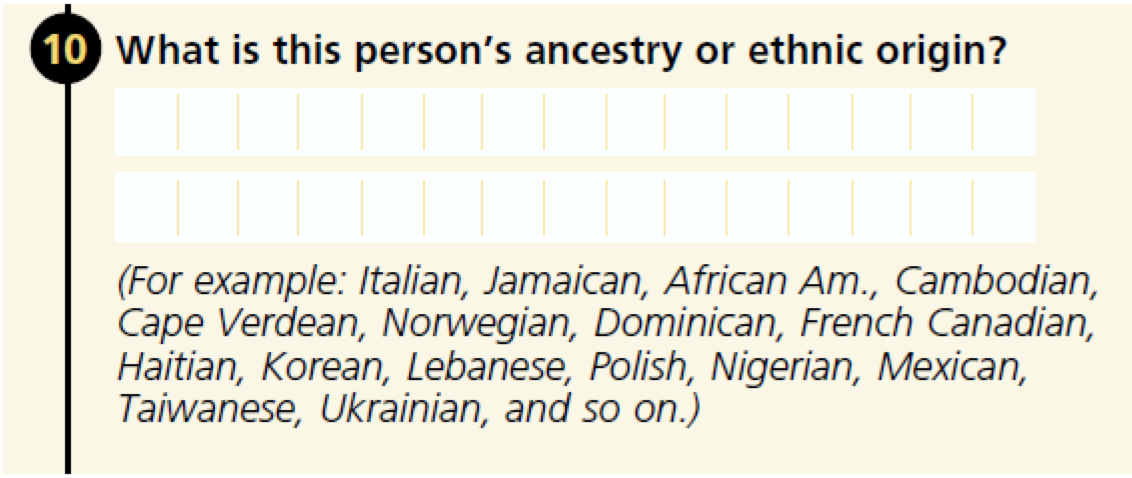


Figure 1.2: Census/American Community Survey Race Question


6 **What is this person's race? *Mark* [X] *one or more races*** *to indicate what this person considers himself/herself to be.*

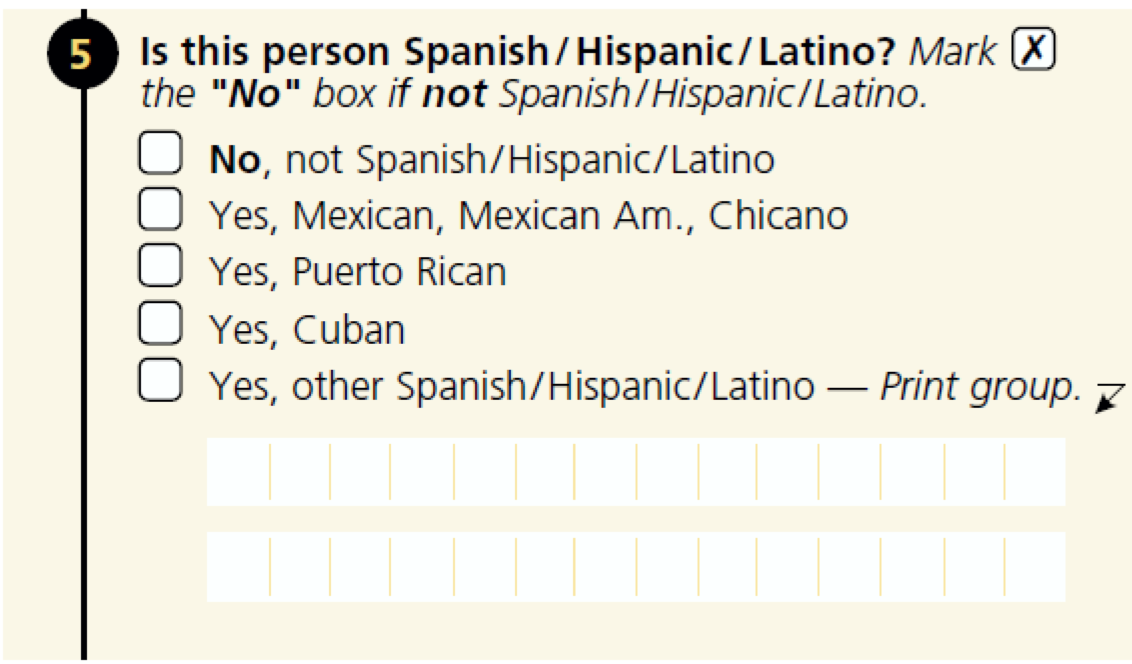
- [ ] White
- [ ] Black, African Am., or Negro
- [ ] American Indian or Alaska Native — *Print name of enrolled or principal tribe.*
- [ ] Asian Indian
- [ ] Chinese
- [ ] Filipino
- [ ] Japanese
- [ ] Korean
- [ ] Vietnamese
- [ ] Other Asian — *Print race.*
- [ ] Native Hawaiian
- [ ] Guamanian or Chamorro
- [ ] Samoan
- [ ] Other Pacific Islander — *Print race.*
- [ ] Some other race — *Print race.*

Figure 1.3: Census/American Community Survey Ancestry Question


10 **What is this person's ancestry or ethnic origin?**

(For example: Italian, Jamaican, African Am., Cambodian, Cape Verdean, Norwegian, Dominican, French Canadian, Haitian, Korean, Lebanese, Polish, Nigerian, Mexican, Taiwanese, Ukrainian, and so on.)

Figure 1.4: Census/American Community Survey Hispanic Origin Question


5 **Is this person Spanish / Hispanic / Latino?** *Mark* ☒ *the* ***"No"*** *box if* ***not*** *Spanish / Hispanic / Latino.*

- ☐ **No**, not Spanish/Hispanic/Latino
- ☐ Yes, Mexican, Mexican Am., Chicano
- ☐ Yes, Puerto Rican
- ☐ Yes, Cuban
- ☐ Yes, other Spanish/Hispanic/Latino — *Print group.*

Figure 1.5: Skin Tone/Phenotype Identity Line

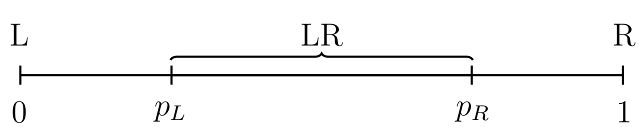


Figure 1.6: Utility for Identity and Action Choices (c_j, a_j) when $v_j = 0$

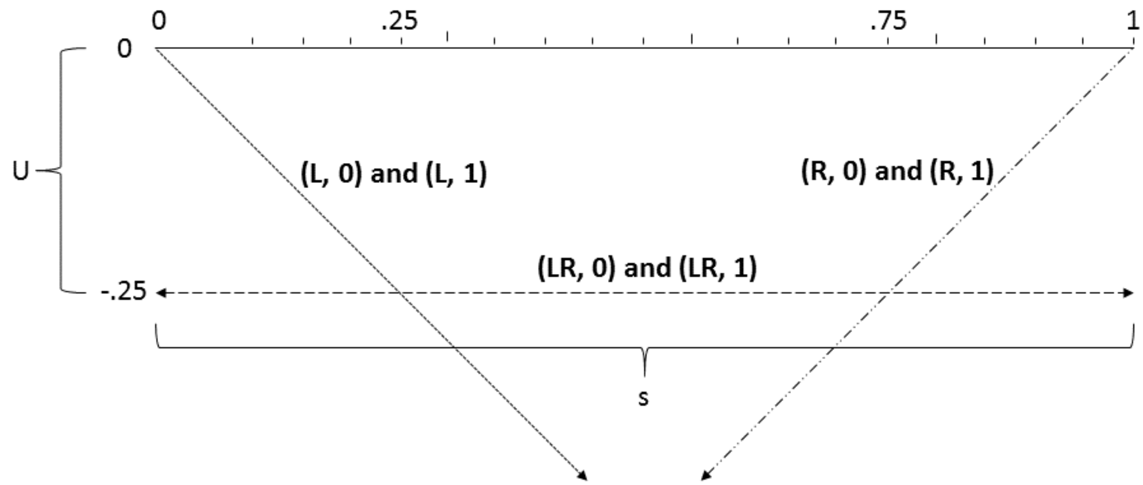


Figure 1.7: Identity and Action Choices (c_j, a_j) with $C_L = C_{LR} = C_R = 0$

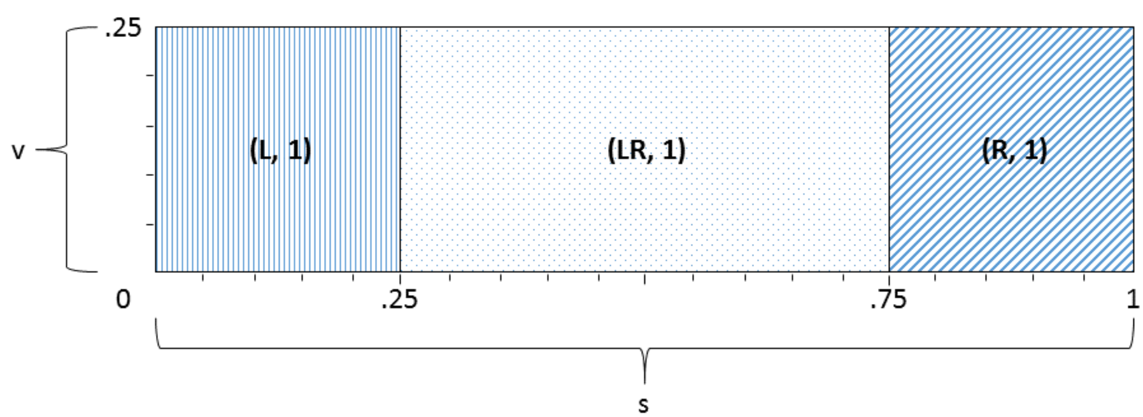


Figure 1.8: Identity and Action Choices (c_j, a_j) with $C_L = .2, C_{LR} = .1$, and $C_R = 0$

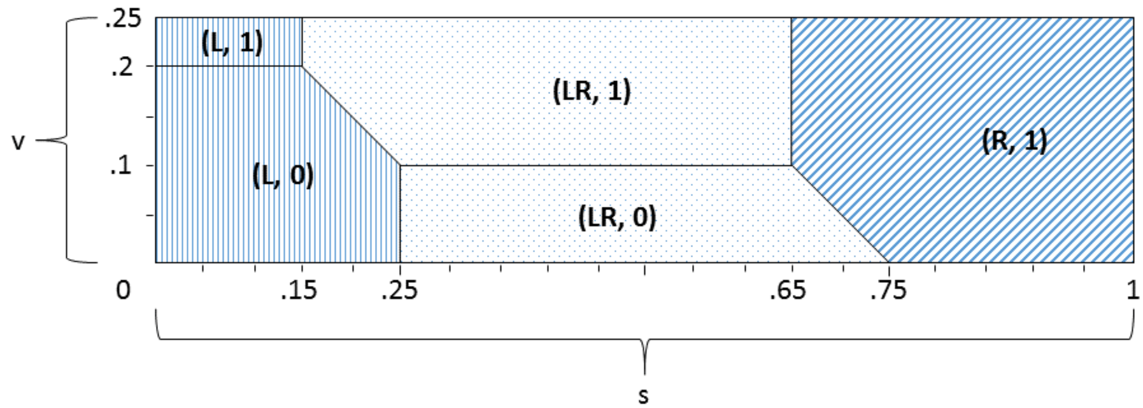


Figure 1.9: Identity "Switching" Areas

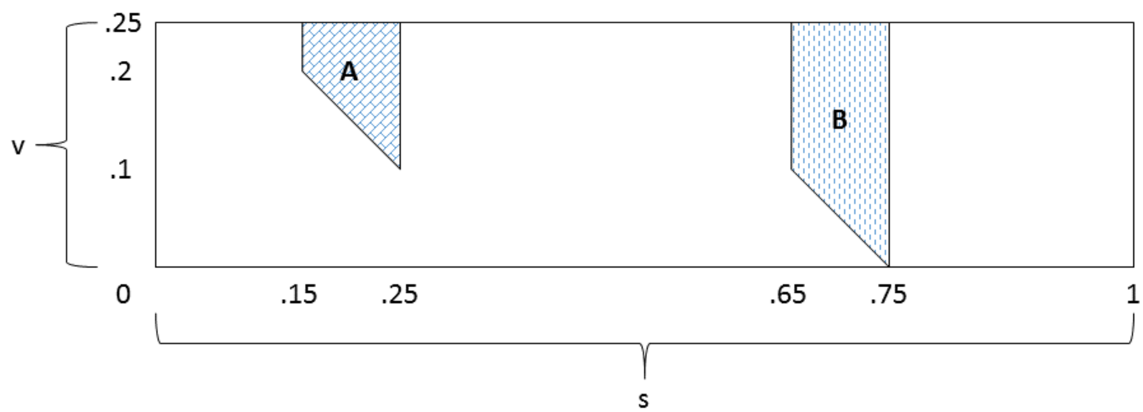


Figure 1.10: Predictions of Race by Division, Conditional on Black/White Ancestry, Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

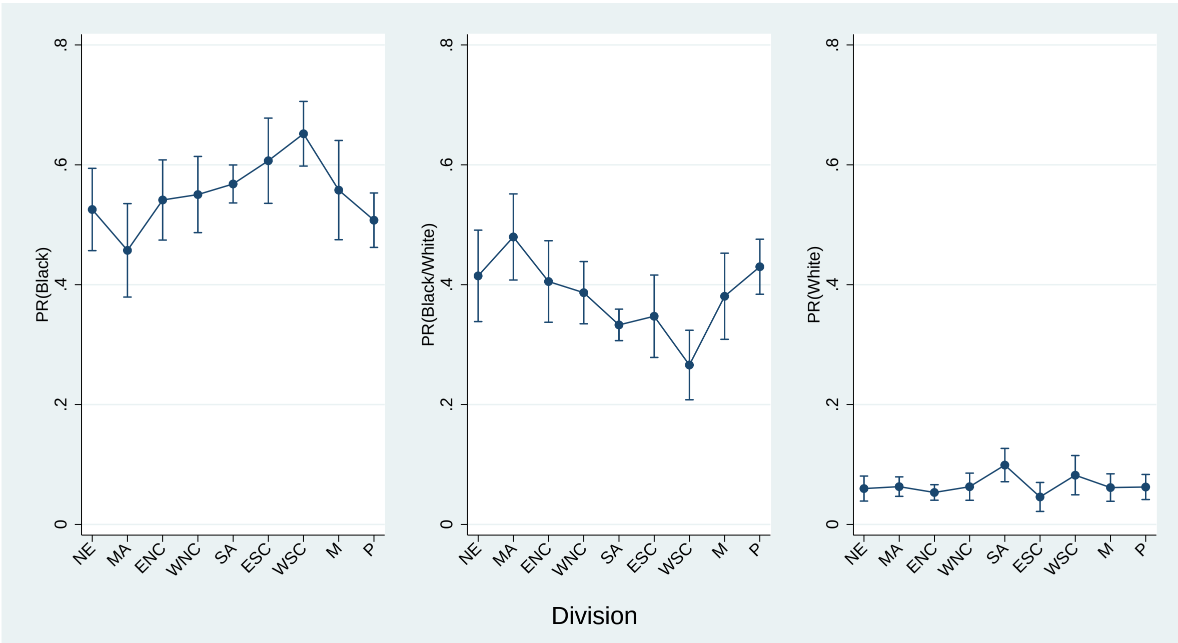


Figure 1.11: Predictions of Race by Year, Conditional on Black/White Ancestry, Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

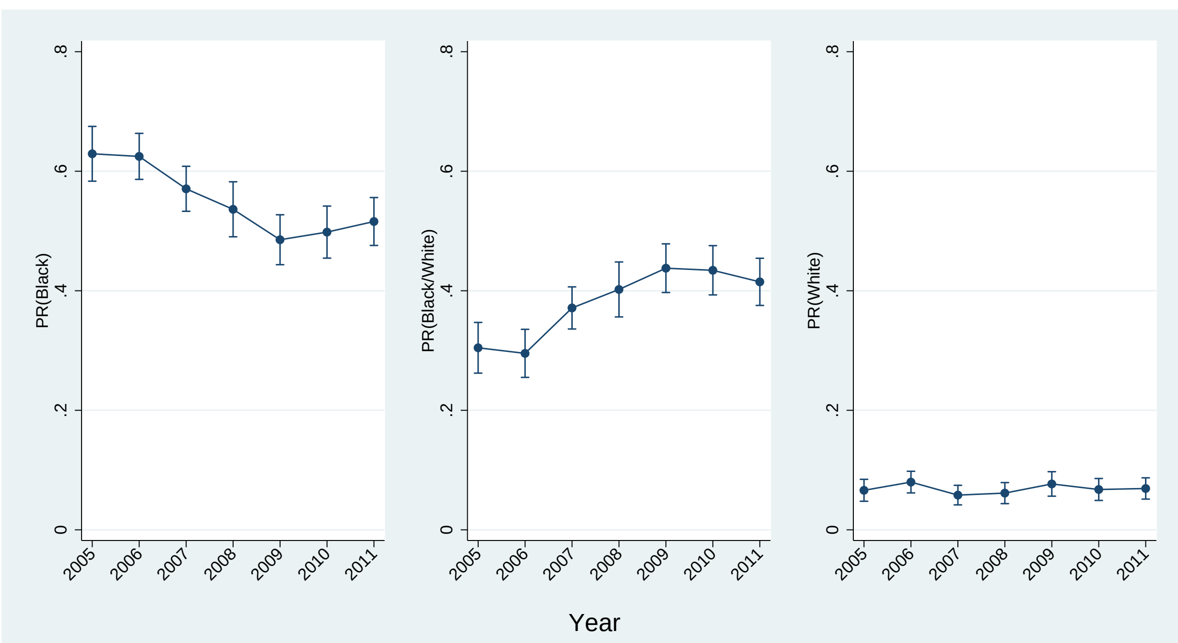


Figure 1.12: Predictions of Race by Age, Conditional on Black/White Ancestry, Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

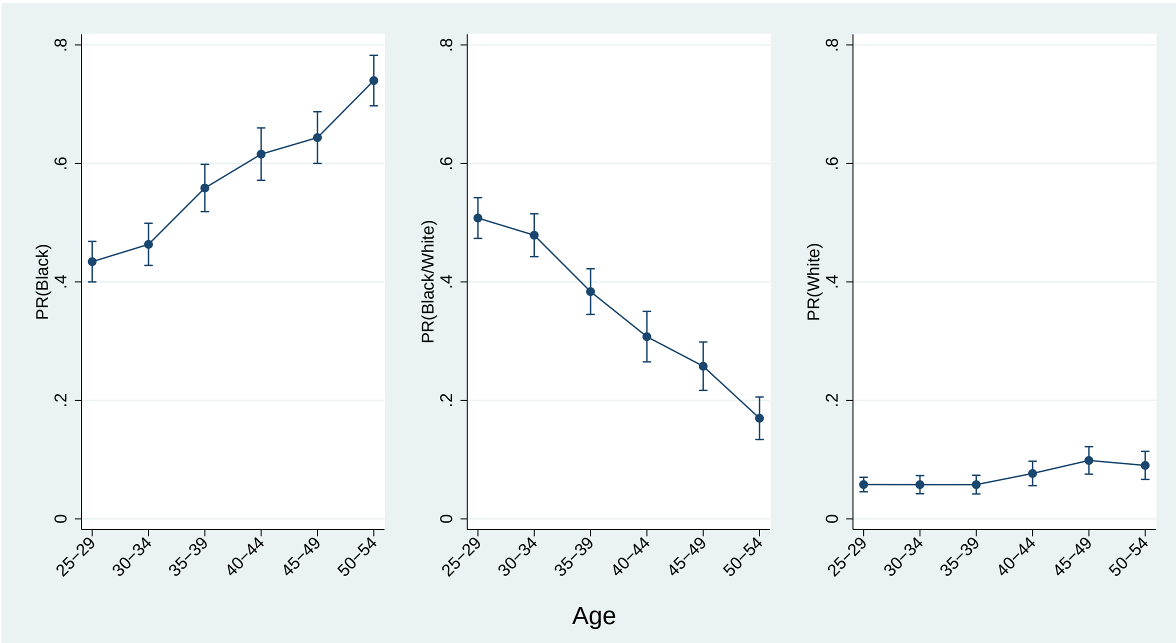


Figure 1.13: Predictions of Race by Expanded Education, Conditional on Black/White Ancestry, Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

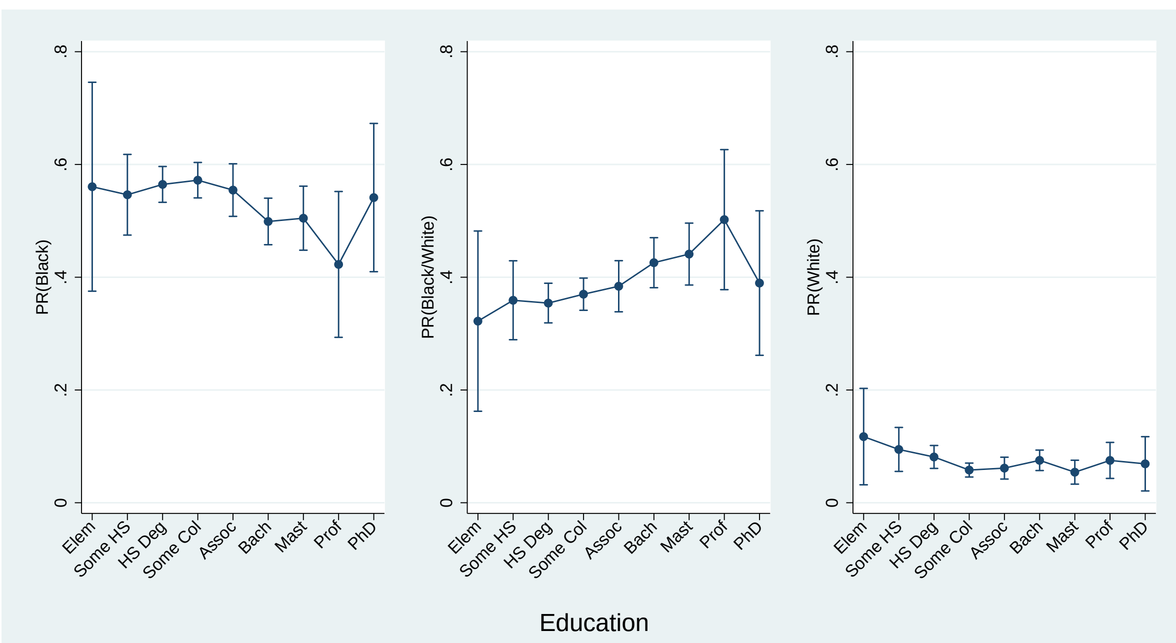


Figure 1.14: Predictions of Race by Division, Conditional on Black/White Ancestry, Full Time Working Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

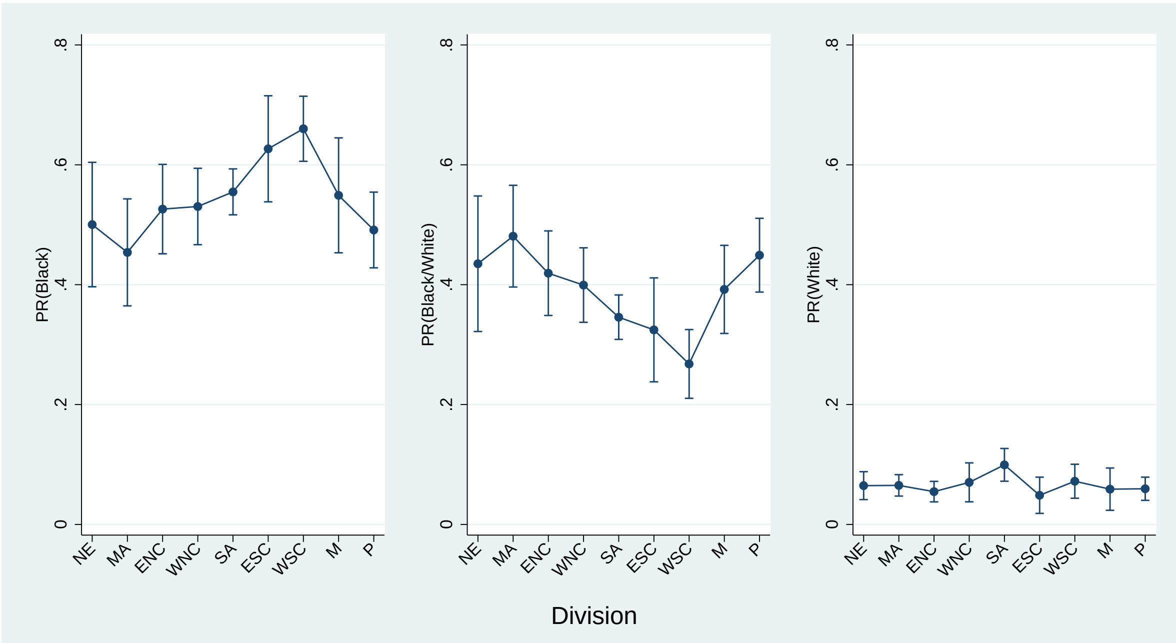


Figure 1.15: Predictions of Race by Year, Conditional on Black/White Ancestry, Full Time Working Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

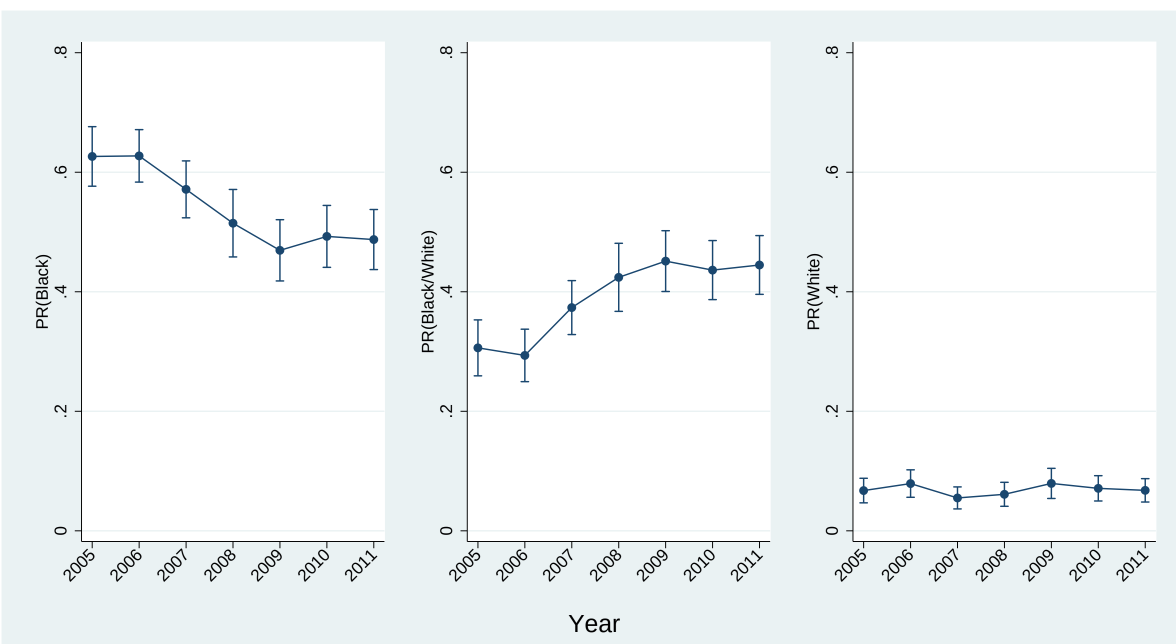


Figure 1.16: Predictions of Race by Age, Conditional on Black/White Ancestry, Full Time Working Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

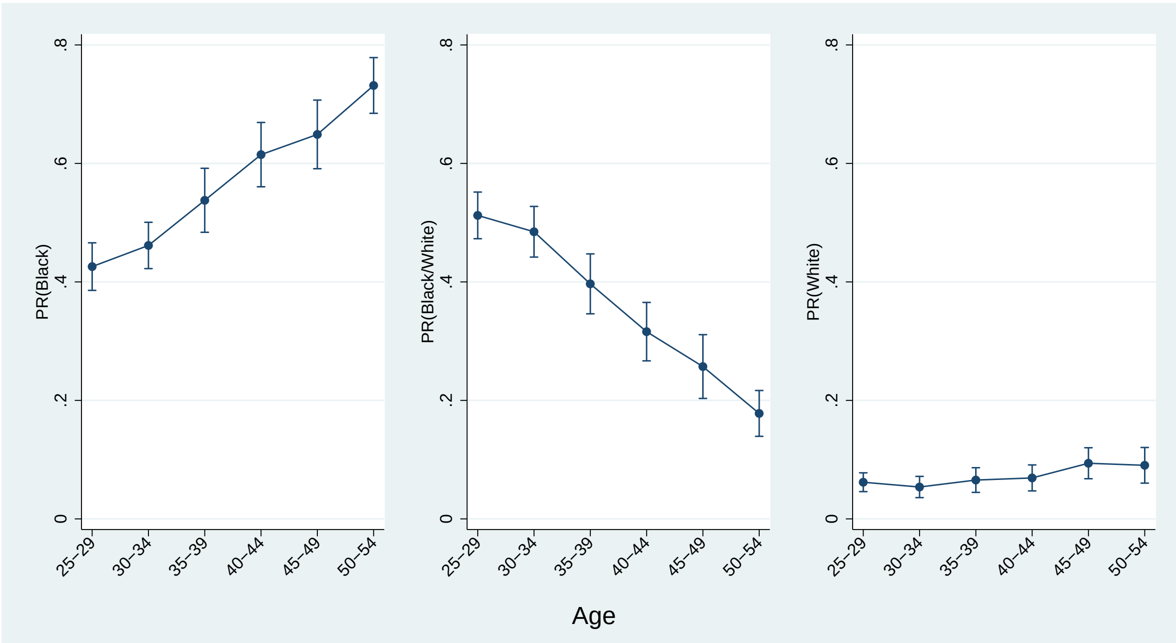
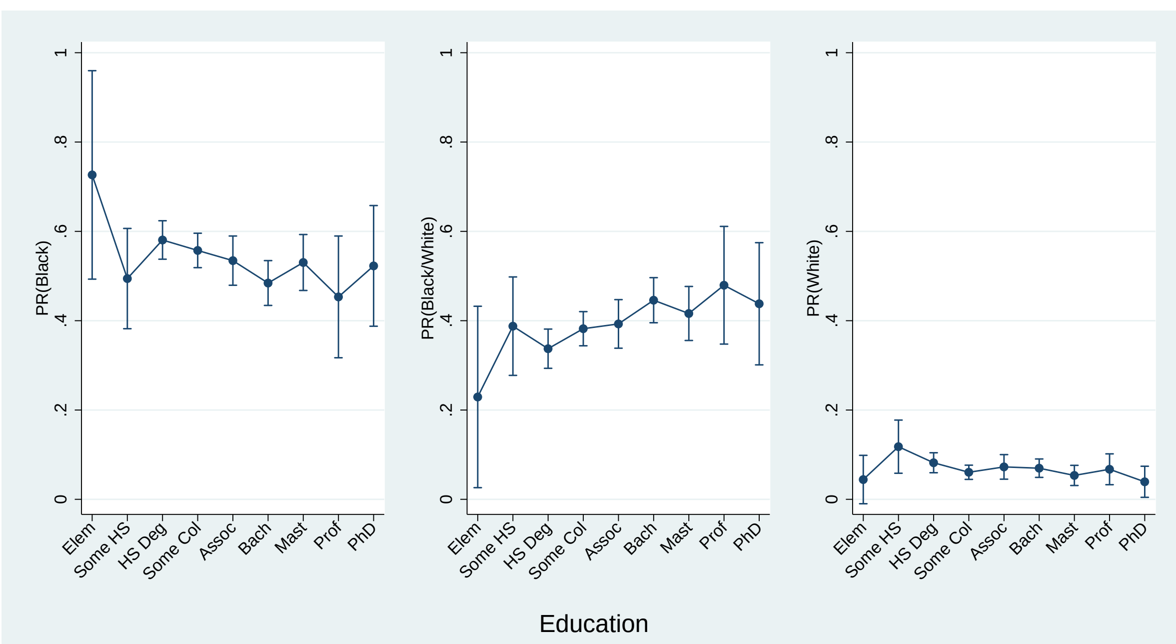
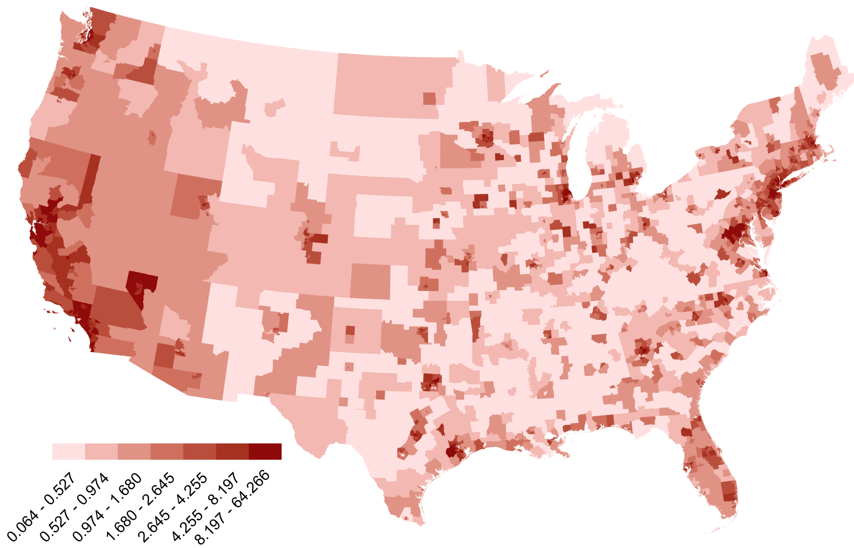
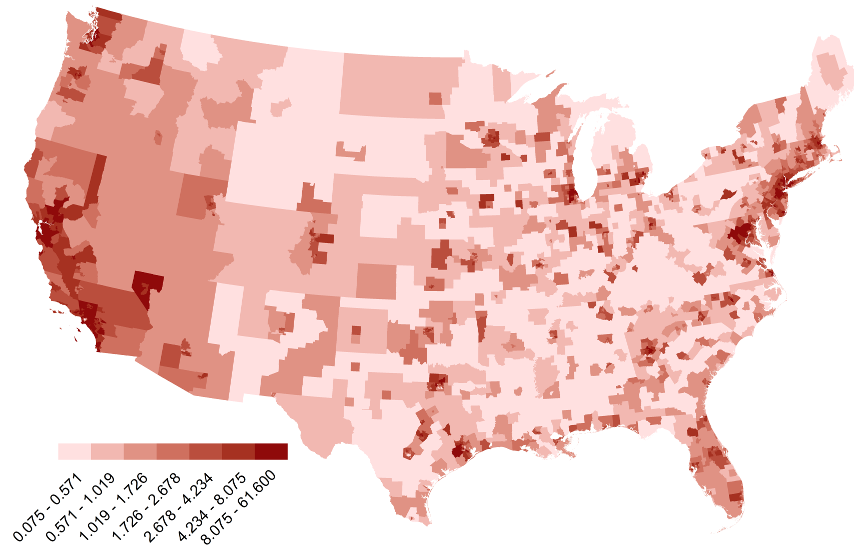


Figure 1.17: Predictions of Race by Education, Conditional on Black/White Ancestry, Full Time Working Adults Aged 25-54, 2005-2011 Sample, Expanded Categories

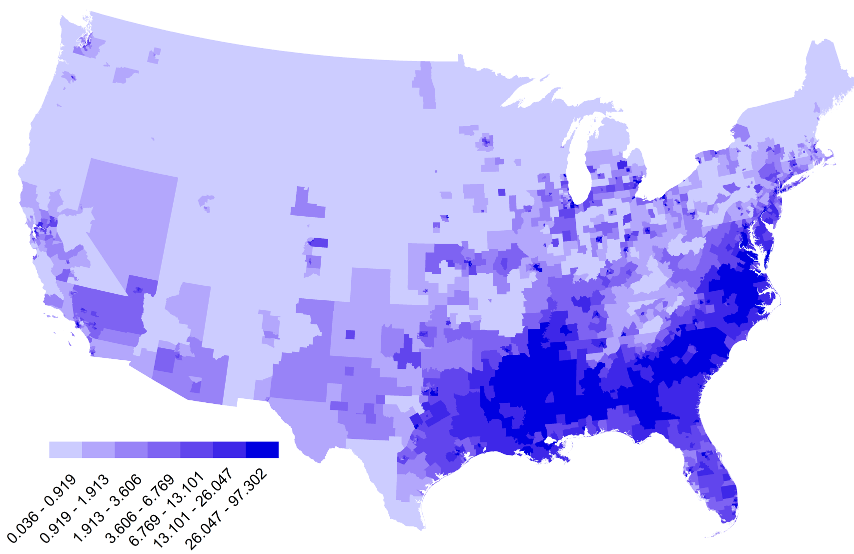




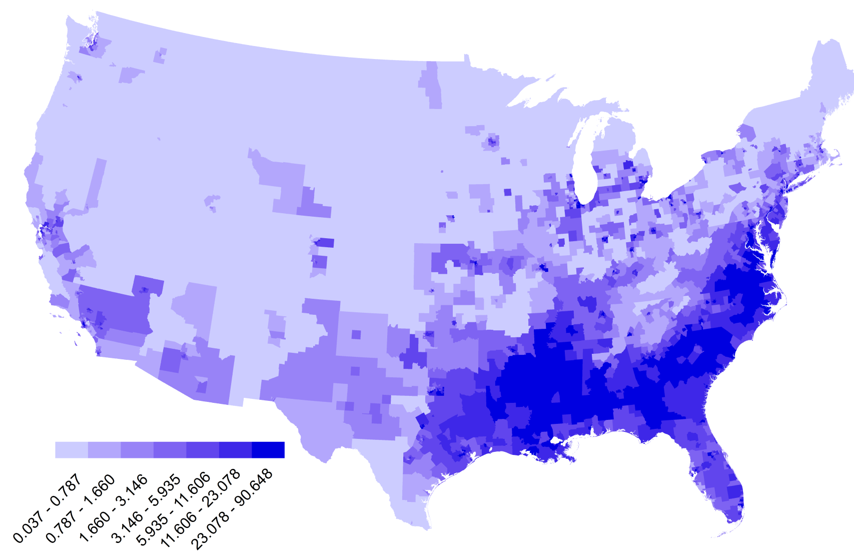
(a) Asian Race



(b) Asian Ancestry

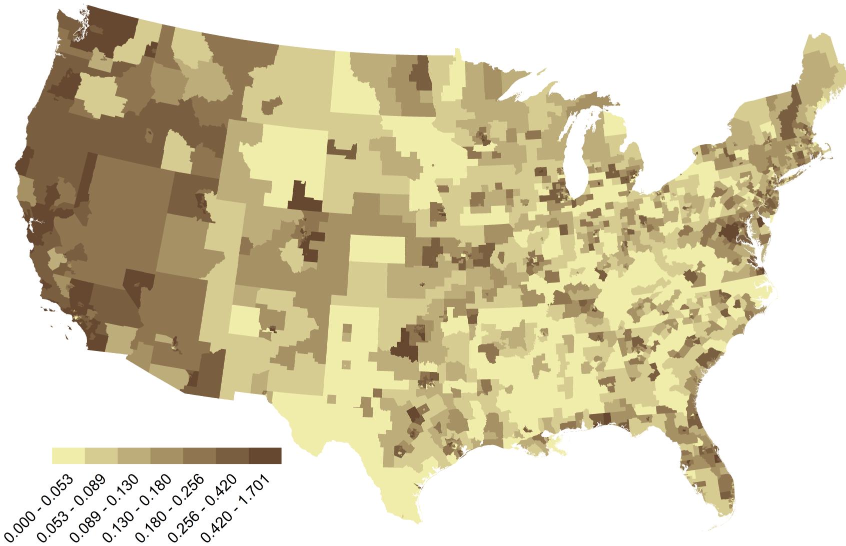


(c) Black Race

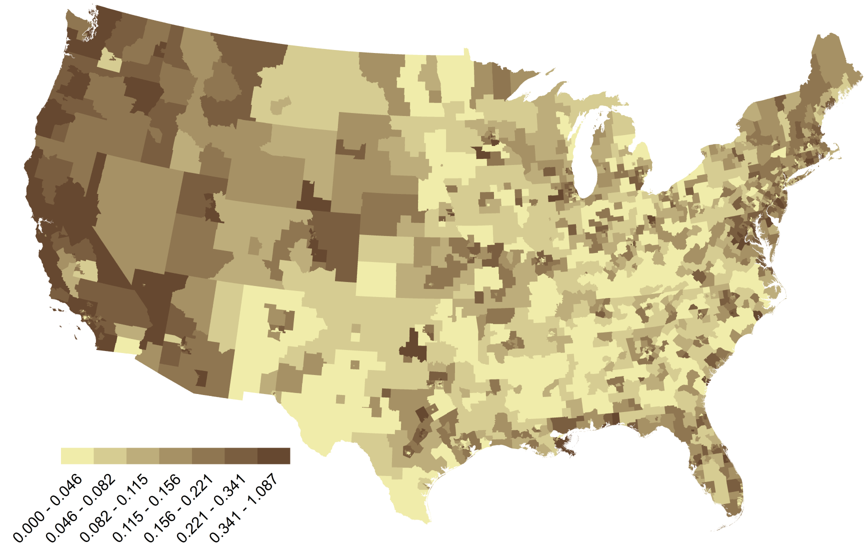


(d) Black Ancestry

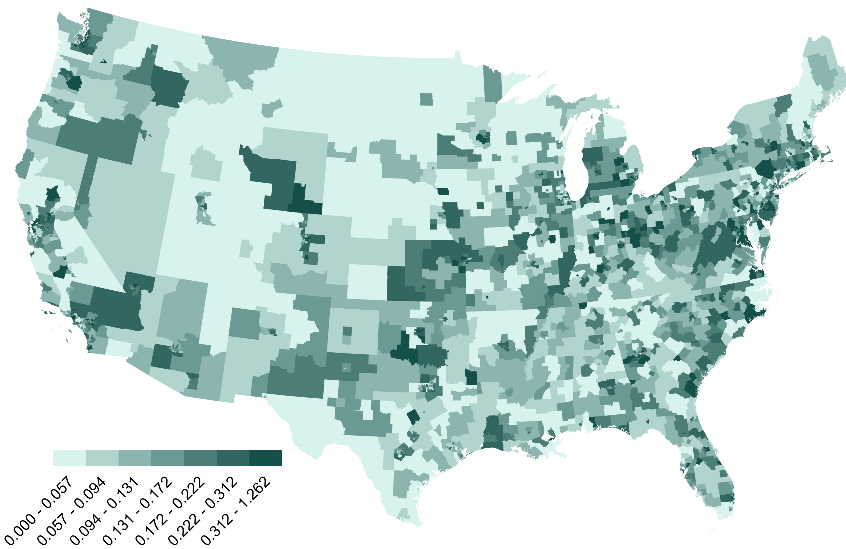
Figure 1.18: Percentage of Monoracial Adults, Quantile Scale, Summarized by PUMA, 2005-2011



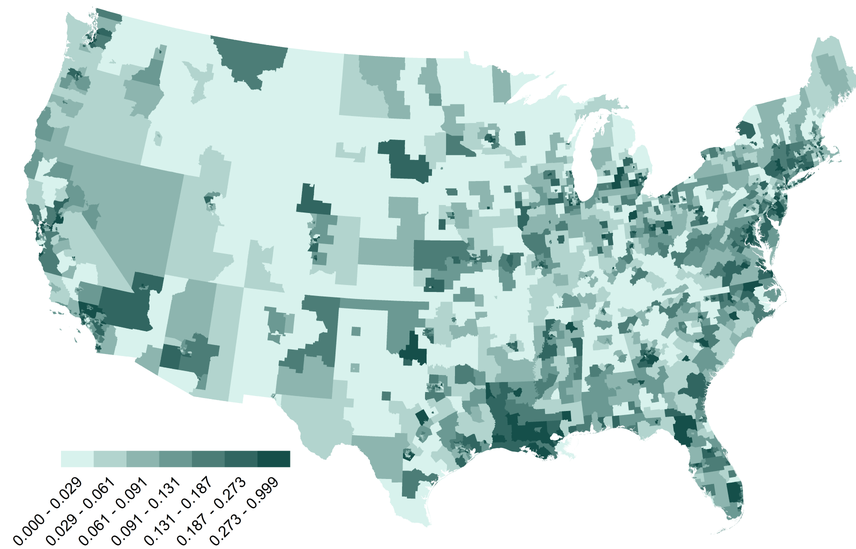
(a) Asian/White Race



(b) Asian/White Ancestry



(c) Black/White Race



(d) Black/White Ancestry

Figure 1.19: Percentage of Biracial Adults, Quantile Scale, Summarized by PUMA, 2005-2011

CHAPTER II

Intergroup relations with changing social identities

(Co-authored with Roy Chen)

2.1 Introduction

The US Census Bureau projections of 2014 indicate that while non-Hispanic Whites make up 62% of the population today, they will make up 44% of the population in 2060. Meanwhile, nearly every other group will increase its share of the population by 2060.[1] This will mark the first time since the United States has conducted the decennial census (starting in 1790) that the non-Hispanic White population will not constitute a majority in the US (Gibson and Jung, 2005). If these trends continue, Hispanics, who are projected to make up 31% of the population in 2060, will eventually become the majority group in the US.

