The Fluidity of Race:

"Passing" in the United States, 1880-1940*

Emily Nix[†] and Nancy Qian[‡]

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Abstract

This paper quantifies the extent to which individuals experience changes in reported racial identity in the historical U.S. context. Using the full population of historical Censuses for 1880-1940, we document that over 19% of black males "passed" for white at some point during their lifetime, around 10% of whom later "reverse-passed" to being black; passing was accompanied by geographic relocation to communities with a higher percentage of whites and occurred the most in Northern states. The evidence suggests that passing was positively associated with better political-economic and social opportunities for whites relative to blacks. As such, endogenous race is likely to be a quantitatively important phenomenon.

Keywords: Economic History, Identity Economics, Political Economy, Endogenous Racial and Ethnic Identity
JEL: N3, J15, J17

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[†]Yale University, emily.nix@yale.edu

[‡]Corresponding author: Yale University, NBER, BREAD, CEPR, nancy.qian@yale.edu

1 Introduction

A large body of work links race and ethnicity (or diversity) to important economic and political outcomes in many different contexts. The interpretation of these empirical associations critically depends on whether one believes that race and ethnicity are exogenous and fixed characteristics.[1] A growing body of evidence from anecdotes, historians, and recent studies suggests that this is not always true. For example, historians have long noted that Americans with African ancestry often chose to "pass" for white to obtain better economic and political opportunities (e.g., O'Toole, 2003; Sharfstein, 2011). Mill and Stein (2012) find that amongst mixed-race siblings, those that identify as white later in life earn significantly higher wages. Recent studies have also documented that individuals have responded to political-economic incentives and changed castes in India (Cassan, 2013), manipulated their racial appearance for higher wages in Brazil (Cornwell, Rivera, and Schmutte, 2014), or have strategically chosen the official ethnicity of mixed children in China (Jia and Persson, 2013). More generally, studies of identity, such as the theoretical work of Akerlof and Kranton (2000), argue that "choice of identity may be the most important 'economic' decision people make. Individuals may—more or less consciously—choose who they want to be ... Previous economic analyses of, for example, poverty, labor supply, and schooling have not considered these possibilities".

To assess the necessity of an overhaul in the way we conceptualize and evaluate the relationship between race and economic and political variables, we need to first know the quantitative importance of race change and whether it is associated with the latter set of variables. Data limitations have made this difficult until now. As recently as 2011, historian Daniel Sharfstein notes that "According to just about anyone who has considered the question, the migration [from black to white in the United States] is impossible to reconstruct ... At best, such evidence is scattered across local archives and county courthouses, in library stacks and microfilm reels. Beyond the isolated anecdotes, there seems to be only silence" (Sharfstein, 2011, p. 4).

[1] The literature typically assumes that racial and ethnic identities are fixed and exogenous. For examples, see the reviews of the political economy literature by Alesina and Ferrara (2004) and of studies of the U.S. black-white wage gap by Lang and Lehmann (2012).

This study aims to make progress on this important question. We focus on the historical U.S. context (1880-1940), because of the recent availability of digitized historical census data and the rich historical and anecdotal evidence that help to guide and interpret the empirical analysis. Motivated by the historical evidence, we ask the following questions: *i*) how many Americans of African descent changed their racial identity from "black" to "white" during their life time? *ii*) how did they achieve race change? *iii*) was the change permanent? *iv*) was it associated with the political-economic and social returns to being white? To the best of our knowledge, our study is the first to document these descriptive facts, which are necessary precursors for assessing the importance of accounting for the endogeneity of race in future research, and for deeper explorations of the linkages between racial identity and other variables.

To motivate the empirical analysis, we begin by summarizing the racial climate in the United States during the period of our study. There were strong social, economic and political incentives for blacks to pass for white. Extensive racial mixing meant that a large proportion of the "black" population could physically pass for "white". Passing for white required intentional effort by the individual such as relocating to a white community where his past was unknown. We discuss many historical cases of individuals passing for white or reverse-passing back to black.

Next, we use the data from the historical U.S. censuses from 1880-1940 to explore the questions raised by the historical and anecdotal evidence. The main empirical goal of this study is to identify the number of individuals who change their racial identity from black to white. This requires us to link individual records across censuses and examine whether a person's race changes from one census to the next. This exercise faces several challenges. First, since passers may be a small percentage of the total population, an accurate assessment of the population pass rate would ideally use the full population data rather than a sample (e.g., the 1% IPUMS data). This was not possible until very recently.

The second difficulty, which is shared by all studies of economic history that trace individuals over time, is the lack of unique individual identifiers such as social security numbers in the historical data. Matches are therefore made from names and the few other variables reported in the historical censuses (e.g., birth place and age), which can result in a large number of multiple potential matches. The problem is compounded by mismatches or non-matches caused by the frequent mis-spelling of names and the misreporting of age.[2] For studies of passing, this is exacerbated by the higher propensity of passers to geographically relocate, especially in the historical context when regional accents were strong and regional names were common. Geographic relocation meant that names were more likely to be spelled inconsistently as survey enumerators recorded names according to the phonetic pronunciation of the respondent.

Recent economic history studies have made important progress on these problems by using various samples of the historical U.S. Censuses, matching names according to their phonetic translations, and then narrowing down the number of potential matches by requiring matches of other variables. These methods are typically able to match less than 30% of the population. For example, the match rates achieved by Abramitzky, Boustan, and Eriksson (2012), Hornbeck and Naidu (2014), Long and Ferrie (2013) and Mill and Stein (2012) are approximately 30%, 24%, 22% and 11-34%, respectively.[3] For our study, having a low match rate would be problematic because it would imply large bounds around the true population statistic.[4]

To address this difficulty, we extend previous matching methods to construct a matching algorithm that achieves much higher match rates, around 61% to 67% of the population. This allows us to estimate a much narrower range of true population pass rates than if we had lower match rates. The key innovation of our procedure is to randomly select amongst

[2]Much of the historical population was uneducated such that many individuals did not know their true age or could not spell their names.

[3]Abramitzky, Boustan, and Eriksson (2012) studies the returns for Norwegians to immigrate to the United States during the late 19th Century and links Norwegian emigrants to the same individuals several decades later when they are living in the United States. Hornbeck and Naidu (2014) studies the effect of the Great Mississippi flood of 1927 on land values and black migration rates and links blacks in the South in the 1920 and 1930 Censuses. Long and Ferrie (2013) documents intergenerational mobility in Britain and the United States. For the U.S. sample, the study matches a sample of 43,438 white males under 25 year of age in 1850 U.S. Census to the 1900 U.S. Census. We discuss Mill and Stein (2012) later in the Introduction.

[4]For example, in our context if we match 20% of blacks in 1900 to individuals in the 1910 census and find that 50% in the matched sample passed for white, then the true pass rate could range anywhere from 10% (if none of the 80% of the unmatched sample passes) to 90% (if everyone in the unmatched sample passes).

multiple potential matches with the same race such that we achieve higher match rates without affecting the pass rate. We also take into account the number of unmatchable individuals by estimating absolute lower bounds of the pass rate. In contrast, previous studies typically drop multiple matches and have not attempted to estimate bounds for the population statistic.[5] Because women change their surnames upon marriage, we follow earlier studies in restricting our attention to men.

A third related difficulty is the extensive computational power required for matching the entire black population - over four million individuals in each census, which previous studies have not attempted. The problem is exacerbated by the fact that in allowing individuals to change race, we cannot use race as a matching variable. This greatly enlarges the number of potential matches for each individual that our algorithms must sift through. The recent improvements of computational power may be another reason why earlier studies have not attempted to quantify race change.

We find that more than 19% of black males passed for white during the four census intervals that we examine. Our estimates are broadly consistent with the recent genetic evidence on U.S. racial composition discussed in Section 6. Consistent with historical cases of individuals who temporarily passed for better employment or schooling opportunities, we find that not all passing was permanent. Amongst those who passed for white, approximately one-tenth "reverse passed" to being black in the following census year. Passers were much more likely to geographically relocate than non-passers, particularly to "whiter" locations. In contrast, reverse-passers were more likely to have moved to "blacker" locations than passers who maintained their white identity. These patterns of moving are consistent with the historical evidence that racial identification was typically based on association (i.e., living with and behaving as a white person).

Finally, we document that passing is associated with the political-economic incentives to be white. Controlling for state and time effects, we find that individuals were more likely

[5] Consider the example where person A, who is black in 1900, matches to 100 individuals in 1910, who are all black. In previous studies, person A will typically be dropped from the sample. Instead, we randomly choose one of the 100 individuals to be a match and say that person A did not pass. We also construct upper and lower bounds of the pass rate. We describe the procedure in detail in Section 4.

to pass for white if the income gap between whites and blacks was larger, or if there were relatively few opportunities for schooling or political enfranchisement for blacks. Given the limited availability of the historical explanatory variables, we conservatively interpret these results as suggestive *prima facie* evidence that passing is endogenous to social and political economic factors.

Our results make three contributions. First, they quantify the degree of passing and show that race change is not confined to anecdotes or case studies, but is instead a widespread and quantitatively important phenomenon. Second, they provide suggestive evidence that race change is likely to be endogenous to variables that the economics literature often examine as outcomes of race. Third, they make a methodological contribution in increasing the match rates of individuals in historical data.

As such, this study adds to several branches of the literature. Within political economy, we are related to the large literature on cultural transmission, which has mostly focused on inter-generational diffusion.[6] Our results imply that attention should also be given to changes within an individual's life time. In that sense, we provide empirical support for studies of identity economics, such as the seminal work of Akerlof and Kranton (2000) and are related to the largely theoretical studies on how behavior is shaped by social sanctions and intrinsic incentives (e.g., Benabou and Tirole).[7] The finding that endogenous race is quantitatively important could be significant for studies of the effect of racial (or ethnic) composition on political and economic outcomes. We discuss the potential implications for these studies in more detail in the conclusion.

We also add to the small number of recent studies documenting such changes in other contexts discussed earlier in the Introduction. In addition, our work is related to Botticini and Eckstein (2012), which shows that historical conversions from Judaism to Christianity

[6] Fernandez (2010) overviews the literature. Also, for example, see the well-known theoretical studies of Bisin and Verdier (2000a,b, 2001), and empirical evidence from Algan and Cahuc (2010), Cipriani, Giuliano, and Jeanne (2007), Fernandez, Fogli, and Olivetti (2004) and Fernandez and Fogli (2009).

[7] In models based on Akerlof and Kranton (2000), individuals choose their identity based on the tradeoff between the pecuniary incentives and the psychic costs of such a choice. Ruebeck, Averett, and Bodenhorn (2009) applies this theory to how mixed-race adolescents today decide whether to act "white" or "black". Bodenhorn and Ruebeck (2003) provides empirical and theoretical evidence that such tradeoffs affect individuals choice of adopting mixed-race identities during the mid-nineteenth century.

can be a response to economic incentives. We differ from these earlier studies by studying the U.S. context and quantifying the phenomenon of race change. In studying racial passing in the United States, we are most closely related to Mill and Stein (2012). Their study uses data from *FamilySearch* to match children ages 3-18 in households with both "mulatto" and "black" siblings (also ages 3-18) in 1910 to individuals in 1940. They find that those who were classified as "mulatto" in 1910 earned more in 1940 than their siblings who were classified as "black"; and amongst children who were classified as "mulatto", those who passed for white in 1940 earned more than those who did not pass. Our study differs in our focus on quantifying the total amount of passing and documenting the correlates of passing. In addition, we are able to achieve much higher match rates than their study because of the modifications in our matching method.[8] Thus, the two studies are complementary in subject and scope.

Finally, in extending the technology for matching individuals across census years, our study makes a general methodological contribution for linking individuals across census years.[9] We discuss the applications of our method to other research questions, as well as its limitations in Section 4 and the conclusion.

This paper is organized as follows. Section 2 discusses the historical background. Section 3 describes the data. Section 4 describes the matching strategy. Section 5 presents the results on passing. Section 6 discusses the recent genetics evidence. Section 7 presents evidence on some correlates of passing. Section 8 offers preliminary conclusions.

2 Historical Background

This section provides a summarized discussion of the 1880-1940 period to help understand the incentives for passing and how individuals were able to pass.

[8]Note that the two studies examine different samples. We examine the entire population of African descent (e.g., blacks, mulattos) for 1880-1940, over seventy million individuals in total, whereas their sample is restricted to approximately 7,000 individuals during 1910 and 1940. They only examine the racial passing of children who were classified as mulatto, whereas we examine mulattos and blacks because the data show that individuals of both groups passed. See Section 3 for more discussion.

[9]See Feigenbaum (2014) for a detailed discussion of automated methods of linking census records.

2.1 Post-Reconstruction and Jim Crow

This study focuses on 1880-1940, which coincided with the end of Reconstruction and Jim Crow, and preceded the Civil Rights act of 1957. Slavery was fully abolished at the end of the Civil War (1861-1865). This was followed by the Reconstruction Era (1865-1877), which introduced many laws to enhance the civil and political rights of the "colored" population. The Thirteenth Amendment (1865) abolished slavery. The Fourteenth Amendment (1868) gave all citizens equal protection of the law. The Fifteenth Amendment (1870) prohibited the federal and state governments from denying a citizen the right to vote based on race, color or previous conditions of servitude. In the Southern states, federal troops were often employed to enforce these laws (Packard, 2003, p. 60-62). During this period, there was a large increase in political representation and education for the "colored" population.

However, the move towards liberality soon ended. In 1877, to gain the support of Southern Democrats for their presidential candidate after Democrat Samuel Tilden won the popular vote, Republicans made an informal compromise with Southern states in exchange for the latter's support of Rutherford Hayes's presidency. The compromise included the removal of all federal troops from Southern states. Moreover, in 1878 Democrats won control of both houses. These two events, together with the North's "growing fatigue" over race issues, effectively gave Southern states control over the enforcement of the laws protecting the black population and, ultimately, allowed the introduction of Jim Crow laws (Keyssar, 2000, loc. 2532).