This phenomenon of majority groups becoming minority groups and vice-versa is not uncommon in recent history. In the US, within certain occupations, such as pharmacists and accountants/auditors (Hegewisch and Hartmann, 2014), female workers have gone from minorities to majorities. The 2010 census shows that fewer than half of all adults are married for the first time in at least a century. Even more recently, supporters of gay marriage in the US have quickly gone from being a minority (35% in 2001) to a majority (54% in 2014).[2] The reasons for these shifts are varied and include demographic, cultural and economic changes.

[1]Source: `http://www.census.gov/population/projections/files/summary/NP2014-T10.xls`, retrieved on 1/1/2015.

[2]Source: `http://www.pewforum.org/2014/03/10/graphics-slideshow-changing-attitudes-on-gay-marriage/`, retrieved on 9/11/2014.

The effects of these shifts are potentially of great importance. Groups are defined by some shared characteristic, for example race. Through these shifts, an individual who starts in a majority group, such as non-Hispanic Whites in the US, would not have to change her group membership to eventually become a member of a minority group. Prislin, in several studies, uses confederates to examine the psychological effects of these shifts in relative group size, finding that "loss of majority position decreased perception of group-self similarity, group attraction, and expectations for positive interactions with the group," while, in certain circumstances, gaining majority position made subjects "more likely to engage in out-group hostility" (Prislin et al., 2000, 2011). In this study, we expand upon this work by providing monetary stakes to examine how behavior rather than just attitudes, in particular intergroup trust, are affected by these types of shifts.

We approach this topic using the framework of social identity. Social identity is the part of a person's sense of self that comes from her membership in social groups. Social identity and group membership are important parts of economic decision making. There is a great deal of work in both social psychology and economics examining how individuals treat members of their group (ingroup) and others outside of their group (outgroup). We study how changes in group size affect individuals' interactions with members of both their ingroup and their outgroup; specifically we explore how trust may change as a minority group becomes a majority group and vice versa.

We first recognize that a group can define a social identity. This social identity can come from any sort of shared characteristic, from shared beliefs to physical traits. The similarity or dissimilarity of individuals along these dimensions help define the social identity. The concept of majorities and minorities deals with the relative sizes of these groups. Therefore, majorities and minorities exist only in the presence of social identities that separate people into different groups. Clearly, majorities and minorities cannot exist without some social identity that creates multiple groups.

Majority and minority identities are more easily changeable than social identities such as race or gender. While an individual cannot easily change many of her social identities, majority and minority identities change automatically with shifts in relative group sizes. The demographic shift in the population of non-Hispanic White Americans discussed earlier is an example of this. This kind of change can also result from changing views and cultural norms, such as attitudes toward gay marriage, as discussed earlier.

To explore the effects of relative group size shifts on intergroup relations, we run a laboratory experiment with unequally sized groups, separating subjects into these laboratory-created majority and minority groups. We use an incentivized trust game as decisions from both parties can easily lead to equitable or inequitable payoffs which addresses issues of "fairness" that often accompany real-world majority and minority interactions. Subjects interact with their own groups (ingroup members) and subjects in other groups (outgroup members), giving us measures of trust and trustworthiness of subjects in majority and minority groups. We find that White subjects who are placed into minority groups are both more trusting and more trustworthy than White subjects in majority groups. We also change the group sizes during the experiment and find that subjects' initial relative group sizes predict their behavior better than their new relative group sizes.

This project adds to the economics literature of social identity by showing how changes in relative group size affect individuals' interactions with members of their ingroup and their outgroup. We also find an interesting interaction between laboratory-induced and real-world social identities. For a specific subset of our subject population, the relative size of their group has a large effect on their trust and trustworthiness, and this effect persists even when their group sizes are changed.

2.2 Literature Review

This work explores the interaction between majority and minority groups (which relates to the literature on social identity) and changing group size. Both the social psychology and economics literatures have previously dealt with these topics.

Majorities and minorities are defined by relative group size. In a population split into two groups, the larger group is the majority, and the smaller group is the minority. If the population is split into more than two groups, and the largest group constitutes more than half of the population, then that group is the majority and all other groups are minorities. In the ethnicity example described previously, since non-Hispanic Whites made up 63% of the population in 2012, this is currently the majority ethnic group in the US while all others are minority groups. Notice that majorities and minorities exist only in the presence of groups with different social identities.

The concept of social identity was first explored in social psychology. Tajfel et al. (1971) presented evidence of ingroup bias, or the tendency for people to treat their fellow group members better than non-group members.[3] Tajfel and Turner (1979, 1986) subsequently formalized the concept of social identity. After the seminal work of Akerlof and Kranton (2000) introduced these ideas to economics, other work such as that of Eckel and Grossman (2005), Charness et al. (2007), and Chen and Li (2009) showed that induced group identity in a laboratory setting can affect strategic decision making.

In other fields, groups with less influence and power are often simply referred to as "minority groups." In this paper, however, we refer to groups with different sizes as majority and minority groups, which define majority and minority *identities*. We refer to groups with different levels of influence and power as having high or low *statuses*.

Tanaka and Camerer (2013) explore the interaction between status and relative group size by looking at a region in South Vietnam where over 90% of the population is Vietnamese, and the Chinese and Khmer together make up less than 10% of the population. With an average income that is twice that of the Vietnamese, the Chinese in the area are considered high status, even though they make up a relatively small proportion of the population. The Khmer are a low-income, low-status minority group in the same area. Tanaka and Camerer separate effects of trust and patronizing behavior and find that the relatively positive treatment of the Chinese towards the Khmer is mainly patronizing, as this positive relationship does not extend to a task that would require trust of the Khmer.

Tsutsui and Zizzo (2013) examine how status interacts with relative group size in a laboratory setting. They assign status to one of the groups by giving only that group a name, the "blue" group, and telling other subjects they are not in the "blue" group. This status difference results in more individuals with status showing more trust of others. They also create differently sized groups, of eight and four members, to create majority and minority

[3]In the economics literature, treating fellow group members better refers to taking actions that increase their payoffs, in the pyschology literature, this extends to positive evaluations of and attribution of positive personality traits to group members.

groups, but find no difference in their behavior. One thing to note is that they do not make this group size difference particularly salient; they just let subjects know how many members were in each group.

Using Tsutsui and Zizzo (2013) as a baseline, we first explore whether relative group size can affect trust in a laboratory setting. Because they do not see any effect of relative group size on behavior, we adjust their experimental design. First, we ensure that each subject plays only one role (either sender or receiver) during the experiment to prevent the potentially confounding effects of role reversal. Next, we strengthen the groups by allowing group members to communicate with each other in order to solve a task before they are aware of the trust game. Finally, we focus on relative group size by not creating status differences between the subjects. The details of this design are described in the next section.

We next explore how changing relative group sizes affects behavior. Weber (2006) shows that groups that grow slowly and with sufficient information about past group behavior can maintain coordination (using a minimum effort game) from the smaller group that would not otherwise be expected. In social psychology, Prislin et al. (2000) examine how group interactions change when groups change from majorities to minorities and vice-versa. Their assignment of group status is achieved through the use of confederates, or fake participants working for the experiment. The experimenters have confederates change their opinions to make subjects feel they are part of the majority or the minority group, and they record differences in self-reported opinions. They find asymmetric effects in that a loss of majority identity has a stronger effect on subjects' perceived group similarity than does a gain of that identity.

This paper examines whether and how changing relative group sizes such that the majority group becomes the minority group, and vice versa, affects trust between and among these groups. We now explain our methods in detail.

2.3 Experimental Design

We employ a 2×2 between-subjects factorial design, as shown in Table 2.1. In one dimension, we vary whether group sizes change during the experiment. In the other dimension,

Table 2.1: Experimental Design

Treatment	Sender group size	No. of sessions	No. of subjects in lab	No. of subjects total
No Change	Majority	9	8	12
	minority	9	4	4
Change	Majority	9	8	8
	minority	9	4	8

we vary whether the groups are larger (majorities) or smaller (minorities). Since our group sizes are defined relative to the sizes of the other group, we run the majority and minority treatments simultaneously. We are primarily interested in how changing a subject's group from a minority to a majority, and vice versa, affects behavior. We therefore designate the "No Change" treatment as a control. The experimental instructions that the subjects read through before the experiment are included in H. This experiment was conducted in the Behavioral and Experimental Economics Lab at the University of Michigan in July and August of 2013. All sessions were run using z-Tree (Fischbacher (2007)).

Each subject is a member of one of two groups, which we label "Green" and "Red." For the first half of the experiment, one of these groups is randomly chosen to be the majority group. Then, depending on the treatment, either eight (Change) or twelve (No Change) subjects are randomly assigned to this group, and all others are assigned to the other group, the minority group.

We recruit sixteen subjects for each session. At all times we have twelve subjects in the lab with eight in the majority group, four in the minority group, and four sitting out in the waiting room. The four subjects sitting out are rotated in halfway through the experiment and a different set of four subjects are rotated out. This is displayed in Figure J.1. The subjects rotated out are all members of the initial majority group. Depending on the treatment, the four subjects rotating in for the second half of the experiment are either all added to the same group as the four that left (No Change treatment - the group sizes do not change) or all added to the other group (Change treatment - the group sizes switch). This way, we can change group sizes without having individual subjects change groups during the experiment: in the Change treatment, the subjects who were in the majority become the minority and vice versa. We refer to subjects who participate in both halves of the experiment as “20-period subjects.”

In order to reinforce subject identification with their teams, we have the subjects perform a group puzzle-solving task.[4] Subjects are shown six photographs from two different named locations, three from each location. Subjects are then asked to identify which photographs match which locations. For instance, subjects are shown photographs labeled “A1,” “A2,” “A3,” “B1,” “B2,” and “B3,” and are told that all of the photographs labeled “A” are either all from the USA or all from Australia. Those labeled “B” are from the other location. They are then asked to identify where the “A” photographs are from. The subjects therefore have a 50% chance of guessing the correct answer. To help answer this question, subjects are allowed to discuss the task with members of their own group using a computer-based group chat, which allows for free text communication between the subjects in a group. Subjects participating in this task know that all other subjects they are chatting with are members of their ingroup, but they do not know any other information about these other subjects. This task is similar to the painting task used in Chen and Li (2009), in which subjects are asked to guess the artists of two paintings after being shown other paintings by the same artists, and it is designed with the same goal of enhancing group identity.

We use trust and trustworthiness as our outcome measures. Each subject is randomly chosen to be a sender or receiver and plays a two-person trust game with her match, a person with the opposite role. In the trust game, the sender is given an endowment of 20 tokens. Then she chooses how many, if any, tokens to pass to the receiver. Before reaching the receiver, the tokens passed are multiplied by 4. The receiver then chooses how many of these tokens to pass back to the sender. The number of tokens the sender passes can be viewed as a measure of the amount of trust the sender places in the receiver. The number of tokens the receiver passes back to the sender can be seen as a measure of the trustworthiness of the receiver. Exactly half of our subjects are senders and half are receivers, and no one changes roles during the experiment. Of the four subjects who do not participate in the first half, we always assign two to be senders and two to be receivers. The same is true for the four

[4]Tajfel and Turner (1979) identify three processes that are important for group identity to affect behavior: (1) Categorization, or the assignment of individuals to groups, (2) identification, or the internal process through which individuals associate themselves with groups, and (3) comparison, the act of comparing an individual’s group to other groups.

subjects they replace. When subjects play the trust game, they know the group membership ("Green" or "Red"), but no other identifying information, of their match.

A session consists of 22 periods. In the first period, all subjects are read the instructions and then four subjects are asked to leave the computer lab and return to the waiting room. Next, subjects are randomly assigned to either the "Green" or the "Red" group. They participate in the photograph identification task while chatting with their group members.

In the second period, subjects' roles in the trust game are revealed and each subject plays the trust game with a random match of the other role. The subjects are then randomly rematched nine more times for a total of 10 periods, each time with another person of the opposite role from their own. In each period, a subject in the majority group has a two-thirds chance of being matched with a member of their own group and a one-third chance of being matched with a member of the other group. The opposite is true for a subject in the minority group. As there are majority and minority groups with ingroup and outgroup matching, this creates four match categories between senders and receivers. When majority (minority) senders are matched with majority (minority) receivers we refer to this as a majority (minority) ingroup match. When majority (minority) senders are matched with minority (majority) receivers we refer to this as a majority (minority) outgroup match.

Halfway through the experiment, the four subjects who did not participate in the first half return to the computer lab and replace four others, who return to the waiting room. The old and new subjects then repeat the first half of the experiment, first completing the photograph identification task (with new photographs) and then playing the trust game for 10 periods. Afterward all subjects return to the lab and fill out a 13-question survey.

Subjects are paid at a rate of one dollar per 50 tokens. Subjects who do not participate in one half of the experiment are paid the average amount earned by the other subjects in who did participate in that half of the experiment.

Subjects were paid a $5 show-up fee in addition to their earnings for the experiment, which were rounded up to the next nearest dollar. The average payment was $16.43 per hour, close to the standard rate for experimental economics study participants at the University of Michigan.

2.4 Hypotheses

Let s denote the proportion of an endowment sent by a sender. We use superscripts xy to describe the relative sizes of the sender's own group, x, and of the receiver's group, y. The induced minority group is denoted m, and the induced majority group is denoted M. For example, the proportion of the endowment sent by a sender who is a member of the minority group and is matched with a receiver who is a member of the majority group is written as s^{mM}. For receivers, we use the same superscripts to describe relative group sizes, but use r to refer to the proportion of the received amount returned to senders. For example, the proportion returned by a receiver who is a member of the majority group to a sender who is a member of the minority group would be written as r^{Mm}. Once group sizes change, we use n to denote new minority and N to denote new majority.

For the following hypotheses, we give predicted orderings for various group comparisons. For receivers, we assume that these orderings are conditional on the amounts they were sent by the senders.

First, we note that the social psychology literature indicates that minorities form more tightly knit groups than majorities (Leonardelli and Brewer, 2001). This yields the following prediction:

Hypothesis 1 (Ingroup minority effect) *Subjects in minorities will send and return more to members of their own groups than their majority counterparts.*

$$s^{mm} > s^{MM}, \qquad r^{mm} > r^{MM} \tag{2.1}$$

Other work in social psychology and economics finds that majorities value minorities' payoffs more than minorities value majorities' payoffs (Gupta et al., 2013; Tanaka and Camerer, 2013):

Hypothesis 2 (Outgroup majority effect) *Subjects in majorities will send and return more to members of other groups than their minority counterparts.*

$$s^{Mm} > s^{mM}, \qquad r^{Mm} > r^{mM} \tag{2.2}$$

Next, we want to consider changing group sizes. In particular, we will focus on how we expect the proportions sent and returned to change when the minority group becomes the majority group and vice versa. We present two competing hypotheses. One possibility is that subjects will immediately adopt their new majority and minority identities. This would result in an ordering of the new amounts sent and returned that are identical to the original orderings:

Hypothesis 3 (Change) *Subjects who change their majority or minority identity will change their behavior; they adopt the predicted behaviors of their new identities. Assuming that Hypotheses 1 and 2 are correct, this predicts the following orderings:*

$$s^{nn} > s^{NN}, \qquad r^{nn} > r^{NN} \qquad \textit{(ingroup new minority effect)} \tag{2.3a}$$

$$s^{Nn} > s^{nN}, \qquad r^{Nn} > r^{nN} \qquad \textit{(outgroup new majority effect)} \tag{2.3b}$$

Another possibility is that subject behavior persists after induced group sizes are changed. In this case, we expect that the ordering will be altered such that new majorities act like old minorities, and new minorities act like old majorities. In this case, we expect the proportions sent and returned to have the following orderings for individuals who are switched from minority to majority and vice versa:

Hypothesis 4 (Persistence) *Subjects who change their majority or minority identity will not change their behavior; they follow the predicted behaviors of their original identities. Assuming that Hypotheses 1 and 2 are correct, this predicts the following orderings:*

$$s^{NN} > s^{nn}, \qquad r^{NN} > r^{nn} \qquad \textit{(ingroup new majority effect)} \tag{2.4a}$$

$$s^{nN} > s^{Nn}, \qquad r^{nN} > r^{Nn} \qquad \textit{(outgroup new minority effect)} \tag{2.4b}$$

It is also possible that subjects will initially follow their original behavior (Hypothesis 4), but will slowly converge towards behavior that fits their new identities (Hypothesis 3). However, it is unclear whether we will be able to observe or test for this shift in the time frame of the experiment.

2.5 Results

Table 2.2: Summary Statistics

	All Subjects		20-Period Subjects	
	Control	Treatment	Control	Treatment
Age	22.16	21.91	22.00	22.14
Race				
Asian Pct	0.42	0.47	0.40	0.54
Black Pct	0.04	0.05	0.01	0.06
Hispanic Pct	0.03	0.01	0.04	0.03
Native Pct	0.01	0.01	0.00	0.00
Other Pct	0.06	0.04	0.04	0.01
White Pct	0.44	0.42	0.50	0.36
Education				
Undergrad Pct	0.72	0.72	0.75	0.69
Graduate Stud Pct	0.18	0.22	0.18	0.24
Not Student Pct	0.10	0.06	0.07	0.07
Siblings	1.43	1.46	1.44	1.38
Observations	144	144	72	72

We run 18 sessions (9 "Change" treatment sessions and 9 "No Change" treatment sessions) with 16 subjects each. Table 2.2 shows summary statistics for all subjects as well as for the 20-period subjects. We focus on 20-period subjects for our analysis unless otherwise specified. Whites and Asians make up the bulk of our subject pool with very few identifying as Black, Hispanic, Native American, or another race.[5] 72% of our subjects are undergraduate students, 20% are graduate students, and 10% are not students. The average age of our subjects is 22.

We first explore both sender and receiver behavior using random effects regressions. Recall that our "Change" treatment switches majority and minority group membership for 20-period subjects in the second half of the experiment. We wish to compare not only majority/minority groups with ingroup/outgroup matching but also potential changes in behavior when majority groups become minority groups and vice versa. Therefore, we categorize individuals who change from majority (minority) to minority (majority) groups in

[5] Though "Hispanic" is not a race according to the census, we treat it as a separate race in our survey (I). For example, subjects cannot state that they are both Hispanic and Black.

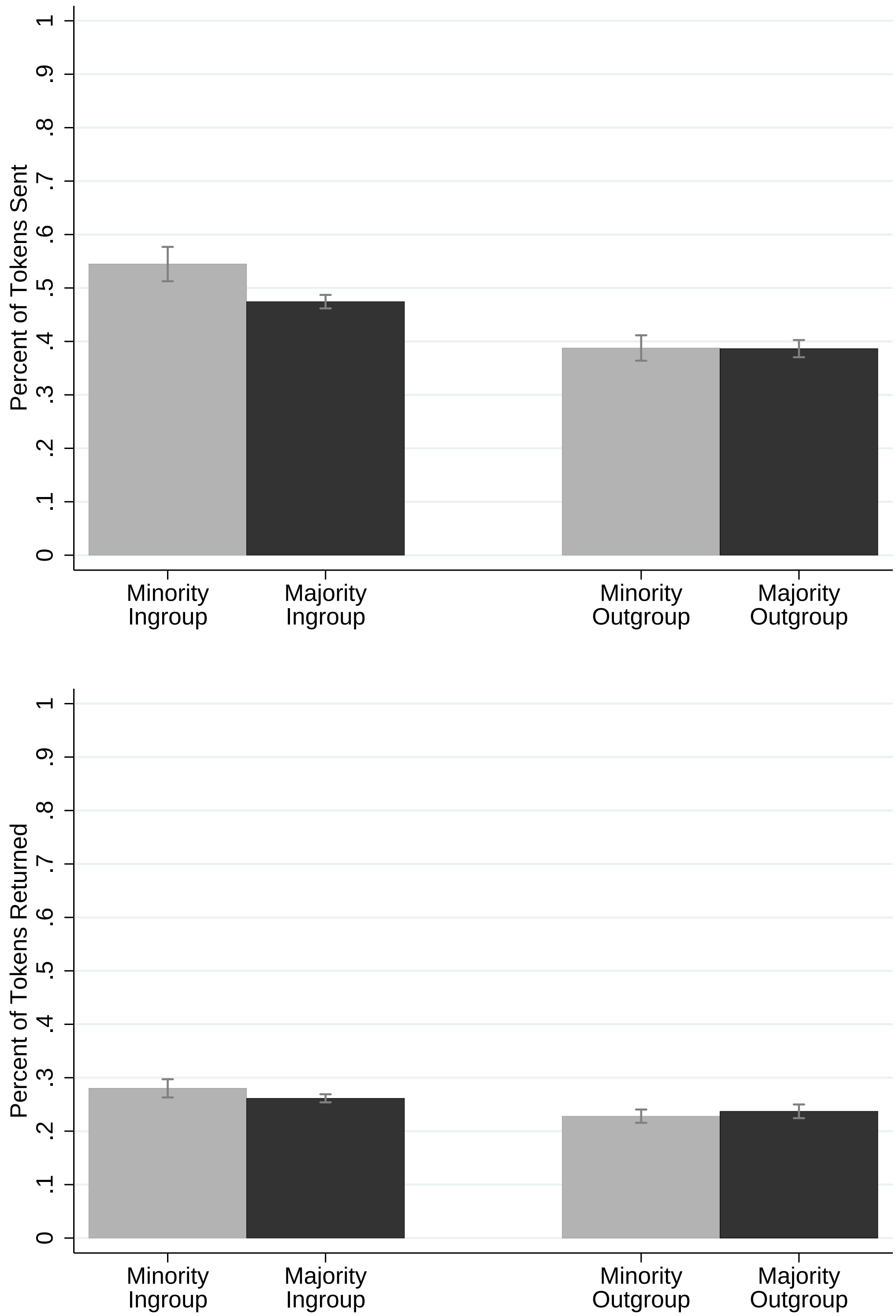


Figure 2.1: % tokens passed by minority/majority senders (top) and receivers (bottom), including standard errors.

the second half as new minority (new majority). As we compare ingroup and outgroup matching for these two groups, we thus have four more match categories to consider for each regression. Figure 2.1 shows the average percentage of tokens sent and returned by all subjects in (original) minority and majority groups. This figure also shows standard error bars for the subsamples. These averages are also shown in Table 2.3, separated by half, majority/minority identity, and treatment. This includes the behavior of all subjects in the first half of the experiment and subjects in the second half of the control sessions.[6]

Table 2.3: % Tokens Passed, 20-Period Senders and Receivers

	Senders			Receivers		
	All	Control	Treatment	All	Control	Treatment
First Half	0.45	0.51	0.39	0.24	0.26	0.21
Majority Ingroup	0.49	0.58	0.40	0.24	0.25	0.23
Majority Outgroup	0.39	0.50	0.29	0.23	0.26	0.19
Minority Ingroup	0.53	0.53	0.52	0.26	0.29	0.23
Minority Outgroup	0.41	0.45	0.37	0.22	0.25	0.18
Second Half	0.43	0.49	0.36	0.25	0.28	0.22
Majority Ingroup	0.53	0.62	0.45	0.24	0.28	0.19
Majority Outgroup	0.37	0.45	0.30	0.28	0.34	0.22
Minority Ingroup	0.50	0.59	0.41	0.30	0.34	0.25
Minority Outgroup	0.32	0.34	0.29	0.24	0.25	0.22
Observations	1440	720	720	983	547	436

Receivers only include those who start with more than 0 tokens.

2.5.1 Full Sample

First, we examine the participants of all races, which we refer to as the *full sample* (we later split the sample according to race). On the full sample, we first regress the percentage

[6]We group together the individuals who do not switch majority/minority identities in the regressions that follow. This means that the minority category includes the behavior of all minority-group members in the first half of the experiment and the behavior of minority-group members in the second half who were also members of the minority group in the first half. As these particular minority-group members in the second half start in the minority group and remain in the same minority group, we do not expect their behavior to differ between halves of the experiment. However, we include a variable denoting the second half of the experiment to control for changing behavior over time. We also describe an alternative specification for categorizing and comparing changing majority/minority identities in G. Results from this specification are almost identical to the specification described in the results below.

of tokens sent on seven dummy variables representing the eight match categories described above with "majority ingroup" as the omitted category. We also include dummy variables for gender, second half, and race, with "White" as the omitted category and all non-White races grouped together.[7] The results for the full sample are presented in column 1 of Table 2.4. Standard errors are adjusted for clustering at the session level.

Similarly, we regress the percentage of tokens returned by receivers on the same variables used in the sender regression. The results for the full sample of receivers are presented in column 1 of Table 2.5, with standard errors adjusted for clustering at the session level. These regressions yield the following result:

Result 1 (Sending and returning by all subjects) *In the full sample, senders and receivers who participate in all 20 periods of the trust game are approximately equally trusting and trustworthy regardless of whether they are in a majority or minority group.*

While Hypothesis 1 predicts that subjects in minority groups will send and return more to ingroup members than their counterparts in majority groups, we do not see evidence of this in the full sample. Senders in minority groups send about 5% more tokens to other members of the minority group than senders in majority groups send to other members of the majority group, which is about one more token of their 20-token endowment. This difference is not significant at the 10% level ($p = 0.550$). Similarly, receivers in minority groups send about 3% more tokens to their ingroup members than receivers in majority groups send to their ingroup members. This difference is also not significant at the 10% level ($p = 0.570$). For the full sample, we cannot reject the null hypothesis in favor of Hypothesis 1.

Also, while Hypothesis 2 predicts that subjects in majorities will send and return more to outgroup members than their counterparts in minority groups, we again do not see evidence of this in the full sample. Senders in majority groups actually send approximately 3% fewer tokens to members of the minority group than senders in minority groups send to members of the majority group, though this difference is not significant at the 10% level ($p = 0.680$, Wald test). Receivers in majority groups return about 5% more of their tokens to outgroup

[7] Results are similar if all races other than White and Asian are excluded from the analysis. Results are also similar if we create three categories, White, Asian, and all other races. We cannot examine any other races separately as we do not have enough non-White, non-Asian participants in the experiment.

members than receivers in minority groups return to outgroup members. This difference is also not significant at the 10% level ($p = 0.284$, Wald test). For the full sample, we cannot reject the null hypothesis in favor of Hypothesis 2.

2.5.2 Restricted Samples

To further explore these (lack of) results, we will now separately analyze subsets of our sample. First, we examine separately the behavior of White and non-White subjects. We justify this exploration by the fact that subjects of different races experience natural majority and natural minority identities differently in day-to-day life. Asians, Blacks, and Whites make up 92% of our experimental subjects. Population estimates of racial groups in the US and in Ann Arbor, MI along with enrollment figures from the University of Michigan indicate that Whites are the majority race while Asians and Blacks are minority races for the population from which we pull our experimental sample.[8] Therefore, in our experimental sample, Whites have a natural majority identity while Asians and Blacks, like other minority races, have natural minority identities. It is possible that these natural identities interact with our laboratory-induced majority and minority identities. The coefficient on "Non-White" in the full-sample sender regression is -0.277 ($p = 0.001$) suggesting that there are at least level differences in trust. Our separate analyses will be able to detect any interaction differences.

Next, for receivers, we analyze the behavior of those who received a large number of tokens from the senders. In contrast to senders, who are all endowed with the same 20 tokens in each period, receivers start with different amounts ranging from 0 to 80 tokens (since the tokens sent are multiplied by 4) depending on the behavior of the senders with whom they are randomly matched. Table 2.6 shows that the average percent returned is higher for those subjects who receive at least 41 tokens.

To explore the possibility that receiver behavior differs according to the initial amount received, we split the receiver sample into four parts. We examine separately subjects who

[8] The 2012 American Community Survey estimates that Whites make up 72.8%, Asians make up 16.4% and Blacks make up 7.0% of the population in Ann Arbor. These patterns hold for the student population at the University of Michigan as well. Data from the University of Michigan Office of the Registrar show that in the Fall semester of 2013, 66.6% of enrolled students were White, 13.3% were Asian, and 4.8% were Black.

receive 1-20, 21-40, 41-60, and 61-80 tokens from the senders. We exclude subjects who receive 0 tokens since they do not make any choice regarding how many tokens to return to the senders. We present results from regressions on the sample of subjects who receive 61-80 tokens.[9] These receivers are trusted by their senders, as evidenced by the high number of tokens received. We can therefore more easily examine the trustworthiness of this group. For receivers who begin with fewer tokens, their behavior might be affected by negative reciprocity, resulting in fewer returned tokens due to retaliation. These effects would attenuate any minority or ingroup effects. In fact, our results show that, for those receivers who begin with fewer tokens, similar to the full sample of receivers, we find no differences in behavior between induced minority and majority groups.

From this point on, we will therefore separately analyze White and non-White subjects. In addition, we will focus only on receivers who receive more than 60 tokens (i.e., to whom the senders sent more than 15 out of 20 tokens). We will refer to these receivers as our *preferred sample* of receivers.

2.5.3 Ingroup minority effect

In our restricted sample, we first examine Hypothesis 1. Figure 2.2 shows the average amounts sent and returned by White subjects in the (original) induced minority and majority groups. The two bars on the left of each graph show the ingroup matches. To explore the possibility of a minority effect in both sending and returning behavior, we run random effects regressions separately for White and non-White subjects. These results are displayed in columns 2 and 3 of Tables 2.4 and 2.7.

Result 2 (Ingroup minority effect among Whites) *White subjects in minority lab groups are more trusting and trustworthy when matched with ingroup members compared to White subjects in majority lab groups when matched with ingroup members. For White members of minority lab groups, this holds for both senders and preferred receivers:*

$$s_W^{mm} > s_W^{MM}, \qquad\qquad r_W^{mm} > r_W^{MM}.$$

[9]Regressions for samples of receivers starting with 60 tokens or fewer are available in J.

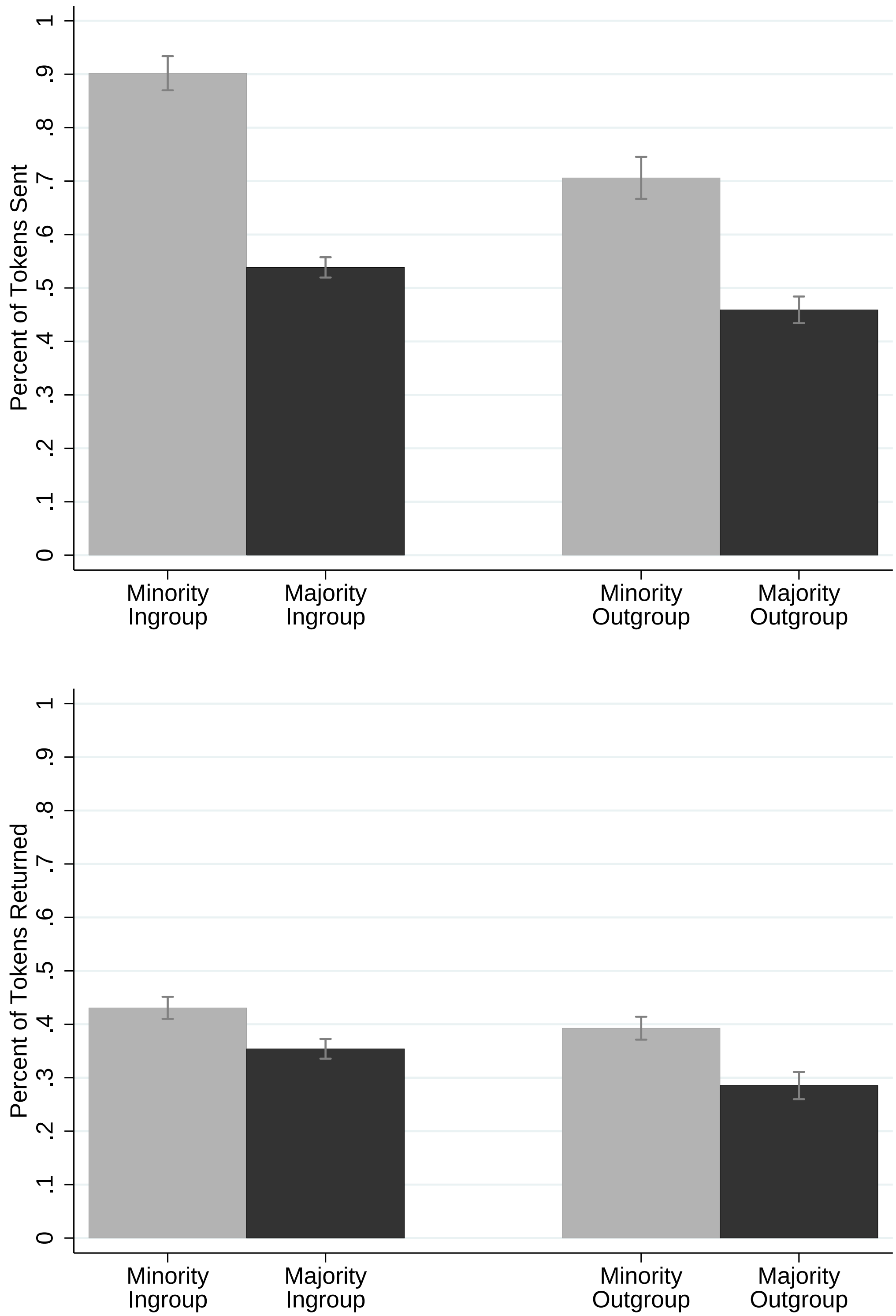


Figure 2.2: % tokens passed by White minority/majority senders (top) and receivers with 61-80 tokens (bottom), including standard errors.

Column 2 of Table 2.4 displays the regression of sending behavior for White senders. Here we see that White minority ingroup sending is significantly higher than White majority ingroup sending ($p = 0.001$). The coefficient on "Minority Ingroup" implies that Whites in minority groups, when matched with subjects in their own group, send 36% more, or about 7.2 more tokens of their 20-token endowment, to receivers than their counterparts in majority groups.

Column 2 of Table 2.7 displays returning behavior for Whites in our preferred sample of receivers. We again see that minority ingroup returning is significantly higher than majority ingroup returning ($p = 0.040$). The coefficient on "Minority Ingroup" here implies that Whites in minority groups who receive 61-80 tokens return 14% more, or roughly 8 more tokens, to ingroup matches than Whites in majority groups.

For our sample of White senders and preferred receivers, we can reject the null hypothesis of no difference in behavior in favor of Hypothesis 1. We find that Whites in induced minority groups treat ingroup members better than Whites in induced majority groups, indicating greater trust and trustworthiness among minority group members.

Result 3 (No ingroup majority/minority effect among non-Whites) *Non-White subjects in minority and majority lab groups exhibit no differences in behavior towards ingroup members. There are no differences found among senders or preferred receivers in this group.*

We examine non-White sending in column 3 of Table 2.4. We cannot reject that minority ingroup sending is the same as majority ingroup sending ($p = 0.487$) among non-Whites. Column 3 of Table 2.7 shows the regression for non-White preferred receivers. We again cannot reject that minority ingroup returning is the same as majority ingroup returning ($p = 0.154$). Therefore, for non-White subjects, we cannot reject the null hypothesis of no differences in behavior towards ingroup members in favor of Hypothesis 1. We find no evidence of an ingroup minority effect as we do with White subjects.

2.5.4 Outgroup minority effect

Having examined behavior towards ingroup members, we now examine behavior towards outgroup members. The two bars on the right of each graph in Figure 2.2 show the average amounts sent and returned by White subjects in outgroup matches. As before, the results for senders are summarized in Table 2.4, and results for the preferred sample of receivers are summarized in Table 2.7. From Hypothesis 2 we expect to find an outgroup majority effect such that minority group members will be more cohesive and thus treat outgroup members worse than majority group members treat outgroup members. We find the opposite result:

Result 4 (Outgroup minority effect among Whites) *White subjects in minority lab groups are more trusting and trustworthy when matched with outgroup members compared to White subjects in majority lab groups when matched with outgroup members. For White members of minority lab groups this holds for both senders and preferred receivers:*

$$s_W^{mM} > s_W^{Mm}, \qquad\qquad r_W^{mM} > r_W^{Mm}$$

Column 2 of Table 2.4 displays sending behavior for White senders. Comparing White minority outgroup sending to White majority outgroup sending, we see that White minority outgroup sending is significantly higher ($p = 0.019$, Wald test). The coefficients imply that Whites in minority groups, when matched with subjects in the other group, send 28%, or 5.6, more tokens to receivers than their counterparts in majority groups.

Column 2 of Table 2.7 displays returning behavior for Whites in our preferred sample of receivers. We again see that minority outgroup returning is significantly higher than majority outgroup returning ($p = 0.035$, Wald test). The coefficients here imply that Whites in minority groups return 14%, or roughly 8.5, more tokens to outgroup matches than Whites in majority groups.

With these results from senders and receivers, we can reject both Hypothesis 2 and the null hypothesis for Whites matched with outgroup members. Instead, these results imply the reverse of Hypothesis 2. We find that Whites in induced minority groups treat outgroup members better than Whites in induced majority groups. Instead of observing our prediction that minority groups would be more cohesive, we instead see that White subjects in minority groups are more trusting and trustworthy overall.

Along with Result 2 for ingroup behavior of Whites in induced minority groups, we now have the result that Whites in induced minority groups are both more trusting and trustworthy, for both ingroup and outgroup matches, than Whites in induced majority groups. We refer to this higher level of sending and returning by White minority group members as the minority effect among Whites.

Result 5 (No outgroup minority/majority effect among non-Whites) *Non-White subjects in minority and majority lab groups exhibit no differences in behavior towards outgroup members. There are no differences found among senders or preferred receivers in this group.*

Column 3 of Table 2.4 shows non-White sending behavior. We cannot reject that minority outgroup sending is the same as majority outgroup sending ($p = 0.444$) among non-Whites. Examining column 3 of Table 2.7, we see the same result among our preferred sample of non-White receivers. We cannot reject that minority outgroup returning is the same as majority outgroup returning ($p = 0.221$). Therefore we cannot reject the null, that there is no majority outgroup effect in this sample of non-Whites. We find no evidence of a minority outgroup effect as we do with White subjects.

With both ingroup and outgroup matches, the similarity in behavior of Whites in induced minority groups indicates that White subjects have a particularly strong reaction to being placed into an induced minority group. For both White ingroup and outgroup matches, this results in more tokens sent and returned. This cannot be interpreted as some form of ingroup same-race bias as senders and receivers are blindly matched with other subjects; they interact through the computer interface and are not able to communicate during rounds of the trust game. In addition, regressions were constructed to show that this induced minority effect is separate from ingroup bias; Whites in induced minority groups send and return more to both ingroup and outgroup matches than Whites in induced majority groups.

2.5.5 Persistence

Having looked at differences between initial induced groups, we now turn to examining behavior when relative group sizes change. We have two competing hypotheses for behavior among treated individuals. Recall that we treat subjects by changing their relative group sizes after 10 periods. Hypothesis 3 predicts that when an individual changes

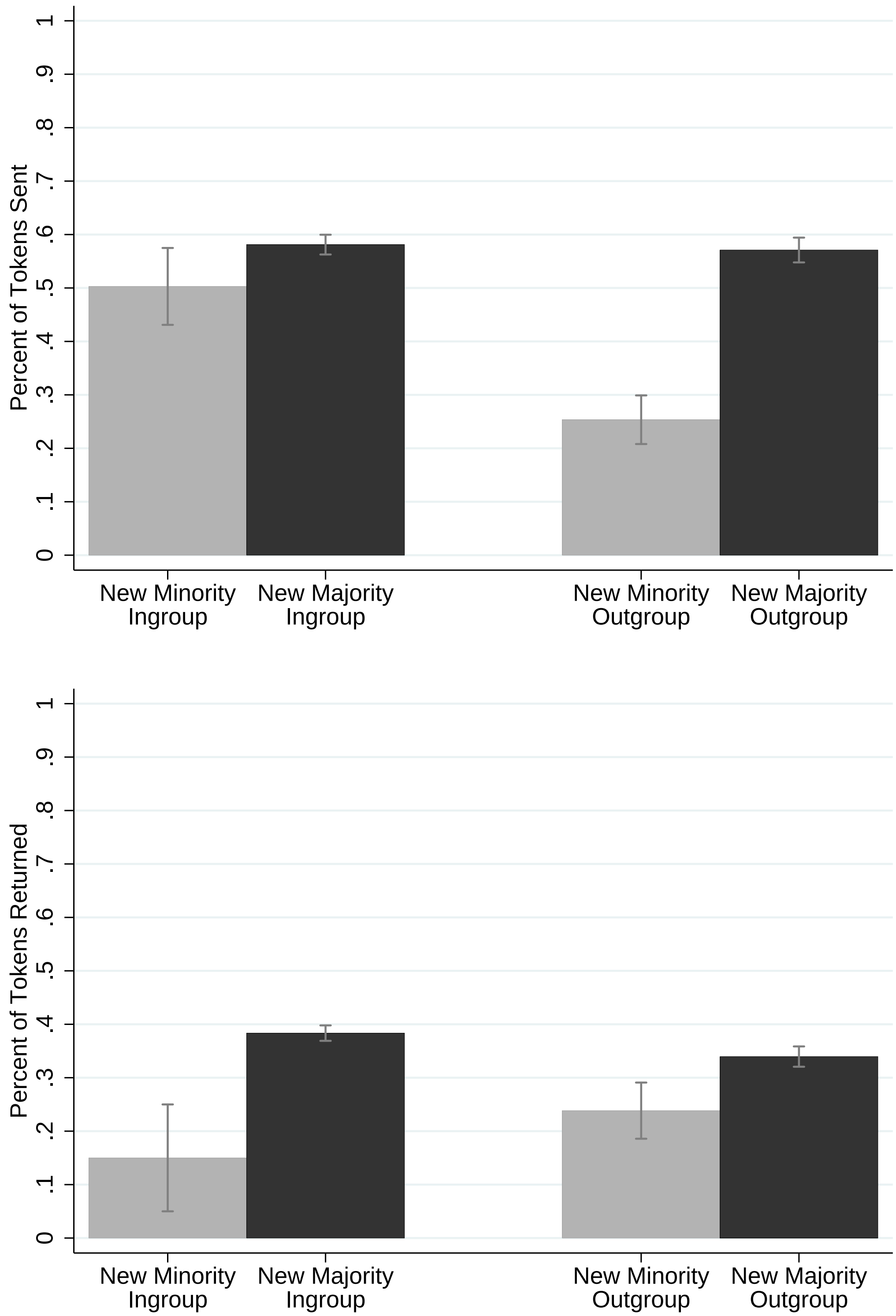


Figure 2.3: % tokens passed by White new minority/new majority senders (top) and receivers with 61-80 tokens (bottom), including standard errors.

minority/majority identity, she will adopt the behavior of the new identity immediately. Hypothesis 4 predicts that an individual will carry the behaviors of her initial minority/majority identity even after changing identity, i.e., when her group changes from a minority (majority) to a new majority (new minority).

We can only differentiate between these two hypotheses when differences exist in initial induced group behavior. When these differences do not exist, both Hypothesis 3 and 4 predict that there will also be no differences in behavior once the relative group sizes are changed. Therefore, we focus on cases in which we do see differences in initial induced group behavior, namely, White ingroup and outgroup matching for both senders and preferred receivers. Figure 2.3 shows the average amounts sent and returned by White subjects in new minority and new majority groups.

Result 6 (Persistence in behavior among Whites) *White subjects who change from minority to new majority exhibit persistence by continuing to be more trusting and trustworthy than their counterparts who change from majority to new minority:*

$$s^{NN} > s^{nn}, \qquad r^{NN} \geq r^{nn} \qquad \textit{(ingroup new majority effect)}$$
$$s^{Nn} = s^{nN}, \qquad r^{Nn} > r^{nN} \qquad \textit{(outgroup new majority effect)}$$

From Results 2 and 4, we see that Whites in induced minority groups send and return more tokens than Whites in induced majority groups. Here, Hypothesis 3 (change) predicts that new majority group members should behave differently than they did when they were induced minority group members, sending and returning fewer tokens than new minority group members. On the other hand, Hypothesis 4 (persistence) predicts that new majority group members should behave the same as they did when they were induced minority group members, sending and returning more tokens than new minority group members. We see evidence that supports Hypothesis 4 (persistence) for White subjects.

First, examining White new majority senders, we see in column 2 of Table 2.4 that new majority ingroup sending is 28%, or 5.5 tokens, higher than new minority ingroup sending ($p = 0.030$), but we cannot reject the null hypothesis that there are no differences between new majority and new minority outgroup sending ($p = 0.244$).

Next, column 2 of Table 2.7 shows that, for our preferred sample of receivers, new majority ingroup sending is weakly higher (14%, or roughly 8.6 tokens) than new minority ingroup sending ($p = 0.098$). In addition, new majority group members return 14.6%, or roughly 8.9 tokens, more than new minority group members when matched with outgroup members ($p = 0.024$). This gives the ordering provided in Result 6. This ordering is mostly consistent with the persistence hypothesis in which the minority effect among Whites carries over to a new majority effect among Whites. The signs of the differences in new majority and new minority sending and receiving are inconsistent with the change hypothesis, as the minority effect found among Whites does not carry over to a new minority effect among Whites.

When White subjects begin in an induced minority group, they trust more and are more trusting than their induced majority group counterparts. When these White subjects are treated and their relative group size switches from induced minority to induced new majority, they still maintain the behavior of induced minority group members, showing high levels of trust and trustworthiness even after their groups become the new majority groups. This indicates that the initial sorting of White subjects into induced minority and majority groups has a strong effect on behavior but that the switch, halfway through the experiment, is not enough to alter this effect.

2.6 Discussion

We find two unexpected results. First, our effects are only present among White subjects. This could be caused by an interaction of real-world majority identity with our lab-created minority identity. There are several studies that directly examine differences between real-world identities. Much of the experimental literature on gender shows differences in preferences for competition (e.g., Niederle and Vesterlund, 2007; Gneezy et al., 2009) and cooperation (e.g. Charness and Rustichini, 2011).[10] Differences are also found by race (e.g., Benjamin et al., 2010; Tanaka and Camerer, 2013). Other studies find an interaction between real-world and lab identities. Salmon and Serra (2013) find that subjects from "high rule of law" countries are more likely than subjects from "low rule of law" countries to reduce rule-

[10]Croson and Gneezy (2009) provide a more complete survey on this literature.

breaking behavior (theft, bribery, and embezzlement) when their actions can be observed by others in the lab. Similar to this, our results suggest that being from a majority group in the real world can affect a subject's behavior when she is in a minority group in the lab. On the other hand, Tsutsui and Zizzo (2013) find no differences between majority and minority groups in their experiment, but the racial make-up of their subject pool is unknown.[11] It is possible that subjects who are not used to being in a minority group in real life respond to being placed in a minority group differently than those who are used to being in a minority group. This may drive our result.

Our other unexpected result is that, instead of an outgroup majority effect (Hypothesis 2), we instead see an outgroup minority effect (Result 4). That is, among White subjects, sending and returning to outgroup members is higher from minority members than from majority members. One possibility is that the effect that we see among White subjects overpowers our hypothesized outgroup majority effect, resulting in higher sending and returning by minority group members to majority group members. Notice that in column 3 of Table 2.4, which gives results for non-White subjects only, majority outgroup sending is higher than minority outgroup sending, though the difference is not significant ($p = 0.444$). This mirrors the finding of Tanaka and Camerer's (2013) that high-status minorities treat majorities well.

2.7 Conclusion

Many economists have studied the effects of social identity on various behaviors, but most have focused on static identities. Identities such as gender and race are, for the most part, fixed and unchanging over time for an individual.[12] In this study, we instead examine the effects of more malleable social identities, majorities and minorities, and provide evidence that a real-world majority identity interacts with a lab-created minority identity, causing White subjects to be more trusting and trustworthy when placed in a lab minority group.

[11] We contacted Tsutsui and Zizzo, who provided their data. While they collect the subjects' countries of origin, they do not record the racial background of their subjects. Since many subjects' country of origin is the UK, where the experiment was run, this does not necessarily indicate race.

[12] Certain race categories may actually be malleable. See Lue (2015) for an examination of the racial identification choices of individuals with mixed ancestry.

Changing subjects' lab identities during our experiment does not appear to shake the initial lab minority group effect. If taken literally, this would indicate that, in the real world, members of minority groups who are originally more trusting and trustworthy in interactions with others will not change this behavior when they gain majority identity.

This interaction of race and minority identity was an unexpected, but robust, finding in our experiment and one that deserves further exploration. While most White subjects have majority identity in the US, perhaps race is correlated with another factor that is interacting with lab minority group identity. Future work could explore if these results are driven in part by an overlap between White racial identity and religious belief (as 78% of White US citizens identify with some denomination of Christianity[13]) or some other demographic factor such as wealth or social status. The interaction between real-world group-size identity and lab group-size identity could perhaps be captured by measuring whether an individual feels a sense of belonging to a real-world majority or minority group before assigning a lab group-size identity.

Research has shown that social identity has an effect on individuals' economic decisions, but researchers are only beginning to explore the effects of altering malleable social identities. As changing demographics and attitudes continue to shape these malleable social identities, the study of the dynamics of changing social identities is an important natural extension of the current literature. The study of these changes will better prepare researchers and policy makers as these changes inevitably occur in the real world.

[13] 2007 Pew Report: `http://religions.pewforum.org/pdf/report-religious-landscape-study-chapter-3.pdf`, page 40.

Table 2.4: % Tokens Passed, 20-Period Senders

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.277***		
	(0.084)		
Female	-0.094	0.044	-0.066
	(0.071)	(0.110)	(0.093)
Second Half	-0.016	0.012	-0.031
	(0.040)	(0.067)	(0.044)
Majority Outgroup	-0.143***	-0.086*	-0.195***
	(0.043)	(0.044)	(0.072)
Minority Ingroup	0.054	0.359***	-0.093
	(0.091)	(0.110)	(0.134)
Minority Outgroup	-0.115	0.194	-0.263**
	(0.080)	(0.124)	(0.110)
New Majority Ingroup	-0.022	0.337**	-0.208
	(0.094)	(0.136)	(0.141)
New Majority Outgroup	-0.168	0.089	-0.288**
	(0.120)	(0.181)	(0.143)
New Minority Ingroup	-0.011	0.060	-0.052
	(0.075)	(0.076)	(0.094)
New Minority Outgroup	-0.092	-0.157	-0.067
	(0.070)	(0.138)	(0.073)
Constant	0.732***	0.500***	0.533***
	(0.083)	(0.130)	(0.103)
Observations	1440	560	880
R-squared	0.1476	0.1559	0.0813

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors clustered at the session level. Non-White race includes Asian, Black, Hispanic, and Native American.

Table 2.5: % Tokens Passed, 20-Period Receivers

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.029		
	(0.035)		
Female	-0.025	-0.031	-0.020
	(0.038)	(0.050)	(0.038)
Second Half	0.013	0.007	0.021
	(0.016)	(0.020)	(0.027)
Majority Outgroup	0.011	0.026	-0.002
	(0.035)	(0.031)	(0.049)
Minority Ingroup	0.026	0.116*	-0.057
	(0.045)	(0.069)	(0.053)
Minority Outgroup	-0.036	0.054	-0.117***
	(0.031)	(0.052)	(0.042)
New Majority Ingroup	-0.016	0.097	-0.124***
	(0.034)	(0.061)	(0.046)
New Majority Outgroup	-0.032	0.111	-0.165***
	(0.047)	(0.088)	(0.062)
New Minority Ingroup	-0.002	-0.031	-0.009
	(0.028)	(0.054)	(0.030)
New Minority Outgroup	-0.011	0.003	-0.029
	(0.030)	(0.040)	(0.041)
Constant	0.268***	0.218***	0.275***
	(0.042)	(0.057)	(0.035)
Observations	983	491	492
R-squared	0.0228	0.0384	0.0742

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors clustered at the session level. non-White race includes Asian, Black, Hispanic, and Native American.

Table 2.6: % Tokens Passed, 20-Period Receivers By Endowment

Endowment	Percent of Endowment Passed	Observations
0	n/a	457
1-20	0.09	211
21-40	0.21	216
41-60	0.30	118
61-80	0.32	438

Table 2.7: % Tokens Passed, 20-Period Receivers with 61 to 80 Tokens

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.050		
	(0.044)		
Female	-0.009	-0.044	0.022
	(0.051)	(0.059)	(0.064)
Second Half	-0.027***	-0.033***	-0.020
	(0.008)	(0.012)	(0.013)
Majority Outgroup	-0.028	-0.004	-0.042
	(0.030)	(0.031)	(0.044)
Minority Ingroup	0.015	0.140**	-0.096
	(0.047)	(0.068)	(0.067)
Minority Outgroup	0.006	0.135**	-0.105*
	(0.046)	(0.066)	(0.058)
New Majority Ingroup	0.017	0.099	-0.066
	(0.044)	(0.076)	(0.071)
New Majority Outgroup	0.024	0.136	-0.091
	(0.065)	(0.092)	(0.076)
New Minority Ingroup	0.030	-0.042	0.082*
	(0.044)	(0.039)	(0.045)
New Minority Outgroup	0.010	-0.010	0.013
	(0.030)	(0.061)	(0.040)
Constant	0.353***	0.308***	0.328***
	(0.048)	(0.071)	(0.050)
Observations	438	212	226
R-squared	0.0225	0.1081	0.0589

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the session level. non-White race includes Asian, Black, Hispanic, and Native American.

CHAPTER III

Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life

(Co-authored with David Albouy)

3.1 Introduction

Households face many trade-offs when they decide where to live, as areas close to high-paying jobs or with desirable amenities are often expensive. Below, we consider how local wage levels, housing costs (or "rents"), and commuting costs vary both within and across metropolitan areas, using the most detailed level of geography in public-use Census files.[1] We then use these measures to construct a local willingness-to-pay index for a typical household based on how high housing and commuting costs are relative to available wages. Under strong conditions, such as household mobility and homogeneity, this index provides the value households place on local amenities, otherwise known as local "quality of life" (QOL).

Given how households are imperfectly mobile and heterogeneous, this one-dimensional quality-of-life index can only provide a limited perspective on the relative desirability of neighborhoods. The index is transparent and provides an economically intuitive complement to other measures of neighborhood quality or "livability" that abound in popular literature. It ranks beautiful areas along the Pacific the highest and areas rife with urban decay the

[1] We often allude to "housing costs" which are either a rent or an imputed rent for housing. We find it important to distinguish land rents from housing rents because construction costs may vary across metro areas.

lowest, lending it some plausibility. It is also positively correlated with various neighborhood amenities such as mild climate, safety, entertainment, and well-funded schools – typically thought of as desirable. While regression methods may be used with this index to try to value specific amenities, these methods are subject to potentially important omitted variable and simultaneity problems, such as household sorting. Indeed, the residents of a neighborhood will not only influence the amenities it provides, but may also be considered an amenity themselves.

Although this work focuses on constructing a single index of neighborhood quality, its elements are pertinent to more complex analyses of hedonic markets and household sorting, e.g. Bajari and Kahn (2005), Yinger (2014), which measure willingness-to-pay through rents alone. Our index makes it easier to compare neighborhoods across metropolitan areas. In particular, we make several adjustments beyond the last similar study of sub-metropolitan quality of life by Blomquist, Berger, and Hoehn (1988). First, following Albouy (2008) – who estimates willingness-to-pay across metro areas – we down-weight the benefit of wage levels to account for federal taxes, and up-weight rent levels to account for unobserved non-housing costs. Second, we add commuting costs to rents to provide a fuller measure of the "urban costs" faced by households. Third, we estimate local wage levels by place of work, rather than place of residence, to mitigate potential biases from unobserved skills. Fourth, we cover the entire United States including non-metro areas, and areas within counties whenever possible.

To complement and contextualize the analysis on willingness to pay, we also describe patterns in local rents, wages, and commuting costs, as well as household characteristics and observable amenities. These patterns involve variation within and across metros, between suburbs and central cities, and across communities of varying densities. Using regression methods, we distinguish how much raw variation in wages, rents, and commutes are explained by the observed characteristics of workers or housing units, as opposed to the locations themselves. We find that rent and wage-predicting characteristics vary more strongly within metros than across them, indicating stronger household sorting. Meanwhile, rent and (especially) wage levels due to location vary much more across metro areas than within. Controlling for local wages, rents fall with commutes in a manner consistent with standard theories of rent gradients.

Section 3.2 motivates our analysis in the context of existing research on local amenities and commuting. We synthesize relevant theories in section 3.3 to provide the basis for the quality-of-life index. Section 3.4 describes the data at the Public Use Microdata Area, or "PUMA," level of geography. We present our measure of quality of life in section 3.5 using maps for for the continental United States, as well as New York, San Francisco, Detroit, and Atlanta. These maps reveal as much disparity in willingness-to-pay within Manhattan as across the most and least desirable states. In section 3.6, we document how a few amenities *predict* much of the variation in quality of life, and how their estimated values are consistent with existing research, while being subject to numerous caveats and limitations.

3.2 Motivation and Related Literature

Our methodology combines insights from two lines of research on how local wages and rents are determined: the first on local amenities, the second on commuting. Beginning with Oates (1969), the empirical literature on amenities (including local public services) builds off of the theory of Tiebout (1956) by assuming that workers are mobile, have access to the same labor market, and that commutes can be ignored or controlled for. In this framework, amenities may be valued by examining how they co-vary with rents inside a metro area, holding other factors constant.

Rosen (1979) adapts this framework to examine amenity differences across metro areas with separate labor markets, arguing that low wages as well as high rents signal amenity values. He and his student, Roback (1982), use several measures of individual amenities as independent variables in wage and rent regressions. The quality-of-life index is then given by the annualized difference in rents to wages predicted by those amenities. One concern with such an index is that it is sensitive to which amenities the researcher considers relevant.[2] Gabriel, Mattey, and Wascher (2003) factor in non-housing costs-of-living in addition to

[2] A more artificial approach is seen in various popular scores of quality of life, often termed "livability." Detailed scores, often at the neighborhood level, are available on websites such as Areavibes.com and Streetadvisor.com. Nate Silver (2010), of election polling fame, provides quality-of-life rankings for neighborhoods in New York City. Streetadvisor.com relies on crowd-sourced user reviews for streets, neighborhoods, and cities. Areavibes.com and Silver (2010) apply weighting algorithms to various observable amenities. For further details see Appendix O.

rents, albeit only at the state level. Not taking a stand on what amenities belong in the quality-of-life index, Beeson and Eberts (1989), Gabriel and Rosenthal (2004), and Chen and Rosenthal (2008) construct indices at the metro level based on how high wages are compared to rents, controlling only for worker and housing characteristics. This "agnostic" index implicitly includes the value of observed and unobserved amenities together.[3] Albouy (2008) incorporates federal taxes and missing non-housing costs into a similar index to infer that willingness-to-pay in high-rent, high-wage (typically large) metro areas is much higher than previous research implied. He regresses the agnostic quality-of-life index in a second-stage regression to infer how much quality of life is predicted by observed amenities.[4] We use a similar methodology, refining it for sub-metropolitan analysis.

Most recent estimates of individual amenity values follow a more quasi-experimental or structural approach. The quasi-experimental approach helps to eliminate problems with unobserved variables, but may still be confounded by household sorting behavior.[5] Furthermore, quasi-experiments are unavailable for many amenities making this approach too limited to provide an overall index of neighborhood desirability. Structural approaches offer a wealth of methods to account for household sorting according to preferences and income, as well as how this sorting may generate local amenities, such as the provision of local public goods. Despite their strengths and flexibility, these models often require strong parametric

[3]Beyond amenity indices, the essential insight of equal indirect utility across areas has also been used by McDuff (2011) to predict migration flows and Kim, Liu and Yezer (2009) to explain intra-city wage differentials.

[4]A recent unpublished working paper by Bieri, Kuminoff, and Pope (2013) performs an analysis similar to Blomquist, Berger, and Hoehn (1988) at the county-level. They incorporate many of the features new in Albouy (2008) regarding taxes and non-housing costs, and correct for selection from inter-state migration using techniques adapted from Dahl (2002). While they find the Dahl correction important, we find it to be negligible, perhaps as we used a larger set of worker controls in our wage equation. Bieri et al. use a set of amenities larger than any similar study to determine relative amenity expenditures. Since many amenities as well as worker and housing characteristics remain unobserved, this technique does not guarantee reduced omitted variable bias. We prefer to use a more agnostic quality-of-life measure and explore how it is *predicted* by a parsimonious set of amenities.

[5]For examples, see Davis (2004) for health, Chay and Greenstone (2005) for air quality, and Cellini et al. (2010) for school facilities. Crime has also been valued using housing prices, see Linden and Rockoff (2008), Pope (2008), or Gautier et al (2009). Crime has even been examined as a cause of misallocation of time at work, see Hamermesh (2009). Over time, residents may re-sort across neighborhoods, causing issues with the estimates, see Kuminoff and Pope (2013) and Banzhaf (2013). Studies that use spatial discontinuities, such as district borders (Black 1999), may be subject to sorting effects (Bayer et al. 2007). Many amenities, like climate or geography, change over long time frames, and so it is sensible to model sorting explicitly. Albouy et al. (2013) do just that using the QOL measures here with the method of Bajari and Benkard (2006) to examine the problem of climate change.

identifying assumptions and computationally-intensive estimation procedures which make their validity difficult to assess.[6]

Research on how commuting impacts local prices is focused on intra-urban gradients. Alonso (1964), Mills (1967), and Muth (1969) predict rent gradients that fall with distance to a central business district, as lower rents compensate households for higher commuting costs. Hoehn, Berger, and Blomquist (1987) consider how a *city-wide* amenity affects wages and prices in a monocentric city, and conclude "the amenity valuation results of Roback's pure inter-regional case carry over." Muth (1969), White (1976) and Straszheim (1984) theorize that wages should fall with distance from urban centers and sub-centers as workers accept lower wages for shorter commutes.[7]

Empirical evidence on wage gradients (e.g. Eberts 1981, Madden 1985, Zax 1991, McMillen and Singell 1992) often supports the above hypothesis. Evidence on rent gradients is more mixed (e.g. Dubin and Sung 1987), at least over short distances, suggesting the importance of confounding amenities. A stark example is metro Detroit, where central-city land is often cheaper and less developed than suburban land, and much employment is decentralized. Gabriel and Rosenthal (1996) provide a more decentralized theory, similar to ours, but use it to address the spatial mismatch of employment for minorities.[8] Busso et al. (2013) demonstrate the practical importance of examining commuting behavior and sub-metropolitan wage levels when examining the impact of the federal urban Empowerment Zone program.

Estimates of local wage and rent levels may be biased by unobserved worker skills or housing quality. Fu and Ross (2013) estimate a positive effect of employment density on wages that is unaffected by detailed controls for place of residence, but is rendered insignif-

[6]See Kuminoff et al. (2013) for a review of this literature. Notable examples include Epple and Sieg (1999) on levels of school funding, and Bayer and Timmins (2005) on equilibrium properties of sorting models. Angrist and Pischke (2010) and Nevo and Winston (2010) provide debate on the pros and cons of structural modeling and credible inference.

[7]Turnbull (1992) examines the role of leisure in a related model and concludes that it matters little for examining wage gradients. "The introduction of leisure choice into the local employment location model does not alter either the form of the location equilibrium location condition or the immediate implication for the wage rate-distance relationship." This occurs since households put the same value on work and leisure on the margin.

[8]While racial segregation is of obvious importance, we defer most questions on race to existing and future research. When we do examine worker heterogeneity, we focus on a single-index that aggregates observable characteristics such race, age, education, and immigrant status according to how these factors impact wages.

icant when commuting is controlled for. This provides evidence that workers' unobserved earnings abilities are unrelated with where they work, even if they are related to where they live.

3.3 A Model of Residential Choice with Commuting

3.3.1 Household Preferences and Constraints

We incorporate commuting into Rosen's (1979) model, expanded by Albouy (2008). Households are homogeneous, mobile, and have information about each community. They consume a traded good, x, with price normalized to one, a non-traded home good, y, with price (or rent) p, leisure time, l, commuting time, f, and a vector of amenities, $\mathbf{Z}$. For simplicity, we aggregate amenities into a single index, $Q = \tilde{Q}(\mathbf{Z})$. Household preferences are modeled by a utility function, $U(x, y, l, f; Q)$, which is quasi-concave and decreasing in f and increasing in x, y, l, and Q.[9]

Households choose their place of residence, j, which differ in local prices, p^j, and quality of life, Q^j. They also choose their hours, h, and place of work, k, which differ in wages, w^k. Commuting between home and work takes time f^{jk}, and is assumed to have a proportional monetary cost, $c \cdot f^{jk}$, where $c \geq 0$ is a constant. Households receive income from wages, $w^k h$, plus non-labor income, I, from a diversified portfolio of land and capital. They pay federal taxes $\tau(w^j h + I)$, which are rebated lump-sum. State taxes and tax benefits to owner-occupied housing are modeled in Appendix M.[10] The resulting household budget constraint

[9]Note that the amenities of a location j may be physically located in adjoining areas, such as museums within the metro area. By aggregating the amenities we impose that preferences for consumption goods and amenities are weakly separable, which is unlikely to hold. Some amenities, such as beaches, may be closer substitutes to leisure than others. Colwell et al. (2012) considers how amenities may impact behavior with varying commutes. In such cases, the utility function would need to incorporate multiple Q or Z arguments. In practice, these concerns could have a second-order importance on QOL estimates that our measures ignore. For instance, in high amenity areas, residents may work less at their market job, and thus put less importance on local wages.

[10]We do not model savings behavior explicitly, as the portfolio or return to savings do not depend on where people live. A degree of household wealth is tied up in home equity, but with perfect capital markets, this will not matter. In real life, homeowners in more expensive areas may have greater equity (or leverage) in local land, but the rate of return on risk-adjusted savings should be the same. In a dynamic setting, it could be interesting to look at income effects from windfall capital gains in local land markets. This would then require us to distinguish individuals from where they used to reside to where they currently do. We save this complex issue for future research.

is then $x + p^j y + cf^{jk} \leq w^j h + I - \tau(w^j h + I)$. The time endowment is normalized to one, so that households satisfy the time constraint $h + l + f^{jk} \leq 1$. The following expenditure function joins the utility function and two constraints to express the after-tax net expenditure necessary for a household to obtain utility u:

$$e(p^j, w^k, f^{jk}; Q^j, u) = \min_{x,y,h,l} \{x + p^j y - w^j h - I + cf^{jk} + \tau(w^j h + I)$$
$$: U(x, y, l, f^{jk}; Q^j) \geq u,\ h + l + f^{jk} \leq 1\},$$

This function, assumed to be continuously differentiable, increases in the urban-cost parameters p^j and f^{jk} and decreases in the local opportunity parameters w^k and Q^j, meaning $\partial e/\partial p,\ \partial e/\partial f \geq 0$ and $\partial e/\partial w,\ \partial e/\partial Q \leq 0$.

3.3.2 Equilibrium in Places of Residence and Work

Mobile and informed households do not choose a place-of-residence and place-of-work combination (j, k) less satisfying than any other. When households are homogeneous, all observed combinations (j, k) must provide the same level of utility, u. This equilibrium can be characterized neatly with the expenditure function:

$$e(p^j, w^k, f^{jk}; Q^j, u) = 0, \tag{3.1}$$

for all (j, k) combinations in the data. No one, on net, needs to be paid extra for where they live and work; everyone is equally satisfied with the conditions they face.

To characterize differences in prices and wages, we implicitly differentiate condition (3.1). By varying the place of residence, j, we find

$$\frac{\partial e}{\partial p} dp^j + \frac{\partial e}{\partial f} df^j + \frac{\partial e}{\partial Q} dQ^j = 0. \tag{3.2}$$

should hold for all observed residences and commutes. With some abuse of notation, df^j denotes the change in commuting time by varying residences. This expression generalizes the rent gradient: higher rents may be associated with lower commute times or higher quality of life.

The urban-wage gradient is expressed by varying the place of work, k, requiring that

$$\frac{\partial e}{\partial w}dw^k + \frac{\partial e}{\partial f}df^k = 0. \tag{3.3}$$

across all observed commutes and workplaces. Here, df^k is the change in commuting time by varying workplaces. Workers will travel longer if they are compensated with higher wages.

The model so far is similar to that on rent and wage gradients (e.g. McMillen and Singell 1992) with amenities added in. The goal here is not to test whether these gradients hold. Instead, we combine (3.2) and (3.3) to infer a local willingness-to-pay measure for changes in quality of life, dQ^j. This yields the expression $-(\partial e/\partial Q)dQ^j = (\partial e/\partial p)dp^j + (\partial e/\partial w)dw^k + (\partial e/\partial f)df^{jk}$ where $df^{jk} \equiv df^j + df^k$ is the total difference in time spent commuting. We apply the envelope theorem (i.e. Shepard's Lemma) to the expenditure function (3.1) to interpret the derivatives, which we evaluate at the national average. Accordingly, $\partial e/\partial p = \bar{y}$ is average housing consumption, $\partial e/\partial w = -(1-\tau')\bar{h}$, average labor supply net of taxes, and $\partial e/\partial f = [c + (1-\tau')\bar{w} - \alpha]$, the sum of monetary and after-tax opportunity cost of working net of the "leisure-value" of commuting, $\alpha \equiv (\partial U/\partial f)/(\partial U/\partial x)$. Combining these, we solve for the marginal willingness-to-pay for local quality of life in terms of local rents relative to wages, adjusted for commuting:

$$p_Q dQ^j = \bar{y} \cdot dp^j - (1-\tau')\bar{h} \cdot dw^k + [c + (1-\tau')\bar{w} - \alpha]\, df^{jk}, \tag{3.4}$$

where $p_Q \equiv \partial e/\partial Q$ is the marginal valuation of Q.[11] If wages are rearranged on the left, the expression relates how higher urban costs, $\bar{y} \cdot dp^j + [c + (1-\tau)\bar{w} - \alpha]\, df^{jk}$ are paid to access residential amenity opportunities, $p_Q dQ^j$, or employment opportunities, $(1-\tau')\bar{h} \cdot dw^k$.[12] In

[11] Since Q does not have natural units, neither p_Q nor dQ^j alone have operational meaning, although their product does as $p_Q dQ^j$ is the marginal willingness-to-pay to enjoy the amenities in location j. Although the approximation sets p_Q at the national average, the price of amenities may change across locations.

[12] Timothy and Wheaton (2001) consider the situation when wages, w^k, are fixed and exogenous. Then, only in knife-edge cases will households commute from the same place of residence to more than one work place . With endogenous wages, wages in further (closer) places may rise (fall) to allow for more varied commuting behavior, as we see in the data. Moreover, in a more realistic model, workers may vary in their transportation costs, preferences of location, or receive idiosyncratic wage offers from different locations, each with mean w^k, all of which could cause workers from the same residences to commute to a large variety of workplaces. For an example of such a model which allows for income heterogeneity, see Gabriel and

other words, high wages compensate workers for high urban costs or low amenities.

3.3.3 Applying and Parametrizing the Model

To operationalize the model, we divide (3.4) by average income $\bar{m}$, re-express the level-differentials in terms of log-differentials $\hat{p}^j \equiv dp^j/\bar{p}$, $\hat{w}^k \equiv dw^k/\bar{w}$, $\hat{f}^{jk} \equiv df^{jk}/\bar{f}$, and replace the coefficients with share parameters. The marginal willingness-to-pay for local amenities, expressed as a fraction of income, $\hat{Q} \equiv p_Q dQ^j/\bar{m}$, is then

$$\hat{Q}^j = s_y\hat{p}^j - (1-\tau')s_w\hat{w}^k + \underbrace{\left[s_c + (1-\tau')s_w\frac{\bar{f}}{\bar{h}} - \alpha\frac{\bar{f}}{\bar{m}}\right]\hat{f}^{jk}}_{\hat{c}^{jk}}, \tag{3.5}$$

where $s_y = \bar{p}\bar{y}/\bar{m}$ is the expenditure share for home goods, $s_w \equiv \bar{w}\bar{h}/\bar{m}$ is the income share from labor, $s_c \equiv c\bar{f}/\bar{m}$ is share of income spent on commuting, and $\bar{f}/\bar{h}$ is the the ratio of time spent commuting to time spent working. The last term on the right, $\hat{c}^{jk}$, is the "commuting-cost differential," which measures the full cost of commuting as a fraction of gross income.

For the non-commuting parameters, we follow Albouy (2008). $s_w = 0.75$ allows for 25 percent of income to come from non-labor sources. $s_y = 0.361$ accounts for typical expenditures on housing (22 percent) plus the costs of non-housing goods, which are strongly related to rents, by raising the share another 14 percentage points. Marginal tax rates, τ, are based on average marginal income tax rates, a portion of payroll tax rates, and state taxes insofar as wages vary within states. Tax advantages for owner-occupied housing are also accounted for.[13]

For the commuting parameters, we use information from the Survey of Income and Program Participation (SIPP) and National Highway Summary of Travel Trends. We take the median percent of income spent on commuting by mode: $s_c = 0.049$ for drivers, $s_c = 0.033$ for transit-users, and $s_c = 0.00$ for walkers. To determine time costs, we calculate that the average worker in 2000 worked 1822 hours and spent 184 hours commuting (U.S. Census),

Rosenthal (1996).

[13] In Appendix M we explain how we adjust marginal rates by state as well as deductions for housing.

roughly 10 percent of the working day, and thus $\bar{f}/\bar{h} = 0.10$.[14]

The greatest uncertainty involves the parameter α: marginal commuting time is valued as work time if it equals zero and as leisure time if it equals the after tax wage, $(1-\tau')\bar{w}$. Studies have suggested a range of values for this parameter, although we find the value of $\alpha = 0$ to be the most plausible and straightforward. This value is supported by evidence from Small et al. (2005), from stated and revealed preference, and Fu and Ross (2013), from wage gradients, that commuting is not preferred to working. Well-being data from Kahneman and Krueger (2006) find that subjective affect while commuting is as low or lower than while working, reinforcing this value. Alternative values of α may be accounted for easily.

3.3.4 Strengths and Limitations of the Model

The quality-of-life index proposed in (3.5) is based on a straightforward integration of standard urban theories. The chosen parametrization of willingness-to-pay applies only to a typical household. Particular households will vary in how they value wages relative to housing and commuting costs. Households with fewer earners, such as retirees, place less value on wages; households with children may value housing costs more. Implicit marginal tax rates in taxes and transfers can also vary. It is straightforward to parametrize the model differently to account for this heterogeneity. [15] While free mobility is a standard assumption, in reality, households do not move unless the benefit merits the cost of moving. Declining areas tend to keep households with greater moving costs, and thus may have inflated measures of willingness-to-pay.

Households may vary considerably in their tastes for local amenities, such as schools or climate. Nevertheless, Pew Research Center (2009) finds that individuals of different ages, gender, income, and education often state similar preferences for which metro areas they find most livable.[16] Research using revealed preferences generally assumes that different

[14] Annual commuting time is the product of 418 commuting trips, averaging 26.4 minutes each way. Commute time is assumed to be equal by mode.

[15] The quality-of-life index is also moderately robust to behavioral responses in leisure or consumption due to differences in rents, wages, or commuting costs – because of the envelope theorem, such considerations have only a second-order effect.

[16] For those making less than $30,000 a year, 13 percent state they would live in Detroit, 30 percent in San Francisco. For those making over $100,000, the rates are 7 percent for Detroit and 48 percent for San Francisco. The differences for most other cities, like Atlanta (24 and 26 percent) and New York (21 and 35

groups pay the same rent and relies on differences in relative population frequencies to infer different tastes (e.g. Bayer et al. 2007). While there is much evidence of sorting by race and income across neighborhoods (e.g. Cutler and Glaeser 1997 and Ioannides 2004), converting relative frequencies into willingness-to-pay measures has generally relied on strong parametric assumptions.

With heterogeneous preferences, the supply and demand of amenities matters. For example, the marginal bid for land on the coast should rise if the supply of coastline per person falls. Although typical households may value car-friendly suburban developments, if these are abundant relative to walkable downtowns, the latter may be costlier, as downtown residences are allocated only to the highest bidders (Gyourko et al. 2013).

Tastes for different areas may depend considerably on the local population either directly or indirectly for the "artificial" amenities they bring. Yinger (2014) finds considerable differences in demand for neighborhood ethnic composition. Boustan (2013) estimates high demand for high-income neighbors, as they provide high-quality schools relative to property tax rates. Ultimately, neighborhood "quality" is a sensitive topic that depends on many subjective factors.

As an example, consider a housing project built for low-income households in a low-wage area, such as Decatur, IL. Even if subsidized residents prefer Decatur to their previous location, say Chicago, they should still have a lower willingness-to-pay than previous residents, who paid full price to be there. As the proportion of low-income households increases, the local per-capita tax base may decline, causing public services to fall. Unless original residents prefer the new mix of residents to the old, or the change in local amenities it brings, the introduction of public housing is likely to reduce local willingness-to-pay, although this remains an empirical question.[17]

As another example, consider the impact of zoning restrictions meant to exclude low-income households. If such zoning is binding, low-income households will have a limited supply of neighborhoods to choose from, say in the central city. These limits may lengthen commuting times and raise rents in those neighborhoods, artificially increasing measured

percent), are smaller, and there are very few cases of inversion.

[17]Diamond and McQuade (2015) estimate how different households value new construction from the Low Income Housing Tax Credit Program.

willingness-to-pay. If low-income households live in less desirable neighborhoods, zoning would attenuate the quality-of-life differences we infer. The resulting segregation of rich from poor could also reinforce differences in artificially produced amenities.

3.4 Wage, Rent, and Commuting-Cost Estimates

3.4.1 Units of Geography

We estimate wage, rent, and commuting-cost differentials from the 5 percent sample of the U.S. Census in the Integrated Public Use Microdata Series (IPUMS) for 2000 (Ruggles et al. 2004).[18] The public-use files identify households' location of residence down to 2071 Public Use Microdata Areas. These areas have an average population of 135,887, and a minimum of 100,000. The Census Bureau does not provide names for 2000 PUMAs; we name them using the counties, municipalities, or neighborhoods they contain.

The geographic detail of the PUMAs increases with population density. 186 PUMAs correspond exactly to counties. 1,266 PUMAs are entirely contained within a subset of 288 counties, and are often identifiable neighborhoods or municipalities. For example, in Washtenaw County, MI, one PUMA corresponds to the city of Ann Arbor while the other refers to areas in Washtenaw County outside Ann Arbor. In the borough of Manhattan (New York County, NY), the PUMAs correspond to sub-boroughs, such as the Upper East Side. 2,654 counties are entirely contained within one of 526 larger PUMAs. For example, Clarke, Madison, and Occonee counties in Georgia form a single PUMA around Athens, GA.