Jim Crow laws were adapted from the earlier Black Codes, a set of laws restricting the rights of the Southern black population. The explicit intention of Jim Crow laws were to circumvent the Reconstruction Amendments and assert white supremacy over blacks. Immediately after the Compromise of 1877, Southern states began to disenfranchise the mostly poor and uneducated black population (Woodward, 2002, p. 83). These changes significantly reduced the number of black voters. For example, in Mississippi, less than 9,000 out of 147,000 voting age blacks were registered to vote. In Louisiana, the number of black registered voters decreased from approximately 130,000 in 1896 to 1,342 by 1904. In Georgia, only four percent of all black males were registered to vote (Keyssar, 2000, loc. 2695).[10]

In 1883, the Supreme Court ruled that the Civil Rights Act of 1875, which gave equal treatment to all citizens in venues for the public (e.g., inns, public transportation, theaters), was unconstitutional because Congress was not given control over private persons or businesses. In the *Plessy v. Ferguson* case of 1896, the Supreme Court ruled that Louisiana's provision of "separate but equal" service on trains to customers of different races was constitutional. These two decisions effectively allowed Southern states to introduce a multitude of laws and regulations that restricted the rights of the non-white population until the Civil Rights Act of 1957.

These restrictions included the complete segregation of whites and non-whites in all facilities (e.g., restaurants, schools, water fountains, buses), with the additional problem that facilities provided to non-whites were rarely equal in quality to those provided to whites. Many regions required that neighborhoods be segregated, where public services such as sewers and electricity ended at the boundaries of the white neighborhoods (Packard, 2003, p. 102-103). Miscegenation – i.e., inter-racial marriages – and sometimes even non-marital sexual relationships were also made illegal (Packard, 2003, p. 99).

Jim Crow laws, which substantially reduced the quality of life and opportunities for non-whites, were enforced formally by state and local law enforcement, and informally by white citizens of organizations such as the Ku Klux Klan. During 1920-25, the Ku Klux Klan was the largest organization in America, with a membership of three to six million (MacVeigh, 1999). Non-whites seen as violating white supremacy were often harassed, and sometimes murdered. Between 1882 and 1968, approximately 3,446 African Americans were lynched (Institute, 2010). Many more were harassed and abused for perceived infringements.

Although Jim Crow is typically associated with the South, severe racial discrimination and the decline of opportunities during the post-Reconstruction era were also prevalent in

[10] In many places, poor whites were also disenfranchised Keyssar (2000, Ch. 4). In other places, to ensure that poor whites were not also excluded, an additional rule that allowed one to vote if his grandfather had the right to vote was introduced (Packard, 2003, Ch. 2). Many laws meant to disenfranchise immigrants also effectively disenfranchised blacks. For example, Massachusetts, Connecticut, California and New York all passed laws to require literacy tests during the end of the nineteenth and the beginning of the twentieth centuries Keyssar (2000, loc. 3052, 3309).

other states. For example, the Ku Klux Klan was based in Indiana during the early 20th Century and had large memberships in Maine and Oregon (Packard, 2003, p. 127). California, which had introduced laws to restrict property ownership of Asians during the 19th Century, extended them to include other non-white races such as blacks (Packard, 2003, p. 100). Until the racial integration of the labor unions in 1930, job opportunities were much more limited for blacks (Brueggemann and Boswell, 1998).[11] When Woodrow Wilson became president, he segregated the the District of Columbia's federal agencies, which, at that time, had been integrated for fifty years (Packard, 2003, p. 123).

Segregation and general racism were also enforced informally in the North. In 1885, on a trip through the South, African American T. McCants Steward noted that he was better served by white waiters in former slave states than in some parts of New England (Woodward, 2002, p. 39). Many schools in Illinois, Ohio, Pennsylvania and New Jersey were completely segregated, even though it was *de jure* illegal. Between 1913 and 1948, 30 out of the then 48 states enforced anti-miscegenation laws (Vile, 2003). Blacks were shut out of most non-menial jobs (Sharfstein, 2011, p. 255). Sundstrom (1994) shows that the large differences in black and white occupational choices were driven in part by social norms that rejected blacks as supervisors over white workers.[12]

2.2 Racial Mixing before 1880

According to the *Trans-Atlantic Slave Trade Database*, a total of 305,326 African Slaves were ever brought to North America. Almost 70% were adult men.[13] However, on the eve of the Civil War in 1860, there were a total of 4,427,294 individuals classified as black, over 3.9 million of whom were slaves.[14]

[11]For example, Maloney and Whatley (1995) show that during 1920-1940, half of black men in Detroit were employed by Ford because Ford was the only viable employment option available to black men at the time.

[12]There was also significant variation in the formal laws which affected the rights and opportunities facing blacks within states, as well as in the informal enforcement of state or federal laws. For example, Carruthers and Wanamaker (2013) document substantial variation in the relative quality of schooling for black students across counties. Keyssar (2000, loc. 3052) notes that the economic qualifications for voting varied across municipalities in New York.

[13]See http://www.slavevoyages.org/tast/assessment/estimates.faces

[14]Children inherited the status of the mother under slavery; the child of a slave woman is always born a slave. Thus a high degree of mixing between white men and black slave women could have contributed to the

To understand the magnitude of passing in our study, it is important to note the large number of light skinned people of African extraction by 1880. There were many voluntary sexual associations and marriages between whites and free African workers on the frontier.[15] There were also many involuntary sexual impositions of white men on African women. The prohibition of slave imports into the United States in 1807 further contributed to the decline of the number of completely African individuals in the United States. Racial mixing became legal during the Reconstruction era and continued in the late 19th Century, when it became nominally illegal under Jim Crow. "By the time that slavery ended, a majority of American Negroes bore in their genetic makeup some degree of white, which is to say European, ancestry" (Packard, 2003, p. 95).

The photographs of emancipated slaves taken in 1863 in Online Appendix Figures A.1 to A.2b provide a striking examples of the gradient of color in the "black" population at the time.

There are several additional facts about racial mixing to keep in mind. First, while there was significant mixing of whites and blacks, there is also evidence that the mixed race population practiced complexion homogamy – i.e., light skinned individuals married light skinned individuals (Bodenhorn, 2002a). This may have allowed the caucasian features resulting from white-black mixing to persist in the post-Reconstruction "black" population. At the same time, two people with the same genetic make up can look very different. For example, in Brazil, there are two non-white racial categories. Geneticists find that there is no significant ancestral difference between light skinned and dark skinned categories (Bodenhorn, 2014).

It is also interesting to note that those who had caucasian features were also likely to have strong incentives to pass because they had the most to lose from Jim Crow laws. Economic historians have noted that many of the most skilled and highly educated members of the

large increase in the slave population.

[15]"African Americans began to migrate from black to white as soon as slaves arrived on American shores" (Sharfstein, 2011, p. 3). Sharfstein (2011, p. 6) points out that "Given the daily struggle to survive and the overriding value of good neighbors in what amounted to a permanent frontier, caring about race was more trouble than it was worth" in discussing the absorption of Africans and mixed race individuals into white communities on the frontier,

population during Reconstruction were light skinned because they typically received better nutrition (Bodenhorn, 2002b). This is consistent with evidence from Bodenhorn (2002a) that amongst freed blacks during the late antebellum period, lighter skin was associated with more property ownership, and the observation that most of the notable African American leaders during the early twentieth century were light skinned (Bodenhorn, 2002b).

2.3 Defining Race

Racial science and eugenics, with beliefs that race captures biological and inherent traits both physical and moral, were popular during the period of our study. Whites were believed to have inherent intelligence, motivation and moral virtues.[16] In contrast, blacks were thought to be simple minded, lazy and sexually aggressive and wanton (Gross, 2009). Much of this was based on Carl Lineaus's 1735 publication, *Systema Naturae*, which classified the races as the following:

> *Africanus*: black, phlegmatic, relaxed; hair black, frizzled; skin silky; nose flat; lips tumid; women without shame, they lactate profusely; crafty, indolent, negligent; anoints himself with grease; governed by caprice.
>
> *Europeaeus*: white, sanguine, muscular; hair long, flowing; eyes blue; gentle, acute, inventive; covers himself with close vestments; governed by laws (Smedley, 1993, p. 164).

These explicitly racists beliefs led whites to believe that if they had been exposed to blacks, they would be able to infer a person's degree of blackness from his appearance and demeanor.[17] The perceived accuracy of this arbitrary method is illustrated in the legal definition of being black, which was always based on the fraction of one's blood that was black. The exact threshold varied across states and over time. By the Jim Crow era, most states used the "one drop" rule, which meant that a person is black if she has only one drop of African blood (Packard, 2003, p. 98).

[16] For women in the 19th and early 20th Century, the latter referred to virtuous sexual demeanor.
[17] See Gross (2009, Ch. 7).

However, this “degree-of-blood rule did not in fact make it impossible for people to cross racial lines” (Gross, 2009, loc. 4123). In practice, for a person with physical features that are shared by Caucasians, race was often determined by how he presented himself. For example, an olive-skinned man who was well-dressed and well-spoken may pass for Italian or Portuguese, while he would be classified as black if he looked poor and spoke with a rural dialect. In describing the successful suit for white identity by a mixed race woman named Alexina Morrison, Gross (2009, p. 55) points out that “.. race was not obvious. Nor did the rule about ‘negro’ identity... decide the question. More persuasive to the [white] witnesses and jurors at the trial were stories about the hidden marks of race as interpreted by experts, and stories about Alexina’s behaviour dancing at white balls, her mingling with white families, her love affairs with white men”. Race was often determined by association. “.. separation became the key to whiteness. People who had associated with whites must be whites themselves, just as people who had associated with blacks had to be black... In other words, race by association ... trumped any other sort of physical or documentary evidence” (Gross, 2009, loc. 1083, 1356).[18]

2.4 Passing for White

In the context of our study, when the one-drop rule was in place, “passing” for white refers to when a person with African ancestry is identified as white. There were no reliable birth records for the period of our study, particularly in the Southern states (Sharfstein, 2011, p. 9). Thus, passing required a person to have physical features that are commonly shared by Caucasians, to behave and dress like a white person and associate with white people. Thus, passing required a person to move to a white community, where the “passer” was not previously known by others as black since “.. Caucasian appearance was irrelevant if public knowledge

[18] There are several examples of racial classification by association from law suits. See the review by legal historian Ariela Gross (Gross, 2009). In each successful case, the person suing to be legally identified as white would demonstrate that she or he has been accepted by white friends and attended all white functions (e.g., assemblies, balls). The women also sometimes agreed to a physical inspection of her whiteness and provided testimony to her virtuous behavior, which was assumed to be impossible if she was of African extraction. In each case, the judge appealed to the jury to use their “common sense”.

existed of one's black ancestry" (Packard, 2003, p. 96).[19] The exceptionally high rates of internal U.S. migration and the large number of European immigrants from Mediterranean countries and white Americans with Spanish and French descent were likely to have made it easier for mixed race individuals to blend in with Caucasians.

Our study takes place when the incentives to pass were arguably at their highest since the end of slavery. Jim Crow had severely eroded the economic opportunities and civil liberties of anyone of African extraction, even as the number of educated and skilled African Americans grew rapidly.[20]

There are anecdotes of passing for all ages. Children sometimes passed from black to white because their parents passed or because parents sent light skinned children to live with white families to allow the children to pass.[21] Some passed as young adults to attend school, obtain a job, or to marry a white person.[22] Others passed when they were older simply because of the overwhelming discrimination they faced or to provide a better life for their children.[23]

Passing did not entirely depend on one's outward appearance. There were many examples

[19] A large body of anecdotal evidence shows that those wishing to pass often completely disassociate themselves with their past lives. For example, historian Allyson Hobbs recalls the experience of her relative who passed for white after high school. Her grandmother said to the relative, "you're going to graduate, you're going to leave Chicago, you're going to go to California, and you're going to become a white woman. And this is the best thing for you". The young girl protested, she didn't want to leave her friends, her family, the only life she'd ever known. And her grandmother said, "no, this is the best thing for you. You'll have the best life chances if you do this" (Sloan, 2013). In his biography, Williams (1996) recounts how his mixed race father passed for white by moving from Indiana to Washington D.C., and married a white woman. In his recount of the experience of the Wall family, Sharfstein (2007) discussed how the children who moved away from their home in Washington D.C. passed for white, and the one son who remained behind and his daughter were classified as black, even though he was light skinned and his daughter had blonde hair and blue eyes (her mother is white).

[20] "The harder whites made it for blacks to earn a living, educate their children, and just make it through a single day without threat or insult, the greater the incentives grew for light-skinned blacks to leave their communities and establish themselves as white... the drumbeat for racial purity, the insistence that any African ancestry – a single drop of blood – tainted a person's very existence, accelerated the migration to new identities and lives" (Sharfstein, 2011, p. 235-236).

[21] For example, Gregory Williams's early childhood identity was white because his father chose to be white (Williams, 1996). An earlier example is white slave owner Healy, who sent all of the children he bore with his slave to New York and Boston, allowing some of them to pass as white (Dawkins, 2012).

[22] For example, in Sharfstein's (2007) historical account, several of the Wall children (who had a mixed race father and a mixed race mother) chose to move away from their family home and pass for white in their twenties and thirties. In his biography, Williams (1996) discusses how his father decided to pass for white in his twenties, after serving in the military.

[23] For example, Sharfstein (2007) discussed how the last Wall child to remain in D.C. finally decided to pass himself and his daughter for white after she is asked to leave several schools because her father would not deny that he was colored.

of individuals who had the choice of passing (i.e., they were typically assumed to be white), but asserted their non-white identity. A prominent example is Gregory Williams, who wrote an autobiography of his and his father's experience with racial passing (Williams, 1996). Another example is Stephen Wall, who chose to live publicly with his black identity (until late in life) (Sharfstein, 2007).

Passing was not always permanent. Sometimes, individuals passed to obtain a job or attend school, and then later pass back. For example, historian Allyson Hobbs recounts the life of Harry Murphy who allowed a navy recruiter to identify him as white in the 1940s. He then attended Ole Miss in Mississippi as a white student, but later self-identified as black (Apel, 2014).[24] Other times, circumstances would force one who has passed as white to pass back to being black. For example, Williams (1996) discusses how alcoholism, divorce and the loss of his business forced his father to move himself and his children back to his childhood home, where he returned to his black identity and told his children for the first time that they were not white. Another example is Stephen Wall, who "For the next ten years the family moved neighborhoods repeatedly from white to black to white again" (Sharfstein, 2007, p. 270).