We aggregate our PUMA level estimates up to the level of Metropolitan Area, as defined by the Office of Management and Budget (1999). These 276 Metropolitan Statistical Areas (MSAs) are supersets of counties – such as the MSA for Athens, GA which coincides with the three counties listed above. 19 of the largest MSAs are categorized as Consolidated MSAs (CMSAs) which are in turn made up of 55 Primary MSAs (PMSAs). Thus, from 2071 PUMAs we may assemble the data into 3081 counties, 276 MSA/CMSAs, and 331

[18] We acknowledge that the quality-of-life estimates are slightly dated. Nevertheless, the 2000 Census offers the last 5 percent snapshot of the U.S. More recent data on housing prices may not be driven by market fundamentals due to the wake of the boom and bust cycle, as detailed in Ferreira and Gyourko (2011). Furthermore, recent evidence in Lee and Lin (2013) highlights remarkable persistence in the desirability of most neighborhoods, especially in areas with natural amenities.

MSA/PMSAs (splitting the 19 CMSAs into 55 PMSAs).[19]

Within metro areas, the Census designates some places as *central cities*, typically the largest population and employment centers. We separate these from other places within MSAs, which we label *suburban*; places completely outside of MSAs are *non-metropolitan*.[20] We also classify areas according to residential population density – calculated at the census-tract level and averaged by population – using cut-offs of 1,000 and 5,000 residents per square mile.

Panel 1 of Table 3.1 presents means of the estimated differentials and related statistics for central city, suburban, and non-metro areas. The rent, wage, and commuting-cost differentials are mapped in Figures 1A, 1B, and 1C. Panel 2 presents this information summarized by the location's average density. Panel 3 presents the standard deviations of the differentials across the United States, and decomposes the variance within and across metro areas. In Table 3.2, these statistics are presented for PUMAs in two well-known counties: New York, NY (Manhattan), and San Francisco, CA. Table 3.3 contains the differential measures for various levels of geography in 5 MSAs; Table A1 in the Appendix contains them of all 2071 PUMAs.

3.4.2 Housing Costs due to Location and Composition

We use both housing values and gross rents, including utilities, to calculate rent, or "housing-cost," differences, interpreted as the flow-cost of housing faced by households. To impute owned housing rents, and make them comparable to gross rents for rental units, we multiply housing values by a rate of 7.85 percent (Peiser and Smith 1985) and add utility costs. We regress rents on place-of-residence indicators, μ_p^j, and controls for housing composition, denoted X_{pi}^j – i.e., size, rooms, acreage, commercial use, kitchen and plumbing

[19]PUMAs can usually be assigned uniquely to counties or MSAs, but in cases where they overlap MSA (or county) boundaries, the observations are subdivided and given a fractional weight according to the proportion of the population that resides in each area. All of our aggregations use population-weighted averages of these PUMA values.

[20]For instance, all of New York City, Bridgeport, Newark, and New Haven are deemed central city, but none of Long Island is. The cities of San Francisco, Oakland, San Jose, Berkeley, and Richmond are all central city, but Fremont, Hayward, Union City, and all of Marin and San Mateo counties are not.

facilities, type and age of building – each interacted with renter status.[21] The resulting regression equation is

$$\ln p_i^j = X_{pi}^j \beta_p + \mu_p^j + \varepsilon_{pi}^j, \tag{3.6}$$

where estimates of μ_p^j are the rent differentials, $\hat{p}^j$, for location j. Remaining differences in mean housing costs, $\overline{\ln p^j} - \mu_p = \bar{X}_p^j \beta^j$, are attributed to mean differences in observable housing composition across areas, $\bar{X}_p^j$, which we call "housing quality." Since X involves measures like the number of rooms, "quality" also refers to quantity of housing. We also include corrections for rent control for New York City and San Francisco.[22]

Our estimates of rent differentials may be contaminated by differences in unobserved housing quality not captured by the variables provided by the Census. For example, two-bedroom apartments built in a 1960s-era Chicago suburb are likely to be more spacious than similar ones built contemporaneously in the Chicago Loop. Biases in rent differentials bias quality-of-life estimates in the same direction. Thus, "quality of life" can reflect unobserved housing quality. If *unobserved* housing quality is biasing the rent estimates, it seems likely that rent estimates would be correlated with measures of *observed* housing quality. As shown in Appendix Figure A, the correlation between the two is almost zero, suggesting that unobserved housing quality is not systematically correlated with willingness-to-pay for local amenities.[23]

[21] We combine rent and imputed-rent measures to avoid potential problems created by local differences in home-ownership (see Table A2). For instance, in Manhattan 80 percent of housing units are rented, whereas in King William Co., VA, only 13 percent are rented. Using more recent data, Albouy and Hanson (2014) calculate an average user cost for owner-occupied housing of 6.2 percent. With our controls for tenure status, the rate used has only a minor effect.

[22] Pollakowski (2003) estimates that in core Manhattan areas, the lower 6 neighborhoods, prices for rent-controlled units would be 37 percent higher without rent control. Using a similar method with Census data, we determine that prices for rent-controlled units in San Francisco would be 22 percent higher in the absence of rent control. To correct for this, we add the fraction of rent-controlled units in each PUMA times $\ln(1+a)$ to the housing cost index, where a is how much prices for units would appreciate in the absence of rent control.

[23] For instance, the compositional component of housing cost is very high in parts of suburban Atlanta (e.g. Alpharetta), although the location is quite average. Meanwhile, the compositional component is quite low where the locational rent is high, such as in Hawaii, Manhattan, and the San Francisco Bay Area. Within Manhattan, units in lower cost Harlem have a higher value than units in Midtown, Downtown, or the Upper East and West Sides. For homes of the very wealthy, possible biases are mitigated by the fact that housing values are censored at $1 million. When density is flexibly controlled for, a one-point increase in housing-cost predicts a 0.1 point increase in the value of housing composition. Nevertheless, Malpezzi et. al. (1998) determine that rent indices derived from the Census using hedonic methods perform as well as most other indices.

Figure 3.1 maps the rent index across the United States. Appendix Table P.1 summarizes the index and details the variables. In Table 3.1, we see rents are 2 percent higher, on average, in the suburbs than in central cities. This fact runs contrary to standard rent-gradient predictions, although from the maps we see that rents do eventually fall away from city centers. Outside of metro areas, rents are 35 percent (42 log points) lower than in suburbs. In Panel B, we see dense areas have the highest rents, as predicted by standard urban models.

In column 3, we see that housing quality in central cities worth 14 percent less than in the suburbs. Quality also falls by about 10 percent each time between high and medium, and medium and low density areas. This is the case as units in denser, central areas are older and smaller.

Panel C provides evidence that differences in housing quality are considerable, but smaller than differences due to location. In addition, rent levels vary more across metro areas than within them, while the opposite is true of housing quality.

3.4.3 Wage Levels Estimated by Residence and Workplace

To calculate wage differentials, $\hat{w}^k$, we use hourly wages from a sample of workers, ages 25 to 55, who worked at least 30 hours a week and 26 weeks a year. We regress log wages on place-of-work indicators, μ_w^k, and controls for worker composition, or skills, X_{wi}^k, – i.e., education, experience, race, occupation, industry, and veteran, marital, and immigrant status – each interacted with gender. The regression equation is

$$\ln w_i^k = X_{wi}^k \beta + \mu_w^k + \varepsilon_{wi}^k. \tag{3.7}$$

We calculate wage differentials for residents in location j by averaging μ_w^k, according to the proportion of residents of j who work in each place k. This is interpreted as the measure of the wage opportunities, $\hat{w}^k$, available to residents, when they incur the commuting costs estimated below. We map the wage index in Figure 1B. The Appendix summarizes related worker measures (Table P.2), and details the variables. We also estimate differences in wages due to average differences in observed characteristics or "skills,' $\bar{X}_w^k$, weighting them by their estimated return, $\hat{\beta}$.

In column 6 of Table 3.1 we see notable variation in observed skills: workers' predicted wages are 4 percent below average in central cities, and 4 percent above average in suburbs. [24] Observed skills are also 6 percent lower in high-density areas, and 4 percent higher in medium-density areas. The typical standard deviation is 10 log points, with most of the variation within metro areas. This highlights the importance of income-sorting at the sub-metropolitan level.

The evidence of sorting on *observed* skills raises concerns about *unobserved* skills. This problem may be mitigated within metros, by measuring wage opportunities by place of work. This depends on evidence in Fu and Ross (2013) that workers do not sort across workplaces according to their unobserved skills.[25] Figure 3.4 graphs wage estimates by place of work against those by residence; the former vary less than the latter.

Estimates of wage levels by residence vary much more than commuting costs. The enormous gains workers could make by changing their commuting behavior suggests that residential choices correlated with unobserved skills is influencing those estimates. In Table 3.2, we see that within Manhattan, the Upper West Side wages by residence are 54 percent higher than in Washington Heights, even though the two areas are separated only by a 14-minute subway ride, costing a $1.50 fare in 2000. Wages by workplace exhibit a much more plausible 5-percent spread. By residence, wages in the Long Island suburbs are often higher than in Manhattan, but by workplace (the two have different PWPUMAs), wages in Long Island are much lower.[26]

[24]This fact is consistent with sorting models when the income elasticity for housing is higher than that for the costs of commuting.

[25]Note that place of work in the public-use files is only available at the Place of Work Public Use Microdata Area (PWPUMA) level. These number 1240, and are made up of the 2071 standard PUMAs. Selection at this coarser level should be no worse than at the PUMA level (used by Fu and Ross). However, the coarser geography eliminates some wage differences mechanically. Appendix N has more details on PWPUMAs. In Appendix Table P.2, we determine that half of the differences between the residential and workplace estimates is due to coarser geography; the remaining half is due to actual commuting. The averaging effect may still reduce potential biases, while introducing new ones if agglomeration effects are highly localized and commutes are short. See Rosenthal and Strange (2001) for more about how agglomeration varies at different levels of geography.

[26]Within San Francisco, wages by residence are 28 percent higher in the primarily residential Marina-Northeastern area than in the skyscraper-filled Downtown. These areas are adjacent, connected by a walk, short drive, or bus ride. Morning commuters head Downtown, contrary to the residential wage gradient. Again, place-of-work wages are much more plausible, exhibiting a 1-percent difference.

On average, residential wage measures indicate wages are lower in central cities; place-of-work wages are equally high in both. Furthermore, they rise with density and eventually fall in the distant suburbs.

Whether we measure wages by residence or workplace, Panel C of Table 3.1 implies that wages vary far more across metro areas than within them. On the other hand, wages due to observed skills vary much more within metros. This supports the hypotheses that residential sorting is greatest within metro areas, while wage level changes across metros are due largely to local firm productivity.

The differences between residence and workplace wage measures provides an index of unobserved skills. In Figure 3.4, this index equals the rightward distance from the diagonal to each PUMA's marker, e.g. unobserved skills for workers is high in Alpharetta and low in East Harlem. Across PUMAs, a one-point increase in observed skills predicts a half-point increase in this unobservable skill measure, and is stronger within MSAs. In column 6 of Table 3.2 both observed and unobserved skill levels are low in Harlem and Bayview, and high in the Upper East Side and N.E. San Francisco. In conclusion, using wages by residence will likely bias quality-of-life estimates upwards in areas with low-skilled workers, confusing them for areas where jobs offer low wages.

3.4.4 Commuting Costs

We estimate commuting-costs using reported commuting times and modes from the same sample used for wages. We regress the square root of commute time, with place-of-residence indicators, μ_f^j, and controls, X_{fi}^j. The controls are the same as in the wage equation, plus controls for children, – each interacted with gender. Thus, the regression equation is

$$\sqrt{f_i^j} = X_{fi}^j \beta_f + \mu_f^j + \varepsilon_{fi}^j. \tag{3.8}$$

We use the square root as it fits the data well and accommodates reports of zero commuting time. The differential is then constructed using $\hat{f}^j = 2\mu_f^j/\overline{\sqrt{f}}$, where $\overline{\sqrt{f}}$ is the average of square-root commuting time.[27]

[27] The R-squared is 0.08 using the square root. Using powers of 0.25 and 1 (linear) caused even worse fits. We forgo discussion of time predicted by observable characteristics, which have little predictive power.

We assume that the time-cost of commuting, α, is independent of transportation mode, and that transportation mode determines monetary costs. Using a linear probability model, we calculate demographically-adjusted probabilities of using each mode of transportation, ρ_l^j, for modes l – own car, carpool, public transportation, and other methods (e.g. walking and biking). The monetary cost of commuting, represented by $s_c \hat{f}^{jk}$, is the weighted average of the mode costs multiplied by the time differential, plus the deviation in average monetary costs:

$$s_c \hat{f}^{jk} = \sum_l \rho_l^j c_l \hat{f}^j + \sum_l \left(\rho_l^j - \bar{\rho} \right) c_l .$$

Outside of New York City, these modal adjustments are minor since most people drive.[28] The Appendix details these methods and summarizes the component measures in Table A4.

Column 7 in Tables 1 and 2 report the index of commuting costs, $\hat{c}^{jk}$, the last term of (3.5), which depends primarily on commuting times, reported in column 8. Consistent with standard urban models, these costs are lower in central cities than in the suburbs. These costs are lowest in non-metro areas where labor markets are more dispersed. They vary slightly less within metropolitan areas than across them. The map in Figure 1C, illustrates these facts. In large metros like Atlanta, Dallas, and Houston, commuting costs exhibit a remarkable annulus or "donut" pattern around their central cities. In other metros, the patterns are more asymmetric: in Detroit they rise going north; in Boston they rise heading south towards Cape Cod. The highest commuting times nationwide are on the outskirts of New York, Los Angeles, Chicago and Washington D.C. The lowest costs are in remote areas, particularly in the Great Plains.

Figure 3.5 plots commuting costs relative to rents within metro areas that contain multiple PUMAs. A one-point increase in commuting costs is associated with a 3.5 point reduction in rents, or a 2.8 point reduction when controlling for wage-levels by place of work. This negative relationship agrees with rent-gradient predictions that the slope should be -3.0 according to our parametrization of equation (3.5), holding quality of life constant. This provides evidence that our parametrization may be accurate and that rent gradients do reflect wage opportunities and commuting costs, even if the gradients are not always mono-centric.

[28]Within the city borders of New York, San Francisco, Boston, Philadelphia, and Chicago, the monetary costs of transit riders are independent of travel time, as their transit agencies charge a flat fare.

3.4.5 Household characteristics

Table 3.3 reports how several household characteristics diverge spatially. Some characteristics vary little. The proportion of children under 18 is 27 percent in central cities, suburbs, and non-metro areas; it does not change with density density either. The standard deviation is 4 percentage points across PUMAs. Those over 65 are located slightly more in non-metropolitan and low-density areas. About 50 percent of the population is in the labor force; this number is only 1 percent higher in the suburbs and in medium-density areas. Household size also varies little. Marriage rates among adults are somewhat lower in central cities relative to the suburbs and non-metro areas.

Differences related to education, race, and ethnicity are more substantial. College degrees are relatively rare outside metro areas. Within metros, college attainment varies considerably, although the difference between central cities and suburbs is small. Blacks are more likely to reside in central cities, constituting 20 percent of the population there. Immigrant status is also concentrated in urban and dense areas, and varies more across metro areas than within. Home ownership rates are much higher in suburban and low-density areas, although this is strongly related to the presence of single-family buildings.

3.5 Quality of Life across the United States

We combine the rent, wage, and commuting differentials to estimate average local willingness-to-pay – or, "quality of life" – from equation (3.5).[29] The geographic units provided by the Census allows us to map quality of life with some detail: Figure 3.6 covers the continental United States, and Figures 5A, 5B, 5C, and 5D cover areas around San Francisco, New York, Detroit, and Atlanta respectively. Quality-of-life differentials for these four MSAs, and for Honolulu, are presented in Table 3.7.[30] In these locations, we aggregate our quality-of-life estimates according to four levels of geography: MSA-equivalents, PMSA-equivalents, counties, and PUMAs. Each level of geography is given its own ranking by type, so there are

[29] The estimates include adjustments for state taxes and housing deductions. Refer to Appendix M for details.

[30] We also estimated the quality-of-life differentials separately for whites and non-whites. The relationship between the two was nearly one-to-one, with a correlation over 0.8. This is remarkable given possible noise in the data as well as segregation within PUMAs.

separate rankings for each of these four geographic levels.[31] A table that ranks and list quality-of-life differentials across all 2071 PUMAs is available upon request.

The highest quality-of-life PUMAs in the United States is the Upper East Side of New York City, famous for its museums and proximity to Central Park. Second is a PUMA that contains the affluent Los Angeles neighborhoods of Brentwood and Bel Air, at the base of the Santa Monica mountains. The third PUMA contains Los Gatos and Cupertino, the home of Apple Inc., in the heart of Silicon Valley. The fourth PUMA contains the communities of East Oahu, including Waialae-Kahala – known for its secluded beaches and accessibility to Honolulu and Diamond Head. Rounding out the top 5 is the PUMA containing the scenic communities of Sausalito, Mill Valley, and San Rafael, just north of San Francisco and the Golden Gate Bridge. To live in these places, households sacrifice the equivalent over 26 percent (30 log points) of real after-tax income relative to the national average.

The highest ranked county is Marin, CA, whose county seat is San Rafael. The second and third ranked counties are San Mateo and San Francisco (see Figure 3.7). Together, these three counties comprise the San Francisco PMSA, which ranks first among PMSA equivalents. When San Francisco is combined with its nearby PMSAs, including Santa Cruz (#3), San Jose (#4) and Oakland (#8), to form the CMSA it ranks second after Honolulu.[32]

New York City is another particularly interesting case. Manhattan, a 34 square-mile island, is split into 10 quite different sub-boroughs (see Figure 3.8). While the labor market on the island appears unified, the rents vary tremendously relative to commuting costs, signalling major differences in quality of life. Five of the sub-boroughs rank in the top 25 PUMAs, while two are in the bottom 100. Most locals are quite aware of these often discontinuous differences in neighborhood desirability, such as between the Upper East Side and East Harlem. As these neighborhoods share the same geography, climate, and municipality, these contrasts raise the issues mentioned earlier regarding heterogeneous populations, endogenous amenities, and sorting. Suburban areas in Long Island and New Jersey show

[31] All measures not at the PUMA level are population weighted means of PUMA estimates.

[32] Blomquist et al. (1988) found Alameda County, which contains Oakland, to be one of the best counties, and Marin County, one of the worst, in the SF Bay Area. Among other things, this is probably due to their use of wage levels based on residence rather than place of work, since unobserved skill levels in Marin are high. As explained in Albouy (2008), the SF Bay Area fared badly in their article as they did not take into account federal taxes and non-housing costs-of-living.

considerable discrepancies in quality of life as well.

The lowest quality of life is found in southwest Detroit, in the area containing the neighborhoods of Chadsey, Condon, and Vernor (see Figure 3.9). Households are compensated with 25 percent (23 log points) higher real income to live here. The Detroit MSA is relatively undesirable on average, though the suburbs of West Bloomfield and Birmingham are in a top 100 PUMA. Detroit has two satellite PMSAs, Flint and Ann Arbor, with contrasting central cities. Both have similar wages and commutes, but the higher rents in Ann Arbor signal its greater attractiveness.

Quality of life discrepancies in Atlanta, GA (Figure 3.10) are less stark. The greatest range is within the city limits: Buckhead is the highest and Center Hill/West Lake is the lowest, with Midtown/Downtown in-between.

Each metro area has its idiosyncrasies, although some national patterns emerge in column 9 of Table 3.1. On average, the typical household prefers suburban areas to central cities, as they pay 2 percent more in rents, and endure commutes 7 percent longer to get the same wages. Quality of life in central cities is still 6 percent of income higher than outside of metro areas altogether.

Quality of life is higher in denser areas. This does not prove that density is itself desirable: more people should want to live in amenable areas, although local housing supply restrictions may impede them. Twenty percent of suburbs have over 5,000 residents per square mile, where quality of life is 7 percent above average. Some central-city areas have densities under 5,000, such as downtown Kansas City, MO: these areas offer a quality of life 2 percent below average.

The results in Panel C reveals that there appears to be almost as much variation in quality of life within metro areas as across them. The standard deviation in values is 5 percent within metros and 6 percent across.[33] This variation is remarkable given that rents, and especially wages, vary less within MSAs than they do across them. This suggests that, geographically, a metro area's labor market is more homogeneous than its amenities.

To highlight the importance of commuting, column 10 presents quality-of-life estimates

[33]While the variation within metro areas appears slightly lower than the variation across, it is probably understated, since PUMAs obscure variation at lower levels of geography. Thus, there is likely to be even more variation within metros than across metros.

that ignore commuting costs and use place-of-residence wages. These estimates make central cities look more desirable to typical households than the suburbs.[34]

3.6 Predictors of Sub-Metropolitan Quality of Life

The quality-of-life index should capture the value of all amenities, many of which may be very difficult to observe, such as smells, beautiful gardens, friendly residents, or charming architecture. Nevertheless, it is reassuring if the quality-of-life index has significant partial correlations of the "correct" sign for ostensibly desirable amenities. We model this relationship using the regression equation

$$\hat{Q}^j = \sum_k \pi_k^Q Z_k^j + \varepsilon^{Qj}, \tag{3.9}$$

In a hedonic framework, where amenities are exogenous and households have the same preferences, this relationship would be taken as causal. The regression coefficients would then be $\pi_k = -(\partial E/\partial Q)\left(\partial \tilde{Q}/\partial Z_k\right)/\bar{m}$, i.e., the fraction of gross income a household is willing to pay for one more unit of amenity k.[35] The residual ε^{Qj} results from measurement error, unobserved amenities, mis-specification, and unobserved housing quality and worker skills. In practice, the requirements needed for this regression to have an error term orthogonal to the amenity measures are not met.[36] Thus, the dollar values we give are merely illustrative. More uniquely, we examine whether estimates within metro areas are similar to those identified across all areas by adding MSA indicators, or "fixed effects," to the regression. This reduces the identifying variation, but may provide some insights, particularly if confounding effects are different within metro areas relative to across them.

Our amenity variables are described in Appendix L, and summarized in Table 3.5. The three climate variables – measuring cold, heat, and sunshine – vary little within metros.

[34]They also lower rankings of large metro areas relative to smaller ones, and to non-metro areas. Without commuting, the San Francisco CMSA drops from 2 to 3, New York from 12 to 36, Atlanta from 70 to 146, and Detroit from 156 to 225.

[35]Multiplying this coefficient by average gross household income ($68,000 in 2000) produces a dollar value.

[36]Amenities are often collinear, making it hard to get precise estimates for a large set of variables. Unmeasured amenities may contribute to omitted variable biases. Artificial amenities may be endogenous to other determinants of quality of life, including local populations with heterogeneous preferences. There may also be important non-linearities in the hedonic equation.

The geography measures – average slope of land and inverse distance to the coast – vary more within. We also use three amenity variables that are largely endogenous to the local population and available nationwide only at the county level. We proxy for safety using the negative murder rate. It varies more within metros than across; murders are more common in central and dense areas. The same is true of bars and restaurants, which is our proxy of local entertainment. Public school revenues exhibit less variation within metros, much like local wage levels, which are likely the main source of cost differences through salaries. These revenues are higher in the suburbs. Because artificial amenities are largely produced by local residents, they may reflect the desirability of the populations themselves.

Table 3.6 reports the estimates from the amenity regressions. The eight variables explain 40 percent of the variation in quality of life over all 2071 PUMAs. The finding that households value areas with mild winters, mild summers, sloped land, sunshine, and coastal proximity echoes those of Albouy (2008) for metro areas; Albouy et al. (2013) explore the influence of climate in greater depth. The main observation here is that the coefficients for temperature and slope are still relatively precise and larger within metros. The sunshine estimate becomes imprecise, mainly since there are fewer weather stations measuring sunshine than metro areas. Fixed effects cause the estimate for coastal proximity to become small and insignificant. This may be the result of how coastal proximity is measured, or because residents in communities near the coasts find that "close is good enough," in the words of Schmidt and Courant (2006).

The estimates for artificial amenities do not change substantially when metro fixed effects are included, with the exception of crime. Whether this is due to particular household sorting within metro areas deserves further investigation.

Although crime rates are available nationally only at the county level, the regressions here associate an increase in the murder rate from 10 to 20 per 100,000 residents – the difference between Los Angeles and Philadelphia – with a reduction in willingness-to-pay of $900 per household, or $1,800 with fixed effects.[37] The geographic coarseness of the crime measure suggests a downward bias, while murder's correlation with other crimes and other

[37]It is worth noting that crime victims may not be residents of the neighborhood where the crime occurred, although our measure is at the fairly broad county level.

disamenities suggest an upward bias. The estimate is smaller than crime valuations in Bishop and Murphy (2011), based on geographically finer data for the SF Bay Area.

The number of local bars and restaurants is strongly associated with willingess-to-pay. Per 1,000, each establishment is associated with $190 rise in willingness-to-pay, or $190,000 total. This is just over a third of the average revenue of a restaurant. This large number likely overstates the value of these establishments, as they are located near other retail and entertainment establishments, in highly visited areas, where residents can afford to eat out. The estimate also cannot reflect the value to residents outside the neighborhood.

The estimates reveal a strong association with school funding, despite the fact that local taxes are not controlled for. An increase in funding of $1,000 per student (or, since there are 0.9 students per household, $900 per household) is associated with a quality-of-life increase of about $700. This number is likely biased from well-funded areas being nicer or having more desirable residents. Interpreting this number causally would indicate that schools are underfunded, especially if, on the margin, households fund schools out of local taxes (see Brueckner 1982). Yet, these estimates have the same order of magnitude as the Cellini et al. (2010) estimates for the value of school facilities and the Black (1999), Bayer et al. (2007), and Caetano (2010) estimates for the value schools with higher test scores.

3.7 Conclusion

Despite the common ranking of neighborhood quality in the popular literature, using a single index involves many simplifications. Our index, based on the consumption "sacrifice" a typical household makes to live somewhere does produce plausible results that should be correlated to many households' tastes. Analogously, it can be useful to characterize political views along a single dimension from "liberal" to "conservative," even though political views are multidimensional. While people may differ on what makes a good neighborhood, it is convenient to have a standardized quality of life measure that reflects "typical" tastes to compare neighborhoods in separate metro areas.

By incorporating commuting and place-of-work wages, our simple quality-of-life model fits in well with the standard model on local rent and wage gradients. The commuting adjustment reveals that willingness-to-pay to live in the suburbs or in dense areas is higher than simpler measures imply. The place-of-work wage adjustment reveals that wages offered in central cities are as high as in the suburbs, even though skill levels are not. Overall, neighborhood quality within metro areas appears to vary substantially. Such nearby differences seem to have less to do with natural amenities, and more to do with local residents and the artificial amenities they produce.

Table 3.1: Rent, Wage, Commuting-Cost, and Quality-of-life differentials across the U.S., 2000

Differential	Population	Rents/Hous. Cost			Wage		Commuting		Quality of Life	
		Location Index or "Rent"	Composition or "Quality"	Index by Workplace	Index by Residence	Composition or "Skill"	Index of Full Cost	Time Diff. Only	Workpla. Adj. Index	Simple (not used)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Central City, Suburban, or non-Metropolitan Area										
Central City (in Metro)	85,401,116	0.070	-0.099	0.033	0.012	-0.044	-0.003	-0.007	0.004	0.016
Suburban (in Metro)	141,255,868	0.088	0.050	0.034	0.053	0.035	0.006	0.058	0.019	0.004
Non-Metropolitan Areas	54,764,922	-0.335	0.026	-0.140	-0.156	-0.020	-0.012	-0.139	-0.054	-0.035
Panel B: By Residential Population Density										
>5,000 per square mile	75,957,757	0.276	-0.138	0.110	0.087	-0.061	0.006	0.109	0.043	0.047
1,000-5,000 per square mile	126,073,690	0.010	0.051	0.004	0.022	0.040	-0.001	-0.026	0.001	-0.006
<1,000 per square mile	79,390,459	-0.280	0.051	-0.111	-0.117	-0.005	-0.005	-0.063	-0.043	-0.035
Panel C:Standard Deviations										
All PUMAs		0.358	0.140	0.128	0.145	0.105	0.018	0.220	0.079	0.066
Across Metropolitan Areas		0.310	0.066	0.123	0.130	0.047	0.014	0.176	0.060	0.052
Within Metropolitan Areas		0.179	0.123	0.033	0.065	0.093	0.011	0.132	0.050	0.041
Fraction of Variance Within		*0.250*	*0.772*	*0.066*	*0.201*	*0.784*	*0.373*	*0.360*	*0.401*	*0.386*

In Panels A and B, the population numbers in column 1 are totals, while the rest are averages. Wage, housing price, and commuting data are taken from the U.S. Census 2000 IPUMS for 2071 Public-Use Microdata Areas (PUMAs). Differentials are relative to the national average. Housing-cost differentials are based on the average logarithm of gross rents or housing prices plus utilities, with the cost-index determined by the indicitor for what PUMA it is located in, and the composition index by the predicted value based on other observable housing characteristics. Wage differentials are based on the average logarithm of hourly wages for full-time workers ages 25 to 55, with the "By workplace" differential estimated off of work-place indicators, averaged over resident workers, the "By Residence" estimated off of residential indicators, and the "Composition" index by the wage predicted by observable characteristics. Commuting-cost differentials for workers are estimated from monetary-cost and time-cost differentials explained in the text, the latter based on time to work. The adjusted quality-of-life index is estimated from the housing-cost, workplace-wage, and commuting-cost indices in columns 2, 3, and 7, according to equation (5), as calibrated in the text, while the simple index is estimated from the housing-cost and residence-wage indices, only. In Panel C, non-metropolitan areas of each state are treated like distinct metropolitan areas, although the results do not change substantially if they are excluded. See text for greater detail.

Table 3.2: Rent, Wage, Commuting-Cost, and Quality-of-life differentials within Manhattan and San Francisco, 2000

		Rents/Hous. Cost		Wage			Commuting		Quality of Life		
Area Name	Population (1)	Location Index or "Rent" (2)	Composition or "Quality" (3)	Index by Work-place (4)	Index by Residence (5)	Composition or "Skill" (6)	Index of Full Cost (7)	Time Diff. Only (8)	Workpla. Adj. Index (9)	Simple (not used) (10)	QOL rank from (9) (11)
New York Co., NY (Manhattan)	*1,537,195*	*0.762*	*-0.528*	*0.255*	*0.282*	*0.002*	*-0.001*	*0.185*	*0.127*	*0.086*	*23*
Upper East Side	217,063	1.409	-0.499	0.273	0.483	0.224	-0.003	0.159	0.327	0.191	1
Stuy Town/Turtle Bay	143,441	1.315	-0.556	0.270	0.434	0.194	-0.017	-0.014	0.284	0.176	7
Greeewich Vlg./Fin. District	125,567	1.284	-0.535	0.272	0.411	0.185	-0.018	-0.081	0.272	0.182	10
Upper West Side	192,213	1.223	-0.535	0.272	0.463	0.208	-0.002	0.142	0.268	0.139	12
Midtown West/Chelsea	122,241	1.078	-0.549	0.270	0.419	0.125	-0.022	-0.118	0.202	0.105	41
Washington Hts./Inwood	216,234	0.289	-0.564	0.225	0.052	-0.222	0.020	0.499	0.008	0.066	820
Morningside Hts./Hamilton Hts.	129,533	0.291	-0.510	0.235	0.110	-0.088	0.008	0.322	-0.008	0.040	993
Lower E. Side/Chinatown	166,379	0.353	-0.548	0.252	0.075	-0.132	-0.006	0.151	-0.009	0.031	996
Central Harlem	109,091	-0.039	-0.474	0.237	0.199	-0.186	0.011	0.305	-0.113	-0.106	1998
East Harlem	115,433	-0.053	-0.474	0.236	0.133	-0.199	0.01	0.352	-0.117	-0.081	2006
San Francisco City & Co., CA	*776,733*	*1.031*	*-0.264*	*0.262*	*0.250*	*-0.002*	*0.008*	*0.185*	*0.218*	*0.186*	*3*
Marina/North Beach/Nob Hill	107,285	1.225	-0.408	0.266	0.387	0.087	-0.002	0.105	0.267	0.179	13
Ingleside	105,194	1.137	-0.155	0.260	0.258	0.007	0.018	0.265	0.261	0.230	14
Sunset	105,532	1.105	-0.215	0.268	0.229	0.050	0.021	0.350	0.251	0.226	17
Beuna Vista/Central/Bernal Hts.	109,355	1.134	-0.266	0.266	0.255	0.077	0.006	0.165	0.247	0.210	21
Richmond/W. Addition	136,975	1.047	-0.269	0.265	0.266	0.053	0.011	0.217	0.225	0.179	30
Downtown/SOMA/Mission	107,054	0.880	-0.361	0.257	0.183	-0.109	-0.014	-0.037	0.152	0.154	103
S. Bayshore/S. Central	105,338	0.681	-0.166	0.248	0.169	-0.200	0.013	0.223	0.118	0.126	170

Differentials are relative to the national average and are expressed in logarithms or logarithm equivalents. The sub-county measures are for Public-Use Microdata Areas, each containing over 100,000 inhabitants. Area names for the PUMAs here are based on sub-borough and planning area names from the Census. To offset bias due to rent control, the fraction of units that are controlled was multiplied by ln(1.37) in the six lower sub-broughs of Manhattan and by ln(1.19) in San Francisco. Quality-of-Life Rankings are out of 2071 PUMAs.

Table 3.3: Household characteristics, within, across, and outside U.S. Metropolitan Areas, 2000

	Percent Under 18 (1)	Percent Over 65 (2)	Percent of Adults Married (3)	House-hold size (4)	In Labor Force (5)	College Degree over 25 (6)	Race: Black (7)	Immi-grant (8)	Renter status (9)
Panel A: Central City, Suburban, or non-Metropolitan Area									
Central City (in Metro)	0.27	0.12	0.50	2.59	0.49	0.31	0.20	0.18	0.44
Suburban (in Metro)	0.27	0.12	0.62	2.68	0.51	0.32	0.09	0.12	0.27
Non-Metropolitan Areas	0.27	0.15	0.63	2.53	0.47	0.20	0.09	0.04	0.23
Panel B: By Residential Population Density									
>5,000 per square mile	0.27	0.12	0.50	2.72	0.48	0.32	0.19	0.26	0.46
1,000-5,000 per square mile	0.27	0.12	0.60	2.60	0.51	0.33	0.11	0.09	0.28
<1,000 per square mile	0.27	0.14	0.64	0.257	0.48	0.22	0.09	0.04	0.22
Panel C:Standard Deviations									
All PUMAs	0.041	0.042	0.091	0.329	0.055	0.137	0.170	0.126	0.142
Across Metropolitan Areas	0.022	0.029	0.035	0.200	0.035	0.076	0.095	0.101	0.069
Within Metropolitan Areas	0.035	0.029	0.060	0.259	0.042	0.156	0.143	0.077	0.129
Fraction of Variance Within	*0.729*	*0.477*	*0.435*	*0.620*	*0.583*	*1.297*	*0.708*	*0.373*	*0.825*

Data are taken from the U.S. Census 2000 IPUMS for 2071 Public-Use Microdata Areas (PUMAs). See Table 3.1 and text for greater detail.

Table 3.4: Rent, Wage, Commuting-Cost, and Quality-of-life differentials for four levels of geography within five Metropolitan Areas, 2000

Area Name	Unit of Geog-raphy	Population (1)	Housing Cost Index (2)	Wage by Work-place (3)	Full Comm-ute Cost (4)	QOL Adj. (5)	QOL Rank in Geog. Unit (6)
Honolulu, HI	**MSA**	**876,156**	**0.618**	**0.017**	**0.001**	**0.195**	**1**
East Oahu/Waialae-Kahala	PUMA	102,724	0.958	0.017	0.005	0.306	4
Kaneohe/Kailua	PUMA	117,994	0.761	0.016	0.009	0.249	18
Pearl City/Waimalu/W. Honolulu	PUMA	144,481	0.646	0.016	-0.008	0.196	45
Waikiki/Alo Maoni/Kapiolani	PUMA	109,509	0.700	0.018	-0.025	0.194	48
Waipahu/Mililani/Ewa	PUMA	178,534	0.476	0.018	0.024	0.174	69
Downtown Honolulu	PUMA	109354	0.526	0.018	-0.016	0.149	105
West Oahu/Midway Islands	PUMA	113560	0.357	0.019	0.008	0.119	169
San Francisco-Oakland-San Jose, CA	**MSA**	**7,039,362**	**0.809**	**0.243**	**0.012**	**0.159**	**2**
San Francisco, CA	PMSA	1,731,183	1.078	0.266	0.008	0.230	1
Marin Co.	*County*	*247,289*	*1.138*	*0.231*	*0.017*	*0.273*	*1*
San Rafael/Sausalito/Mill Valley	PUMA	146,373	1.251	0.233	0.014	0.304	5
Novato/Lucas Valley/Point Reyes	PUMA	100,916	0.974	0.228	0.022	0.227	29
San Mateo Co.	*County*	*707,161*	*1.109*	*0.283*	*0.006*	*0.230*	*2*
San Francisco Co.	*County*	*776,733*	*1.031*	*0.262*	*0.008*	*0.218*	*3*
Santa Cruz-Watsonville, CA	PMSA	255,602	0.799	0.164	0.006	0.185	3
San Jose, CA	PMSA	1,682,585	0.977	0.302	0.006	0.180	4
Santa Rosa, CA	PMSA	458,614	0.577	0.134	0.004	0.125	7
Oakland, CA	PMSA	2,392,557	0.638	0.233	0.020	0.118	8
Vallejo-Fairfield-Napa, CA	PMSA	518,821	0.359	0.154	0.010	0.054	36

Table 3.4: Rent, Wage, Commuting-Cost, and Quality-of-life differentials for four levels of geography within five Metropolitan Areas, 2000

Area Name	Unit of Geog-raphy	Population (1)	Housing Cost Index (2)	Wage by Work-place (3)	Full Comm-ute Cost (4)	QOL Adj. (5)	QOL Rank in Geog. Unit (6)
NYC, N. NJ, Long Is., NY-NJ-CT-PA	**MSA**	**22,767,645**	**0.430**	**0.198**	**0.023**	**0.067**	**12**
Nassau-Suffolk, NY	PMSA	2,753,913	0.541	0.185	0.030	0.117	9
New York, NY	PMSA	9,314,235	0.473	0.202	0.027	0.086	20
Westchester Co.	*County*	*923,459*	*0.678*	*0.212*	*0.025*	*0.145*	*17*
New York Co. (Manhattan)	*County*	*1,537,195*	*0.762*	*0.255*	*-0.001*	*0.127*	*23*
Putnam Co.	*County*	*95,745*	*0.478*	*0.191*	*0.053*	*0.117*	*31*
Queens Co.	*County*	*2,229,379*	*0.500*	*0.192*	*0.037*	*0.108*	*43*
Richmond Co. (Staten Island)	*County*	*443,728*	*0.449*	*0.191*	*0.049*	*0.104*	*47*
Rockland Co.	*County*	*286,753*	*0.491*	*0.182*	*0.024*	*0.097*	*54*
Kings Co. (Brooklyn)	*County*	*2,465,326*	*0.361*	*0.184*	*0.031*	*0.061*	*117*
Bronx Co.	*County*	*1,332,650*	*0.168*	*0.192*	*0.030*	*-0.006*	*525*
Bergen-Passaic, NJ	PMSA	1,373,167	0.551	0.220	0.012	0.083	22
Stamford-Norwalk, CT	PMSA	882,567	0.603	0.270	0.010	0.075	24
Danbury, CT	PMSA	1,064,760	0.535	0.245	0.009	0.064	29
Middlesex-Somerset-Hunterdon, NJ	PMSA	1,549,507	0.400	0.223	0.025	0.046	43
Newark, NJ	PMSA	2,030,197	0.393	0.216	0.020	0.041	47
Monmouth-Ocean, NJ	PMSA	1,330,939	0.279	0.171	0.034	0.039	52
Bridgeport, CT	PMSA	701,891	0.411	0.209	0.003	0.034	56
Dutchess County, NY	PMSA	277,140	0.163	0.105	0.021	0.022	73
Newburgh, NY-PA	PMSA	477,918	0.095	0.079	0.030	0.021	76
Jersey City, NJ	PMSA	612,562	0.345	0.235	0.019	0.017	79
Waterbury, CT	PMSA	413,598	0.204	0.141	-0.001	-0.005	117
New Haven-Meriden, CT	PMSA	870,785	0.208	0.143	-0.002	-0.006	118
Trenton, NJ	PMSA	350,093	0.249	0.197	0.005	-0.011	128

Table 3.4: Rent, Wage, Commuting-Cost, and Quality-of-life differentials for four levels of geography within five Metropolitan Areas, 2000

Area Name	Unit of Geog-raphy	Population (1)	Housing Cost Index (2)	Wage by Work-place (3)	Full Comm-ute Cost (4)	QOL Adj. (5)	QOL Rank in Geog. Unit (6)
Atlanta, GA	**MSA**	**4,112,198**	**0.025**	**0.062**	**0.018**	**-0.002**	**70**
DeKalb Co.	*County*	*665,865*	*0.133*	*0.076*	*0.018*	*0.026*	*267*
Fulton Co.	*County*	*816,006*	*0.171*	*0.093*	*0.006*	*0.019*	*299*
Cobb Co.	*County*	*607,751*	*0.092*	*0.079*	*0.022*	*0.016*	*313*
Forsyth & Pickens Cos.	*County*	*121,390*	*0.015*	*0.042*	*0.023*	*0.006*	*440*
Cherokee Co.	*County*	*141,903*	*-0.015*	*0.046*	*0.029*	*0.004*	*406*
Gwinnett Co.	*County*	*588,448*	*0.023*	*0.067*	*0.023*	*-0.004*	*579*
Coweta, Fayette, & Spalding Cos.	*County*	*238,895*	*-0.119*	*0.017*	*0.015*	*-0.030*	*905*
Henry Co.	*County*	*119,341*	*-0.193*	*-0.004*	*0.021*	*-0.036*	*1185*
Carroll & Douglas Cos.	*County*	*179,442*	*-0.201*	*-0.002*	*0.020*	*-0.044*	*1128*
Bartow & Paulding Cos.	*County*	*157,697*	*-0.226*	*0.017*	*0.035*	*-0.046*	*1183*
Newton & Rockdale Cos.	*County*	*132,112*	*-0.167*	*0.021*	*0.017*	*-0.047*	*1189*
Barrow & Walton Cos.	*County*	*106,831*	*-0.221*	*0.009*	*0.026*	*-0.049*	*1260*
Clayton Co.	*County*	*236,517*	*-0.119*	*0.056*	*0.012*	*-0.051*	*1304*

Table 3.4: Rent, Wage, Commuting-Cost, and Quality-of-life differentials for four levels of geography within five Metropolitan Areas, 2000

Area Name	Unit of Geog-raphy	Population (1)	Housing Cost Index (2)	Wage by Work-place (3)	Full Comm-ute Cost (4)	QOL Adj. (5)	QOL Rank in Geog. Unit (6)
Detroit-Ann Arbor-Flint, MI	**MSA**	**5,456,428**	**0.031**	**0.117**	**0.008**	**-0.039**	**156**
Ann Arbor, MI	PMSA	578,736	0.141	0.079	0.003	0.009	93
Livingston Co.	*County*	*156,951*	*0.187*	*0.101*	*0.024*	*0.035*	*219*
Washtenaw Co.	*County*	*322,895*	*0.220*	*0.096*	*-0.006*	*0.018*	*304*
Ann Arbor	PUMA	114,024	0.364	0.086	-0.021	0.054	453
Ypsilanti/Saline/Pittsfield Twp.	PUMA	208,871	0.142	0.101	0.002	-0.002	915
Lenawee Co.	*County*	*98,890*	*-0.192*	*-0.009*	*0.001*	*-0.059*	*1467*
Detroit, MI	PMSA	4,441,551	0.045	0.129	0.009	-0.038	204
Oakland Co.	*County*	*1,194,156*	*0.277*	*0.146*	*0.012*	*0.032*	*242*
Macomb Co.	*County*	*788,149*	*0.106*	*0.131*	*0.014*	*-0.015*	*652*
St. Clair & Lapeer Co.	*County*	*252,139*	*-0.045*	*0.046*	*0.021*	*-0.018*	*690*
Monroe Co.	*County*	*145,945*	*-0.025*	*0.072*	*0.008*	*-0.036*	*995*
Wayne Co.	*County*	*2,061,162*	*-0.098*	*0.131*	*0.004*	*-0.091*	*2521*
Flint, MI	PMSA	436,141	-0.226	0.060	0.003	-0.099	322

Units of geography are MSA, PMSA, County, and PUMA. MSAs that contain several PMSAs, are also called “CMSAs”. The PMSA ranking also includes MSAs that do not contain PMSAs. Counties may be larger, equal to, or smaller than PUMAs. For example, one PUMA contains St. Clair & Lapeer counties, and so they are listed together. Only some sub-geographies are shown. The rankings in column 6 are different for each type of geography, and are indented at the same levels as the names. Our rankings are out of 3202 counties or equivalents (parishes, boroughs, independent cities, census areas), 2071 PUMAs, 332 PMSAs, and 276 MSAs.

Table 3.5: Selected amenities within, across, and outside U.S. Metropolitan Areas, 2000

	Annual Heating Degree Days (1)	Annual Cooling Degree Days (2)	Annual Sunshine Percent Possible (3)	Inverse Distance to Coast (4)	Average Slope of Land (4)	Murder Rate per 1,000 (5)	Rest-aurants and Bars per 1,000 (6)	Public School Revenues per Student (7)
Panel A: Central City, Suburban, or non-Metropolitan Area								
Central City (in Metro)	3.98	1.40	0.62	0.13	0.01	0.09	1.80	0.81
Suburban (in Metro)	4.31	1.28	0.60	0.07	0.02	0.05	1.68	0.85
Non-Metropolitan Areas	5.15	1.13	0.59	0.02	0.02	0.04	1.68	0.75
Panel B: By Residential Population Density								
>5,000 per square mile	3.71	1.28	0.63	0.19	0.01	0.09	1.80	0.88
1,000-5,000 per square mile	4.49	1.33	0.60	0.05	0.02	0.05	1.73	0.82
<1,000 per square mile	4.79	1.22	0.59	0.02	0.02	0.04	1.61	0.75
Panel C: Standard Deviations								
All PUMAs	2.199	0.912	0.079	0.158	0.022	0.057	0.477	0.168
Across Metropolitan Areas	2.155	0.888	0.078	0.094	0.016	0.035	0.279	0.153
Within Metropolitan Areas	0.438	0.208	0.012	0.127	0.014	0.046	0.387	0.070
Fraction of Variance Within	*0.040*	*0.052*	*0.023*	*0.646*	*0.405*	*0.651*	*0.658*	*0.174*

Data are taken from sources described in the appendix. Murder rate, restaurants and bars and public school revenues are at the county level. Cooling and heating degree days are from a 65F base. Revenues per student are measured in $10,000 units. See text for greater detail.

Table 3.6: Amenity predictors of local quality of life

Dependent Variables	All QOL by PUMA (1)	Within MSA Adj QOL (2)
Minus 1000s of Heating Degree Days, 65F base	0.022***	0.035***
(mean = 4.50, sd = 2.25)	(0.001)	(0.004)
Minus 1000s of Cooling Degree Days, 65F base	0.043***	0.059***
(mean = 1.25, sd = 0.91)	(0.003)	(0.008)
Sunshine, percent possible	0.157***	-0.101
(mean = 0.060, sd = 0.078)	(0.021)	(0.098)
Inverse distance to coast	0.115***	0.021
(mean = 0.71, sd =0.14)	(0.017)	(0.018)
Average Slope of Land, in percent	0.608***	0.909***
(mean = 1.80, sd = 2.22)	(0.068)	(0.101)
Minus Murder Rate per 1,000	0.133***	0.263***
(mean = 0.05, sd = 0.053)	(0.033)	(0.030)
Restaurants and Bars per Thousand	0.029***	0.028***
(mean = 1.71, sd = 0.28)	(0.004)	(0.004)
Public School Revenues per Student, $10,000s	0.117***	0.093**
(mean = 0.50, sd = 0.13)	(0.010)	(0.021)
R-squared	0.41	0.64
Number of Observations	1948	1948

Robust standard errors shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Regressions weighted by population. Variables are described in the Appendix, including Appendix Table A6.

Figure 3.1: Residential Rents (Gross or Imputed) across the United States, 2000

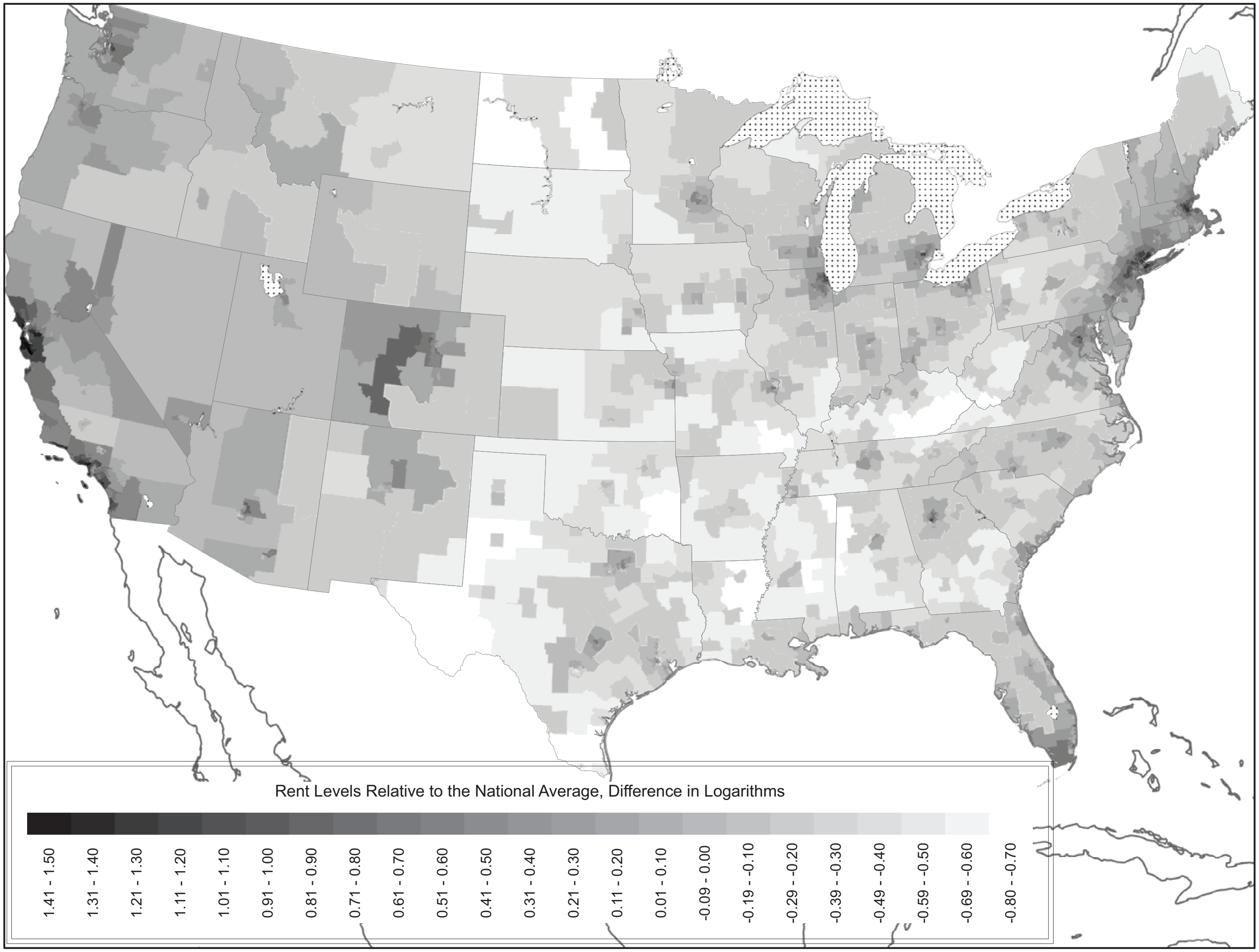


Figure 3.2: Wage Levels by Workplace across the United States, 2000

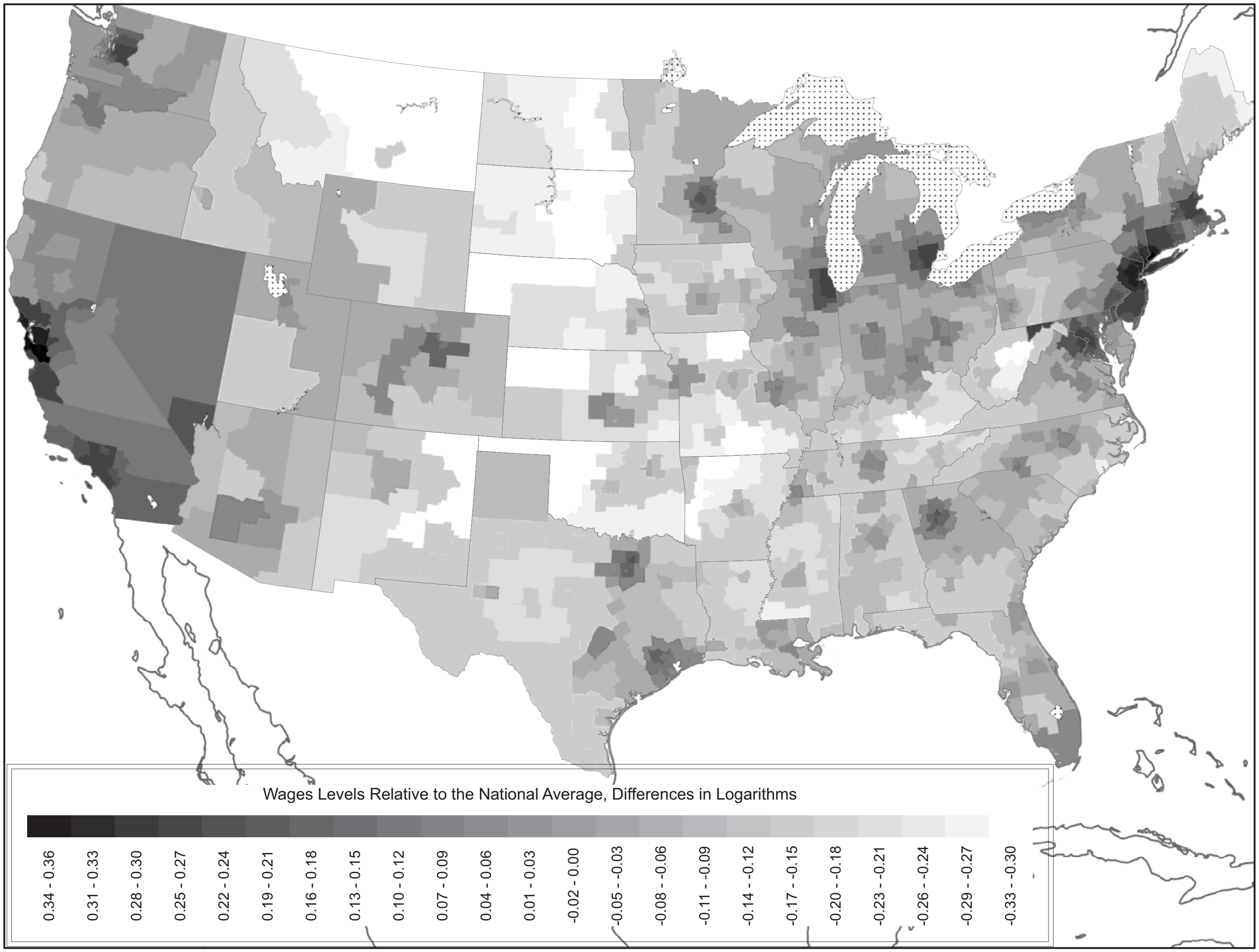


Figure 3.3: Commuting Costs across the United States, 2000

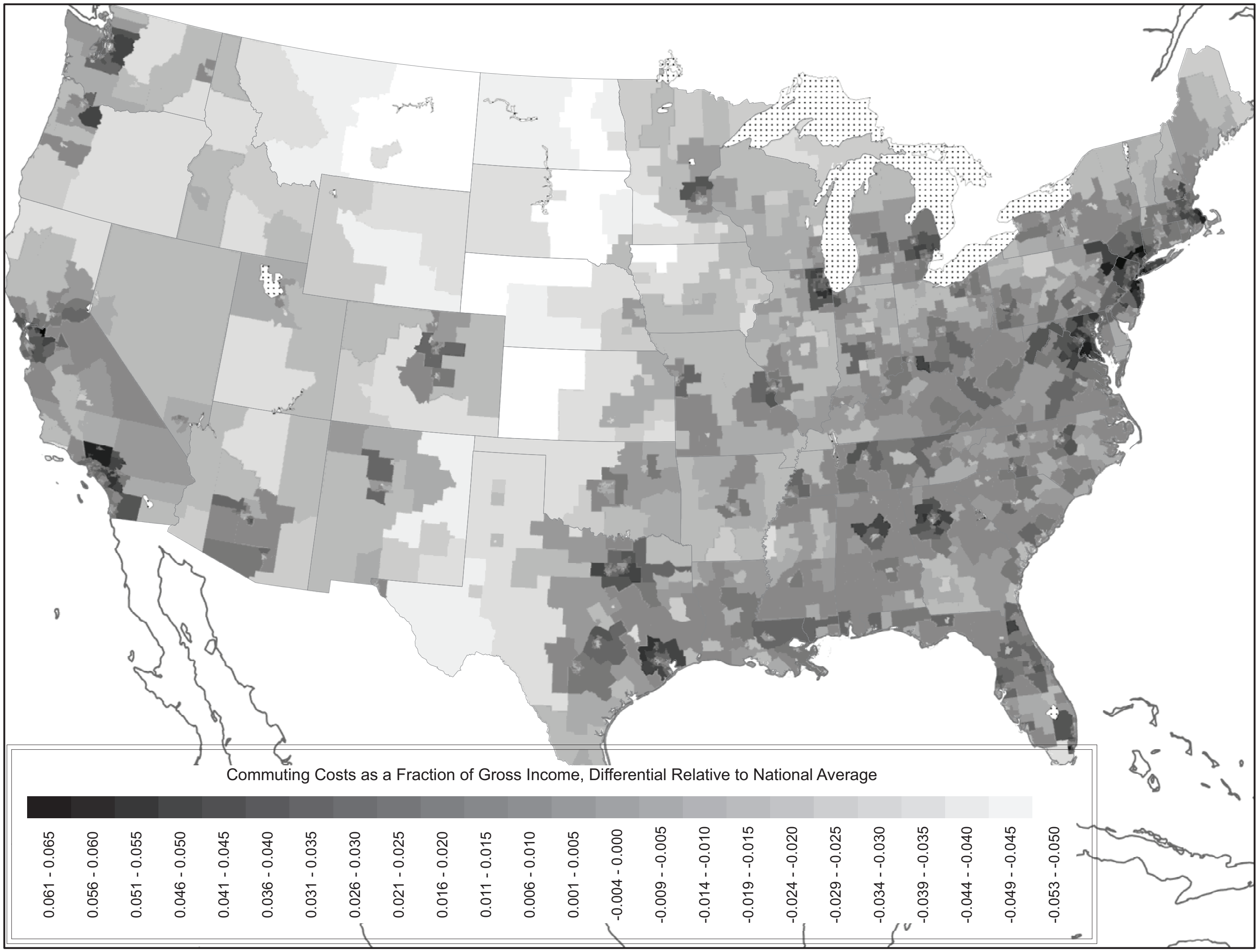
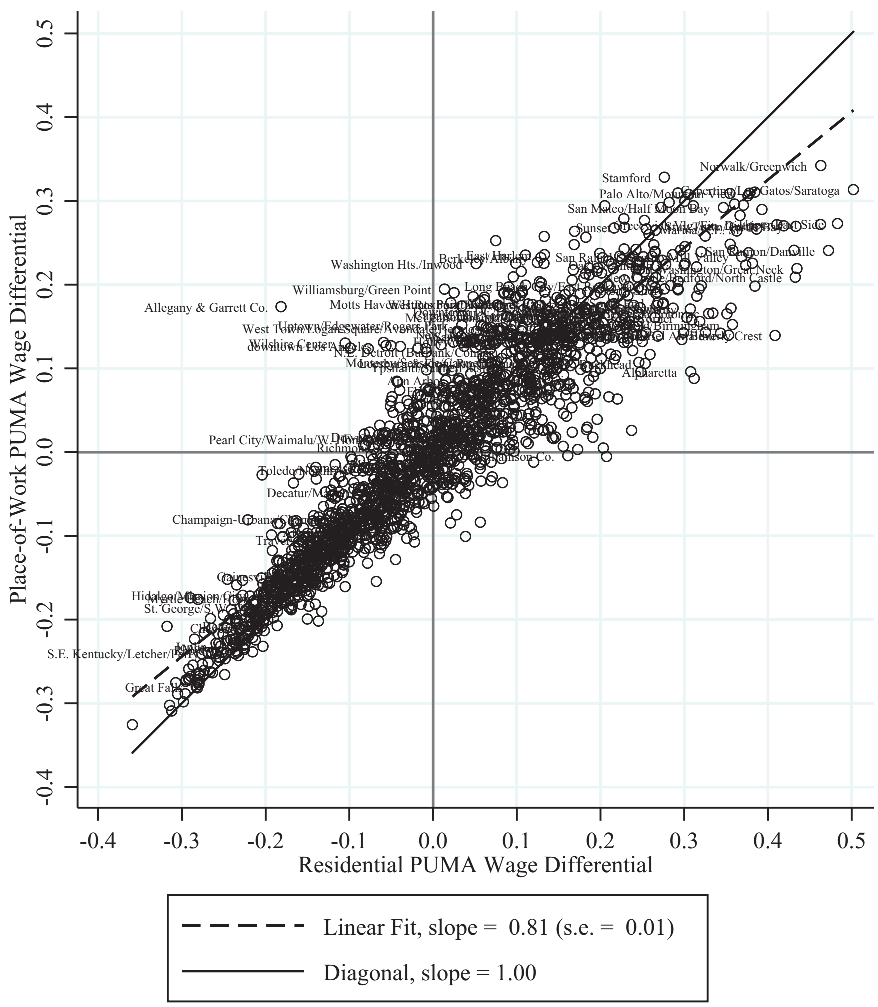
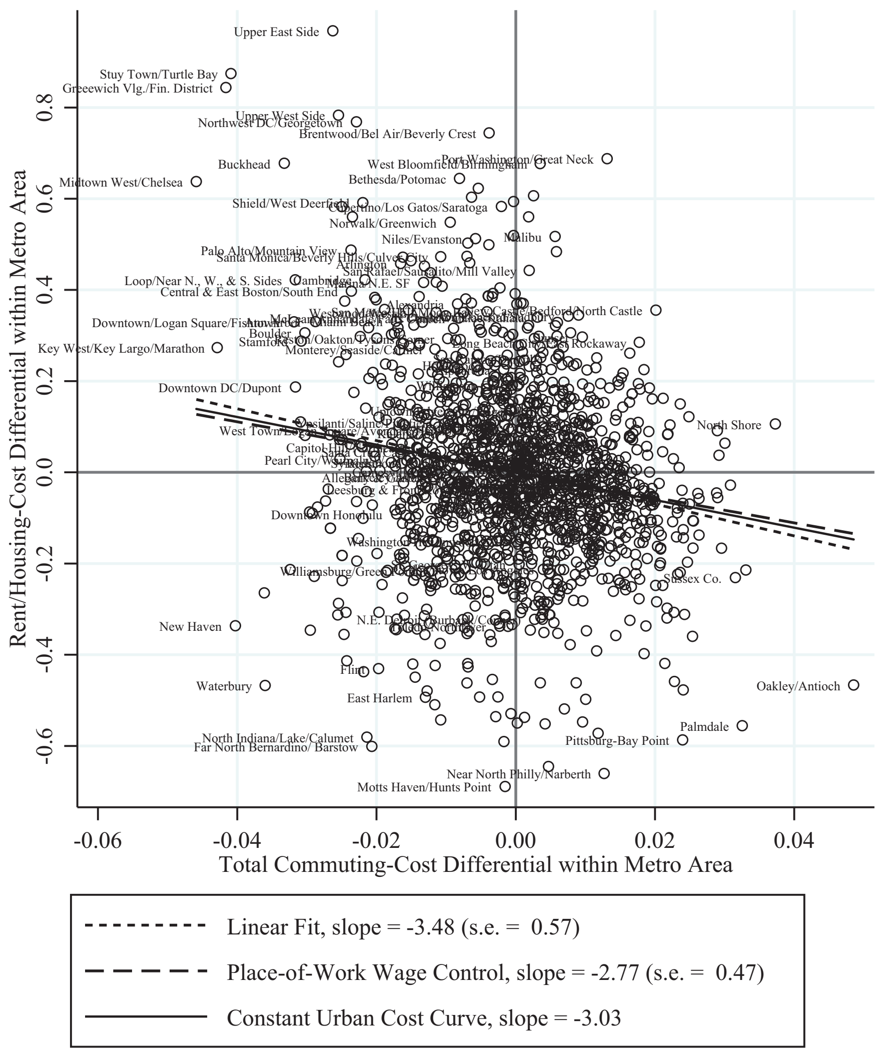


Figure 3.4: Wages Estimated by Workplace or by Residence, 2000



Unit of observation is the residential PUMA.

Figure 3.5: Rents and Commuting Costs, 2000



Housing and commuting-cost differentials are residuals from separate regressions on metro-area (MSA/CMSA) indicators (i.e., fixed effects).

Figure 3.6: Quality of Life across the United States, 2000

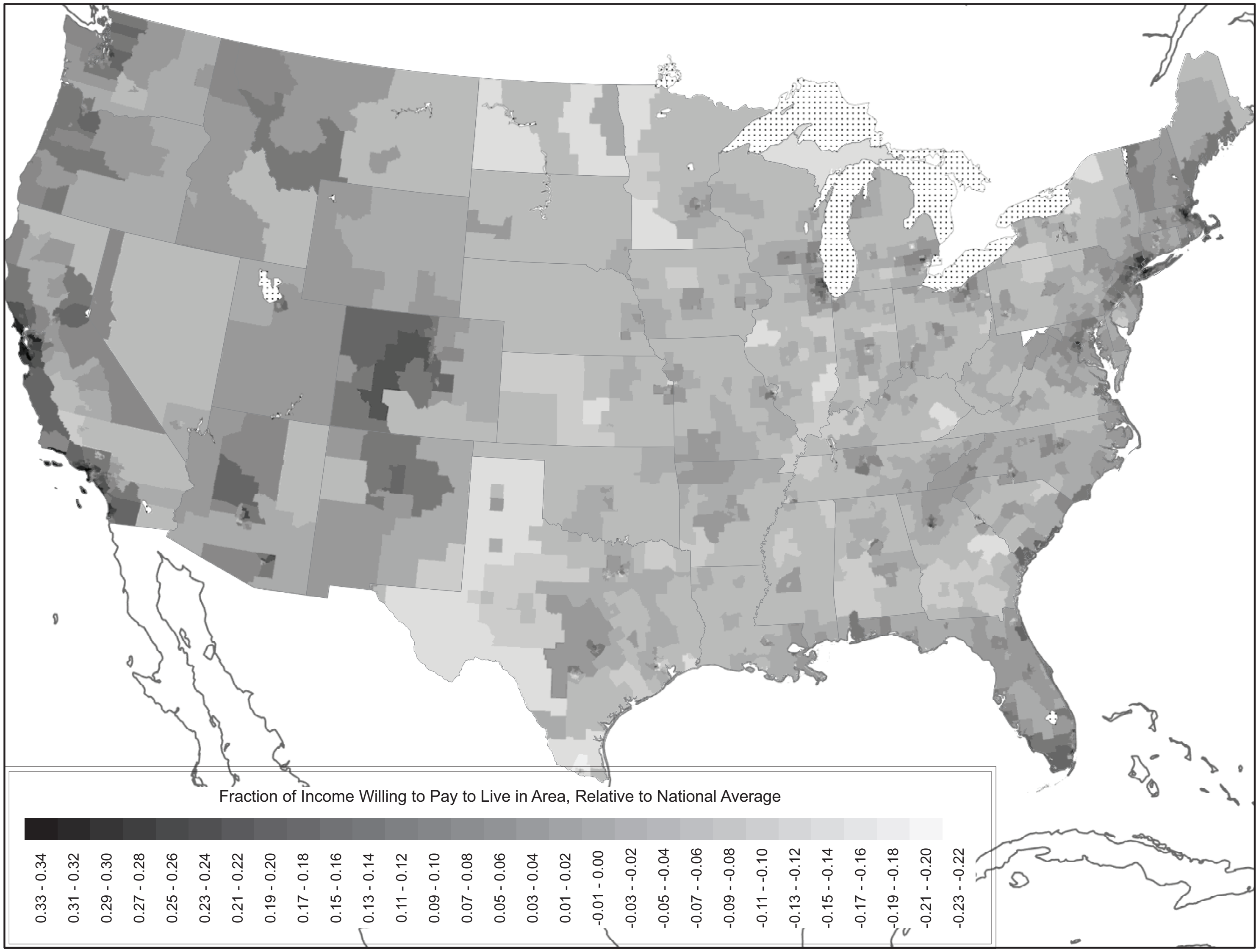


Figure 3.7: Quality of Life in the San Francisco Bay Area, 2000

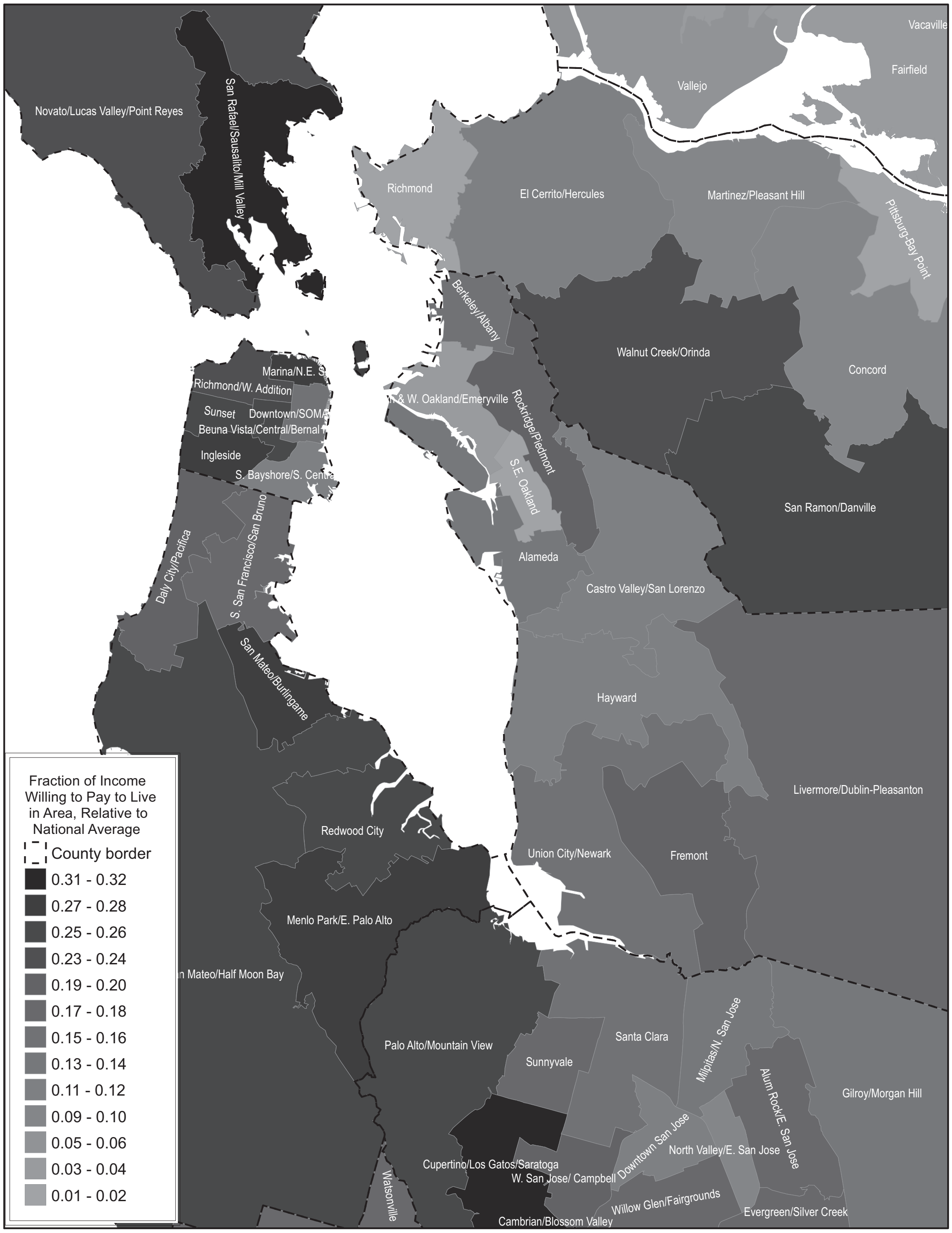


Figure 3.8: Quality of Life in and around Manhattan, 2000

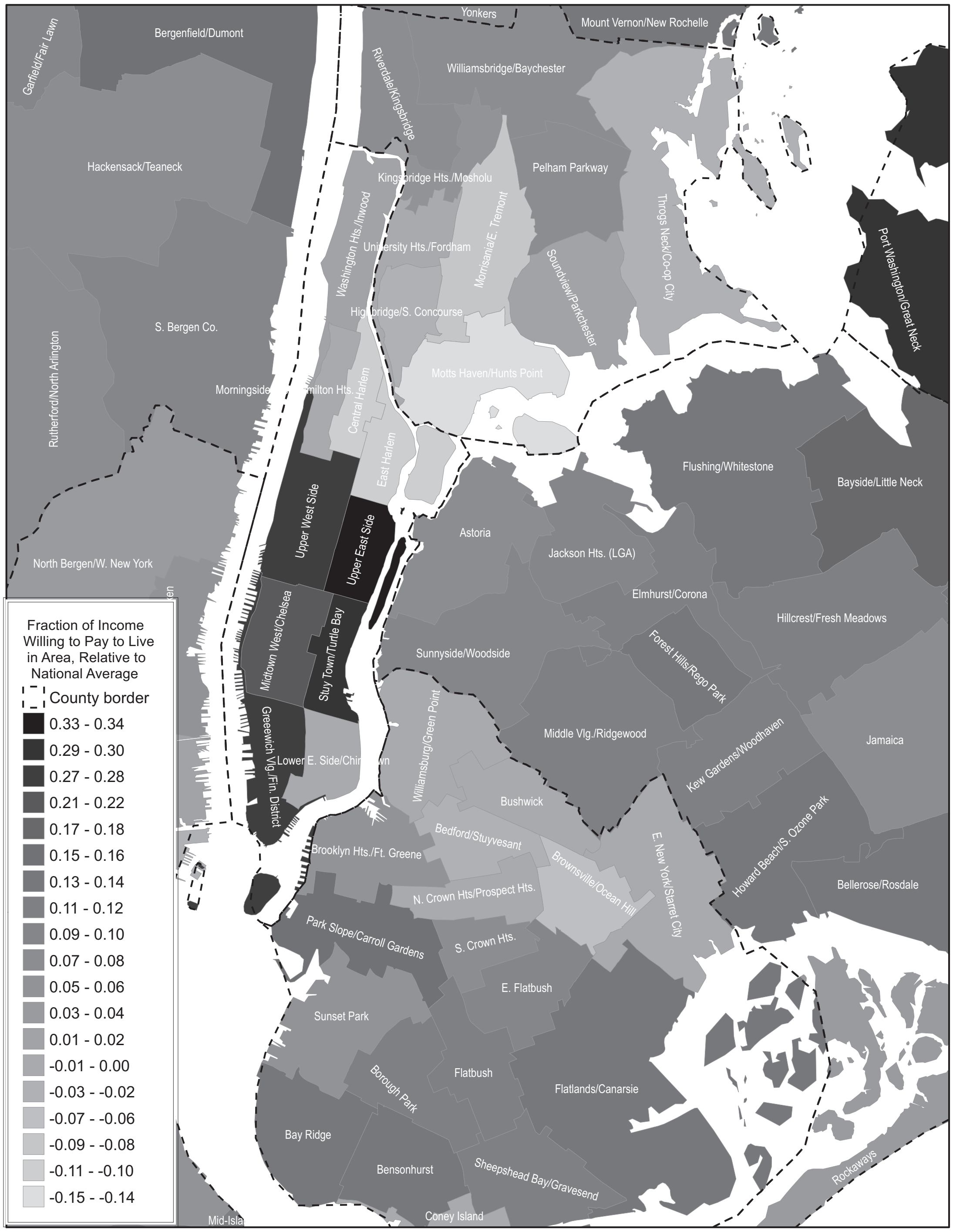


Figure 3.9: Quality of Life in Detroit and Southeast Michigan, 2000

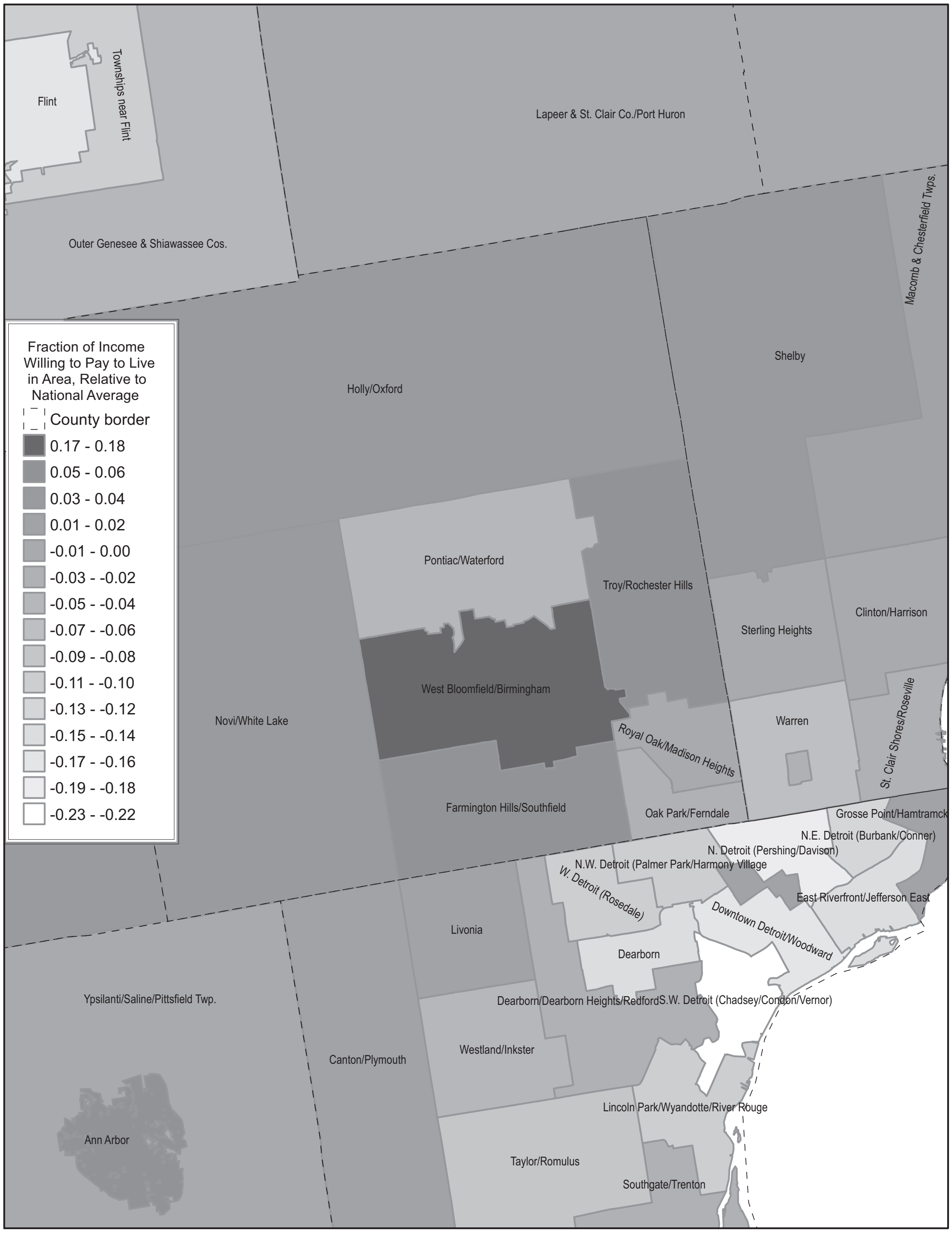
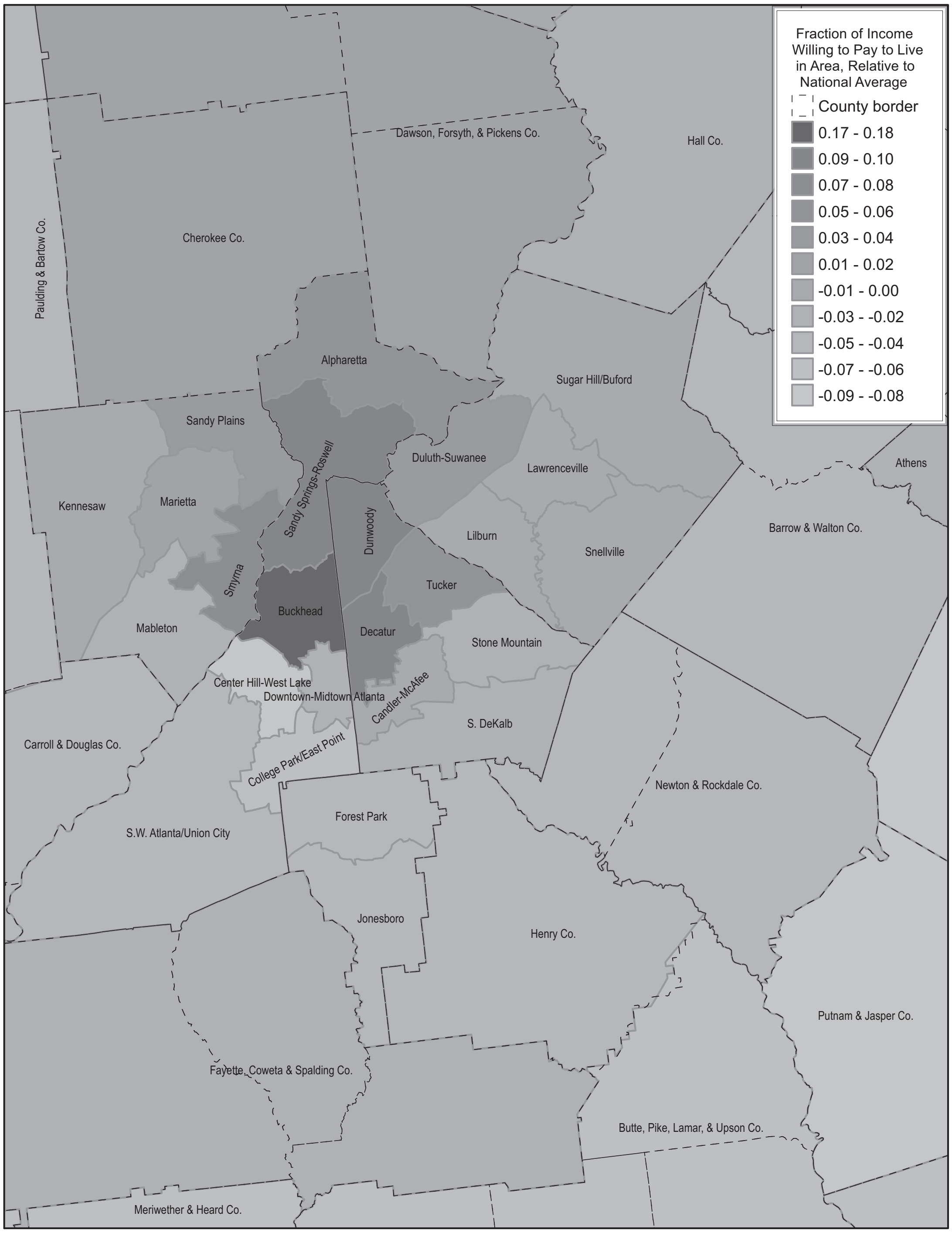


Figure 3.10: Quality of Life in and around Atlanta, 2000



APPENDICES

APPENDIX A

Examples using the model

For all the examples that follow I will assume that v_j is uniformly distributed $(0, .25)$ across each value of s_j which itself is uniformly distributed $(0, 1)$ for mixed race individuals. For simplicity, if individuals are indifferent between actions 1 and 0, I assume they choose action 1.