Note that the First Great Migration of blacks from the South to the North occurred during our study, when the advantageous economic and social opportunities of the North caused up to 40% of the black population in the south to migrate north (Carrington, Detragiache, and Vishwanath (1996)). This could partly contribute to the high pass rates that we will find if some took this move as an opportunity to pass for white.

In the Online Appendix, we provide some illustrative examples of historical persons who passed for white, as well as contemporary figures who would be "black" under the one-drop rule.

[24]See Online Appendix Section B for a more detailed discussion and photograph.

3 Data

We use the digitized U.S. Historical Censuses for the years 1880 - 1940.[25] 1880 is provided by the North Atlantic Population Project (NAPP). For 1900 - 1940, we obtained digitized data for a large number of variables from FamilySearch, a genealogical organization.[26] These variables include first name, last name, age, birth year, county, state, state or country of birth, race, gender, marital status and enumerator districts. Father's and mother's birth states and countries are also available for the years 1880 to 1930.[27]

Racial classification was determined by the census enumerator. In 1880, 1910 and 1920, racial categories included "white", "black" and "mulatto". In 1900, 1930 and 1940, the categories were only white and black, with mulatto merged into the black category. The instructions to enumerators were vague. For example, in 1900 they stated "Be particularly careful in reporting the class mulatto. The word is here generic, and includes quadroons, octoroons, and all persons having any perceptible trace of African blood. Important scientific results depend upon the correct determination of this class in schedules 1 and 5". In 1910 and 1920, they stipulated that "For census purposes the term 'black' (B) includes all Negroes of full blood, while the term 'mulatto' (Mu) includes all Negroes having some proportion of white blood" (Steven Ruggles and Sobek, 2010). In 1930 and 1940, the instructions were similar, except that the category of mulatto was removed.

From these instructions and the legal definition of race discussed earlier, it is reasonable to believe that enumerators inferred the race of respondents based on physical appearance, behavior and association. The requirements for a person of African extraction to be classified as white in the census were presumably similar to the requirements for the legal cases discussed by Gross (2009) in Section 2.3.

Our study focuses on males because of the difficulties in tracing women over time (women

[25] The 1850 and 1860 Censuses only reported names of free blacks. Since most of the black population was under slavery, this means that these earlier data contain names only for a small subset of the population in which we are interested. For the 1870 Census, only the 1% sample is currently digitized. The data from 1890 were lost to a fire.

[26] We obtained all of the variables that they have already digitized.

[27] Father's and mother's names are also available for some years. We currently do not use these variables because of the high number of missing values.

change their names when they marry). The main exercise divides individuals into two race categories: white and black. Black in our study includes mulattoes (for 1880, 1910 and 1920) so that the categories are consistent over time.[28]

Passing in our context refers to a change in census identification from black to white from one census to the next, and *reverse-passing* refers to a change from white to black. As we discussed in Sections 2.3 and 2.4, being classified as white required an individual to behave as and live with whites (in addition to having a caucasian appearance). Since mixing was highly discouraged in most places and illegal under segregation, passing in the census was almost certainly an intentional act and can also be interpreted as an individual identifying himself as white in everyday life.

For the purposes of our study, there are several interesting facts to note about the census data. First, the main purpose of the U.S. census was to determine the number of representatives per state in the house and the number of electoral votes. It is also used to compute aggregate statistics. To the best of our knowledge, individual census data have never been shared across government agencies such as those for tax collection or assessing an individual's immigration status. By law, identifiable information is not released until 72 years later. Besides racial passing, there was no obvious reasons for respondents (or enumerators) to fabricate information in the census.

Second, enumerators in our sample appear to all be white and mostly local.[29] This means that they are likely to apply the definitions of white that we discussed earlier and that it would have been difficult for an individual to pass without geographically relocating. This also means that individuals passing for white in everyday life would have wanted to maintain their white identity for the census enumerator.

One problem with the historical censuses is that it undercounts approximately four to five

[28] We examine mulattoes as a separate category for the years when data are available in Online Appendix Section J and Online Appendix Table A.4. Mulattoes have slightly higher pass rates than blacks.

[29] Enumerator information has not been digitized. We selected a sample of enumerators from microfilms, which contain unique enumerator IDs for each district and the names of the enumerators. We then manually coded these data and searched for the enumerators in the digitized census data to identify his or her county of residence and race. We examined select districts with a gradient of racial compositions (all white, mixed, all black). In all cases, we find that the enumerators were white and resided in the same county (or neighboring county in the case of all black counties).

percent of the population (Prewitt, 2013, p. 107, Table 1). We discuss this in the Online Appendix Section D.

4 Tracing Individuals Over Time

4.1 Matching

To identify a change in race, we need to trace individuals over time by linking individual identifiers across censuses, the most important of which is the name.[30] However, matching names across censuses faces several significant challenges. First, names are rarely unique within a given population. Second, in populations with low literacy rates, names are frequently misspelled. This problem is particularly prominent for studies of historical racial passing due to the low literacy rates amongst the black population, because racial passing is presumably facilitated by geographic relocation, and because there is a prevalence of strong regional accents and region-specific names during the period of our study. For example, an illiterate individual from Louisiana with the surname of Thibideaux, who chooses to move to another state, would likely have his name spelled phonetically as Tibido. In addition, there are frequent errors from the entry of the name by the enumerator or during the digitization process.

To allow names to be misspelled because the enumerator spells the name phonetically, we must match two names according to their phonetics. Our matching algorithm will employ several methods that have been developed by linguists and computer scientists.

Figure 1 provides a flow chart to illustrate the matching algorithms we use. As an example, we will discuss matching an individual in 1900 to his future self in 1910. Because it is computationally infeasible to run our entire algorithm while allowing every person in 1910 to be a potential match for each person in 1900, we must first restrict the pool of potential matches. Since we want to maximize the chances that the true match is within the restricted pool, we use the phonetic translation that is known to yield the largest number of matches, Phonex.[31]

[30] Social Security numbers were introduced in the United States in 1935 with the New Deal.

[31] See the Online Appendix Section E for a discussion of Phonex and other phonetic translation methods.

This still yields a very large number of potential matches. Thus, we broadly follow Ferrie (1996) and use age, birth state and parental birth state (when available) to further restrict the sample. Specifically, we implement the following steps to construct a "using sample" of manageable size.

1. Match the phonetics of first and last names that are standardized using the Phonex algorithm. If there are no Phonex matches, then an individual is dropped from the sample. This creates sample (1).

2. From sample (1), drop any matches whose matched age is more than three years older or three years younger than the predicted age. If all matches are outside of this age interval, the individual is dropped from the sample.[32] This creates sample (2).

3. From sample (2), match birth states. If there is at least one match, then drop all those from sample (2) who do not have matching birth states. If none from sample (2) have matching birth states, then keep all potential matches. This creates sample (3).

4. From sample (3), match on parental birth states. If there is at least one match, then drop all those from sample (3) who do not have matching parental birth states. If none from sample (3) have matching parental birth states, then keep all potential matches. This creates the "using sample".

We then apply three matching algorithms to the using sample – *Perfect*, *Ferrie* and *Jaro-Winkler* (JW) – and four alternative sets of restrictions – "unique", "closest age", "upper bound" and "lower bound" – for each algorithm to construct twelve samples that are used in our main analysis.

We begin by constructing the three types of matches. First, we construct Perfect matches. These are matches for which the spelling of the first and last names are identical. If there exists a perfect match, we remove the imperfectly matched names from the using sample sample (e.g., if Ravale Thibodeaux in 1900 has the potential matches of Ravale Thibodeaux and Raval Tibido in 1910, the latter is dropped from the using sample).

[32]We show that our results are robust to alternatively restricting potential matches to those who are within -/+ five years of the predicted age in the Online Appendix Section G.

From the resulting sample, we construct Ferrie and JW matches. For Ferrie Matches, we follow Ferrie (1996) and translate each name into Soundex codes. If the Soundex codes match across years, then we have a match.[33]

For JW matches, we construct Jaro-Winkler scores for each potential match. The Jaro-Winkler approach, first used in economics by Mill and Stein (2012), assigns a score designating how close each potential match's first name in 1910 is to a given individual's first name in 1900. The score is a continuous number from 0 to 1, where a higher score reflects a "closer" match for a given pair of names. Perfect matches will obviously have a JW score of 1. For imperfect matches, JW provides a score that reflects the number of matching characters and the required changes necessary to go from the potential match to the name that is to be matched. It puts more weight on the first part of a string than the last part.

The JW score is our preferred matching method *ex ante* because relative to previous matching methods, it contains more information. This is because the translation it uses retains more information from the original name than previous phonetic methods (e.g., it retains all the vowels and does not drop any part of the name). Moreover, phonetic matching algorithms are binary - i.e., a name either matches phonetically or it does not – and do not rank the relative closeness of the match amongst names that match perfectly phonetically. In contrast, JW scores are continuous measures of all potential matches ranging from pairs that are almost certainly not a match to perfect matches. The downside of the JW score is that it is much more computationally intensive, which is probably why it has been so rarely used until very recently.

We calculate the JW score for first and last names independently. The maximum sum of the two scores is two. In the data, we find that the match rate (for any of the matching restrictions that we discuss later) is constant for thresholds where the sum is between one and 1.6. As the threshold increases from 1.6 to two, the match rates decline. We therefore arbitrarily identify a match as a pair where the sum of the scores is more than 1.8, which is the middle of the range between 1.6 and two. This allows the JW match to allow more matches

[33]See Online Appendix Section E for a description of Soundex.

than the Perfect match, but still be potentially more rigorous than the Ferrie match.[34]

Among the three matching methods, Perfect matches are the most restrictive and, by construction, are included in both the Ferrie and JW matches, which we find *ex post* to be similar to the results produced by the Ferrie method.

The second step is to impose restrictions on the matches so that we have single matched pairs (i.e., one person in 1910 to correspond to each given name in 1900). Figure 2 provides a flow chart to illustrate the restrictions we impose from this point onward to construct the final samples.[35]

All three matching methods can produce *unique* or multiple matches. A *unique* match results when there is only one match after implementing the matching algorithms discussed above. For example, in the case of a perfect match, a unique match for Ravale Thibodeaux in 1900 results when there is exactly one Ravale Thibodeaux in 1910. Such matches will enter the *Perfect Unique* sample. Similarly, unique matches from using the Ferrie or JW methods will enter the *Ferrie Unique* or *JW Unique* samples.

Multiple matches result when there are, for example, more than one Ravale Thibodeaux in 1910. In this case, we first restrict the sample to the potential match with the closest age. We then identify the individual with the closest age as a match. If there are multiple people with the same closest age, we then examine whether they have the same race or a different race. If they all have the same race, then we randomly choose one of the potential matches as "the" match. This is the *Closest Age* sample. We call the sample constructed from multiple Perfect matches the *Perfect Closest Age* sample. Similarly, we call the samples constructed from multiple Ferrie and JW matches the *Ferrie Closest Age* and the *JW Closest Age* samples.

As we will discuss later, the construction of the Closest Age sample achieves the largest gains for our match rates relative to previous studies. Since we are forcing a match by randomly choosing amongst potential matches only if they all have the same race, this step does not affect the pass rate.

[34] We discuss alternative thresholds in Online Appendix Section H.

[35] In Online Appendix Section F, we also provide an illustrative example of the number of potential matches at the different stages of the algorithm.

If there are multiple people with the same closest age and some of them have different races, we create two samples which will produce upper and lower bounds of the true pass rate. The *Upper Bound Sample* will choose a closest age potential match with a different race, thus maximizing the probability that we observe passing. If there are multiple potential matches at this point (e.g., potential matches have the same closest age and the same race, which is a different race from the individual we are trying to match), then we randomly choose one to be the match. In contrast, the *Lower Bound Sample* will choose the closest age potential matches with the same race as the individual we are trying to match, thus minimizing the probability that we observe passing. From this procedure, we construct six samples: *Perfect Upper Bound*, *Perfect Lower Bound*, *Ferrie Upper Bound*, *Ferrie Lower Bound*, *JW Upper Bound* and *JW Lower Bound*.

By construction, all matches in the Closest Age Sample are included in both the Upper and Lower Bound Samples, and for any given restriction (closest age, upper bound, lower bound), matches from the Perfect matching method will be included in matches from the Ferrie and JW methods.

We designed our matching algorithm to be as similar as possible to existing studies for comparability. The key innovation of our method is to allow for multiple matches, which increases the match rate in a way that does not bias estimates of the pass rate.

Our method mainly departs from existing methods in two places. The first is in constructing the using sample. Like most previous studies, we drop the potential matches with non-matching birth states if there are potential matches with matching birth states. However, we keep all potential matches if they all have non-matching birth states, whereas previous studies typically would have dropped these.

Note that relative to most existing studies, our matching exercise is much more computationally intensive. This is because we attempt to match the entire black population, more than four million individuals, in each census. This is a much larger sample than previous studies have attempted to match. Moreover, in allowing individuals to change race, we cannot use race as a matching variable, which greatly enlarges the number of potential matches for each individual that our algorithm must sift through.

The second point of departure is when we have multiple matches after applying the Perfect, JW or Ferrie algorithms to the using sample. Previous studies would mostly drop these multiple matches. In contrast, we randomly select amongst multiple potential matches of the same race so that we force a match, but do not bias the pass rate. This step, as we will show in the next section, provides the largest gains in matches relative to existing studies. We then achieve additional matches by constructing our upper and lower bounds.

The only unmatched individuals in our sample are individuals that *i*) are not in the using sample, or *ii*) those within the using sample, who fail to have any Perfect, JW, or Ferrie match. We will take this into account when we calculate the absolute bounds for the population pass rates in Section 5.

Even with the perfect technology for tracing individuals, we expect a certain level of non-matches due to individuals who exit the population (e.g., death, emigration) and those that intentionally change their names. If passers are more likely to emigrate, then our estimates (i.e., the absolute lower bound estimates that we discuss in the next section) will undercount passers. Based on anecdotal evidence, this seems to have been true for many mixed race individuals who moved to Europe, where racial discrimination was relatively less extreme. On the other hand, if passers were less likely to emigrate, we will over-count passers. It is unclear whether this relationship would be true for the African Americans who migrated to other places such as Africa. However, the total number of such emigrants after emancipation was extremely small.[36] Thus, this is unlikely to affect our population estimates of passing.