Example 1: This example looks at identity choices in a location with no strong racial bias where mixed-race identity is fairly common. We parametrize this situation by letting $C_L = C_{LR} = C_R = 0$, so there is no association between identity and action, and setting $(p_L, p_R) = (.25, .75)$ in this location, providing a wide identity measure range for mixed-race identity.

The case where there is no tie between identity and action leaves trivial choices for action and identity. Since there is a positive return to action 1, all individuals choose this independent of identity choice. Each individual then chooses an identity based on endowed phenotype, s_j, according to where this falls on the identity measure line. This can easily be seen from 1.6c and 1.7c, where after plugging in the parameters above, individuals will choose L when $s_j < .25$, LR when $.25 < s_j < .75$, and R when $.75 < s_j$.

I illustrate identity choices in Figure F.5 in two dimensional space with ability, v, on the y-axis and skin tone, s, on the x-axis. It is clear that there should be twice as many mixed-race individuals declaring identity LR than identity L and identity R. All individuals, regardless of identity, choose action 1. We can calculate the average values of v, for all individuals choosing identity L, LR, and R, and denote these as $\bar{v_L}$, $\bar{v_{LR}}$, $\bar{v_R}$ respectively. For any given s_j, since v_j is distributed uniformly $(0, .25)$, the average value,$\bar{v}$, will be

$$\frac{1}{2}(.25 + 0) = \frac{1}{8}$$

All individuals with $s_j < .25$ will choose identity L, therefore we can calculate $\bar{v_L}$ as the weighted value of v divided by the area of individuals choosing L. This is the area denoted by L in Figure F.5. First, the weighted value of v can be calculated as follows:

$$\int_0^{.25} \underbrace{(.25 - 0)}_{\text{weight}} \overbrace{\frac{1}{2}(.25 + 0)}^{\text{average v}} ds = \frac{1}{128}$$

Next we calculate the area of individuals choosing L:

$$\int_0^{.25} (.25 - 0) ds = \frac{1}{16}$$

Therefore the average ability of individuals who choose identity L is

$$\bar{v_L} = \frac{1}{8}.$$

Trivially, as $\bar{v}$ is the same for each value of s_j, and each s_j only maps to one identity, $\bar{v_L} = \bar{v_{LR}} = \bar{v_R} = \frac{1}{8}$. In this example where there is no association between action and identity, we see then that everyone chooses action 1 and average ability, as measured by v, is equal across all identity choices. With ranges of s_j tied to identity as described above, this results in 25% of mixed race individuals choosing identity L, 50% choosing identity LR, and 25% choosing identity R. The combination of identity and action choice mapped over possible values of ability and phenotype is shown in Figure 1.7.

In the case where identity is equally negatively associated with all identities, like $C_L = C_{LR} = C_R = .1$, we still have no change the the average ability across identity, or in the range of phenotype that results in different identities. However, we would see a change in the proportion of individuals that choose action 1 as illustrated in Figure F.7. Only individuals with ability higher than the identity cost, $v_j > .1$, would choose action 1.

Example 2: This example looks at identity choices for mixed-race individuals in a location where there is racial bias and a strong negative association for certain identities and actions, but where mixed-race identity is still common.

We parametrize this situation by having both L and LR negatively associated with action 1; let $C_L = .2 > C_{LR} = .1$ and $C_R = 0$. As in example 1, we set the phenotype range for mixed-race identity as $(p_L, p_R) = (.25, .75)$ and allow ability, v_j to be uniformly distributed (0,.25).

First, for a given s_j we look at the choice between identity L and LR. We can plug in our parameters into 1.6a,1.6b, and 1.6c and get the following:

$$s_j > .25 \qquad \text{if } .1 > v_j \tag{A.1a}$$

$$s_j > .35 - v_j \qquad \text{if } .2 > v_j > .1 \tag{A.1b}$$

$$s_j > .15 \qquad \text{if } v_j > .2 > .1 \tag{A.1c}$$

We see for certain ranges of s_j we again have individuals of all abilities, v_j, choosing only one identity. No matter the value of v_j, when $s_j < .15$ all individuals will choose identity L. Likewise when $s_j > .25$ all individuals will choose identity R.

The interesting choices occur when $.15 < s_j < .25$. From A.1a, for values of $v_j < .1$ in this range of phenotype, all individuals will choose LR, whereas from A.1c, for values of $v_j > .2$ in this range of phenotype, all individuals will choose R. In-between behavior is governed by A.1b. This is perhaps best illustrated graphically in Figure F.6.

Here we can plainly see that for the boundary range of phenotype where $.15 < s_j < .25$, conditional on a particular phenotype value, individuals with higher relative values of v_j choose identity LR and those with lower relative values choose identity L. This can be interpreted as positive selection into identity LR and negative selection into identity L. Contrasting this with example 1, we see that individuals with high ability and phenotypes close to $p_L = .25$ are "switching" into identity LR. This is driven by the larger negative association of identity L with action 1, relative to the negative association of identity LR with action 1.

Next, for a given s_j, we can examine the choice between identity LR and R. Plugging our parameters into 1.7a, 1.7b, and 1.7c we can examine when individuals choose identity R over identity LR and get the following:

$$s_j > .75 \qquad \text{if } 0 > v_j \tag{A.2a}$$

$$s_j > .75 - v_j \qquad \text{if } .1 > v_j > 0 \tag{A.2b}$$

$$s_j > .65 \qquad \text{if } v_j > .1 > 0 \tag{A.2c}$$

We see that no matter the value of v_j, when $s_j < .65$ all individuals choose identity LR and when $s_j > .75$ all individuals choose identity R.

The interesting choices occur over the middle range of phenotype $.65 < s_j < .75$ where, depending on v_j, individuals with the same phenotype will choose different identities. From A.2c, whenever $v_j > .1$ these individuals choose R. A.2b shows that the range of v_j that leads to identity LR gets smaller as s_j increases. We can refer again to Figure F.6 to illustrate identity choices at the LR and R boundary.

As with choices of individuals near the phenotype boundary of L and LR, near the phenotype boundary of LR and R, where $.65 < s_j < .75$ we see what we can interpret as positive selection into identity R and negative selection into identity LR. This is driven by the larger negative association of identity LR and action 1, the value of $C_{LR} = .1$, in contrast to the lack of association between identity R and action 1, with $C_R = 0$.

With positive selection into identity R, negative and positive selection into identity LR, and negative selection into LR, we can now show that $\bar{v_L} < \bar{v_{LR}} < \bar{v_R}$ in this example.

First, we calculate $\bar{v_R}$. Since v_j is distributed uniformly across each s_j, we calculate the average v_j for each s_j and sum over the weighted values of s_j. We need to weight values of s_j as, for certain values, only a fraction of individuals with that phenotype choose identity R. This weight is the height of the line segment of v_j where individuals choose R. In this range of $.65 < s_j < .75$, this is $.25 - (.75 - s) = s - .5$. We must also calculate the average value of v_j for individuals choosing identity R, and in this range this also depends on s_j. We are calculating the average value of v for individuals in trapezoid labeled B in Figure 1.9.

This gives us:

$$\int_{.65}^{.75} \underbrace{(s-.5)}_{\text{weight}} \overbrace{\frac{1}{2}(.25+(.75-s))}^{\text{average v}} ds = \frac{71}{24000}$$

The area of trapezoid B where identity choice is R and $.65 < s_j < .75$ can be calculated as

$$\int_{.65}^{.75} (.25-(.75-s))ds = \frac{1}{50}.$$

For individuals with phenotype $s_j > .75$, these individuals all choose identity R, and we calculated the weighted value of v in this range as

$$\int_{.75}^{1} (.25)\frac{1}{2}(.25)ds = \frac{1}{128}.$$

This area for R where $s_j > .75$ is

$$\int_{.75}^{1} (.25)ds = \frac{1}{16}.$$

Now to calculate the $\bar{v_R}$ we combine weighted averages of the trapezoid and square and divide by sum of their areas. We are calculating the average $\bar{v}$ of the shaded R area in Figure F.6 below.

$$\bar{v_R} = \frac{47}{360} \approx 0.1306 \tag{A.3}$$

Now we calculate $\bar{v_L}$. First, the average v of the trapezoid area (see Figure 1.9, labeled A) of individuals from $.15 < s_j < .25$, some of whom switch to identity LR instead of staying in identity L. This weight is the height of the line segment of v where individuals choose LR instead of L. In this range of $.15 < s_j < .25$, this is $.25 - (.35 - s) = s - .1$.

$$\int_{.15}^{.25} \underbrace{(s-.1)}_{\text{weight}} \overbrace{\frac{1}{2}(.25+(.35-s))}^{\text{average v}} ds = \frac{47}{24000}$$

The area of the trapezoid A for identity LR where $.15 < s_i < .25$ is just the sum of the LR

range over these values of s:

$$\int_{.15}^{.25} (.25 - (.35 - s))ds = \frac{1}{100}$$

Now to calculate $\bar{v_L}$ we subtract the weighted average of the trapezoid from the weighted average of the square and divide by the area of the entire shape. The square has identical dimensions and same average v to the box calculated for R above. We are calculating the average v of the shaded L area in Figure F.6.

$$\bar{v_L} = \frac{281}{2520} \approx 0.1115 \tag{A.4}$$

Finally we can calculate the value of $\bar{v_{LR}}$ by taking the weighted average of trapezoid A, adding that to the weighted average of the rectangle from $.25 < s_j < .75$, subtracting the weighted average of trapezoid B, and dividing the whole thing by the area of the dotted LR area shown in Figure F.6.

$$\bar{v_{LR}} = \frac{117}{920} \approx 0.1272 \tag{A.5}$$

We can also illustrate some interesting comparative statics, as the relationship between skin tone, s_j, ability, v_j, behavioral norms captured by C_R, C_{LR}, and C_L, and skin tone norms captured by p_L and p_R dictate how individuals choose their actions. Figure 1.8 illustrates individual choices of identity and action in this example. The y-axis shows endowed ability and the x-axis shows endowed phenotype. Based on the calculations above, we illustrate here the combinations of s_j and v_j) that lead to each identity. In contrast to Figure 1.7, which illustrates example 1, where there is no relationship between action and identity, in example 2 we see that individuals from a greater range of s choose identity R, leading to a greater proportion choosing identity R overall. We also see that those switching into identity R have higher ability than those that stay in LR in the $.65 < s_j < .75$ range. This is positive selection into identity R and will bring up the average ability of individuals who choose identity R.

We see the opposite for identity L. Again comparing Figure F.5 and Figure F.6, while the range of phenotype of individuals choosing identity L has not declined, individuals with relatively higher ability in the $.15 < s_j < .25$ range of phenotype switch into identity LR. This leads to a lower proportion of mixed-race individuals choosing identity L overall. This switching can be thought of as positive selection out of identity L, and will lead to $\bar{v_L}$ being relatively lower than in example one, and certainly less than $\bar{v_R}$.

Identity LR is the interesting intermediate case. On the left hand side we have an expanded range of s where individuals choose identity LR, and relatively high ability types will switch into LR from $.15 < s_j < .25$, however, on the right hand side where $.65 < s_j < .75$, we see relatively high ability individuals select out of LR compared to those that stay in LR conditional on s_j.

From calculations performed above, we see that the parameters in example 2 result in $\bar{v_L} < \bar{v_{LR}} < \bar{v_R}$. Identity LR has, on average, higher ability types switching in from L than switching out to R. Additionally we can calculate the area of v, s space of each identity and see that the area gained from LR does not make up for the area lost from LR. This means that compared to example 1, with these parameters we have more individuals choosing identity R and less choosing both identity LR and identity L.

Figure 1.8 shows how different behavioral norms, values of C_X can affect action choice. In this example $C_R < C_{LR} < C_L$ leads to selection into identities with a lower identity/action cost. Now individuals with $v_j < C_I$ may still choose to work, by switching into a different identity. These individuals choose this course of action if the decreased cost in C makes up for the lower identity payoff. We also see that the proportion of individuals who choose action 0 for each identity increases with the value of C_X for that identity. Therefore the fraction of individuals choosing action 1 is lowest for identity L, higher for identity LR, and highest for identity R.

APPENDIX B

Census and ACS Race Coding

The 2000 census uses a combination of questions to ask about a person's racial/ethnic identity. First individuals are asked about Hispanic identity, Figure 1.4. "Is this person Spanish/Hispanic/Latino? Mark the 'No' box if not Spanish/Hispanic/Latino." Next, the 2000 census form asks about race, Figure 1.2, "What is this person's race? Mark one or more races to indicate what this person considers himself/herself to be." There are places for write-ins of specific tribe, other Asian or Pacific Islander, and some other race. The form makes clear that individuals should answer both of these questions.

On a later, separate page individuals are asked about ancestry, Figure 1.3, "What is this person's ancestry or ethnic origin?" There are two spaces for write-ins along with some examples listed below like Italian, Jamaican, African American, etc. In the 1970 version of the census this question asked about parents' place of birth; this question has asked about ancestry since 1980.

To construct measures of race by ancestry we follow a method based on the one used by the Census Bureau to match write-ins to the race question to the major race categories: White, Black, Asian, etc. This method is described in Farley (2004)[1]. I modify this slightly

[1]Roughly, individuals who wrote in answers for race were assigned to a major race category if 70% or more of respondents in a previous Census year who used that write-in value for ancestry chose the same major category for race. For example, if a person wrote in "French" for race in the 2000 Census, they would be assigned to the "White" race category as more than 70% of individuals using "French" as an ancestry term in the 1990 Census identified as "White." Individuals that wrote in some Spanish-origin group were classified as "Other" for race.

and use race data from individuals who declare only a single ancestry from 2000 to 2012. If 80% or more of respondents with the same single ancestry declare the same race, this ancestry is matched with this race. In the case that a single ancestry has more than 10% of respondents declare in each of two separate single race categories, I associate this ancestry with "Other" race. For example, using 2000 to 2012 Census and ACS data, 80% of respondents with the single ancestry "South African" declare their race as "white" but 14% declare their race as "Black." We would match "South African" ancestry with "other" race in order to avoid incorrectly assigning a respondent "Black" or "White" ancestry. We also appeal to Bureau of the Census (2007), which documents some specific mappings between write-in answers to the race question and the Census's major race categories and we use these associations for ancestry and race where appropriate, particularly for many Native and Pacific Islander ancestry responses.

The Census recodes and cleans ancestry responses. There are two lines on the form, but the number of responses allowed is open ended. However, the Census will only record and code two ancestry responses.[2] In addition, the Census has a priority system for coding responses. If multiple responses are listed, but one response is considered a subgroup of another, only the most specific response is listed. For example, an individual who listed "French" and "European" would be coded as "French" only. Prior to the 2010 ACS, this system treated Hispanic and Race responses as lower priority than ethnic origin responses, with the justification being that Hispanic origin and Race were already captured through other questions on the survey. Certain write-in responses were therefore only recorded in the absence of any other response; "White/Caucasian" was recorded as an ancestry only when it was the sole ancestry response of an individual. In other words, "White/Caucasian" was not accepted as an ancestry response when provided in combination with any other ancestry response prior to 2010. However, starting in 2010, Race and Hispanic responses have been given the same priority as other ethnic origin responses.

The censorship in ancestry responses prior to 2010 results in systematic misclassification of ancestry, pushing many mixed-ancestry respondents into single-ancestry categories. For this study, the dropping of "White/Caucasian" when used in combination with another an-

[2]http://www.census.gov/population/ancestry/about/faq.html, retrieved 3/14/15.

cestry response is most impactful. A natural question then, is whether individuals coded with Black/White ancestry censored due to their white ancestry answer being "White/Caucasian" are the same as those with a different White ancestry. Table 1.15 compares some characteristics of individuals with "White/Caucasian" ancestry in combination with some Black ancestry (Censored) to those with other Black/White ancestry (Uncensored). These groups can only be fully compared for 2010-2013, as for 2009 and earlier, individuals who responded with Black/White ancestry using the "White/Caucasian" ancestry response had this response dropped and were classified as having Black only ancestry.

This change in ancestry coding greatly affects the counts of biracial Black/Whites and biracial Asian/Whites as coded by ancestry. Figures F.9 and F.10 shows Black/White and Asian/White ancestry over time. When I exclude responses of "White/Caucasian," I see a pattern that matches the 2000-2009 period where such responses were censored by the Census Bureau. I gain around an additional 270 thousand Asian/Whites in 2011, 2012, and 2013 and roughly 440 thousand Black/Whites in 2011, 2012, and 2013. 2010 is an anomaly, and the magnitude of increase here is significantly lower than in 2011, 2012, and 2013. This data and discussions with staff at the Census suggests there was a incomplete transition in coding for 2010 where some "White/Caucasian" ancestry responses were coded when used in combination with other ancestries and some were not.

Figure F.8 shows the 6 most common mixed black/white ancestry categories between 2000-2013. This clearly illustrates that the jump in individuals with black/white ancestry is largely driven by new coding of "White/Caucasian" in combination with "African-American." There is no reason to believe that this jump in responses is solely due to some behavioral change; the text of the ancestry question is identical from the 2000 Census to the 2013 ACS.

APPENDIX C

"Hidden" Mixed-Race Individuals

This project explores the potential endogeneity of racial classification among mixed-race individuals in the United States. If all multiracial Americans, by our definition, self-report as being multiracial Americans, there is no selection issue as all measures of being multiracial are the same. In such a case, using self-reported race measures for multiracial individuals is the same as using self-reported race measures for monoracial individuals and I can continue to treat race as exogenous to various labor market outcomes, as it has usually been treated in the labor economics literature. I provide evidence here that this in not the case, and that the set of individuals who self-identify or are identified on the Census and ACS as mixed-race are only a subset of the mixed-race population I wish to consider. For ease of notation, I refer to this mixed-race population that chooses not to self-identify or is not identified as such as the "hidden" mixed-race population. Again, I make no claims about how any individual should express their racial identity, only that these individuals do not adhere to the same rules I apply to construct the mixed-race population I wish to measure.

This "hidden" population is most easily seen with children, as surveys that involve children often also document the self-reported race of parents, and this allows researchers to see the difference between the reported race of children and their racial ancestry. Studies in this vein exploit parents' self-reported race since interracial couples have biological children who have multiracial ancestry and who can be identified in this way regardless of how these children are identified in surveys. Roth (2005) provides evidence from the 2000 Census that many mixed-race couples do not identify their children as mixed-race. Brunsma (2005) finds evidence from the Early Childhood Longitudinal Study that as socioeconomic status of parents increases, so does the likelihood of identifying children as mixed rather than monoracial for Asians, but the same is not true for biracial White/Blacks. Harris and Sim (2002) use data from Add Health which has measures of race for the same child in multiple contexts. The authors find that mixed race children identify as such consistently for White/Blacks and White/Asians. Their findings also suggest that children from single parent households are more likely to be multiracial than those from two parent households.

Using Census and ACS data, I find that there are still substantial amounts of "hidden" mixed-race children in recent years. I construct a sample of mixed-children from individuals, ages 18 and younger, in households with married parents from 2000 and 2008-2011, since I can separate out probable biological children from adopted and step-children for these years only[1]. This is not the full set of children that could identify as mixed-race as I can only identify children in two parent, married households. Figures F.1 and F.2 show results for probable biological children of interracial Black/White and Asian/White married couples for various years. The percent of biological children of interracial Black/White couples has increased from 49% to 62% in a little over a decade, but that around a quarter of these children are identified as monoracial Black; much fewer are identified as monoracial White. For biological children of interracial Asian/White couples, the percentage identified as mixed-race has increased from 50% to 69% over that same time period, but the White monoracial categorization is much more frequent than the Asian monoracial categorization. This makes it clear that interracial parents do not always declare children as mixed race, and this is a population that could clearly be identified as such. These results show how parents identify their children, but does this carry over to how adults identify themselves?

To provide evidence that there are indeed a significant number of "hidden" mixed-race adults in the Census, I compare Census data to birth data from the National Center for Health Statistics (NCHS), another source of data on the race of Americans. Legal authority for registering data on births is held by the 50 US states and 7 US territories (District

[1]The 2001-2007 ACS do not explicitly measure step-parent or adopted child status as these other years do

of Columbia, New York City, American Samoa, Guam, Northern Marianas, Puerto Rico, and the Virgin Islands). The NCHS is required by federal law to produce national vital statistics, such as those on birth records, and so compiles information that the states and territories provide (Division of Vital Statistics, 2000). To assist in ensuring uniformity of the data, the NCHS designs standard birth certificate forms with assistance and input from States. The NCHS even assists by creating templates of "model" regulations that states can choose to implement (Public Health Service, 1992). However, some studies reveal that there are issues with the validity and reliability of the data (Northam and Knapp, 2006) as they pertain to some health outcomes, which is somewhat unsurprising given that collection methods and training of staff to assemble the data may vary within a state, let alone between them (Northam et al., 2003). Fortunately for my purposes, a study on Californian mothers shows the data on race and ethnicity for mothers is 94-95% accurate for racial groups besides Native Americans (only 54% accurate) when comparing birth certificate data to later surveys (Baumeister et al., 2000).

The most recent revision to the standard birth certificate occurred in 2003. In keeping with the Office of Management and Budget's new requirements for collecting race data, this revision allows the race of child, mother, and father to be collected in the same way as in the 2000 census, with "check all that apply." In 2003, only 6 states adopted the form, and only as of 2015 have all states adopted it.[2]

As I am interested in calculating an estimates of adults, I do not require the most recent birth certificate data. I use data on US births compiled by the NCHS for births from 1970-2000. This data has at least a 50% sample of all births in the United States for this time period as well as data on the race of mothers and fathers. Since the birth data does not record Hispanic identity over the entire 1970-2000 time period, I must compare to the full Census sample including Hispanics for this analysis. With this data I construct an alternative count of mixed-race individuals by looking at births that occur to fathers and mothers of different races. I use the number of births in 1970 to predict the number of 30 year olds in 2000.[3]

This data may still under count the mixed-race population since I am unable to see

[2]Source: `http://www.cdc.gov/nchs/features/birth_certificate_goes_final.htm`, retrieved on 2/27/2015

[3]I adjust these population estimates with survival rates.

parents' potential mixed-ancestry. If a multiracial parent self-reports as monoracial on a birth certificate, I lose that person's other racial background.

The increasing prevalence of children out of wedlock over this time period leads to an increasing amount of missing race data on fathers, and previous research (Harris and Sim, 2002) suggests that children from single parent households are more likely to be mixed race. Therefore, this data can be thought of as a lower bound on the number of individuals of mixed-race. Comparing two of the most populous mixed-race pairings, Black/White and Asian/White, Census 2000 self-report of race is much lower than the number of mixed-race individuals estimated through birth data, see figure F.4.[4] For individuals of Black/White ancestry born in 1970, the ratio of those that declare Black/White race to the estimate of those who could is 47.2%. This stays consistent at 47.0% for those born in 1982. For individuals of Asian/White ancestry born in 1970, the ratio of those that declare Asian/White race to the estimate of those who could is high at 69.6%. This is lower at 65.0% for those born in 1982. For both of these groups Census race counts show many fewer self-reported mixed-race individuals than those that could declare as mixed-race, and the gap is sizable and relatively consistent for the birth years reported. Individuals born between 1970 and 1982 are aged 18 to 30 by the time of the 2000 Census, so this analysis covers the self-report of adults as well as parents' report of their childrens' race.[5]

To illustrate that this undercount is not merely an artifact of inconsistencies between Census population estimates and population estimates from birth certificate data, figure F.3 shows the comparisons for monoracial Whites, Asians, and Blacks respectively. With the exception of Blacks, there are only small difference between self-reported race counts from the Census and those predicted from vital statistics births, unlike the very large differences shown for some multi-racial groups. For monoracial Blacks, the underprediction of the Black population from birth data seems to be largely driven by the amount of missing information for the race of fathers on birth certificates of children with Black mothers. For children with Black mothers this percentage of missing race data for fathers increases from 26% to 37%

[4]The pattern is very similar when comparing self-reported race data from the ACS 2001-2009 for this same birth cohort of individuals born between 1970 and 2000.

[5]For individuals younger than 18, I recognize that their parents may be filling out the race response for them

from 1970 to 2000, compared to children with White or Asian mothers which increases from 4% to 10% over that same time period. When grouping children with Black mothers and missing fathers with children with both Black parents races reported, the birth data matches the Census population count more closely.[6]

[6]Adding missing father births for Whites and Asians does not significantly change the patterns in their respective graphs.

APPENDIX D

American Community Survey Design

The American Community Survey is particularly useful for summarizing demographic characteristics of Americans because of its sample size and success in achieving a high response rate. The survey is administered in monthly waves. A household will first be contacted by mail and asked to complete the survey. In the following month, if this household has not responded, the Census bureau will attempt to contact the household by phone. If appropriate, a census representative will administer the survey over the telephone, also known as computer-assisted telephone interviewing (CATI). In the third month, if the household cannot be contacted by phone or refuses to answer by phone, for a sample of these non-responsive households, a field agent will be dispatched to attempt a computer-assisted personal interview (CAPI). Throughout the entire 3 month period, the household may mail back the completed survey at any time. Public use data groups survey response types into mail and CATI/CAPI. Although we cannot verify this through publicly available data, Census documentation (Bureau of the Census (2009)) indicates that there is roughly a 1:4 ratio between CATI and CAPI.

APPENDIX E

Birth and Mortality Data

The birth data in 1970 was a 50% sample for all states. Beginning in 1972 some states were a full sample and by 1985 all states and Washington, D.C. were a full 100% sample for births. The earliest year that Hispanics can be identified for most of the population, 47 states and Washington, D.C. is 1989. For this reason, self-reported race for Census counts include Hispanics when compared to the birth data.

Arias et al. (2010) provide cohort survival data for individuals of Black and White race by gender. I used these to adjust birth counts down for a more accurate comparison to self-reported race numbers, matching individuals by race and gender. Black survival rates are lower than other races for males particularly. Black survival rates were assigned to those with a Black parent and White survival rates were assigned to all other races.

APPENDIX F

Additional Tables and Figures for "Mark one or more"

Table F.1: Self-Reported Race by Hispanic Status and Ancestry

	HISPANIC		ANCESTRY, NON-HISPANIC			
			Not White/Black/Asian		No Ancestry	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
	(1)	(2)	(3)	(4)	(5)	(6)
RACE						
White	417,593	62.27	1,026,440	90.78	1,047,912	89.91
Black	14,127	2.11	82,626	7.31	83,712	7.18
Native	10,462	1.56	4,752	0.42	5,339	0.46
Asian	4,974	0.74	6,085	0.54	6,453	0.55
Other	189,754	28.29	2,225	0.20	11,806	1.01
White/Black	2,392	0.36	1,732	0.15	1,873	0.16
White/Native	5,377	0.80	3,327	0.29	3,524	0.30
White/Asian	2,292	0.34	1,231	0.11	1,350	0.12
White/Other	15,072	2.25	343	0.03	1,124	0.10
Black/Native	512	0.08	521	0.05	552	0.05
Black/Asian	180	0.03	174	0.02	202	0.02
Black/Other	1,792	0.27	119	0.01	229	0.02
Asian/Native	219	0.03	51	0.00	72	0.01
Asian/Other	1,277	0.19	70	0.01	129	0.01
Other/Native	1,393	0.21	23	0.00	89	0.01
Three or More	3234	0.48	965	0.09	1204	0.1
Total	670,650	100	1,130,684	100	1,165,570	100

Source: Pooled 2001-2013 ACS

The samples consists of native-born adults, ages 25-54

Table F.2: Relative Risk Ratios of Race Compared to Black/White by Division of Birth and Residence, Adults Aged 25-54, 2001-2013 Sample

	Division of Birth				Division of Residence			
	Black		White		Black		White	
	RRR	SE	RRR	SE	RRR	SE	RRR	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Division (New England Excluded)								
Mid Atlantic	1.089	(0.175)	1.004	(0.286)	0.955	(0.197)	0.630**	(0.141)
East North Central	1.438**	(0.233)	0.935	(0.241)	1.331	(0.256)	0.627**	(0.137)
West North Central	1.117	(0.278)	1.221	(0.348)	1.037	(0.256)	0.854	(0.172)
South Atlantic	2.358***	(0.379)	2.060**	(0.736)	2.125***	(0.435)	1.273	(0.443)
East South Central	3.270***	(0.763)	1.604*	(0.457)	3.151***	(0.982)	1.498*	(0.327)
West South Central	4.683***	(1.148)	3.005***	(1.134)	3.302***	(1.017)	1.768	(0.642)
Mountain	0.849	(0.188)	1.478	(0.512)	1.082	(0.253)	1.101	(0.243)
Pacific	0.976	(0.172)	0.872	(0.233)	0.857	(0.176)	0.673**	(0.121)
Year Category (2001-2002 Excluded)								
2003-2004	1.039	(0.139)	0.821	(0.178)	1.044	(0.136)	0.829	(0.175)
2005-2006	0.953	(0.192)	0.704	(0.177)	0.958	(0.190)	0.707	(0.173)
2007-2008	0.661**	(0.123)	0.428***	(0.097)	0.655**	(0.124)	0.427***	(0.095)
2009-2010	0.513***	(0.085)	0.440***	(0.104)	0.516***	(0.084)	0.444***	(0.101)
2011, 2012, 2013	0.482***	(0.079)	0.394***	(0.089)	0.474***	(0.074)	0.391***	(0.085)
Age (35-44 Excluded)								
25-34	0.523***	(0.038)	0.653***	(0.067)	0.520***	(0.039)	0.658***	(0.065)
45-54	1.799***	(0.155)	2.020***	(0.199)	1.888***	(0.151)	2.089***	(0.202)
Education (Bachelor's Degree Excluded)								
No High School Degree	1.103	(0.198)	1.217	(0.197)	1.101	(0.203)	1.257	(0.200)
High School Degree	1.289***	(0.100)	0.951	(0.098)	1.303***	(0.102)	0.965	(0.097)
Master's Degree	0.990	(0.138)	0.716	(0.160)	1.009	(0.159)	0.730	(0.174)
Professional Degree	0.684**	(0.132)	1.103	(0.308)	0.695*	(0.134)	1.098	(0.318)
PhD	1.076	(0.232)	1.031	(0.367)	1.057	(0.228)	0.982	(0.365)
Employment Fraction	0.884*	(0.065)	1.041	(0.100)	0.868**	(0.059)	1.029	(0.102)
Female	1.073	(0.076)	1.017	(0.096)	1.061	(0.074)	1.015	(0.095)
Observations	11,599				11,599			
Pseudo R2	0.0699				0.0659			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level. Ancestry adjusted for 2010-2013.