Intentional name changes would affect our study if some of those who pass intentionally change their name to avoid former associations. For example, Cook, Logan, and Parman (2013) finds that some names (e.g., Abe, Abraham or Alonzo) were much more racially distinctive than other names (i.e., shared by a high percentage of blacks). If an individual with a distinctively black name wished to pass and changed his name completely so that there is no phonetic match, he will be dropped from the using sample. This will cause our method (i.e.,

[36] See Jenkins (1975).

the absolute lower bound estimates that we discuss in the next section) to understate the true pass rate. Alternatively, he could change his name so that there is still a phonetic match, but to a different person. If the other characteristics fulfill the matching criteria of this second person, this would result in a false match.[37] If the false match is more likely to be black, then our estimates will understate passing. However, since an individual who changes his name intentionally to pass would presumably choose a new name that is common to whites, the false match would arguably be more likely to be white. In this case, our estimated pass rates would be unaffected.

Note that a given individual in the following census year can be matched to multiple individuals in the base census year. This is true for all matching methods used in past studies and will not bias the pass rate estimates.

The main advantage of our matching method over past methods is to increase the match rates, and hence improve the bounds around any true population statistic. The most important caveat for our method is that it introduces random measurement error in the estimated statistic (since we mostly randomly choose amongst multiple matches). This does not affect analyses where the estimate of interest is a dependent variable, such as in our study or past studies that we discussed in the Introduction. However, for analyses that use the estimated population statistic as an explanatory variable, the classical measurement error introduced by our method can generate attenuation bias and will need to be corrected by methods such as Split-Sample IV (Angrist and Krueger, 1995).

4.2 Match Rates

Table 1 presents the match rates for the full sample. We present the percentage of the population that enters our using sample and then the match rates for individuals within the using sample for each matching algorithm and restriction combination. The table shows that approximately 72% of the full population enters the using sample.

The match rates across matching algorithms and restrictions are as expected. Perfect

[37]If the other characteristics do not, then we would have a non-match and again understate the true pass rate.

matches result in many fewer matches than JW or Ferrie for all restrictions. For example, Perfect Unique matches achieve only a 22% match rate, while JW and Ferrie Unique matches achieve 37% and 41% match rates. For each matching algorithm, Closest Age matches achieve nearly double the match rates as Unique matches. They range from 45% for Perfect Closest Age to 79% and 86% for JW and Ferrie. By construction, Lower and Upper Bound match rates are identical for each matching algorithm and higher than the Closest Age match rates. It is interesting to note that the bounds are quite close to the Closest Age match rates. For example, for JW, the bounds achieve an 84% match rate. Thus, our matching algorithms achieve most of its gains relative to past studies in moving from Unique matches, which are similar to previous studies, to Closest Age matches, which allow for multiple matches.[38]

Our JW algorithm and Closest-Age restriction (Table 1 column (2) row (B)) is most comparable to the method used by Mill and Stein (2012). However, there are three key differences. First, they only keep potential matches with the same birth state. Second, when they have multiple matches of the same closest age, they identify a match when a potential match is the next closest JW score which is above a certain arbitrary threshold. If the next closest JW score is below the threshold, then there is no match.[39] Finally, they use a different sample – i.e., we are examining the full population rather than only households with mixed race and black children.

To obtain the match rate for the full population, we multiply the percentage of those that enter the using sample with the JW Closest Age match rate as reported in Table 1, which is 57% ($.72 \times .79 = 0.57$). For the bounded matching methods, the match rate is 61% ($.72 \times .84 = 0.61$). The highest full sample match rate we achieve is the product of the percent that enter the using sample and the Ferrie bounded match rates 67% ($.72 \times .93 = .67$). Note that one of the key reasons for an individual to not enter the using sample is mortality

[38]Online Appendix Figure A.9 presents the match rates for each census interval and each matching algorithm-restriction combination. They show that the match rates are broadly similar over Census intervals for all matching methods.

[39]This suggests that an alternative method for us to identify a match amongst multiple closest-age matches is to choose the potential match with the next highest JW score. As long as the ranking of JW scores are unrelated to passing, this will achieve the same result as our current algorithm. Since we are unsure whether this is true, we prefer our current algorithm, where the random selection amongst multiple closest age matches forces randomness.

between census years. We discuss this in Online Appendix Section I.

5 Passing

5.1 Rates of Racial Passing

Table 1 panel II presents the pass rates for each algorithm-restriction combination for the full sample. Column (2) row (B) shows that according to the JW Closest Age method, 34% of individuals who were black during 1880-1930 passed for white in the following census. The lower and upper bound pass rates are 32% and 38%. Note that the JW Unique pass rate is also very high, at 29%.

As with the match rates, JW and Ferrie algorithms produce very similar pass rates. Both are unsurprisingly higher than Perfect pass rates, although the difference is not big. To understand the difference, let us for simplicity focus on the Unique restriction, where the main difference between JW or Ferrie and Perfect is that the first two require perfect phonetic matches of names, whereas the latter require perfect spelling matches of names. If passers are more likely to geographically relocate, then regional names and pronunciations will cause Perfect pass rates to be lower than JW or Ferrie pass rates. Nevertheless, even if we restrict the sample to Perfect Unique matches, the pass rate is 25%.

The same logic can explain why Ferrie pass rates are slightly higher than JW pass rates, since Ferrie requires a looser phonetic match than JW.[40]

That the Closest Age restriction results in slightly higher pass rates than the Unique restriction for any matching algorithm could be due to passers having relatively common names. The differences in the bounded restrictions are mechanical.

To obtain bounds for the true population pass rates, we need to also take into account individuals who do not enter the using sample and also do not obtain any Perfect, JW or Ferrie matches. Table 2 presents the "absolute" upper and lower bounds for each of the three matching algorithms for the whole sample period. For a given algorithm, the absolute upper

[40]Online Appendix Figure A.10 presents the pass rates for each census interval using each algorithm-restriction combination. It shows that pass rates are highest for the 1880-1900 interval. This is likely to be due to the fact that this interval covers two decades instead of one decade as in the subsequent intervals.

bound is obtained by combining the upper bound pass rate from Table 1 with individuals that were excluded from the using sample and those in the using sample for whom we were unable to find any matches, and assuming that all of the excluded and unmatchable individuals passed. Analogously, the absolute lower bound is obtained the same way, except that we assume that none of the excluded and unmatchable individuals passed. For example, the absolute lower bound pass rate using the JW algorithm is the product of the JW Lower Bound pass rate shown in column (2) of the table (32%, also see Table 1 Panel I), the percentage of individuals that entered the using sample (72%, see Table 1) and the percentage of those in the using sample that had any matches using the JW Lower Bound algorithm-restriction combination (84%, see Table 1). These absolute bounds substantially under and over state the true pass rate because, as we discussed earlier, a large number of unmatchable individuals come from population exits or (presumably) deliberate name changes when passing. The estimates using the JW Closest Age method in column (2) show that the true population pass rates is at least 19% and no more than 63%. The Ferrie pass rates are very similar. The perfect matches have larger bounds, which is due to there being fewer perfect matches.

For brevity and to be conservative, the rest of the paper focuses on absolute lower bound pass rates from using the JW matching algorithm. As we discuss earlier, they are very similar to (only slightly lower than) pass rates from using the Ferrie algorithm.[41]

To compare the pass rates that we estimate to what they would be if we used the same matching procedure as previous studies, recall that past methods would have produced results similar to the unique pass rates in Table 1 Panel II row A (Perfect, JW and Ferrie unique pass rates are 25%, 29% and 34%). Thus, the absolute lower bound pass rates for the JW method that we focus on in Table 2 column (2), 19%, are substantially lower than the pass rates from using past methods.

[41] All of our results using the Perfect and Ferrie algorithms are available upon request.

5.2 Passing by Cohort

Thus far, we have focused on the "flow" of passers – i.e., what percentage of blacks passed for white between each census interval? We can also examine the "stock" – i.e., what percentage of individuals who were black in 1880 became white by 1940? Table 3 presents these estimates. Panel I shows the pass rates for those who were black and age five to fourteen in 1880. We focus on this age group to avoid interpretation difficulties from high child mortality rates.[42] Column (2) presents the JW Closest Age estimates. Column (3) presents the JW lower bound estimates. Column (4) presents the absolute lower bound estimates, which is calculated the same way as before.[43] This shows that for black children who were ages five to fourteen in 1880, at least 20% had passed for white by 1940. Panels II and III present similar statistics for the analogous age groups observed starting in 1900 and 1910. We do not repeat this for 1920 and 1930 since we would only be able to observe them twenty and ten years later at most.

The three cohorts exhibit similar patterns. The stock of passers grew little over time. This suggests that a significant proportion of total passing occurred before age fifteen to twenty-four, with a modest amount of additional passing afterwards. However, note that we will later show that approximately 10% of passers reverse-pass to being black. Thus, the incremental passing over time for a given cohort is net of the reverse-passers. In other words, the change in the stock shown in this table will slightly understate the flow of passing during each census interval.

When comparing the stock of total passers, we also see that there is little change in passing across cohorts. For example, 18% of the 1880 cohort had passed by thirty years later (Panel I row B). This is similar to the 20% for the 1900 cohort (Panel II row C) and the 19% for the 1910 cohort (Panel III row C). It will be interesting to examine the pass rates for more recent periods (especially after the Civil Rights Act of 1957) when individual data from more recent censuses become available.

[42] See Online Appendix Section I for a discussion of mortality rates.

[43] For example, in examining what percentage passed in 1920 amongst those who were age 5-14 in 1880, we assume that all individuals who are not in this using sample or have JW lower bound match did not pass.

5.3 Reverse Passing

To investigate the degree to which passing was temporary, we estimate the percentage of passers who return to being black in the following census year. Table 4 column (1) restates the JW Closest Age pass rates for each census interval. For this exercise, we focus on reverse-passers amongst JW Closest Age passers because the procedure is simpler to explain.[44]

Column (2) shows the reverse pass rates. Both columns (1) and (2) use the JW Closest Age method. In Column (3), we calculate the lower bound of reverse pass rates. Column (3) row A shows that amongst the 41% of black males who passed for white during 1880 and 1900, more than 15% reverse-passed to being black in 1920. Column (4) presents the absolute lower bound of reverse passing by assuming that individuals who pass (e.g., 1880-1900), but do not have a JW lower bound match in the subsequent year (e.g., 1910) did not reverse-pass. It shows that for the same time period, at least 11% reverse passed.

Similarly, for the following census intervals, the lower bounds pass rates show that at least 8% to 13% reverse-passed. Such high percentages of reverse passers confirm the historical case studies discussed in Section 2, where passing could be temporary in reaction to changing opportunities and circumstances. That an individual can pass back and forth emphasizes the fluidity of race.

5.4 Geography of Passing

5.4.1 Geographic Relocation

According to the historical evidence discussed in Section 2, an individual who wished to pass needed to relocate geographically to a place where his former race was unknown and, since race was determined mainly by association, passers needed to move to white communities. We can investigate both of these hypotheses with our data.

The historical census allows us to identify the county and state of residence. Thus, we can test the hypothesis that passers are more likely to move than non-passers, and that almost

[44]The reverse-passing results are nearly identical if we look for reverse-passers amongst JW Lower Bound passers or JW Absolute Lower Bound passers. These results are available upon request.

all passers move. Table 5 presents the move rates for passers and non-passers (i.e., black individuals who remain black in the subsequent census) for each census interval. Panel I presents the percentage of those who move counties (within or across states). A mover is someone who resides in a county that is different from where he resided in the previous census year. We present three statistics. The first is the percent of those who pass according to the JW closest age algorithm and who also move. The second statistic is the percent of those who pass according to the JW lower bound matching algorithm and who also move. For passers in column (1), this will be mechanically identical to the JW closest age move rate.[45] Finally, we present an absolute lower bound move rate. For passers, this assumes that all those who do not have a JW lower bound match and do not enter the using sample pass, but do not move. For non-passers in column (2), we make the symmetric assumption that all of those who do not have a JW lower bound match and do not enter the using sample do not pass and do not move.

The absolute lower bound move rates in Panel I row (C) show that between 1880 and 1900, at least 53% of passers and 44% of non-passers moved counties. That the move rate is higher for passers is consistent with the fact that geographic relocation was necessary for passing. That the absolute lower bound move rates for passers is lower than 100% is likely to be due to the fact that many will move communities within counties, and that our absolute lower bound estimates are extremely conservative.

To assess the credibility of our estimated migration rates, we compare the estimates for non-passers to estimates of white inter-county migration rates during 1870 and 1900 by Ferrie (2005, Table 2). He finds the rate to be approximately 54.7%, which is similar to the absolute lower bound move rates for passers and in between the absolute lower bound and closest-age move rates for non-passers for our 1880-1900 estimates. Thus our estimates are broadly comparable to those in the literature.

In Panel II, we present the same statistics for the rates of moving across states. Row

[45]This is because passers in the JW closest age and lower bound groups are identical. The two groups only differ in that the latter includes multiple matches in a way that forces them to not pass. Thus, the two restrictions will produce different move rates only for non-passers.

(C) columns (3) and (4) show that at least 32% of passers and 15% of non-passers moved states. Again, the higher rates of moving for passers is consistent with historical evidence that moving is necessary for passing. That the rates of moving states for both passers and non-passers is lower than the rates of moving across counties is consistent with the fact that it is costlier to move longer distances. As with the cross-county move rates, note that the absolute lower bound estimates are extremely conservative.

In the subsequent rows, we present the analogous move rates for the later census intervals. The pattern that passers are more likely to move than non-passers, and that both groups are more likely to move across counties than across states are consistent throughout the sample. In comparing the move rates over time, note that the 1880-1900 interval covers two decades rather than one. Thus, the fact that move rates are similar between 1880-1900 and the subsequent one-decade census intervals is consistent with the fact that U.S. migration increased during this time. That the rate of relocation is very high for non-passers is consistent with the fact that this is a period of extremely high migration.[46]

5.4.2 Which states do passers come from?

To examine where passers come from, Table 6 presents the pass rates by the state of origin (where an individual lives when he is observed to be black – i.e., the beginning of a census interval). Column (1) restates the results for all states. Column (2) includes the former non-slavery Union states.[47] Column (3) presents pass rates for individuals that originate in the former Confederate States.[48] Column (4) includes the former Confederate states and the

[46]The disparity between the cross-county and cross-state migration rates implies that many passers moved counties within the same state. This suggests that there may have been variation in pass rates within states. We investigate this by estimating pass rates for each county and census interval. For brevity, we calculate the average pass rate for each county. Online Appendix Table A.1 presents the mean and standard deviation of this average for each state. Column (3) normalizes the standard deviation by dividing it by the cross-county mean and shows that there is substantial variation in pass rates across counties within the same state. The table shows that there is within-state variation. Note that the average pass rates are very high for some of the western and plains states. This is due to the fact that Native Americans and Asians are categorized as blacks in these states. We discuss this in detail in the next section.

[47]Massachusetts, Connecticut, California, Illinois, Indiana, Iowa, Maine, Michigan, Minnesota, New Hampshire, New Jersey, New York, Ohio, Oregon, Pennsylvania, Rhode Island, Vermont and Wisconsin.

[48]Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Tennessee and Virginia.

four states that had legalized slavery in 1860, but did not join the Confederacy.[49] Column (5) includes the states where 98% of the black population resided.[50]

We do not separately examine the western and some of the plains states because the way we have defined black (i.e., to include mulattoes in years when mulattoes are a separate category) means that our definition mostly capture Asians and Native Americans for these states.[51] Thus, pass rates for these states are not informative for our research question. Because of the small population of blacks in "other" states, they do not enter the sample in column (5) or affect the pass rates for all states shown in column (1).

Table 6 shows that pass rates are highest in the Northern states in column (2). Also, note that restricting the sample to the states where most of the black population resided in column (5) unsurprisingly results in very similar pass rates for the full sample.

To more easily visualize the data, we map the absolute lower bound pass rates in column (5) over our entire sample period (row C). In Figure 3a, the states are divided into five groups according to their absolute lower bound pass rates, where darker shades indicate higher pass rates. We see that pass rates are the highest in the Northern states and lowest in the deep South.

5.4.3 Where do passers live?

To investigate where an individual resides after he has passed, we present the pass rates in the state of residence during the second year of each census interval. This will capture those who pass and do not move states, as well as those who originated in another state, passed and moved to the current state of residence. These are presented in Table 7. We divide the states into the same categories as before. Note that for these pass rates, we can only compute the absolute lower bound pass rates for all states, which will be mechanically identical to those

[49] Delaware, Kentucky, Maryland and Missouri.

[50] In descending order of the size of the black population (as a percentage of total U.S. black population), they are Georgia, Mississippi, Alabama, South Carolina, North Carolina, Louisiana, Texas, Virginia, Tennessee, Arkansas, Florida, Washington, Kentucky, Maryland, Pennsylvania, New York, Missouri, Ohio, Illinois, New Jersey, Oklahoma, Indiana, West Virginia, Michigan and Kansas. See Online Appendix Table A.3.

[51] This can be seen by the fact that in years when mulattoes are separately categorized, there are almost no blacks in these states.

by origin state in Table 6. We are unable to compute the absolute lower bound pass rates by region because we do not know individuals' destination state for those that do not have a match.

A comparison across columns show that pass rates are highest for those residing in the North for all periods. This can be seen clearly in Figure 3b, which maps the JW lower bound pass rates for the entire period for the states where 98% of the black population reside (column (5) row B).

5.4.4 Do passers move to "whiter" communities?

According to the historical evidence in Section 2, an important determinant of moving was the need for passers to reside in a white community such that he can pass by association. To see whether this was true on average, we examine whether passers move into white communities. The limitations of the data force us to identify a community as a county.[52] We calculate the fraction of individuals (males) that report as white in each county. To see if passers move to "whiter" counties, we calculate the difference in the percent white of the county of residence during the current census year (when the individual has passed for white) and the percent white of the county of residence during the last census year (when the individual reported as black). If the historical evidence is correct, we would expect to see an increase in the "whiteness" of counties for passers relative to that of non-passers. However, since there are many communities within a county and most counties have mixed populations, we would not expect passers to move to 100% white counties even if segregation is fully enforced at the community level.

Figure 4 plots the CDF for passers and non-passers, where the x-axis is the change in the percentage of the county of residence that is white. Both for passers and non-passers, we restrict the sample to individuals who move counties. For completeness, we show the results for the entire sample. The CDF for passers who move (illustrated by the thick solid blue

[52]The historical census also reports enumeration districts. However, since district boundaries change across censuses, while county boundaries are relatively stable, we choose to use counties as the level of the community. Specifically, we would be concerned that enumeration district boundaries were changing in response to changes in the racial composition.

line) is to the right of the CDF for non-passers who move (illustrated by the thin solid red line). This means that passers are more likely to move to "whiter" counties than non-passers. Moreover, the CDF for passers is mostly to the right of zero, which means that passers on average moved to whiter communities. In contrast, the CDF for non-passers is centered around zero, which means that non-passers who move are just as likely to move to whiter as to less white communities.

Figure 4b plots the analogous CDF for those who pass and remain white versus those who reverse-pass to black. The figure shows that the relocation pattern of reverse passers is a mirror image of the pattern for passers: reverse passers (illustrated by the thick solid blue line) move to communities with a lower percentage of whites than those who remain white and move (illustrated by the thin solid red line).

6 Comparison with Recent Genetic Evidence

Given the lack of quantitative research on the extent of passing, we have few benchmarks to compare our estimates to assess their credibility. One possible comparison is with the recent genetic evidence. Research by *23andme* find that for the United States as a whole, the number of whites who would be black under the one-drop rule is approximately 20% of the 2010 African American population (Gates, 2014). While *23andme* does not have a random sample of the population and examines a different time period, it may still be useful to speculate about the comparability of our estimates with theirs under what are perhaps heroic assumptions. Specifically, under the assumptions that there was no more passing after 1940 and that passers had the same natural population growth rates (i.e., fertility and mortality) as blacks since 1940, then the percent of blacks in the full population who passed in 1940 should be the same as the percent of blacks who passed today. That we currently estimate the absolute lower bound stock of passers to be approximately 19% means that our estimates are very similar to the genetic evidence.[53]

[53] There is little evidence on the population growth patterns of passers at present. However, there was almost certainly more passing after 1940, which probably means that the *23andme* estimates of passing will increase over time as its sample expands to approximate a nationally representative sample.

7 The Correlates of Passing

The main goal of the paper is to quantify racial passing. In this section, we provide suggestive evidence on the correlates of passing to help motivate some future lines of research that are discussed in the conclusion.

The large magnitude of passing that we uncover naturally raises the question of why people pass. Moreover, for assessing how important it is to change our interpretation of racial variables from being exogenous to endogenous in future empirical studies that use race as an explanatory variable, we would like to know the extent to which passing is endogenous to political, economic and social factors –i.e., if the decision to pass was random, then finding a high rate of passing would not affect the current interpretation that race is exogenous.[54]

For this analysis, we restrict the observations to state and census years that have at least 10,000 black males. The association between the probability of passing and the explanatory variables of interest can be written as the following:

$$p_{jt} = \alpha + \beta E_{jt} + \theta_j + \gamma_t + \varepsilon_{jt},$$

where the pass rate of state j during base year t, p_{jt}, is a function of a constant, α; the explanatory variable in state j during base year t, E_{jt}; dummy variables for the state of residence in the base year (the first year of each census interval), θ_j; base year fixed effects, γ_t; and an error term, ε_{jt}. We present robust standard errors. State fixed effects control for time-invariant differences across states. Time fixed effects control for changes over time that affect all states similarly.

For each explanatory variable, we calculate the average for each state and census interval. We then match that to the state and base year of our pass rate estimates. This assumes that the probability of passing between 1900 and 1910, for example, depends on the conditions in an individual's state in 1900. Since passing can only be detected if we have two consecutive census years, the data for the political economic variables will include the base years, 1880

[54]If the decision to pass is random, then the high pass rate would imply that the estimated effect of race in previous studies is attenuated due to measurement error.

to 1930 (depending on data availability), while the pass rates use data from 1880 to 1940. In the table notes we report the base years.

Table 8 presents the regression results. Column (1) examines the influence of relative income on pass rates. Since income data is unavailable in the historical censuses, we follow previous studies to proxy for income with the occupational income score. IPUMS identifies the median income for each occupation using data from the 1950 Census. We then use data on the occupations of white and black workers for each census year and state to compute the average income of whites and blacks for our sample. Finally, we calculate the ratio of average black to average white income for each state and year and interpret this measure as a proxy for wage discrimination against blacks. This measure captures discrimination to the extent that blacks work in different occupations relative to whites (e.g., blacks are typically excluded from managerial positions). However, it is likely to severely understate true discrimination since it cannot capture wage differences between black and white workers within the same occupation. In our sample, the white-to-black income ratio is 1.43 on average. The estimate shows that pass rates are higher in places and times when whites earn more relative to blacks. The estimate is significant at the 5% level. The standardized coefficient in brackets shows that a one standard deviation change in the relative income score explains 0.14 standard deviations in pass rates.

Column (2) examines whether there is a lower rate of passing when and where miscegenation is legal.[55] We find that this is indeed the case. The coefficient is negative and significant at the 1% level. The standardized coefficient shows that a one standard deviation change in miscegenation laws explains 0.35 standard deviations of the variation in pass rates.

Column (3) examines the influence of political attitudes on pass rates. Specifically, we estimate the association between the fraction of Democratic votes for presidential and congressional elections and pass rates.[56] Both coefficients are positive in sign. The coefficient

[55] We collected data on the presence of anti-miscegenation laws. We code a variable as one if miscegenation (mixed race marriages) is legal. All of the variation for this variable occurs during 1880-1900. By 1900, it is illegal in all of the states in the sample.

[56] In our sample, the means for these variables are 58% and 62%, respectively. These data were generously shared with us by Suresh Naidu and are used in his paper, Naidu (2012).

for congressional votes is statistically significant at the 5% level. The standardized coefficient shows that a one standard deviation change in the fraction of Democratic congressional votes explains 0.29 standard deviations of the variation in pass rates.

Column (4) examines the association between access to education for blacks and pass rates. We proxy for access with the number of colleges that allowed black students.[57] During the period in our sample, schools were segregated. Since black students were prohibited from attending white universities, the presence of a black university significantly enhanced opportunities for blacks. We can also proxy for access to education for black students with measures of the quality of secondary schooling for blacks relative to quality of secondary schooling for whites. In particular, we use measures of teacher salary and the school term length.[58] The sample size of this regression is limited by the secondary schooling variables, which are only available for fourteen states starting in 1900. The estimates show that more black universities is associated with lower pass rates, while longer school terms for white students relative to black students lead to higher pass rates. As with the other explanatory variables, the standardized coefficients for these variables are large.

The results show that passing is associated with the social and political-economic returns to being white, and that these variables can explain a significant amount of the variation in passing. Thus, endogenous passing is likely to be a quantitatively important phenomenon. Note that we do not interpret these relationships as causal. Nor do we interpret the variables literally. Rather, these policy variables are likely to be strongly correlated with social racial attitudes.

Note that since much of the change in the incentives to pass may vary only across states or only over time, the inclusion of fixed effects is likely to absorb much of the variation that we are interested in (e.g., changes in general American racial attitudes over time). In this sense, our estimates should be interpreted as conservative estimates of the association between the

[57]This is provided by the U.S. Department of Education. In our sample, the average state-census year observation has less than four universities that allow black students, with only a small increase over time from almost three in 1880 to four in 1930.

[58]These variables are taken from Card and Krueger (1992), which also discusses how they capture quality differences in schooling. The data show that relative to black schools, teachers in white schools are paid almost twice the salary and the school term is 13% longer.

social, political and economic conditions and pass rates.

The scope of this analysis is unfortunately limited by the data availability for historical variables. For example, examining all of the variables in one regression would reduce the number of observations to 33.[59] Expanding the data and constructing empirical strategies to understand the causal determinants of passing is an important avenue of future research.

8 Conclusion

This study attempts to quantify the magnitude of racial passing in the United States during 1880 to 1940. We find that at least 19% of males of African extraction passed for white at some point in their lives. Consistent with the anecdotal and historical evidence, passing was accompanied by geographic relocation to "whiter" communities; reverse passing was common and accompanied by relocation to "blacker" communities. The latter supports the historical evidence that many individuals crossed back and forth from black to white and white to black. Thus, race is not a fixed characteristic over an individual's lifetime. Rather, it is fluid.

We also provide evidence that passing was positively correlated with social and political-economic opportunities for being white, or more generally, racial attitudes discriminating against blacks. This is hardly surprising, but provides novel, albeit suggestive, quantitative evidence that race is likely to be a choice and endogenous to many of the variables that the economics literature has examined as outcomes of race. As such, the relationship between race/ethnicity and economic and political outcomes is likely to be much more complex than typically conceived by the empirical literature.

Our matching algorithm makes a methodological contribution to studies that match individuals over time by substantially increasing match rates relative to past studies. This can be helpful for any study interested in population statistics that require linked individual data (e.g., migration). Our method of randomly choosing amongst multiple matches and constructing bounded estimates is not restricted to U.S. data and can be applied to data from other

[59] In that case, variables for congressional Democratic votes, the number of black universities, and school term length are still statistically significant.

countries or languages for which there exist phonetic translation methods. Our method does not necessarily increase the number of "true" matches. However, by increasing the match rate with mostly random selections, we are able to calculate tighter bounds around the estimated population statistic.

The main limitation of our method arises from the fact that such random selection mechanically increases measurement error around the estimated statistic. Since most of the additional error is random, this is not a significant problem for our study or other studies that use the estimated statistic as a dependent variable. However, for studies that wish to use the estimate as an explanatory variable, classical measurement error will increase attenuation bias. This may still be an improvement since the error structure of traditional methods could be classical or non-classical, and thus more difficult to correct. In contrast, one could potentially use methods such as Split-Sample IV to correct for classical measurement error (Angrist and Krueger, 1995).