Figure F.1: Racial Identification for Children of White/Black Married Couples

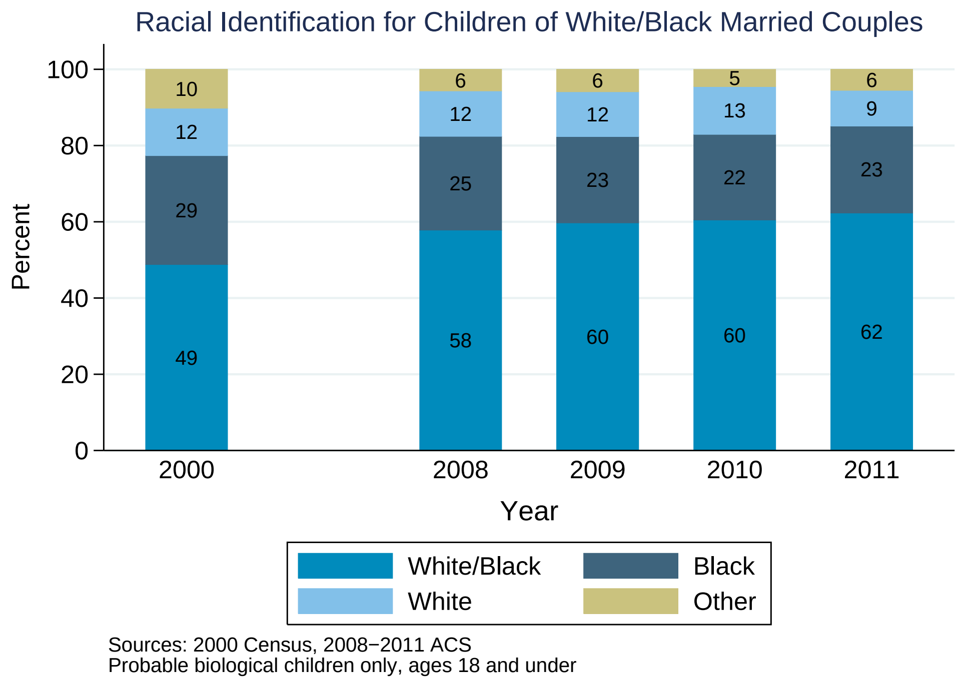


Figure F.2: Racial Identification for Children of White/Asian Married Couples

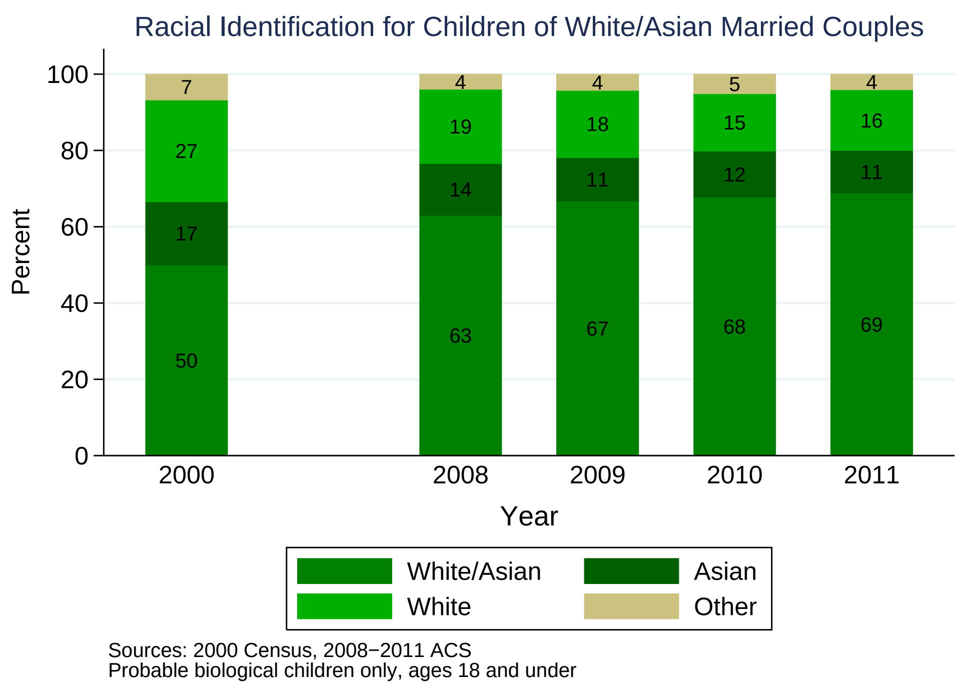


Figure F.3: Monoracial Birth and Population Comparison, 2000

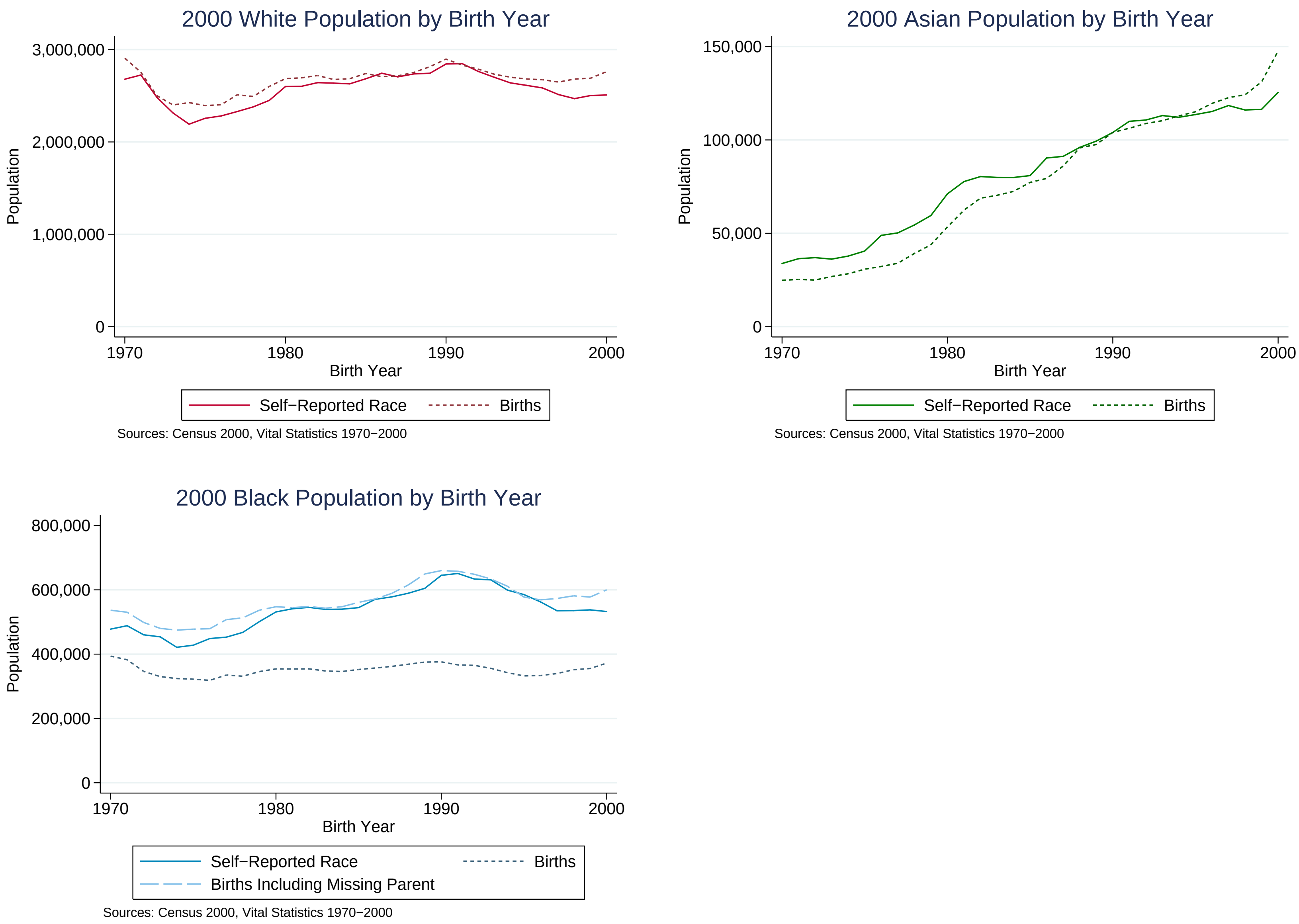


Figure F.4: Biracial Birth and Population Comparison, 2000

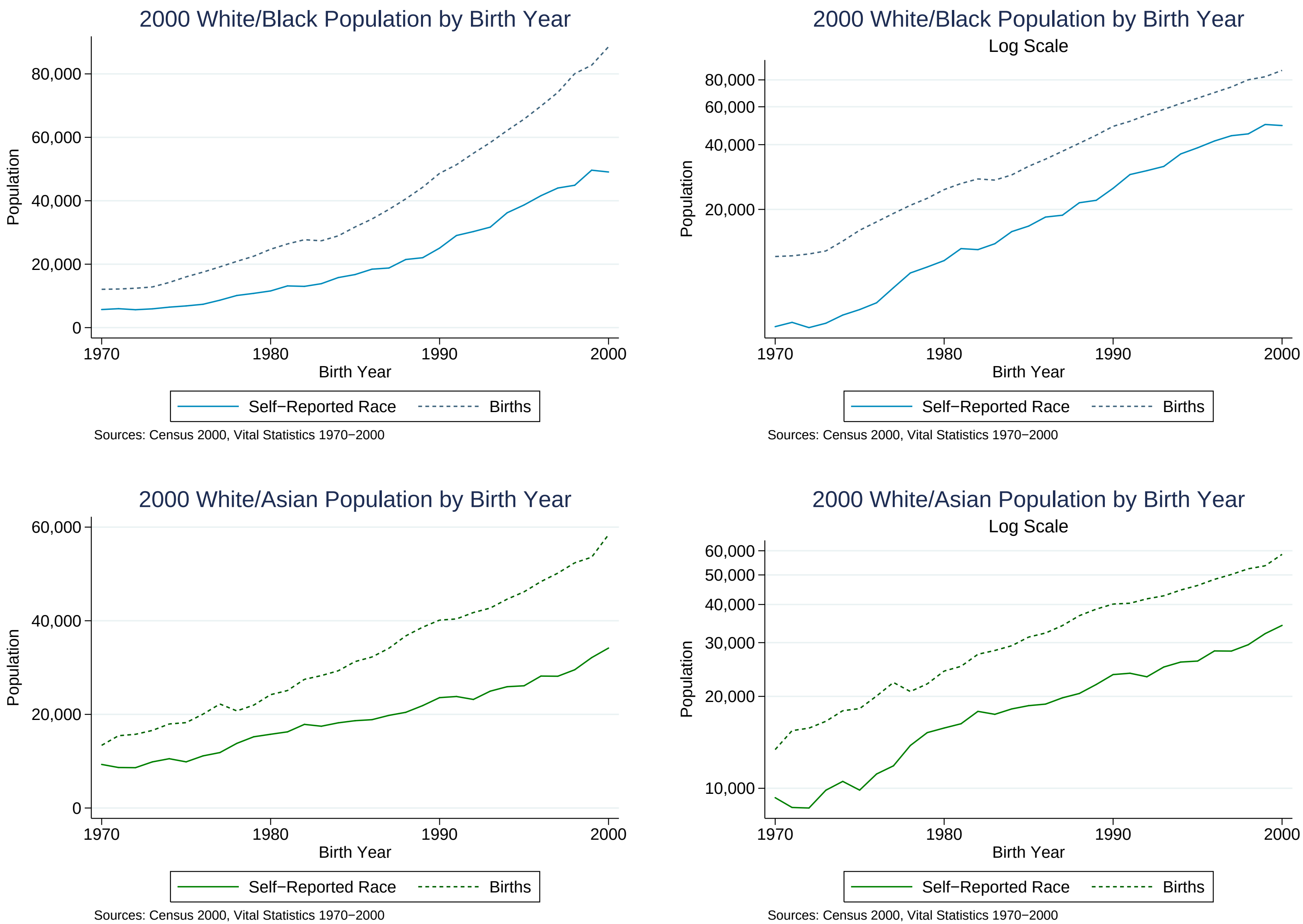


Figure F.5: Identity Choices for Example 1

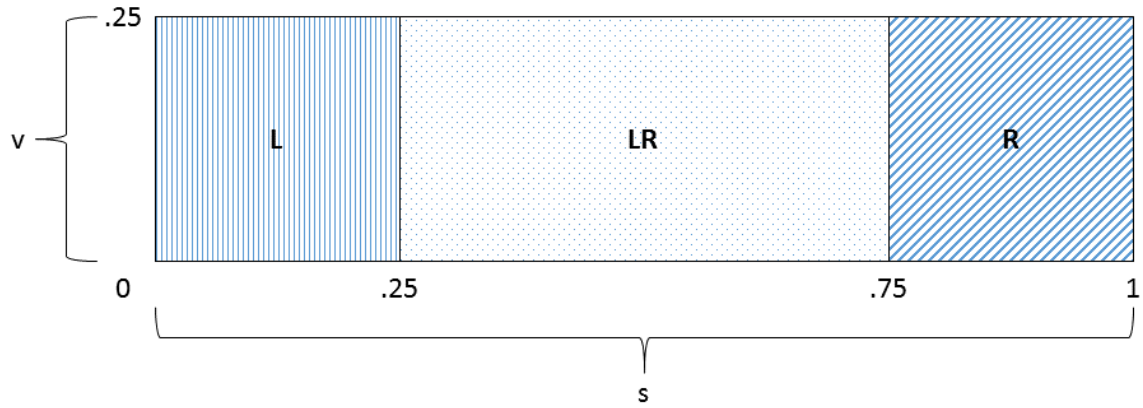


Figure F.6: Identity Choices for Example 2

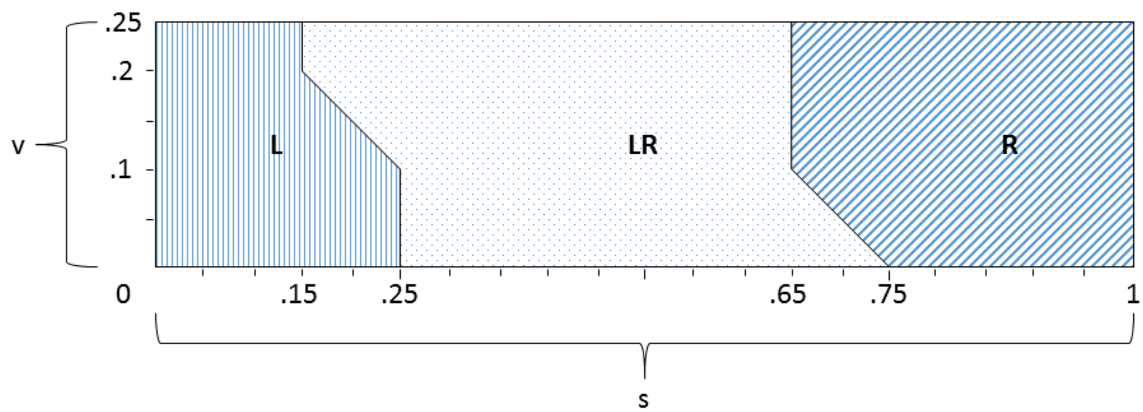


Figure F.7: Identity and Action Choices (c_j, a_j) with $C_L = C_{LR} = C_R = -.1$

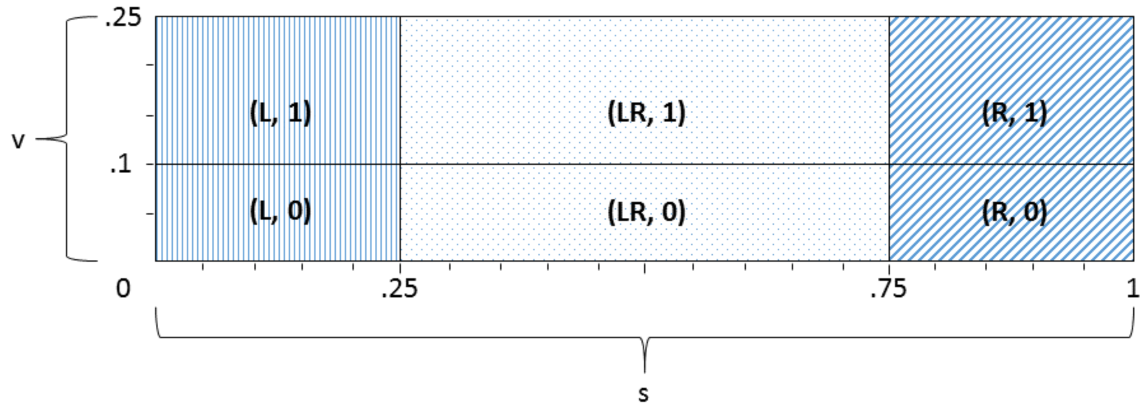


Figure F.8: Black/White Ancestry Categories

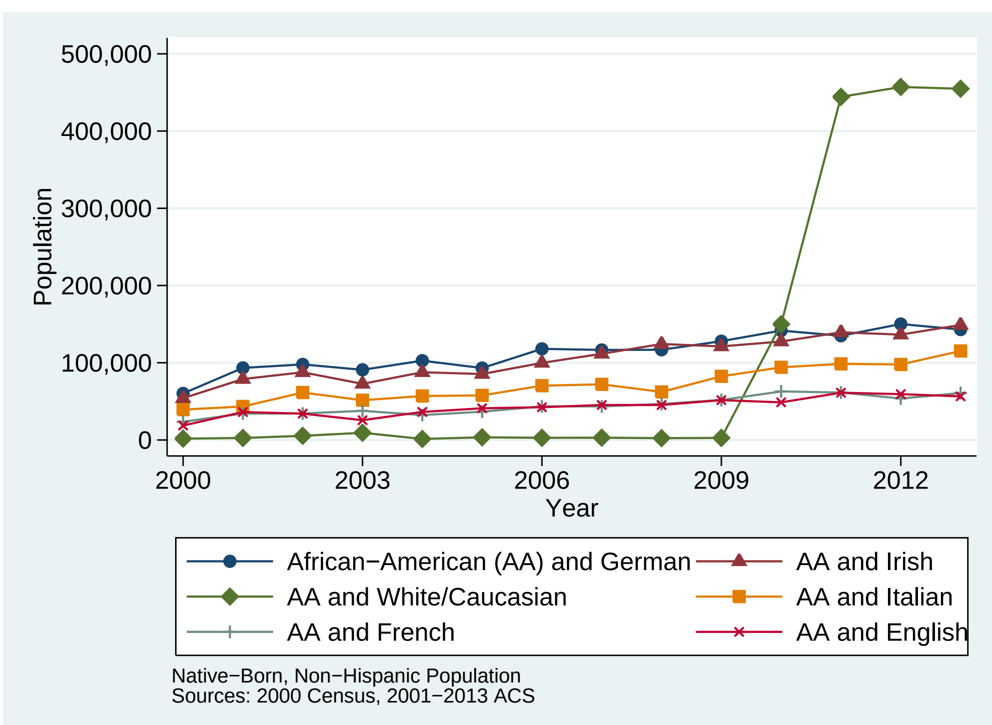


Figure F.9: Black/White Ancestry

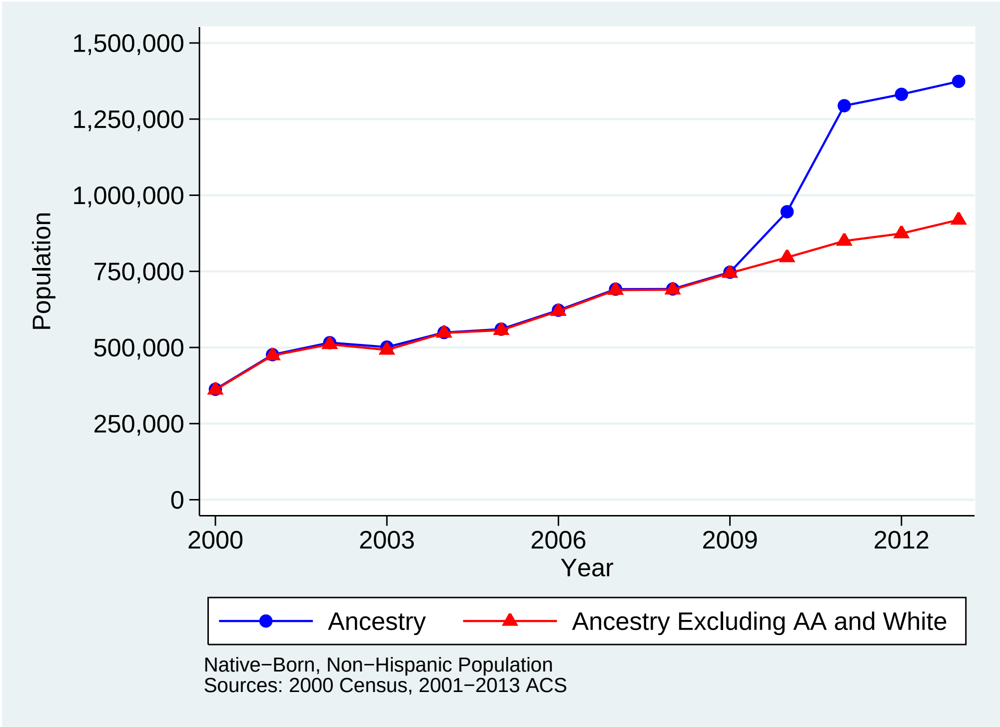
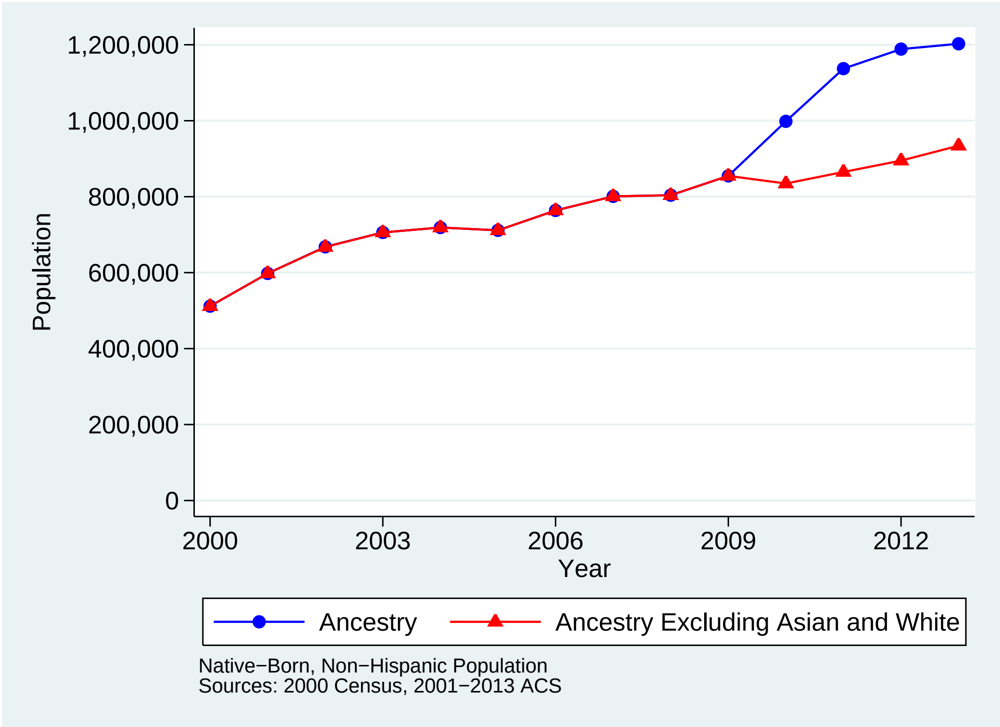


Figure F.10: Asian/White Ancestry



APPENDIX G

Alternative Specification

This alternative specification uses all 20 rounds of the trust game, but separates first half control from second half control by category, rather than with a variable (*secondhalf*) separating first half and second half behavior. In addition to majority/minority and new majority/new minority, we have two new categories: consistent majority/consistent minority. Individuals in the control in the second half of the experiment are referred to as consistent majority/consistent minority as these individuals have the same majority/minority identity in the first and second half of the experiment. Although we lose some power with this setup compared to our preferred specification, we still see many of the same patterns for White and non-White senders and receivers.

Regressions on senders using this alternative specification are shown in Appendix Table J.4. Column 1 shows the results for our full sample of senders. As with our preferred specification described in the main results, we find no consistent differences between our group-size categories. We see evidence of ingroup bias, but no categorical differences between majority/minority, new majority/new minority, or consistent majority/consistent minority sending.

Column 2 shows the results of our alternative specification after restricting to White senders. Here we see patterns that are almost the same as the patterns from our preferred specification. White minority senders in the first half exhibit higher ingroup ($p = 0.002$) and outgroup ($p = 0.021$) giving than their majority counterparts. White new majority senders still send more than new minority senders to ingroup matches ($p = 0.0307$) but not to outgroup matches ($p = 0.2520$). When we compare consistent minority senders with consistent majority senders we see that they weakly send more to ingroup matches ($p = 0.100$) and more to outgroup matches ($p = 0.034$). These results support both the White minority group effect as well as the persistence in behavior for White initial minority group members; whether these initial minority group members are put in treatment or control, they generally continue to send more than their initial majority group counterparts.

Results for non-White senders are displayed in column 3, and like in our preferred specification, we find no significant patterns among group-size categories.

We repeat the regression analysis with our alternative specification on receivers who start with 61-80 tokens in Appendix Table J.5. Column 1 and Column 3 show the full sample and non-White receivers respectively. Again, as with our preferred specification, we find no significant patterns among group-size categories in these cases.

However, using this alternative specification we still find similar results to our preferred specification with White receivers who start with 61-80 tokens. White minority receivers send more to ingroup members ($p = 0.016$) and weakly more to outgroup members ($p = 0.072$) than White majority receivers. White new majority senders send weakly more to ingroup matches ($p = 0.0831$) and more to outgroup matches ($p = 0.021$) than new minority senders. White consistent majority senders send more to outgroup matches ($p = 0.042$) but not to ingroup matches ($p = 0.123$) compared to consistent minority senders. Together the results for White senders and receivers in this alternative specification largely match with our preferred specification providing evidence that our particular choice of categorization is not driving our results.

APPENDIX H

Experimental Instructions

Welcome!

This is an experiment in decision making. Your earnings for the experiment will be in tokens, which will be converted to money. The number of tokens you earn will depend on the decisions you make and on the decisions other people make. **Every 50 tokens you earn is worth $1 to you.** At the end of the experiment, you will be paid your earnings plus a $5 show-up fee in cash. Everyone will be paid in private and you are under no obligation to tell others how much you earn.

Please do not communicate with each other during the experiment unless you are asked to do so. We have provided you with a blank sheet of paper on your desk. If you need to write anything, please do so only on this blank sheet of paper. Please do not use any calculators or cell phones during the experiment. Also, if your computer screen asks you to wait for the experiment to continue, please do not do anything else while you are waiting. If you have a question, feel free to raise your hand, and an experimenter will assist you.

On your payment form, please write your computer number (upper left-hand corner of your station) in the space labeled "Study Subject ID."

Once we finish these instructions, you will be randomly assigned to either the Green team or the Red team. These teams will always be unequally sized. You will make two types of decisions during the experiment:

<u>Decision 1 - Photo Task</u>

For the photo task, you will work with your team members to identify locations displayed in a series of photos. Everyone will be shown six pictures, three from each of two locations. Each picture will be labeled with a letter and a number, such as picture "A1." All photos with the same letter are from the same location. You will be asked to identify which photos come from which location.

For example, you could be given pictures "A1", "A2", "A3", "B1", "B2" and "B3." You would also be told that the two locations are "Europe" and "Asia." Then, there are two possibilities. The first is that "A1", "A2" and "A3" all show European locations, and "B1", "B2" and "B3" all show Asian locations. The second is that "B1", "B2" and "B3" all show European locations, and "A1", "A2" and "A3" all show Asian locations. You would then be asked to identify which of these two possibilities is correct.

During this task, you will be able to work with the other members of your team using a chat box that will be on the screen. Messages that are entered there will be shared with the other members of your team and not with the people in the other team. Similarly, the members of the other team will be able to share messages with each other that you will not be able to see. You may enter any messages in the chat box except for the following restrictions:

1. Please do not identify yourself or send any information that could be used to identify you (e.g. age, race, professional background, etc.).
2. Please refrain from using obscene or offensive language.
3. Please do not discuss the other task.

If your messages violate any of these restrictions, your total earnings for the experiment will be reduced by $5. You will have 5 minutes to submit your answer. In those 5 minutes, you will be able to change your answer as many times as you like. You will earn 75 tokens if you answer the question correctly. We will reveal the correct answer to you at the end of the experiment.

Decision 2 - Passing Task

For the passing task, you will either be a Sender or a Receiver. Once you are randomly assigned to one of these roles, you will remain in that role for the rest of the experiment. Your role will be revealed to you when you make your first decision for the task.

The Sender will be given 20 tokens and choose how many of these tokens to pass to the Receiver. Before reaching the Receiver, the number of tokens passed will be multiplied by 4, so the Receiver will start with 4 times the number of tokens passed. The Receiver then chooses how many of these tokens to pass back to the Sender. Each persons earnings will be the number of tokens they have after this procedure.

For example, suppose that the Sender passes 13 of his or her 20 tokens to the Receiver. The Receiver then starts with 13*4 = 52 tokens. Now suppose that the Receiver passes 15 of his or her 52 tokens back to the Sender. Then the Sender earns 7 + 15 = 22 tokens and the Receiver earns 52 15 = 37 tokens.

Note that either the Sender or Receiver may choose to pass no tokens to the other person. If the Sender chooses to pass no tokens to the Receiver, then the Receiver does not make a choice.

You will be able to test your choice with an on-screen calculator before you submit it. Once you submit your answer, you will not be able to change it.

Procedure

The experiment will proceed in two halves. For each half, you will make the photo task decision once with your team and then make the passing task decision 10 times. Each time you make the passing task decision, you will be randomly rematched with a person in this room. Since the teams will always have unequal size, you are more likely to be matched a member of the larger team.

For each half, some of you will be asked to leave the computer lab and return to the waiting room. These people are chosen at random. If you are one of these people, you will not be making decisions for that half of the experiment. Instead of earning tokens from making decisions for that half, you will be paid the average amount earned by the participants in that half of the experiment.

Are there any questions? If not, please click the button to begin the experiment.

APPENDIX I

Post-Experiment Survey

Please answer the following survey questions. Your answer will be used for this study only. Individual data will not be released. (*summary statistics in italics*)

1. What is your age? (*Mean 22.03, Std Dev 4.72, Median 21, Min 18, Max 60*)

2. What is your gender? (*Female 61.46%, Male 38.54%*)

3. Are you an undergraduate or a graduate student? (*Undergraduate 71.53%, Graduate 20.14%, Neither 8.33%*)

4. Which year of your current educational program did you complete in April/May of 2013? (1^{st} *year 18.40%,* 2^{nd} *year 24.65%,* 3^{rd} *year 25.69%,* 4^{th} *year 12.85%, Higher year 7.29%, N/A 11.11%*)

5. Which of the following best describes your racial or ethnic background? (*Asian/Pacific Islander 44.44%, Black 4.51%, Hispanic/Latino 2.43%, Native American 0.69%, White 43.06%, Other 4.86%*)

6. What is your marital status? (*Never Married 95.14%, Currently Married 4.86%, Previously Married 0.00%*)

7. How many siblings do you have? (*Mean 1.44, Std Dev 1.14, Median 1, Min 0, Max 6*)

8. How would you best describe your employment status? (*Employed, Full Time 6.60%; Employed, Part Time 41.32%; Not Employed 52.08%*)

9. Who in your household is primarily responsible for expenses and budget decisions? (*Self 30.21%, Spouse 1.04%, Shared Responsibility with spouse 3.47%, Parent(s) 63.19%, Other 2.08%*)

10. Have you ever voted in a government election (in any country)? (*Yes 68.75%, No 31.25%*)

11. Before today, how many times have you participated in any economics or psychology experimental studies? (*Mean 9.71, Std Dev 53.28, Median 5, Min 0, Max 900*)

12. In the past twelve months, have you donated money to or done volunteer work for charities or other nonprofit organizations? (*Yes 75.35%, No 24.65%*)

13. On a scale from 1 to 10, please rate how closely attached you felt to your team throughout the experiment, with 1 meaning "not closely at all". (*Mean 3.67, Std Dev 2.36, Median 3, Min 1, Max 10*)

APPENDIX J

Additional Tables and Figures for “Intergroup relations”

Table J.1: % Tokens Passed, 20-Period Receivers with 1 to 20 Tokens

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.042		
	(0.027)		
Female	-0.007	-0.007	0.003
	(0.025)	(0.041)	(0.032)
Second Half	0.027	0.078	-0.064**
	(0.048)	(0.051)	(0.028)
Majority Outgroup	0.105	0.141	0.061
	(0.069)	(0.104)	(0.050)
Minority Ingroup	-0.041	-0.013	-0.078***
	(0.027)	(0.051)	(0.027)
Minority Outgroup	0.018	0.072	-0.026
	(0.045)	(0.081)	(0.027)
New Majority Ingroup	-0.060*	-0.064	-0.015
	(0.035)	(0.050)	(0.016)
New Majority Outgroup	-0.060	-0.074	0.014
	(0.042)	(0.065)	(0.052)
New Minority Ingroup	-0.094**	-0.132***	-0.031
	(0.038)	(0.036)	(0.025)
New Minority Outgroup	0.012	-0.004	0.076**
	(0.051)	(0.102)	(0.033)
Constant	0.098***	0.053	0.087*
	(0.032)	(0.041)	(0.045)
Observations	211	115	96
R-squared	0.0923	0.1024	0.1248

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the session level. non-White race includes Asian, Black, Hispanic, and Native American.

Table J.2: % Tokens Passed, 20-Period Receivers with 21 to 40 Tokens

	(1)	(2)	(3)
	All	White	Non-White
Non-White	0.000		
	(0.032)		
Female	-0.049	-0.026	-0.057
	(0.045)	(0.068)	(0.042)
Second Half	0.002	0.006	0.002
	(0.020)	(0.028)	(0.040)
Majority Outgroup	-0.074	-0.053	-0.107*
	(0.062)	(0.091)	(0.056)
Minority Ingroup	0.016	0.099**	-0.081
	(0.056)	(0.048)	(0.072)
Minority Outgroup	-0.049	0.058	-0.159**
	(0.044)	(0.057)	(0.077)
New Majority Ingroup	-0.029	0.020	-0.105
	(0.046)	(0.065)	(0.074)
New Majority Outgroup	-0.016	0.142**	-0.173*
	(0.055)	(0.056)	(0.092)
New Minority Ingroup	-0.053	-	-0.074
	(0.081)	-	(0.085)
New Minority Outgroup	-0.064	-0.067	-0.101
	(0.082)	(0.060)	(0.097)
Constant	0.256***	0.187***	0.319***
	(0.056)	(0.068)	(0.067)
Observations	216	111	105
R-squared	0.0635	0.1322	0.1596

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. - indicates no observations in this category. Standard errors clustered at the session level. non-White race includes Asian, Black, Hispanic, and Native American.

Table J.3: % Tokens Passed, 20-Period Receivers with 41 to 60 Tokens

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.003		
	(0.039)		
Female	-0.017	0.032	-0.065
	(0.071)	(0.075)	(0.090)
Second Half	-0.030	-0.063	0.012
	(0.019)	(0.047)	(0.024)
Majority Outgroup	-0.056***	-	-0.070***
	(0.007)	-	(0.011)
Minority Ingroup	0.059	0.157**	-0.037
	(0.053)	(0.062)	(0.080)
Minority Outgroup	0.042	0.161**	-0.093
	(0.048)	(0.068)	(0.060)
New Majority Ingroup	0.047	0.092	-0.034
	(0.059)	(0.075)	(0.080)
New Majority Outgroup	-0.007	0.341***	-0.165*
	(0.063)	(0.086)	(0.096)
New Minority Ingroup	0.120***	-	0.066***
	(0.023)	-	(0.024)
New Minority Outgroup	0.031	-	-0.031
	(0.042)	-	(0.032)
Constant	0.295***	0.222***	0.369***
	(0.070)	(0.078)	(0.072)
Observations	118	53	65
R-squared	0.0163	0.1107	0.1167

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. - indicates no observations in this category. Standard errors clustered at the session level. non-White race includes Asian, Black, Hispanic, and Native American.

Table J.4: Alternate Specification: % Tokens Passed, 20-Period Senders

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.273***		
	(0.084)		
Female	-0.093	0.045	-0.064
	(0.071)	(0.112)	(0.092)
Majority Outgroup	-0.115***	-0.081*	-0.145***
	(0.035)	(0.044)	(0.053)
Minority Ingroup	0.056	0.373***	-0.095
	(0.072)	(0.118)	(0.107)
Minority Outgroup	-0.076	0.182	-0.194*
	(0.077)	(0.119)	(0.104)
New Majority Ingroup	-0.013	0.346***	-0.197*
	(0.071)	(0.130)	(0.107)
New Majority Outgroup	-0.159	0.099	-0.278**
	(0.103)	(0.174)	(0.112)
New Minority Ingroup	-0.017	0.075**	-0.067
	(0.064)	(0.032)	(0.083)
New Minority Outgroup	-0.098*	-0.142	-0.082
	(0.059)	(0.125)	(0.055)
Control Majority Ingroup	0.043	0.009	0.095
	(0.053)	(0.068)	(0.087)
Control Majority Outgroup	-0.156**	-0.089	-0.226**
	(0.060)	(0.073)	(0.103)
Control Minority Ingroup	0.085	0.335**	-0.035
	(0.123)	(0.158)	(0.161)
Control Minority Outgroup	-0.162*	0.239	-0.339***
	(0.084)	(0.194)	(0.094)
Constant	0.712***	0.499***	0.500***
	(0.078)	(0.132)	(0.098)
Observations	1440	560	880
R-squared	0.1514	0.1540	0.0940

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors clustered at the session level. Non-White race includes Asian, Black, Hispanic, and Native American.

Table J.5: Alternate Specification: % Tokens Passed, 20-Period Receivers with 61 to 80 Tokens

	(1)	(2)	(3)
	All	White	Non-White
Non-White	-0.050		
	(0.044)		
Female	-0.010	-0.047	0.022
	(0.051)	(0.058)	(0.066)
Majority Outgroup	-0.024	0.020	-0.051
	(0.035)	(0.046)	(0.042)
Minority Ingroup	0.014	0.147**	-0.102
	(0.049)	(0.061)	(0.081)
Minority Outgroup	0.018	0.158**	-0.102*
	(0.047)	(0.070)	(0.057)
New Majority Ingroup	-(0.007)	(0.078)	-(0.090)
	(0.046)	(0.073)	(0.076)
New Majority Outgroup	(0.001)	(0.115)	-(0.114)
	(0.066)	(0.088)	(0.085)
New Minority Ingroup	(0.005)	-0.064**	(0.059)
	(0.044)	(0.032)	(0.046)
New Minority Outgroup	-(0.015)	-(0.032)	-(0.011)
	(0.026)	(0.054)	(0.039)
Control Majority Ingroup	-0.016	-0.002	-0.025
	(0.012)	(0.016)	(0.016)
Control Majority Outgroup	-0.048	-0.039	-0.039
	(0.034)	(0.027)	(0.055)
Control Minority Ingroup	-0.004	0.130	-0.115*
	(0.053)	(0.082)	(0.066)
Control Minority Outgroup	-0.028	0.103	-0.135*
	(0.052)	(0.065)	(0.070)
Constant	0.350***	0.296***	0.332***
	(0.048)	(0.070)	(0.051)
Observations	438	212	226
R-squared	0.0269	0.1090	0.0632

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the session level. non-White race includes Asian, Black, Hispanic, and Native American.

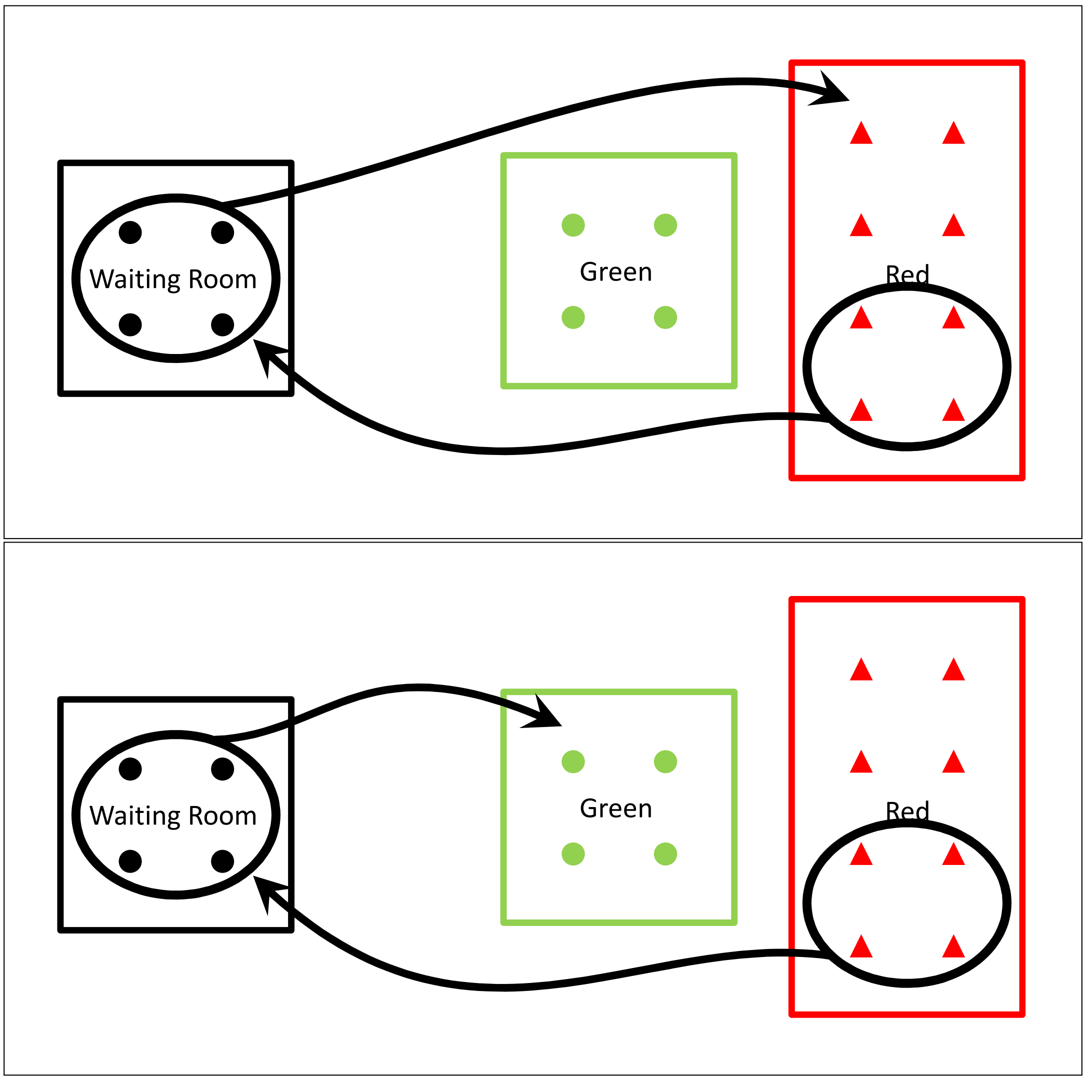


Figure J.1: Subject movement at start of second half of experiment for the No Change (top) and the Change (bottom) treatments.

APPENDIX K

Wage, Housing-Cost, and Commuting-Cost Data and Estimation

United States Census data from the 2000 Integrated Public-Use Microdata Series (IPUMS), from Ruggles et al. (2004), are used to calculate wage, rent, and commuting-time differentials.

Reported differentials are calculated using the logarithm of reported gross rents and imputed rents from housing values. We use occupied units that are not farms or group quarters. The rent differentials are calculated using a set of PUMA indicators and the following set of co-variates

- 9 indicators of building size;
- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, number of rooms interacted with number of bedrooms, and the number of household members per room;
- 2 indicators for lot size;
- 7 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- an indicator for commercial use;

- an indicator for condominium status (owned units only).

We run our regression with household weights. Housing cost rent and quality measures from Table 1 are repeated in Appendix Table P.1 in columns 1 and 2, while column 3 adds the two together to determine a "raw" index, similar to what would be available in an index available from aggregated data. Columns 4 and 5 describe the variation from indices using only or only imputed rents from housing prices or actual rented units: the two appear fairly similar. Column 6 describes an index that weighs housing units by their observable quality.[1] Column 7 reports time spent in dwelling, showing slightly higher numbers in non-metro and low density areas. Columns 8 and 9 show how buildings in central and denser areas tend to be older and have fewer rooms.

The wage differentials are calculated for workers ages 25 to 55, who report working at least 30 hours a week, 26 weeks a year. The wage differentials are found by regressing log hourly wages on individual covariates and indicators for which PWPUMA a worker works in, using the coefficients on these indicators. The covariates consist of

- 12 indicators of educational attainment;
- a quartic in potential experience, and potential experience interacted with years of education;
- 9 indicators of industry at the one-digit level (1950 classification);
- 9 indicators of occupation at the one-digit level (1950 classification);
- 4 indicators of marital status (married, divorced, widowed, separated);
- an indicator for veteran status, and veteran status interacted with age;
- 5 indicators of minority status (Black, Hispanic, Asian, Native American, and other);

[1] We calculate a value-adjusted weight by multiplying the census-housing weights by the predicted value from this first regression using housing characteristics alone, controlling for PUMA. A second regression is run using these new weights for all units, rented and owner-occupied, on the housing characteristics fully interacted with tenure, along with the PUMA indicators, which are not interacted. The house-price differentials are taken from the PUMA indicator variables in this second regression. As with the wage differentials, this adjusted weighting method has only a small impact on the measured price differentials.

- an indicator of immigrant status, years since immigration, and immigrant status interacted with black, Hispanic, Asian, and other;
- 2 indicators for English proficiency (none or poor).

All covariates are interacted with gender.

We run our regression with census-person weights. In columns 1 through 3, Appendix Table P.2 repeats the three wage measures from Table 1. Column 4 reports the difference between the workplace and residential measures, showing them be negative in central cities and in non-metro areas and positive in the suburbs, suggesting selection according to unobserved skills in the same direction. Column 5 describes raw variation in wages, not controlling for skills. Raw wages are higher in the more skilled suburbs, even though the wage effects are the same. Column 6 reports the variation that would occur if PWPUMAs are used instead of regular PUMAs: this accounts for roughly half of the variance between the workplace and residential measures. Column 7 reveals that almost half of commuters work in a PWPUMA outside the one they reside in; this is especially true if they live in the suburbs. Column 8 measures the wage index weighting workers by the wage predicted by their non-location characteristics, producing nearly identical results.[2] Column 9 corrects for inter-state migration using the methods outlined in Dahl (2002), which changes the numbers only slightly.[3]

We calculate commuting-time differentials in a similar manner. The sample restriction is the same as that used for the wage differential calculation, except that those with missing commute time are dropped from the sample. The individual covariates for the commute time regression are the same as those used for wages, except that they include four variables

[2] We weight using the single-index of "skill" that a worker has. From the regressions, a predicted wage is calculated using individual characteristics alone, controlling for PWPUMA, to form a new weight equal to the predicted wage times the census-person weight. These new income-adjusted weights are used so workers can be weighted by their income share. The new weights are then used in a second regression, which is used to calculate the PUMA wage differentials from the PWPUMA indicator variables.

[3] To correct for selection effects on our wage estimates due to inter-state migration we control for the probability of moving from the state of birth to the current state, as well as the probability of staying in the state of birth, by category according to various demographic characteristics. We use the exact same categories as Dahl for movers (20 for each state) and stayers (70). We also add a separate mover category/"birth-state" for those born outside the US. As Dahl only used male, white, and ages 25-34, we create 12 times the number of original categories to account for female, non-white, and age categories 35-44, and 45-55. To identify the constants across states, we constrain the coefficients to be the same across states, unlike in Dahl. Accounting for selection through inter-state migration had only tiny effects on our wage estimates.

for the presence and number of children, total and under 6. We calculate PUMA commute-time differentials from the coefficients of the PUMA indicator variables, using the proper transformation for square roots to get the analog of df/f.

Commuting mode proportions are estimated for all PUMAs using a linear probability model with US Census Data. Mode of transportation to work is split into four broad categories; travel to work by own automobile, carpool, public transportation, and a no-cost method. The public transportation category includes bus, streetcar, rail, subway, and ferry. The no-cost methods are working from home, walking, biking, and other. Binary variables for these four categories are separately regressed on 2071 PUMA dummies and the same set of variables used for commute times.

The resulting estimated probabilities fall between 0 and 1 except for a small number of PUMAs all in Texas, which have tiny negative numbers. We decided against making any adjustments to negative numbers as they were tiny and had negligible effects on the estimates.

Table A4 reports various measures of commuting and associated statistics. Column 1 reports the full cost of commuting. The cost is highest in the densest areas and higher in the suburbs compared to central city and non-metro areas. Column 2 shows the same pattern in time costs. Furthermore, column 3 shows there is little variation in commuting time across areas predicted by the workforce composition, making the raw differential in column 4 not much different than that in column 2. When the full cost of commuting is broken down, we see that material costs, in column 6, tend to be higher in the suburbs. This partly reflects the higher proportion that drive relative to those who use transit, seen in columns 7 and 8. Variations in those driving and using transit are due more to variation across metros than within them. This reinforces ideas of certain cities being more car friendly than others.