The results of this paper raise many questions for future research. An obvious next step for researchers interested in evaluating the causal influences of race and ethnicity variables is to better understand the determinants of race change, which is necessary for developing plausible identification strategies. For example, economic historian Lisa Cook is constructing a comprehensive data set on lynchings, which could potentially be interpreted as a proxy for the extent of racial violence in a community and linked to pass rates. Similarly, as more indicators of socio-economic status are digitized from the historical censuses, researchers can begin to examine which types of individuals were most likely to pass, and which types of communities were most likely to induce passing.[60]

How endogenous race change affects the interpretation of empirical relationships partly depends on whether passers behave more like whites or blacks. For example, for political economy studies of the effect of regional racial diversity on voting outcomes, the interpretation would be unchanged if passers who identify as white vote like whites. However, if passers

[60]The historical censuses report the race and name of the spouse. When this information is digitized, researchers can also analyze in more detail the extent to which passing was driven by mixed marriages. For a recent study of the effects of miscegenation laws on interracial births, see Briseno (2013).

vote like blacks, then current estimates could be misleading. Similarly, for traditional wage regressions that examine the relationship of being black on earnings, the bias of the black dummy variable depends on the earnings of the average passer relative to the average black worker who does not pass and the average white worker. Thus, another important avenue of future research is to examine the political and economic behavior of passers relative to non-passers and whites.

The implications of endogenous race change will also depend on the research question that is being asked. For example, our results do not affect the interpretation of a regression of wages on whether a worker self-identifies as black today if one is interested in the effect of self-identity on earnings. In contrast, if one is interested in the impact of historical enslavement on wages today, then the econometrician would need to somehow account for the fact that many former slaves have since passed for white.

Our findings are related to a recent study by Cook, Logan, and Parman (2013), which documents racially distinctive names and points out that there is no evidence that blacks historically changed their names to overcome the probable economic disadvantage associated with distinctively black names. The high rate of passing we find suggests that an interesting avenue for future research is to explore whether individuals with distinctively black names changed their names and race such that matching methods that match on race cannot detect such name changes. Such an exercise would require a large number of variables so that researchers can identify matches without names, which may be possible in the near future with the expansion of digitized databases and computational power.

Finally, it is interesting to expand our exploration of endogenous race change beyond the U.S. context to others such as Sub-Saharan Africa, where ethnic and racial variables have been shown to be strongly influential for outcomes such as growth, institutions, public goods and conflict.[61]

[61]For some examples of this vast literature, see Easterly and Levine (1997), Bates (2000), Miguel and Gugerty (2005) and Caselli and Coleman (2013). The studies we discussed in the Introduction have already made some progress on this in the contexts of China, India and medieval Europe.

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Table 1: Match Rates and Pass Rates

Restrictions	Matching Algorithm: Perfect (1)	JW (2)	Ferrie (3)
	I. Match Rates		
Using Sample		*72%*	
A. Unique	22%	37%	41%
B. Closest Age	45%	79%	86%
C. Lower Bound	48%	84%	93%
D. Upper Bound	48%	84%	93%
	II. Pass Rates		
A. Unique	25%	29%	34%
B. Closest Age	27%	34%	39%
C. Lower Bound	26%	32%	36%
D. Upper Bound	32%	38%	43%

Notes: In Panel I, match rates refer to the percentage of matches within the using sample. A match is when an individual in year t can be matched to himself in the following census year. The sample includes all years, 1880-1940. In Panel II, pass rates are for the corresponding matched sample in Panel I.

Table 2: Pass Rates – Absolute Bounds

	Matching Algorithm		
	Perfect	JW	Ferrie
Restrictions	(1)	(2)	(3)
Absolute Lower Bound	9%	19%	24%
Lower Bound	26%	32%	36%
Upper Bound	32%	38%	43%
Absolute Upper Bound	76%	63%	62%

Notes: The absolute lower bound (upper bound) assumes that no (all) individuals excluded from the using sample or those in the using sample whom were unmatchable passed. The sample includes all years, 1880-1940.

Table 3: The "Stock" of Passing for Black Children

		% White		
	Year	JW Closest Age	JW Lower Bound	Abs Lower Bound
	(1)	(2)	(3)	(4)
	I. Black, 5-14 Years of Age in 1880			
A.	1900	38%	36%	19%
B.	1910	36%	34%	18%
C.	1920	39%	37%	20%
D.	1930	45%	44%	23%
E.	1940	54%	50%	20%
	II. Black, 5-14 Years of Age in 1900			
A.	1910	29%	28%	17%
B.	1920	39%	37%	20%
C.	1930	39%	37%	20%
D.	1940	47%	44%	20%
	III. Black, 5-14 Years of Age in 1910			
A.	1920	30%	28%	16%
B.	1930	34%	32%	18%
C.	1940	42%	39%	19%

Notes: Pass rates correspond to those who are black in the year stated in the panel heading, who become white in the years stated in column (1). The absolute lower bound assumes that no individuals excluded from the using sample or those in the using sample whom were unmatchable passed.

Table 4: Reverse Passing

	Pass Rates	Reverse Passed to Black in the Following Census Year		
	JW Closest Age	JW Closest Age	JW Lower Bound	Absolute Lower Bounds
	(1)	(2)	(3)	(4)
A. 1880-1900	41%	15%	15%	11%
B. 1900-1910	32%	11%	11%	8%
C. 1910-1920	33%	12%	13%	10%
D. 1920-1930	31%	17%	17%	13%

Notes: Pass rates and reverse pass rates are calculated using the JW Closest Age method. Column (2) reports the % who have passed during a census interval, who have returned to being black in the next census year. Column (3) presents the lower bound of reverse pass rates, where passers that cannot be matched to the following census year are assumed to all remain white. Column (4) presents the absolute lower bounds, which assumes that individuals who pass (e.g., 1880-1900), but do not have a JW lower bound match in the subsequent year (e.g., 1910) remain "white".

Table 5: Moving Rates across Counties and States

Year		JW Restriction	Passers (1)	Non-Passers (2)	Passers (3)	Non-Passers (4)
			I. Move Counties		II. Move States	
	A.	Closest Age	98%	79%	58%	27%
1880-1900	B.	Lower Bound	98%	81%	58%	28%
	C.	Absolute Lower Bound	53%	44%	32%	15%
	D.	Closest Age	94%	56%	55%	19%
1900-1910	E.	Lower Bound	94%	59%	55%	20%
	F.	Absolute Lower Bound	56%	35%	33%	12%
	G.	Closest Age	94%	56%	54%	20%
1910-1920	H.	Lower Bound	94%	60%	54%	21%
	I.	Absolute Lower Bound	56%	35%	32%	13%
	J.	Closest Age	95%	55%	60%	27%
1920-1930	K.	Lower Bound	95%	58%	60%	29%
	L.	Absolute Lower Bound	58%	36%	37%	18%
	M.	Closest Age	93%	49%	58%	24%
1930-1940	N.	Lower Bound	93%	53%	58%	27%
	O.	Absolute Lower Bound	57%	34%	37%	17%

Notes: Absolute lower bound move rates for passers (non-passers) assume that those who do not have JW lower bound matches and those who do not enter the using samples all pass (do not pass) and do not move. In Panel I, those who move across counties include both those who move within and across states.

Table 6: Pass Rates by Region (State of Origin)

			JW Pass Rates				
Year	JW Restriction		All States (1)	North (Union States) (2)	South (Confederate States) (3)	All slave states in 1860 (4)	States that Comprise 98% of the Black Population (5)
All	Closest Age	A.	34%	49%	31%	32%	34%
	Lower Bound	B.	32%	46%	29%	30%	32%
	Absolute Lower Bound	C.	19%	28%	16%	17%	18%
1880-1900	Closest Age	D.	41%	65%	37%	38%	41%
	Lower Bound	E.	37%	61%	34%	35%	37%
	Absolute Lower Bound	F.	20%	36%	18%	19%	20%
1900-1910	Closest Age	G.	32%	50%	29%	31%	32%
	Lower Bound	H.	30%	48%	27%	29%	30%
	Absolute Lower Bound	I.	18%	31%	16%	17%	18%
1910-1920	Closest Age	J.	33%	52%	30%	31%	33%
	Lower Bound	K.	32%	50%	28%	29%	31%
	Absolute Lower Bound	L.	19%	31%	16%	17%	19%
1920-1930	Closest Age	M.	31%	44%	28%	29%	31%
	Lower Bound	N.	30%	41%	27%	28%	30%
	Absolute Lower Bound	O.	18%	27%	16%	17%	18%
1930-1940	Closest Age	P.	37%	47%	32%	34%	37%
	Lower Bound	Q.	35%	44%	30%	32%	34%
	Absolute Lower Bound	R.	22%	29%	19%	20%	22%

Notes: The absolute lower bound (upper bound) assumes that no (all) individuals excluded from the using sample or those in the using sample whom were unmatchable passed. Column (2) includes Massachusetts, Connecticut, California, Illinois, Indiana, Iowa, Maine, Michigan, Minnesota, New Hampshire, New Jersey, New York, Ohio, Oregon, Pennsylvania, Rhode Island, Vermont and Wisconsin. Column (3) includes Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Tennessee and Virginia. Column (4) includes the states in column (3) and Delaware, Kentucky, Maryland and Missouri. Column (5) includes Georgia, Mississippi, Alabama, South, Carolina, North Carolina, Louisiana, Texas, Virginia, Tennessee, Arkansas, Florida, Washington, Kentucky, Maryland, Pennsylvania, New York, Missouri, Ohio, Illinois, New Jersey, Oklahoma, Indiana, West Virginia, Michigan and Kansas.

Table 7: Pass Rates by Region (Destination State)

			JW Pass Rates				
Year	JW Restriction		All States (1)	North (Union States) (2)	South (Confederate States) (3)	All slave states in 1860 (4)	States that Comprise 98% of the Black Population (5)
All	Closest Age	A.	34%	52%	25%	27%	31%
	Lower Bound	B.	32%	48%	23%	25%	29%
	Absolute Lower Bound	C.	19%	-	-	-	-
1880-1900	Closest Age	D.	41%	64%	27%	31%	38%
	Lower Bound	E.	37%	60%	24%	28%	35%
	Absolute Lower Bound	F.	20%	-	-	-	-
1900-1910	Closest Age	G.	32%	53%	22%	25%	30%
	Lower Bound	H.	30%	50%	21%	23%	28%
	Absolute Lower Bound	I.	18%	-	-	-	-
1910-1920	Closest Age	J.	33%	53%	24%	26%	31%
	Lower Bound	K.	32%	50%	23%	25%	29%
	Absolute Lower Bound	L.	19%	-	-	-	-
1920-1930	Closest Age	M.	31%	47%	23%	25%	27%
	Lower Bound	N.	30%	44%	22%	24%	25%
	Absolute Lower Bound	O.	18%	-	-	-	-
1930-1940	Closest Age	P.	37%	51%	27%	30%	32%
	Lower Bound	Q.	35%	48%	25%	28%	30%
	Absolute Lower Bound	R.	22%	-	-	-	-

Notes: The absolute lower bound (upper bound) assumes that no (all) individuals excluded from the using sample or those in the using sample whom were unmatchable passed. Column (2) includes Massachusetts, Connecticut, California, Illinois, Indiana, Iowa, Maine, Michigan, Minnesota, New Hampshire, New Jersey, New York, Ohio, Oregon, Pennsylvania, Rhode Island, Vermont and Wisconsin. Column (3) includes Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Tennessee and Virginia. Column (4) includes the states in column (3) and Delaware, Kentucky, Maryland and Missouri. Column (5) includes Georgia, Mississippi, Alabama, South, Carolina, North Carolina, Louisiana, Texas, Virginia, Tennessee, Arkansas, Florida, Washington, Kentucky, Maryland, Pennsylvania, New York, Missouri, Ohio, Illinois, New Jersey, Oklahoma, Indiana, West Virginia, Michigan and Kansas.

Table 8: The Correlation between Passing and the Political and Economic Advantages of being White

	Dependent Variable: Pass Rates* (JW Closest Age)			
	(1)	(2)	(3)	(4)
Dependent Variable Mean	**0.408**	**0.408**	**0.410**	**0.317**
WTB Occupational Income Score	0.0937			
	(0.0423)			
	[0.140]			
Miscegnation Legal		-0.143		
		(0.0178)		
		[-0.347]		
Presidential Democrat Votes			0.0724	
			(0.0876)	
			[0.115]	
Congressional Democrat Votes			0.145	
			(0.0650)	
			[0.290]	
# Black Universities				-0.0306
				(0.00617)
				[-1.243]
WTB Teacher Salary				0.0130
				(0.0189)
				[0.110]
WTB School Term Length				0.125
				(0.0506)
				[0.308]
Observations	306	306	291	92
R-squared	0.858	0.863	0.874	0.846
Years*	1880-1930	1880-1930	1880-1930	1900-1930
# States	28	28	27	14

Notes: All regressions control for state and year fixed effects. Robust standard errors are in parentheses. Standardized coefficients are in brackets. The samples are stated at the bottom of the table. They are unbalanced panels at the state-census year level. *Note that the pass rates for 1930 refer to the pass rates for the 1930-1940 interval.

Figure 1: Matching Procedure Part I: 3 matching algorithms are used to create 12 final samples

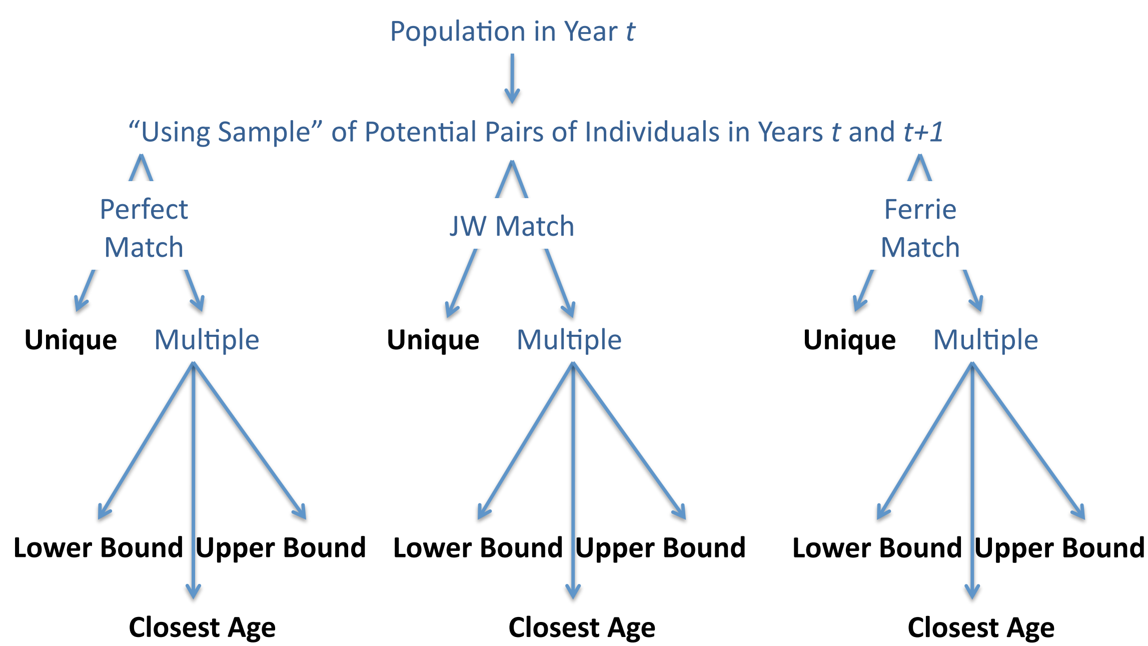


Figure 2: Matching Procedure Part II: The restrictions applied to each algorithm to create the final samples

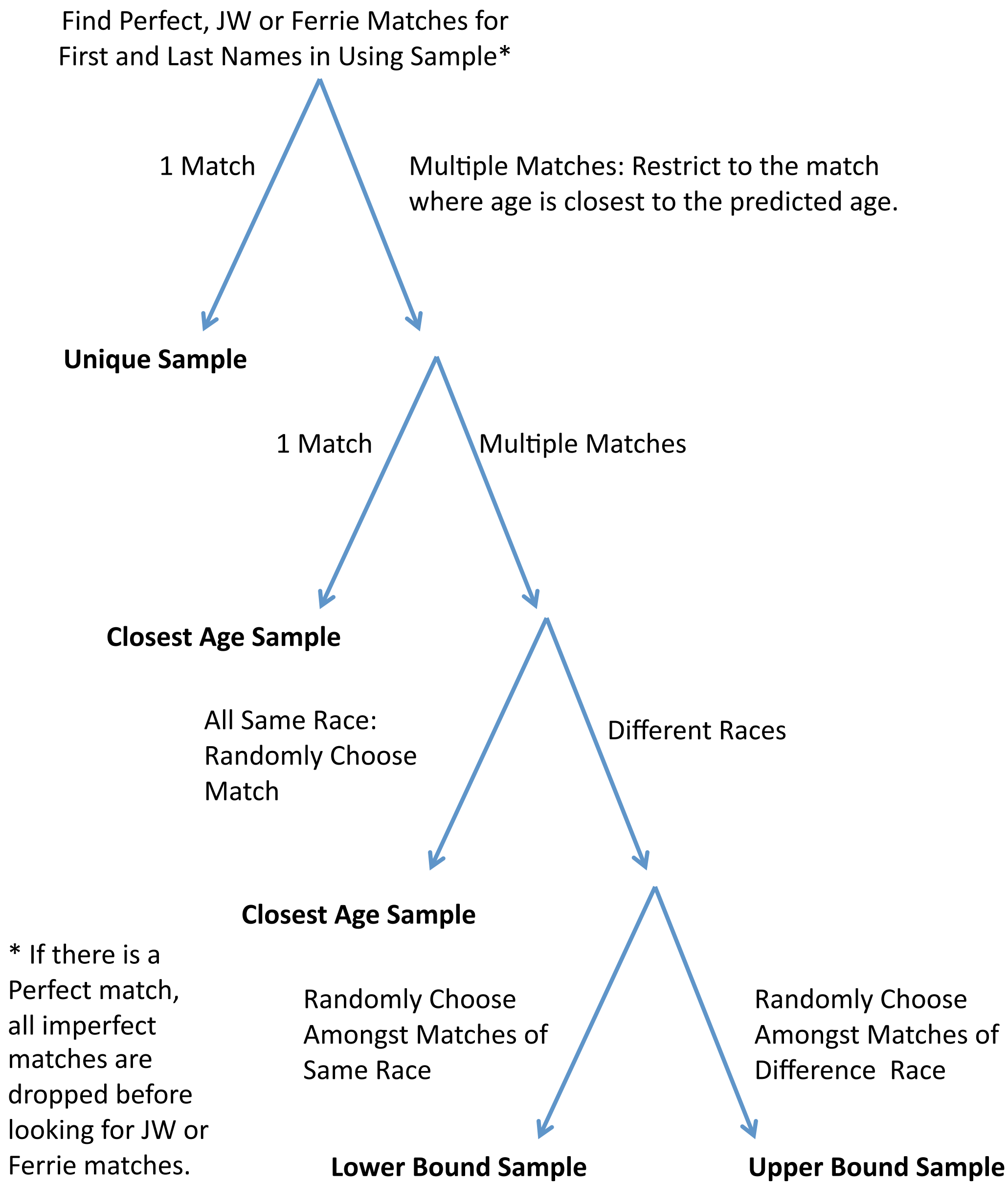
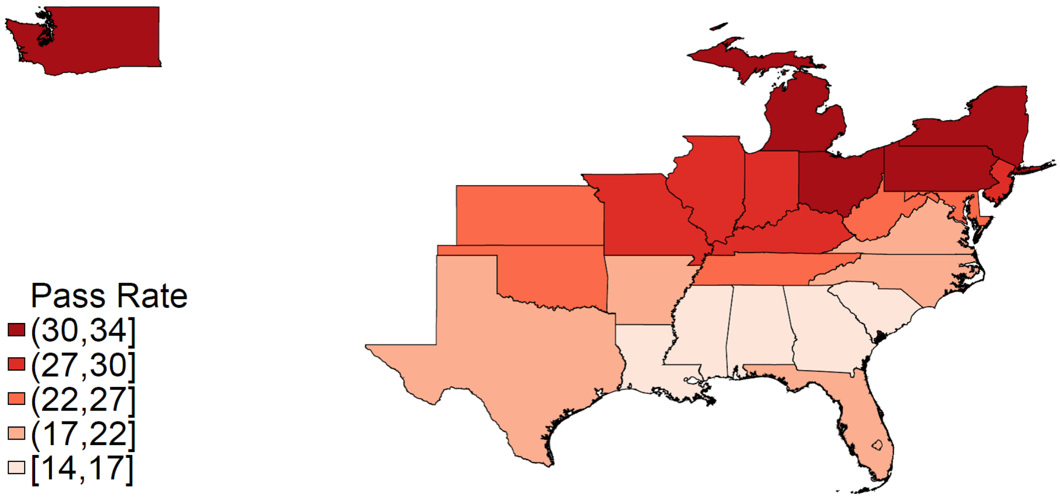
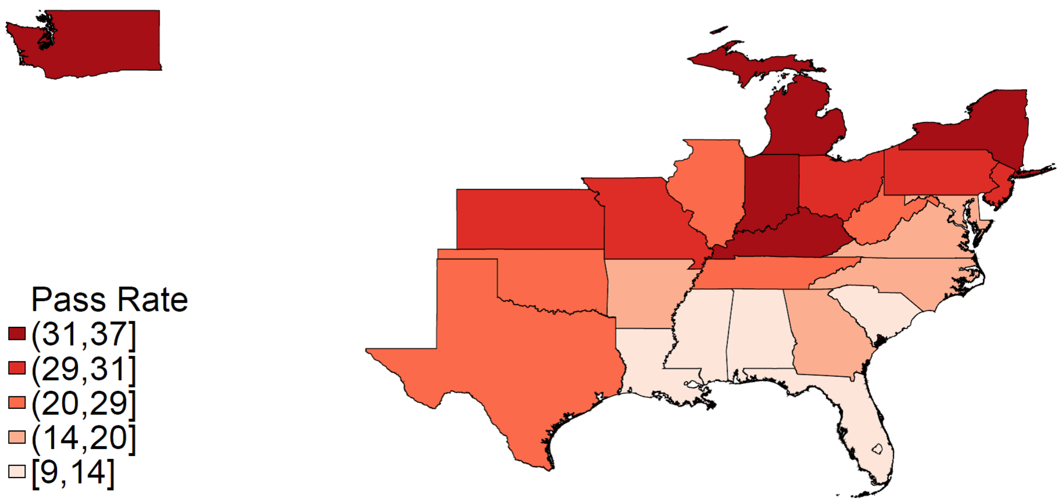


Figure 3: Pass Rates by State

(a) According to the State of Origin before Passing – JW Absolute Lower Bound Pass Rates



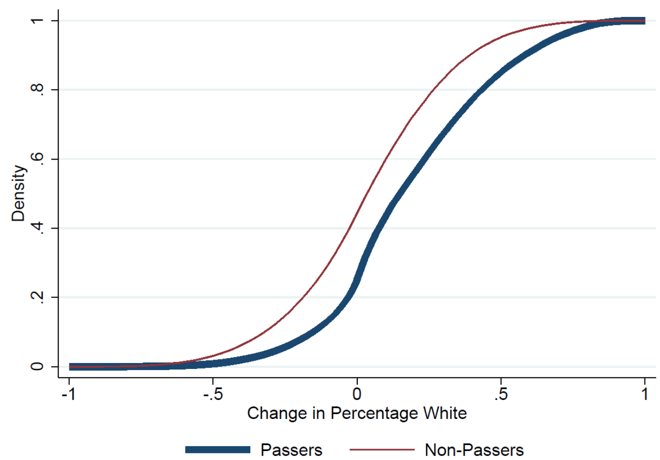
(b) According to the State of Residence after Passing – JW Lower Bound Pass Rates



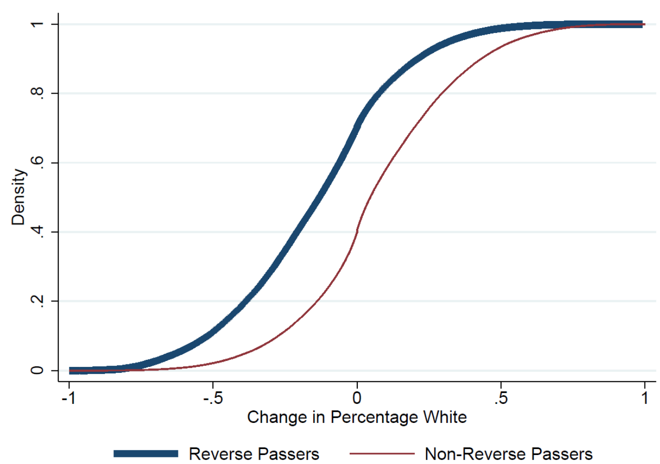
Notes: Sample includes the states where 98% of the black population resides: Georgia, Mississippi, Alabama, South, Carolina, North Carolina, Louisiana, Texas, Virginia, Tennessee, Arkansas, Florida, Washington, Kentucky, Maryland, Pennsylvania, New York, Missouri, Ohio, Illinois, New Jersey, Oklahoma, Indiana, West Virginia, Michigan and Kansas.

Figure 4: Racial Composition of the County of Residence for Movers

(a) Passers vs. Non-Passers



(b) Reverse-passers vs. Passers who remain "white"



Notes: The y-axis is the CDF. The x-axis is the % white in the county of residence in the current year minus the % white in the county of residence in the previous census year. Sample includes passers and non-passers who move counties.

Online Appendix

A The Racial Gradient of Emancipated Slaves in 1863

To illustrate the wide gradient of color for former slaves and the fact that many of those classified as black during 1880-1930 could physically pass for white, we borrowed photographs from M. H. Kimball. Appendix Figures A.1-A.2b show emancipated slaves who were chosen for a propaganda tour of the North in 1863. They were selected specifically to show the vast differences in skin color of slaves. The former slaves are described in "White and Colored Slaves" by C. C. Leigh (*Harper's Weekly*, January 30, 1864, p. 71).

B Two Cases of Racial Passing: Anita Hemming and Harry Murphy

There are many cases of racial passing that are discussed in fascinating detail by historians, some of which we cite in the Background Section in our paper. Two such cases are Anita Hemmings and Harry Murphy.

Anita Hemmings, shown in Appendix Figure A.3a, had parents who were both biracial and identified as "black". She attended Vassar College as a white student, was discovered to be black in 1987, but still graduated. She later married another mixed race man. Both passed for white and raised their children as white. Her daughter, Ellen Love, also attend Vassar as a white woman. Figure A.3b shows Anita Hemmings with the Vassar Glee Club. She is the fourth from the right. Source: "Passing as White: Anita Hemmings 1897" by Olivia Mancini in *Vassar, the Alumnae Quarterly*, Winter 2001.

Harry Murphy is an example of an individual who passed temporarily for white, and then reverse passed to black. His photo in Appendix Figure A.4, which we borrow from Hobbs (2014), shows that he had wavy hair and light skin. When he entered the navy, an official checked the box for "white" for his race. This allowed him to participate in the Navy's V-12 program for training officers and take classes at Ole Miss in 1945 as a white student, where no one questioned his identity. When the V-12 program ended, he transferred to Morehouse College in his hometown of Atlanta, where he returned to living as a black man. He later moved to New York City, where he may have lived as a white man again. He committed suicide at age 63. See Hobbs (2014).

C Mixed Race Individuals Today

Many individuals with known black ancestry would be officially classified as "black" in the historical censuses. (Note that today, race is a self-reported category). An example is Wentworth Miller (Appendix Figure A.5a), who has professionally taken on roles of caucasian characters, as well as mixed race characters. Appendix Figure A.5b shows Wentworth Miller with his father and uncle. A comparison of his father and uncle shows the difference in skin color that can exist amongst siblings.

Another mixed race actor is Halle Berry. In playing an emancipated mixed race slave who passed for white and then reverse-passed later in *Queen*, which was based on the life of the paternal grandmother of author Alex Haley (see Appendix Figure A.6a), she vividly illustrates how one can cross back and forth on the color line.

Pictures of Rashida Jones, who is mixed-race, show how an individual's racial appearance can change at different ages (see Appendix Figures A.7b and A.7c).