APPENDIX L

Amenity Data

Heating and cooling degree days are measurements used to estimate amounts of energy required to maintain comfortable indoor temperature levels. Daily values are computed from each day's mean temperature ($\frac{max+min}{2}$). Daily heating degree day values are equal to $\max\{0, 65 - meantemp\}$ and daily cooling degree day values are $\max\{0, meantemp - 65\}$. Annual degree days are the sum of daily degree day values over the year. The data here refer to averages from 1970 to 2000 (National Climactic Data Center 2008).

Sunshine is measured as average percentage of possible. This data set contains information on sunshine as percent of possible sunshine received, by month, for 156 stations in the contiguous United States. The total time that sunshine reaches the surface of the earth is expressed as the percentage of the maximum amount possible from sunrise to sunset with clear sky conditions. (National Climactic Data Center 2008)

Inverse Distance to Coast is equal to one over the distance in miles from the population-weighted centroid of the PUMA to the nearest coastline of an Ocean or Great Lake. Coded by author.

Average Slope of Land measures the average slope of the land according to census tract data. We used high-resolution elevation data from the Global 30 Arc Second Elevation

Data (GTOPO30) digital elevation model (DEM) available from the United States Geological Survey. These data are set on a high resolution grid of roughly 11 kilometers. We mapped the girded elevation data to our PUMA geography averaging the value of all grid points falling within the boundary of each geography. The slope is computed using the average maximum technique, where the slope at each grid point is the maximum rate of change of elevation from that grid point to its eight neighbors. Due to the high resolution of the data, all geographic units had at least one grid falling inside its boundary. (United States Geological Survey)

Murder Rate is the average number of murders per 1,000 inhabitants. It is reported at the county level. (FBI 2000 Uniform Crime Reports)

Bars and restaurants data are the number of establishments classified as eating and drinking places, NAICS 722. (County Business Patterns 2000).

School Revenues per Student data is at the county level and applies to public schools. (2000 Common Core)

Table 5 reports how these amenities are distributed by area type and density classifications. Panel A shows that central city areas are closer to the coast, have higher murder rates, and more restaurants and bars. Suburban areas have higher public school revenues per student. Panel B splits the US by population density and shows that denser areas have higher school revenues per student, higher murder rates, a greater frequency of restaurants and bars, and are located closest to the coasts. Panel C compares how different amenities vary across and within metropolitan area. Unsurprisingly, because climate is strongly correlated spatially, natural climate related amenities vary more across metros than within. The higher variation within than across metropolitan areas in restaurants and bars reflects a number of splits, including that between residential and commercial areas. Similar variation pattern in the murder rate suggests that there are unsafe areas in many metro areas, rather than being wholly safe and unsafe metros.

APPENDIX M

Additional Tax Details

Tax Advantages for Housing and Local Taxes

We model tax advantages for owner-occupied housing by allowing households to deduct a fraction $\delta \in [0,1]$ of home-good expenditures, py, from their federal income taxes, so that taxes paid are $\tau\left(m^j - \delta p^j y\right)$. δ should be less than 1 as these advantages do not apply to certain taxes (e.g. payroll) or to certain home goods, such as haircuts or restaurant meals. Nor are these advantages available to all workers: many renters and home-owners do not itemize deductions for mortgage interest or local taxes. Ignoring for now commuting and leisure, incorporating the home-good deduction into the income tax, $\tau\left(m - \delta py\right)$, changes the expenditure function to $e(p, u, \tau(m-\delta py); Q) \equiv \min_{x,y}\{x+py+\tau(m-\delta py) : U\left(x, y; Q\right) \geq u\}$. Differentiating the mobility condition and using the envelope theorem yields the log-linearized mobility condition

$$\hat{Q}^j = \left(1 - \delta\tau'\right) s_y \hat{p}^j - \left(1 - \tau'\right) s_w \hat{w}^j \tag{M.1}$$

which replaces (3.5). As calibrated in Albouy (2008), this reduces the weight on $\hat{p}^j$ from 0.36 to 0.33.

Including State Tax Differences

Differences in within-state tax burdens are worth considering as wages and prices can often vary significantly within a state, while state services largely do not. We compute state-tax differentials by multiplying state tax and deduction rates by the wage and price differentials within state

$$d\tau_S^j/m = \tau_S'[s_w(\hat{w}^j - \hat{w}^S) - \delta_S s_y(\hat{p}^j - \hat{p}^S)] \tag{M.2}$$

where τ_S' and δ_S are are marginal tax and deduction rates at the state-level, net of federal deductions, and $\hat{w}^S$ and $\hat{p}^S$ are the differentials for state S as a whole relative to the entire country. These state tax rates incorporate sales as well as income taxes, since sales taxes reduce the buying power of labor income. This tax differential is added to (M.1) above to determine local quality of life.

APPENDIX N

Note on Geography

The 5-percent Public Use Microdata Sample (PUMS) from the 2000 Census contains detail for geographic areas known as Public Use Microdata Areas(PUMAs). These PUMAs are required to contain a minimum population of 100,000 and not cross state boundaries. Any collection of counties, census tracts, minor civil divisions (MCDs) can be defined as a PUMA as well as large incorporated places with a minimum population of at least 100,000.

Place of Work Public Use Microdata Areas (POWPUMAs or PWPUMAs) were created to publish information about work location. These areas use the 5-percent PUMAs as building blocks and contain one or more whole PUMAs. Published information from the Census Bureau claiming that PWPUMAs must include entire counties, outside the New England States, is incorrect. [1] Examples include Washtenaw county in Michigan that contains two place-of-work PUMAs: 03200 containing Ann Arbor and 03300 mapping surrounding areas and Hamilton county in Ohio that contains two place of work PUMAs, 04500 containing Cincinatti, and 4400 the surrounding areas.

In application, many densely populated urban areas are split into multiple PUMAs as the minimum population restriction of 100,000 allows, but may be encompassed by only one or two populous PWPUMAs. For example, NY PWPUMA 03800 encompasses New York

[1] Phone and email correspondence with the Geographic Standards & Criteria Branch of the U.S. Census Bureau verified that this PWPUMAs definition, that PWPUMAs are constructed to encompass whole counties, is present in several of their publications and is incorrect.

county, Manhattan, but is made up of 10 different PUMAs 03801-03810. Cincinatti is one PWPUMA 04500, while the same area is split into three PUMAs 04501-04503.

APPENDIX O

Rankings in Popular Media

"Livability" rankings are common in popular media. These rankings are typically presented as references to assist people making decisions about where to live or buy real estate. The comparisons are usually performed at a sub-metropolitan level acknowledging the variation in amenities and prices within cities. Streetadvisor.com[1] relies on crowdsourced reviews written by users for streets, neighborhoods, and cities. Areavibes.com[2] and Silver (2010) apply weighting algorithms to various observable amenities; Silver focuses solely on neighborhoods around New York City.

Somewhat surprisingly, rankings from these various methods sometimes match rankings the approach used here. Streetadvisor ranks Carnegie Hill and Roosevelt Island as the two best neighborhoods in New York City. These two neighborhoods are located in NY PUMA 03805, the Upper East Side, which is the 6th highest rated PUMA in the country in our rankings. Areavibes has Springfield MA, Hartford CT, Detroit MI, and Flint MI as the worst cities to live in; each of the PUMAs that contain these areas are in the bottom 10 percent of our rankings, with the PUMA containing Southwest Detroit being our lowest rated PUMA overall. Silver's (2010) ranking are more difficult to compare to ours as he defines neighborhoods at a much finer level of detail than our PUMA analysis will allow.

[1] "Best cities in New York City," `http://www.streetadvisor.com/search/cities-in-new-york-city-new-york`, retrieved 2/2/14.

[2] "Top 10 Cities - Best Place To Live 2013," `http://www.areavibes.com/library/top-10-best-cities-to-live-2013/`, retrieved 2/2/14.

In his write-up, Silver does point out the difficulty of constructing a ranking with weights on observable amenities; he admits that his rankings are quite sensitive to the weights he chooses. With the crowdsourced reviews on Streetadvisor, the concern is not the weighting but selection, as it is unclear what population decides to take the time to write reviews of neighborhoods. While we are satisfied that our PUMA rankings align with some popular measures, we are partial to our methodology which avoids these issues.

APPENDIX P

Additional Tables for "Driving to opportunity"

Table P.1: Rent/Housing cost differentials across the U.S.: Alternative measures and related statistics, 2000

	Rental Cost Index (1)	Housing Compo-sition "Quality" (2)	Raw Rent Differential (1) + (2) (3)	Owned Units/ Imputed Rents (4)	Actual Gross Rents (5)	Weighted Rent Index (6)	Years in Resi-dence (7)	Number of Rooms (8)	Age of Building in Years (9)
Panel A: Central City, Suburban, or non-Metropolitan Area									
Central City (in Metro)	0.060	-0.100	-0.030	0.100	0.057	0.071	10.11	5.0	38
Suburban (in Metro)	0.083	0.057	0.138	0.073	0.105	0.092	10.59	5.7	30
Non-Metropolitan Areas	-0.329	0.009	-0.309	-0.343	-0.359	-0.347	11.74	5.6	33
Panel B: By Residential Population Density									
>5,000 per square mile	0.276	-0.138	0.138	0.343	0.218	0.281	10.50	4.8	41
1,000-5,000 per square mile	0.010	0.051	0.061	-0.023	0.053	0.012	10.31	5.7	30
<1,000 per square mile	-0.280	0.051	-0.229	-0.292	-0.292	-0.288	11.40	5.7	31
Panel C:Standard Deviations									
All PUMAs	0.358	0.140	0.361	0.417	0.315	0.370	2.17	0.68	10.0
Across Metropolitan Areas	0.310	0.066	0.283	0.358	0.273	0.319	1.70	0.39	7.0
Within Metropolitan Areas	0.179	0.123	0.224	0.215	0.157	0.188	1.35	0.55	7.2
Fraction of Variance Within	*0.250*	*0.772*	*0.385*	*0.266*	*0.248*	*0.258*	*0.387*	*0.667*	*0.512*

Columns 1 through 6 report deviations from the national average. See Table 1 and Appendix for more detail.

Table P.2: Wage differentials across the U.S.: Alternative measures and related statistics, 2000

	Wage by Work-place (1)	Wage by Resi-dence (2)	Wage by Compo-sition (3)	Workplace minus Residence (4)	Raw Wage Differential (1) + (3) (5)	By Resi-dence PWPUMA (6)	Commute out of PWPUMA (7)	By Work place Weighted (8)	By Work place (Dahl) (9)
Panel A: Central City, Suburban, or non-Metropolitan Area									
Central City (in Metro)	0.033	0.012	-0.044	-0.022	0.028	0.020	0.352	0.032	0.031
Suburban (in Metro)	0.034	0.053	0.035	0.019	0.041	0.043	0.487	0.032	0.031
Non-Metropolitan Areas	-0.140	-0.156	-0.020	-0.016	-0.152	-0.154	0.310	-0.140	-0.138
Panel B: By Residential Population Density									
>5,000 per square mile	0.110	0.087	-0.061	-0.023	0.095	0.099	0.439	0.109	0.108
1,000-5,000 per square mile	0.004	0.022	0.040	0.018	0.016	0.013	0.412	0.003	0.003
<1,000 per square mile	-0.111	-0.117	-0.005	-0.006	-0.119	-0.115	0.380	-0.110	-0.108
Panel C:Standard Deviations									
All PUMAs	0.128	0.145	0.105	0.055	0.140	0.135	0.206	0.125	0.124
Across Metropolitan Areas	0.123	0.130	0.047	0.015	0.132	0.127	0.157	0.121	0.119
Within Metropolitan Areas	0.033	0.065	0.093	0.053	0.045	0.046	0.133	0.034	0.033
Fraction of Variance Within	*0.066*	*0.201*	*0.784*	*0.929*	*0.103*	*0.116*	*0.417*	*0.074*	*0.071*

Columns 1 through 6, 8 and 9 are log differences relative to the national average. Column 7 is a proportion. See Table 1 and Appendix for more detail.

Table P.3: Commuting differentials across the U.S.: Alternative measures and related statistics, 2000

	Full Cost (1)	Commute Time Differential (2)	Composition (3)	Raw Differential (4)	Division of Full Cost: Time Cost (5)	Division of Full Cost: Material Cost (6)	Fraction Driving (7)	Fraction Transit (8)
Panel A: Central City, Suburban, or non-Metropolitan Area								
Central City (in Metro)	-0.003	-0.007	0.005	0.005	0.000	-0.003	0.848	0.098
Suburban (in Metro)	0.006	0.058	-0.001	0.065	0.003	0.004	0.933	0.031
Non-Metropolitan Areas	-0.012	-0.139	-0.005	-0.137	-0.007	-0.006	0.948	0.008
Panel B: By Residential Population Density								
>5,000 per square mile	0.006	0.109	0.006	0.123	0.005	0.001	0.814	0.129
1,000-5,000 per square mile	-0.001	-0.026	-0.001	-0.020	-0.001	0.001	0.941	0.022
<1,000 per square mile	-0.005	-0.063	-0.004	-0.060	-0.003	-0.002	0.953	0.008
Panel C:Standard Deviations								
All PUMAs	0.018	0.220	0.012	0.225	0.010	0.008	0.118	0.100
Across Metropolitan Areas	0.014	0.176	0.007	0.180	0.008	0.006	0.078	0.070
Within Metropolitan Areas	0.011	0.132	0.010	0.134	0.006	0.006	0.088	0.072
Fraction of Variance Within	*0.373*	*0.360*	*0.694*	*0.355*	*0.360*	*0.563*	*0.556*	*0.518*

Columns 1 through 6 are deviations from the national average; 7 and 8 are proportions. See Table 1 and Appendix for more detail.

BIBLIOGRAPHY

BIBLIOGRAPHY

Akerlof, George A. and Rachel E. Kranton, "Economics and Identity," *The Quarterly Journal of Economics*, 2000, *115* (3), 715–753.

Albouy, David, "The Wage Gap Between Francophones and Anglophones: a Canadian perspective, 1970-2000," *Canadian Journal of Economics*, 2008, *41* (4), 1211–1238.

_ , "The Unequal Geographic Burden of Federal Taxation," *Journal of Political Economy*, 2009, *117* (4), 635–667.

_ , "Are Big Cities Bad Places to Live: Estimating Quality of Life across Metropolitan Areas," *National Bureau of Economic Research Working Paper No. 14472*, pp. 1–65.

Alonso, William, *Location and Land Use: Towards a General Theory of Land Rent*, Harvard University Press, 1964.

Angrist, Joshua D. and Jorn-Steffen Pischke, "The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics," *Journal of Economic Perspectives*, 2010, *24* (2), 3–30.

Antman, Francisca and Brian Duncan, "Incentives to Identify: Racial Identity in the Age of Affirmative Action," *Working Paper*, 2014, pp. 1–58.

Arias, Elizabeth, *United States Life Tables, 2008*, Vol. 61, National Center for Health Statistics, 2012.

_ **, Brian Rostron, and Betzaida Tejada-Vera**, *United States Life Tables, 2005*, Vol. 58, National Center for Health Statistics, 2010.

Bajari, Pat and Matthew Kahn, "Estimating Housing Demand With an Application to Explaining Racial Segregation in Cities.," *Journal of Business and Economic Statistics*, 2005, *23* (1), 20–33.

Bamshad, Michael, Stephen Wooding, Benjamin A. Salisbury, and J. Claiborne Stephens, "Deconstructing the Relationship Between Genetics and Race," *Nature Reviews Genetics*, 2004, *5*, 598–608.

Battu, Harminder and Yves Zenou, "Oppositional identities and employment for ethnic minorities: evidence from england," *Economic Journal*, 2010, *120*, F52–F71.

Baum-Snow, Nathaniel and Ronni Pavan, "Understanding the City Size Wage Gap," *Review of Economic Studies*, 2012, *79*, 88–127.

Baumeister, Lisa, Kristen Marchi, Michelle Pearl, Ronald Williams, and Paula Braveman, "The Validity of Information on "Race" and "Hispanic Ethnicity" in California Birth Certificate Data," *Health Services Research*, 2000, *34* (4), 869–883.

Bayer, Patrick and Christopher Timmins, "On the Equilibrium Properties of Locational Sorting Models.," *Journal of Urban Economics*, 2005, *57*, 462–77.

_ , Fernando Ferreira, and Robert McMillan, "A Unified Framework for Measuring Preferences for Schools and Neighborhoods.," *Journal of Political Economy*, 2007, *115.*

Becker, Gary S., *The Economics of Discrimination*, 2nd ed., University of Chicago Press, 1971.

Becker, Richard A, Lorraine Denby, Robert McGill, and Allan R. Wilks, "Analysis of Data from the Places Rated Almanac," *The American Statistician*, 1987, *41*, 169–186.

Beeson, Patricia E. and Randall W. Eberts, "Identifying Productivity and Amenity Effects in Interurban Wage Differentials," *The Review of Economics and Statistics*, 1989, *71*, 443–452.

Benjamin, Daniel J., James J. Choi, and A. Joshua Strickland, "Social Identity and Preferences," *American Economic Review*, 2010, *100*, 1913–1928.

Bentley, Michael, Tracy Mattingly, Christine Hough, and Claudette Bennett, "Census quality survey to evaluate responses to the Census 2000 question on race: An introduction to the data," United States Census Bureau April 2003.

Berger, Mark C., Glenn C. Blomquist, and Werner Waldner, "A Revealed-Preference Ranking of Quality of Life for Metropolitan Areas," *Social Science Quarterly*, 1987, *68*, 761–779.

Bieri, David S., Nicolai V. Kuminoff, and Jaren C. Pope, "National Expenditures on Local Amenities," *Unpublished manuscript*, 2013.

Bishop, Kelly and Alvin Murphy, "Estimating the Willingness to Pay to Avoid Violent Crime: A Dynamic Approach," *American Economic Review Papers and Proceedings*, 2011, *101*, 625–629.

Black, Dan, Natalia Kolesnikova, and Lowell Taylor, "Earnings Functions When Wages and Prices Vary by Location," *Journal of Labor Economics*, 2009, *27* (1), 21–47.

Black, Sandra E., "Do Better Schools Matter? Parental Valuation of Elementary Education," *Quarterly Journal of Economics*, 1999, *114*, 577–599.

Blomquist, Glenn C., Mark C. Berger, and John P. Hoehn, "New Estimates of Quality of Life in Urban Areas," *The American Economic Review*, 1988, *78* (1), 89–107.

Boustan, Leah Platt, "Local Public Goods and the Demand for High-Income Municipalities," *Journal of Urban Economics*, 2013, *76*, 71–82.

Brownstone, David and Kenneth A. Small, "Valuing Time and Reliability: Assessing the Evidence from Road Pricing Demonstrations," *Transportation Research Part A*, 2005, *39*, 279–293.

Brueckner, Jan K., "A Test for Allocative Efficiency in the Local Public Sector," *Journal of Public Economics*, 1982, *15.*

Brunsma, David L., "Interracial Families and the Racial Identification of Mixed-Race Children: Evindence from the Early Childhood Longitudinal Study," *Social Forces*, 2005, *84* (2), 1131–1157.

Bureau of the Census, "Overview of race and Hispanic origin: Census 2000 Brief," Technical Report, U.S. Department of Commerce 2001.

_ , "Summary File 1: 2000 Census of Population and Housing," Technical Report, U.S. Department of Commerce 2007.

_ , "Design and Methodology: American Community Survey," Technical Report ACS-DM1, U.S. Department of Commerce April 2009.

Caetano, Gregorio, "Identification and Estimation of Parental Valuation of School Quality in the U.S," *Unpublished manuscript*, 2010.

Cellini, Stephanie, Fernando Ferreira, and Jesse Rothstein, "The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design," *Quarterly Journal of Economics*, 2010, *125*, 215–261.

Charles, Kerwin Kofi and Jonathan Guryan, "Studying Discrimination: Fundamental Challenges and Recent Progress," *NBER Working Paper Series*, 2011, (17156), 1–51.

Charness, Gary and Aldo Rustichini, "Gender differences in cooperation with group membership," *Games and Economic Behavior*, May 2011, *72* (1), 77–85.

_ , Luca Rigotti, and Aldo Rustichini, "Individual Behavior and Group Membership," *American Economic Review*, September 2007, *97* (4), 1340–1352.

Chen, Yan and Sherry Xin Li, "Group Identity and Social Preferences," *American Economic Review*, March 2009, *99* (1), 431–457.

Chen, Yu and Stuart Rosenthal, "Local Amenities and Life-Cycle Migration: Do People Move for Jobs or Fun?," *Journal of Urban Economics*, 2008, *64*, 519–537.

Colwell, Peter F., Carolyn A. Dehring, and Geoffrey K. Turnbull, "Recreation Demand and Residential Location," *Journal of Urban Economics*, 2002, *51*, 418–428.

Combes, Pierre-Philippe, Gilles Duranton, and Gobillon Laurent, "Spatial Wage Disparities: Sorting Matters!," *Journal of Urban Economics*, 2008, *63*, 723–742.

Constant, Amelie F., "Ethnic Identity and work," *IZA Discussion Paper*, 2014, (8571), 1–18.

_ **, Liliya Gataullina, and Klaus F. Zimmermann**, "Ethnosizing immigrants," *Journal of Economic Behavior and Organization*, 2009, *69* (3), 274–287.

Croson, Rachel and Uri Gneezy, "Gender Differences in Preferences," *Journal of Economic Literature*, 2009, *47* (2), 448–474.

Cutler, David M. and Edward L. Glaeser, "Are Ghettos Good or Bad?," *The Quarterly Journal of Economics*, 1997, *112*, 827–872.

Darity, Jr., William A., Patrick L. Mason, and James B. Stewart, "The economics of identity: The origin and persistence of racial identity norms," *Journal of Economic Behavior and Organization*, 2006, *60*, 283–305.

Davis, Lucas, "The Effect of Health Risk on Houisng Values: Evidence from a Cancer Cluster," *American Economic Review*, 2004, *94*, 1693–1704.

Diamond, Rebecca and Tim McQuade, "Who Wants Affordable Housing in their Backyard? An Equilibrium Analysis of Low Income Property Development," *Unpublished manuscript*, 2015.

Division of Vital Statistics, "Report of the Panel to Evaluate the U.S. Standard Certificates," 2000.

Duncan, Brian and Stephen J. Trejo, "Intermarriage and the Intergenerational Transmission of Ethnic Identity and Human Capital for Mexican Americans," *Journal of Labor Economics*, 2011, *29* (2), 195–227.

_ **and** _ , "Tracking Intergenerational Progress for Immigrant Groups: The Problem of Ethnic Attrition," *American Economic Review: Papers and Proceedings*, 2011, *101* (3), 603–608.

_ **and** _ , "The Complexity of Immigrant Generations: Implications for Assessing the Socioeconomic Integration of Hispanics and Asians," *IZA Discussion Paper*, 2012, (6276), 1–66.

Eckel, Catherine C. and Philip J. Grossman, "Managing diversity by creating team identity," *Journal of Economic Behavior and Organization*, 2005, *58* (3), 371–392.

Epple, Dennis and Holger Sieg, "Estimating Equilibrium Models of Locational Sorting," *Journal of Political Economy*, 1999, *107*, 645–681.

Fairlie, Robert W., "Can the 'one-drop rule' tell us anything about racial discrimination? New evidence from the multiple race question on the 2000 Census," *Labour Economics*, 2009, *16*, 451–460.

Farley, Reynolds, "Identifying with Multiple Races: A Social Movement That Succeeded But Failed?," in "The Changing Terrain of Race and Ethnicity," New York: Russell Sage Foundation, 2004, pp. 123–148.

Feenberg, Daniel R. and Elisabeth Coutts, "An Introduction to the TAXSIM Model," *Journal of Policy Analysis and Management*, 1993, *12* (1), 189–194.

Ferreira, Fernando and Joseph Gyourko, "Anatomy of the Beginning of the Housing Boom: U.S. Neighborhoods and Metropolitan Areas, 1993-2009," *National Bureau of Economic Research Working Paper No. 17374*, 2011.

Fischbacher, Urs, "z-Tree: Zurich Toolbox for Ready-made Economic Experiments," *Experimental Economics*, June 2007, *10* (2), 171–178.

Francis, Andrew M. and Maria Tannuri-Pianto, "Endogenous Race in Brazil: Affirmative Action and the Construction of Racial Identity among Young Adults," *Economic Development and Cultural Change*, 2013, *61* (4), 731–753.

Fryer, Jr., Roland G., "Guess Who's Been Coming to Dinner? Trends in Interracial Marriage over the 20th Century," *Journal of Economic Perspectives*, 2007, *21* (2), 71–90.

_ **and Paul Torelli**, "An Empirical Analysis of 'acting white'," *Journal of Public Economics*, 2010, *94* (5-6), 380–396.

_ **, Lisa Kahn, Steven D. Levitt, and Jorg L Spenkuch**, "The Plight of Mixed-Race Adolescents," *Review of Economics and Statistics*, 2012, *94* (3), 621–634.

Fu, Shihe and Stephen L. Ross, "Wage Premia in Employment Clusters: Agglomeration or Worker Heterogeneity?," *Journal of Labor Economics*, 2013, *31*, 271–304.

_ **and** _ , "Wage Premia in Employment Clusters: How Important Is Worker Heterogeneity?," *Journal of Labor Economics*, 2013, *31* (2), 271–304.

Gabriel, Stuart A. and Stuart S. Rosenthal, "Commutes, Neighborhood Effects, and Earnings: An Analysis of Racial Discrimination and Compensating Differentials," *Journal of Urban Economics*, 1996, *40*, 61–83.

_ **and** _ , "Quality of the Business Environment Versus Quality of Life: Do Firms and Households Like the Same Cities?," *The Review of Economics and Statistics*, February 2004, *86* (1), 438–444.

_ **, Joe P. Mattey, and William L. Wascher**, "Compensating differentials and evolution in the quality-of-life among U.S. states," *Regional Science and Urban Economics*, 2003, *33*, 619–649.

Gibson, Campbell and Kay Jung, "Historical Census Statistics On Population Totals By Race, 1790 to 1990, and By Hispanic Origin, 1970 to 1990, For Large Cities And Other Urban Places In The United States," 2005. Population Division Working Paper No. 76.

Glaeser, Edward L. and David Mare, "Cities and Skills," *Journal of Labor Economics*, 2001, *19*, 316–342.

Gneezy, Uri, Kenneth L. Leonard, and John A. List, "Gender Differences in Competition: Evidence from a Matrilineal and a Patriarchal Society," *Econometrica*, 2009, *77* (5), 1637–1664.

Goldsmith, Arthur H., Darrick Hamilton, and William Darity, Jr., "From Dark to Light: Skin Color and Wages Among African-Americans," *The Journal of Human Resources*, 2007, *42* (4), 701–738.

Goldstein, Joshua and Ann Morning, "The multiple-race population of the United States: Issues and estimates," *Proceedings of the National Academy of Sciences*, 2000, *97* (11), 6230–6235.

Gullickson, Aaron and Ann Morning, "Choosing race: Multiracial ancestry and identification," *Social Science Research*, 2011, *40*, 498–512.

Gupta, Gautam, Minhaj Mahmud, Pushkar Maitra, Santanu Mitra, and Ananta Neelim, "Religion, Minority Status and Trust: Evidence from a Field Experiment," *Working Paper*, 2013, pp. 1–43.

Gyourko, Joseph and Joseph Tracy, "The Importance of Local Fiscal Conditions in Analyzing Local Labor Markets," *Journal of Political Economy*, 1989, *97*, 1208–1231.

_ and _ , "The Structure of Local Public Finance and the Quality of Life," *Journal of Political Economy*, 1991, *99*, 774–806.

_ , Christopher Mayer, and Todd Sinai, "Superstar Cities," *American Economic Journal: Economic Policy*, 2013, *5*, 167–199.

_ , Matthew Kahn, and Joseph Tracy, "Quality of Life and Environmental Comparisons," in Edwin S. Mills and Paul Cheshire, eds., *Handbook of Regional and Urban Economics*, Vol. 3, Elsevier Science, 1999, pp. 1413–1454.

Hamermesh, Daniel, "Crime and the Timing of Work," *Journal of Urban Economics*, 1999, *45*, 311–330.

Harris, David R. and Jeremiah J. Sim, "Who Is Multiracial? Assessing the Complexity of Lived Race," *American Sociological Review*, 2002, *67*, 614–627.

Hegewisch, Ariane and Heidi Hartmann, "Occupational segregation and the gender wage gap: a job half done," *Institute for Women's Policy Research Scholars' Papers*, 2014, pp. 1–27.

Hersch, Joni, "Profiling the New Immigrant Worker: The Effects of Skin Color and Height," *Journal of Labor Economics*, 2008, *26* (2), 345–386.

_ , "The Persistence of skin color discrimination for immigrants," *Social Science Research*, 2011, *40* (5), 1337–1349.

Hochschild, Jennifer L. and Brenna Marea Powell, “Racial Reorganization and the United States Census 1850-1930: Mulattoes, Half-Breeds, Mixed Parentage, Hindoos, and the Mexican Race,” *Studies in American Political Development*, 2008, *22*, 59–96.

Hoehn, John P., Mark C. Berger, and Glenn C. Blomquist, “A Hedonic Model of Interregional Wages, Rents, and Amenity Values,” *Journal of Regional Science*, 1987, *27*, 605–620.

Ioannides, Yannis M., “Neighborhood income distributions,” *Journal of Urban Economics*, 2004, *56*, 435–457.

Jorde, Lynn B and Stephen P Wooding, “Genetic variation, classification and ‘race’,” *Nature Genetics*, 2004, *36* (11), 528–533.

Kahneman, Daniel and Alan Krueger, “Developments in the Measurement of Subjective Well-Being,” *Journal of Economic Perspectives*, 2006, *20*, 3–24.

Khanna, Nikki, *Biracial in America*, 2nd ed., Lexington Books, 2011.

Kim, ChangHwan and Arthur Sakamoto, “Have Asian American Men Achieved Labor Market Parity with White Men?,” *American Sociological Review*, 2010, *75* (6).

Kim, Dongsoo, Feng Liu, and Anthony Yezer, “Do inter-city differences in intra-city wage differentials have any interesting implications?,” *Journal of Urban Economics*, 2009, *66*, 151–232.

Klein, Richard G., *The Human Career*, third ed., University of Chicago Press, 2009.

Krueger, Alan B., “Measuring Labor’s Share,” *American Economic Review*, 1999, *89*, 45–51.

Kuminoff, Nicolai and Jaren Pope, “Do ’Capitalization’ Effects for Public Goods Reveal the Public’s Willingness to Pay?,” *International Economic Review*, 2013.

Kuminoff, Nicolai V., Kerry Smith, and Christopher Timmins, “The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets,” *Journal of Economic Literature*, 2013, *51*, 1007–1062.

Lee, Sanghoon and Jeffrey Lin, “Natural Amenities, Neighborhood Dynamics, and Persistence in the Spatial Distribution of Income,” *Federal Reserve Bank of Philadelphia Working Paper No. 13-48*, 2013.

Leonardelli, Geoffrey J. and Marilynn B. Brewer, “Minority and Majority Discrimination: When and Why,” *Journal of Experimental Psychology*, 2001, *37* (6), 468–485.

Light, Audry and Alita Nandi, “Identifying race and ethnicity in the 1979 National Logitudinal Survey of Youth,” *Population Research and Policy Review*, 2007, *26*, 125–144.

Linden, Leigh and Jonah E. Rockoff, “Estimates of the Impact of Crime Risk on Property Values from Megan’s Laws,” *American Economic Review*, 2008, *98*, 1103–1127.

Loury, Linda Datcher, "Am I still too Black for you?: Schooling and secular change in skin tone effects," *Economics of Education Review*, 2009, *28*, 428–433.

Lue, Bert, "Mark one or more: Identity choice among multiracial individuals," 2015. Working Paper.

Malpezzi, Sephen, Gregory H. Chun, and Richard K. Green, "New Place-to-Place Housing Price Indexes for U.S. Metropolitan Areas, and Their Determinants," *Real Estate Economics*, 1998, *26*, 235–274.

Mason, Patrick L. and Andrew Matella, "Stigmatization and racial selection after September 11, 2001: self-identity among arab and islamic americans," *IZA Journal of Migration*, 2014, *3*, 1–21.

McDuff, DeForest, "Demand Substitution Across US Cities: Observable Similarity and Home Price Correlation," *Journal of Urban Economics*, 2011, *70*, 1–14.

McMillen, Daniel P. and Larry D. Singell, Jr., "Work Location, Residence Location, and the Intraurban Wage Gradient," *Journal of Urban Economics*, 1992, *32*, 195–213.

Mills, Edwin S, "An Aggregative Model of Resource Allocation in a Metropolitan Area," *American Economic Review Papers and Proceedings*, 1967, *57* (2), 197–210.

Muth, Richard F., *Cities and Housing: The Spatial Pattern of Urban Land Use*, University of Chicago Press, 1969.

National Center for Health Statistics, "Data File Documentations, Natalilty," 1970-2000.

Neal, Derek A. and William R. Johnson, "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 1996, *104* (5), 869–895.

Nevo, Avia and Michael D. Whinston, "Taking the Dogma out of Econometrics: Structural Modleing and Credible Inference," *Journal of Economic Perspectives*, 2010, *24*, 69–82.

Niederle, Muriel and Lise Vesterlund, "Do Women Shy Away From Competition? Do Men Compete Too Much?," *Quarterly Journal of Economics*, 2007, *122* (3), 1067–1101.

Northam, Sally and Thomas R. Knapp, "The Reliability and Validity of Birth Certificates," *Journal of Obstetric, Gynecologic, and Neonatal Nursing*, 2006, *35* (1), 3–12.

_ , Shea Polancich, and Elizabeth Restrepo, "Birth Certificate Methods in Five Hospitals," *Public Health Nursing*, 2003, *20* (4), 318–327.

Oates, Wallace E., "The Effects of Property Taxes and Local Public Spending on Property Values: An Empirical Study of Tax Capitalization and the Tiebout Hypothesis," *Journal of Political Economy*, 1969, *77*, 957–971.

Office of Management and Budget, "Revisions to the Standards for the Classification of Federal Data on Race and Ethnicity," 1997.

_ , "Standards for Defining Metropolitan and Micropolitan Statistical Areas; Notice," 2000.

Peiser, Richard B. and Lawrence B. Smith, "Homeownership Returns, Tenure Choice and Inflation," *American Real Estate and Urban Economics Journal*, 1985, *13*, 343–360.

Perez, Anthony D. and Charles Hirschman, "The Changing Racial and Ethnic Composition of the US Population: Emerging American Identities," *Population and Development Review*, 2009, *35* (1), 1–51.

Petitte, Ryan A. and Stephen L. Ross, "Commutes, Neighborhood Effects, and Compensating Differentials: Revisited," *Journal of Urban Economics*, 1999, *46*, 1–24. *Pieter A. Gautier and Arjen Siegmann and Aico Van Vuuren*

Pieter A. Gautier and Arjen Siegmann and Aico Van Vuuren, *Journal of Urban Economics, 2009, 65, 113–126.*

Pollakowski, Henry O., *"Who Really Benefits from New York City's Rent Regulation System?," Civic Report, 2003, 34, 1–27.*

Pope, Jaren C., *"Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries," Journal of Urban Economics, 2008, 64, 601–614.*

Prislin, Radmila, Vanessa Sawicki, and Kipling Williams, *"New majorities' abuse of power: Effects of perceived control and social support," Group Processes and Intergroup Relations, 2011, 14 (4), 489–504.*

_ , Wendy M. Limbert, and Evamarie Bauer, *"From Majority to Minority and Vice Versa: The Asymmetrical Effects of Losing and Gaining Majority Position Within a Group," Journal of Personality and Social Psychology, 2000, 79 (3), 385–397.*

Public Health Service, *"Model State Vital Statistics Act and Regulations, 1992 Revision," 1992.*

Roback, Jennifer, *"The Value of Local Urban Amenities: Theory and Measurement," Ph.D. dissertation, University of Rochester, 1980.*

_ , *"Wages, Rents, and the Quality of Life," Journal of Political Economy, 1982, 90, 1257–1278.*

_ , *"Wages, Rents, and Amenities: Differences among Workers and Regions," Economic Inquiry, 1988, 26, 23–41.*

Roberts, Sam and Peter Baker, *"Asked to Declare His Race, Obama Checks 'Black'," The New York Times, April 2010.*

Rosen, Sherwin, *"Wages-based Indexes of Urban Quality of Life," in P. Mieszkowski and M. Straszheim, eds., Current Issues in Urban Economics, Baltimore, MD: John Hopkins Univ. Press, 1979.*

Rosenthal, Stuart and Amanda Ross, *"Violent Crime, Entrepreneurship, and Cities," Journal of Urban Economics, 2010, 67, 135–149.*

_ **and William Strange**, *"The Determinants of Agglomeration," Journal of Urban Economics, 2001, 50, 191–229.*

Roth, Wendy D., *"The End of the One-Drop Rule? Labeling of Multiracial Children in Black Intermarriages," Sociological Forum, 2005, 20 (1), 35–67.*

Ruebeck, Christopher S, Susan L. Averett, and Howard N. Bodenhorn, *"Acting White or Acting Black: Mixed-Race Adolescents' Identity and Behavior," The B.E. Journal of Economic Analysis and Policy, 2009, 9 (1), 1–42.*

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek, *Integrated Public Use Microdata Series: Version 5.0 [Machine Readable Database], Minneapolis: University of Minnesota, 2010.*

_ **, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander**, *Integrated Public Use Microdata Series: Version 3.0 [Machine Readable Database], Minneapolis: Minnesota Population Center, 2004.*

Salmon, Timohty C. and Danila Serra, *"Does Social Judgment Diminish Rule Breaking?," 2013. Working Paper.*

Saperstein, Aliya and Andrew M. Penner, *"The Race of a Criminal Record: How Incarceration Colors Racial Perceptions," Social Problems, 2010, 57 (1), 99–113.*

Savageau, David, *Places Rated Almanac, Foster City, CA: IDG Books Worldwide, 1999.*

Schmidt, Lucie and Paul Courant, *"Sometimes Close is Good Enough: The Value of Nearby Environmental Amenities," Journal of Regional Science, 2006, 46, 931–951.*

Silver, Nate, *"The Most Livable Neighborhoods in New York: A quantitative index of the 50 most satisfying places to live," 2010.* http://nymag.com/realestate/neighborhoods/2010/65374/.

Small, Kenneth A. and E. T. Verhoef, *The Economics of Urban Transportation, New York, NY: Routledge, 2007.*

_ **, Clifford Winston, and Jia Yan**, *"Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability," Econometrica, 2005, 73 (4), 1367–1382.*

Straszheim, Mahlon R., *"Urban Agglomeration Effects and Employment and Wage Gradients," Journal of Urban Economics, 1984, 16, 187–207.*

Tafoya, Sonya M., Hans Johnson, and Laura E. Hill, *"Who Chooses to Choose Two?," in Reynolds Farley and John Haaga, eds., The American People: Census 2000, Russell Sage Foundation, 2005.*

Tajfel, Henri and John C. Turner, *"An Integrative Theory of Intergroup Conflict," in Stephen Worchel and William G. Austin, eds., The Social Psychology of Intergroup Relations, Monterey, CA: Brooks/Cole, 1979, pp. 33–47.*

_ and _ , *"The Social Identity Theory of Intergroup Behavior," in Stephen Worchel and William Austin, eds., The Social Psychology of Intergroup Relations, Chicago: Nelson-Hall, 1986, pp. 276–293.*

_ , M. Billig, R. Bundy, and Claude L. Flament, *"Social categorization and intergroup behavior," European Journal of Social Psychology, 1971, 1 (2), 149–177.*

Tanaka, Tomomi and Colin F. Camerer, *"Handouts without handshakes: Patronizing out-group preferences in humans," Working Paper, 2013, pp. 1–46.*

Telles, Edward E. and Christina A. Sue, *"Race Mixture: Boundary Crossing in Comparative Perspective," Annual Review of Sociology, 2009, 35, 129–146.*

Tiebout, Charles, *"A Pure Theory of Local Expenditures," Journal of Political Economy, 1956, 64 (5), 416–426.*

Timothy, Darren and William C. Wheaton, *"Intra-Urban Wage Variation, Employment Locations, and Commuting Times," Journal of Urban Economics, 2001, 50, 338–366.*

Tishkoff, Sarah A., *"The Genetic Structure and History of Africans and African Americans," Science, 2009, 324, 1035–1043.*

Tsutsui, Kei and Daniel John Zizzo, *"Group status, minorities and trust," Experimental Economics, 2013, pp. 1–30.*

Turnbull, Geoffrey K., *"Location, Housing, and Leisure Demand under Local Employment," Land Economics, 1992, 68, 62–71.*

_ , *Urban Consumer Theory, Washington D.C.: Urban Institute Press, 1995.*

Wang, Wendy, *"The Rise of Intermarriage," Pew Research Center: Social and Demographic Trends, 2012, pp. 1–56.*

Weber, Roberto A., *"Managing Growth to Achieve Efficient Coordination in Large Groups," American Economic Review, 2006, pp. 114–126.*

Xie, Yu and Kimberly Goyette, *"The Racial Identification of Biracial Children with One Asian Parent: Evidence from the 1990 Census," Social Forces, 1997, 76 (2), 547–570.*

Yinger, John, *"Hedonic Markets and Sorting Equilibria: Bid-functions for Public Services and Neighborhood Amenities," Forthcoming in Journal of Urban Economics, 2014.*

Zax, Jeffrey S., *"Compensation for Commutes in Labor and Housing Markets," Journal of Urban Economics, 1991, 30, 192–207.*