D Undercounting in the Historical Census Data

Undercounting could bias our pass rates if the probability of being excluded from the Census differs for passers. For example, Prewitt (2013, p. 106) notes that those living in isolation and away from friends and family are more likely to be omitted. Since passing requires that an individual disassociates himself from his family and original community, this would cause the census to undercount passers and our estimates will understate the true pass rate. Prewitt (2013, p. 107, Table 2) shows that the undercount of blacks is twice as high as that of non-blacks. This could bias our pass rates upwards or downwards, depending on whether this increases or reduces the probability that we link a black individual who passes relative to one who remains black. For example, if the undercount of blacks mean that there are fewer blacks in the base year such that we cannot match passers to when they were black in the previous census, then our pass rate will understate the true pass rate. Alternatively, if the undercount of blacks was such that we are able to match fewer black individuals to themselves in the previous census year, then our estimates could overstate the true pass rate. We note that given that the undercount of blacks in 1940 is approximately 8.4% and that passers constitute a relatively small proportion of blacks, the margin of error that is implied for our pass rates is not likely to be large.

Cook, Logan, and Parman (2013) discusses this issue in their study of the racial concentration of names. They address it by comparing names and race in the Census to names and race in historical death registry data for Alabama, Illinois and North Carolina. They find that the death registry data corresponds to the Census data.

E Phonetic Translation Methods

Phonex, described in Lait and Randell (1996), is a combination of the Soundex and Metaphone methods. Soundex is one of the most popular translation methods. It works as follows. First, it retains the first letter of the name. Next, all vowels are dropped and the consonants are replaced with a number, with consonants that sound the same (for example, c and k) assigned the same number. Last, all but the first three numbers are dropped, so that all translations consist of a letter followed by three numbers.

Metaphone is another method of phonetic translation. Snae (2007) shows that Phonex achieves a higher percentage of the true matches relative to all other methods excluding hybrid methods, and that the Phonex method not only outperforms all other methods in terms of percent of true matches, but it also does so without sacrificing accuracy.

Another popular method in the literature is NYSIIS, which has been used by studies such as Ferrie (1996). The main difference between Soundex and NYSIIS is that the latter preserves the position of vowels in its translation of names - all vowels are replaced with the letter A - and more than 4 characters are retained. Snae (2007) shows that compared to NYSIIS, Phonex yields twice the number of true matches without sacrificing accuracy.

F Number of Potential Matches

To give a concrete sense of how our matching algorithms gradually restrict the number of potential matches, we show the average number of potential matches at each stage of the matching process in Appendix Figure A.8. For computational ease, we use data from three states from 1900 to 1910. The three states are Georgia, Louisiana and South Carolina. They are randomly chosen from the ten states with the largest black populations. .

G Alternative Age Restrictions for Matching

In the main paper, we restricted potential matches to be within three years younger or older than the predicted age of an individual. Here, we show that our match rates are robust to alternatively restricting the potential matches to be within five years younger or older than an individual's predicted age. This addresses the concern that there is non-random age heaping such that passers are more or less likely to round their age than non-passers, so that we systematically have higher or lower match rates for passers. Note that we do not find patterns of differential heaping in the data. Nevertheless, Appendix Table A.2 further removes this concern by showing that the two types of age restrictions result in virtually the same pass rate. Note that for this exercise, we only use three states for computational ease. We randomly selected these from the ten states with the largest black populations. They are Georgia, Louisiana and South Carolina.

H Alternative JW Thresholds

The main JW matches use a threshold of 1.8, where a JW score of two is essentially a perfect match. Thus, as the JW threshold increases, the match and pass rates will approach those of the Perfect match. Similarly, as the threshold decreases, the rates will approach those of a

Ferrie match. For example, with a higher threshold of 1.9, the absolute lower bound pass rate (which we define in Section 4) is 11%, which is still higher than the Perfect Match absolute lower bound pass rate of 9% (see Table 2 column (1)). With a lower threshold of 1.7, the absolute lower bound pass rate is 19%, which is still lower than the Ferrie absolute lower bound pass rate of 24% (see Table 2 column (3)).

I Mortality in between Census Years

Two groups of individuals are excluded from our samples. The first group comprises those that are excluded from the using sample. A large proportion of these are driven by mortality. Appendix Figure A.7 plots the percentage of each age group that is excluded from the using sample. It shows that amongst those who are younger than 50, few are excluded – i.e., we are able to identify potential matches for around 80% of this group. The proportion that we are unable to identify potential matches for increases with age after this point. This is consistent with the fact that mortality rates increase significantly for these age groups. Similarly, the small spike at age zero reflects high infant mortality.[62]

The second group comprises those within the using sample who do not have any Perfect, Ferrie or JW matches. These comprise less than 10% of the using sample and are uncorrelated with age.

J Mulattoes

The census has separate categories for mulattoes, who are, in principle, more caucasian in appearance, in 1880, 1910 and 1920. Whether mulattoes are more or less likely to pass than individuals in the black category depend on several factors. For example, mulattoes may be

[62] See Linder and Grove (1947) for mortality rates by age and race during 1900-1940. Note that the aggregate historical mortality data may be measured with error (Haines, 1994, 2002). In particular, some estimates are generated by comparing year-to-year black population figures. If a high percentage of the black population passes, as we have shown to be the case, this will greatly overstate black mortality rates and would also understate white mortality rates. But this does not affect our point that mortality rates for blacks were highest for infants and those who are older than fifty, especially since the mortality rates for the full population (which are not biased by passing using year to year changes) are also highest for infants and those who are older than 50.

more likely to pass because it is easier for them to appear white. However, mulattoes may face different incentives to pass if they are treated differently. Also, the appearance of "whiteness", which is partly based on the lightness of one's skin, is to some extent under the discretion of an individual. For example, tanning of the skin from sun exposure could cause a surveyor to change the classification of an individual from mulatto to black. Similarly, appearances can change as an individual ages (e.g., hair becomes less curly), which can cause black individuals to look more mulatto or white. Thus, the same individual could arguably be classified as mulatto or black, or even as white.[63] This makes the distinction between mulatto and black very fuzzy, especially since the enumerator instructions were vague. For example, historians have noted that "After 1920, the U.S. census bureau dropped the 'mulatto' category, the government having concluded that at least three-quarters of all American Negroes bore white genes and thus officially specifying people as mulattoes no longer made much sense" (Packard, 2003, p. 98).

Table A.4 presents the JW closest age pass rates for the two groups separately. A comparison of Panels A (Black) and B (Mulatto) shows that unsurprisingly, mulattos have slightly higher pass rates. The absolute lower bound estimates show that at least 17% to 18% of blacks passed for white during these three census intervals, while at least 18% to 21% of mulattos passed. That the difference in pass rates between mulattos and blacks is small is consistent with the arbitrary racial definitions used at the time.

Panel C shows that mulattos comprise approximately 14% to 20% of the total population that we define as black for the main exercises. Thus, most of the pass rates that we discuss as our main results are driven by individuals who would have been classified as black (during years when mulatto was a separate category).

Note that the pass rates for mulattoes during the 1880-1900 and 1920-1930 intervals (18% - 21% absolute lower bounds) are nearly identical to the pass rates during the 1910-1920 intervals (19%) and the removal of the mulatto category in 1900 and 1930 did not have an obvious effect on the percent of passers. This is interesting because it goes against the hypothesis that

[63]Gross (2009) provides historical examples in the context of legal race suits. In Online Appendix Section C, we provide examples of individuals whose racial appearance changes over time.

pass rates over time were sensitive to changes in census enumerator instructions.

Table A.1: County Level Pass Rates

	County Level Pass Rates						
	Mean (1)	S.D. (2)	S.D./Mean (3)		Mean (4)	S.D. (5)	S.D./Mean (6)
Alabama	0.31	0.05	0.17	Nebraska	0.56	0.31	0.55
Arizona	0.55	0.18	0.32	Nevada	0.57	0.28	0.49
Arkansas	0.36	0.11	0.30	New Hampshire	0.61	0.21	0.35
California	0.59	0.20	0.34	New Jersey	0.50	0.06	0.12
Colorado	0.56	0.27	0.48	New Mexico	0.56	0.27	0.48
Connecticut	0.51	0.04	0.08	New York	0.59	0.11	0.18
Delaware	0.45	0.03	0.06	North Carolina	0.41	0.08	0.20
Florida	0.33	0.04	0.12	North Dakota	0.82	0.10	0.12
Georgia	0.30	0.05	0.15	Ohio	0.61	0.13	0.22
Idaho	0.60	0.32	0.53	Oklahoma	0.47	0.19	0.40
Illinois	0.56	0.16	0.29	Oregon	0.55	0.32	0.58
Indiana	0.56	0.18	0.31	Pennsylvania	0.55	0.14	0.25
Iowa	0.57	0.26	0.44	Rhode_Island	0.50	0.12	0.24
Kansas	0.45	0.18	0.41	South Carolina	0.26	0.05	0.17
Kentucky	0.49	0.08	0.17	South Dakota	0.60	0.34	0.57
Louisiana	0.26	0.03	0.12	Tennessee	0.49	0.08	0.17
Maine	0.62	0.22	0.36	Texas	0.38	0.18	0.48
Maryland	0.40	0.05	0.14	Utah	0.60	0.36	0.60
Massachusetts	0.54	0.08	0.15	Vermont	0.59	0.21	0.36
Michigan	0.57	0.23	0.41	Virginia	0.32	0.06	0.20
Minnesota	0.62	0.33	0.54	Washington	0.63	0.28	0.45
Mississippi	0.29	0.05	0.18	West Virginia	0.49	0.14	0.29
Missouri	0.51	0.17	0.33	Wisconsin	0.64	0.29	0.44
Montana	0.63	0.26	0.41	Wyoming	0.53	0.24	0.45

Notes: Pass rates are calculated with the JW Closest Age method. They are averaged over time for each county.

Table A.4: Pass Rates for Mulattoes

	Census Intervals		
	1880-1900	1910-1920	1920-1930
	(1)	(2)	(3)
	A. Black		
Absolute Lower Bound	18%	17%	17%
Lower Bound	37%	31%	30%
Upper Bound	45%	37%	35%
Absolute Upper Bound	68%	61%	59%
	B. Mulatto		
Absolute Lower Bound	21%	19%	18%
Lower Bound	41%	34%	30%
Upper Bound	49%	39%	35%
Absolute Upper Bound	74%	66%	62%
	C. Mulatto Percent of Black + Mulatto Population		
Percent Mulatto	14%	20%	15%

Notes: The absolute lower bound (upper bound) assumes that no (all) individuals excluded from the using sample or those in the using sample whom were unmatchable passed. The category for mulatto is merged into black in for 1900, 1930 and 1940.

Table A.2: Pass Rates – Robustness to Alternative Age Restriction (+/-5 years) in Matching Algorithm

	Matching Algorithm		
	Perfect	JW	Ferrie
Restrictions	(1)	(2)	(3)
	A. Main Sample, Age of Match is +/- 3 of Predicted Age		
Absolute Lower Bound	7%	15%	19%
Lower Bound	19%	25%	29%
Upper Bound	25%	31%	36%
Absolute Upper Bound	73%	58%	57%
	B. Main Sample, Age of Match is +/- 5 of Predicted Age		
Absolute Lower Bound	7%	16%	19%
Lower Bound	18%	25%	28%
Upper Bound	23%	30%	34%
Absolute Upper Bound	71%	54%	54%

Notes: The absolute lower bound (upper bound) assumes that no (all) individuals excluded from the using sample or those in the using sample whom were unmatchable passed. The sample includes all years, 1880-1940 for Louisiana, Georgia and South Carolina.

Table A.3: U.S. Historical Black Population by Year and State for States where 98% of the Black Population Resides

	Black Population/U.S. Black Population						
	1880	1900	1910	1920	1930	1940	Avg.
Georgia	0.11	0.12	0.12	0.11	0.09	0.08	0.10
Mississippi	0.10	0.10	0.10	0.09	0.08	0.08	0.09
Alabama	0.09	0.09	0.09	0.08	0.08	0.07	0.09
South Carolina	0.09	0.09	0.08	0.08	0.07	0.06	0.08
North Carolina	0.08	0.07	0.07	0.07	0.08	0.07	0.07
Louisiana	0.07	0.07	0.07	0.07	0.06	0.06	0.07
Texas	0.06	0.07	0.07	0.07	0.07	0.07	0.07
Virginia	0.10	0.07	0.07	0.06	0.05	0.05	0.07
Tennessee	0.06	0.05	0.05	0.04	0.04	0.04	0.05
Arkansas	0.03	0.04	0.04	0.04	0.04	0.04	0.04
Florida	0.02	0.03	0.03	0.03	0.04	0.04	0.03
Washington	0.00	0.02	0.03	0.03	0.03	0.04	0.03
Kentucky	0.04	0.03	0.03	0.02	0.02	0.02	0.03
Maryland	0.03	0.03	0.02	0.02	0.02	0.02	0.03
Pennsylvania	0.01	0.02	0.02	0.03	0.04	0.04	0.02
New York	0.01	0.01	0.01	0.02	0.03	0.04	0.02
Missouri	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Ohio	0.01	0.01	0.01	0.02	0.03	0.03	0.02
Illinois	0.01	0.01	0.01	0.02	0.03	0.03	0.02
New Jersey	0.01	0.01	0.01	0.01	0.02	0.02	0.01
Oklahoma	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Indiana	0.01	0.01	0.01	0.01	0.01	0.01	0.01
West Virginia	0.00	0.00	0.01	0.01	0.01	0.01	0.01
Michigan	0.00	0.00	0.00	0.01	0.01	0.02	0.01
Kansas	0.01	0.01	0.01	0.01	0.01	0.00	0.01

Notes: Calculated by authors from U.S. Population Censuses.

Figure A.1: Emancipated Slaves in 1863

Figure A.2: Emancipated Slaves in 1863

(a) Isaac and Rosa

(b) Colored Children Turned Away from White Schools

Figure A.3: Anita Hemmings

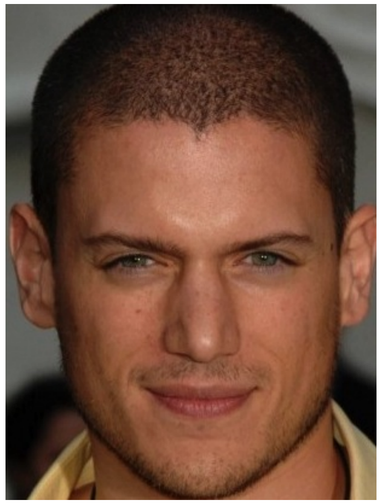
(a) Anita Hemmings

(b) Anita Hemmings (fourth from the right)

Figure A.4: Harry Murphy

Figure A.5: Contemporary Figures who would be "Black" under the One Drop Rule

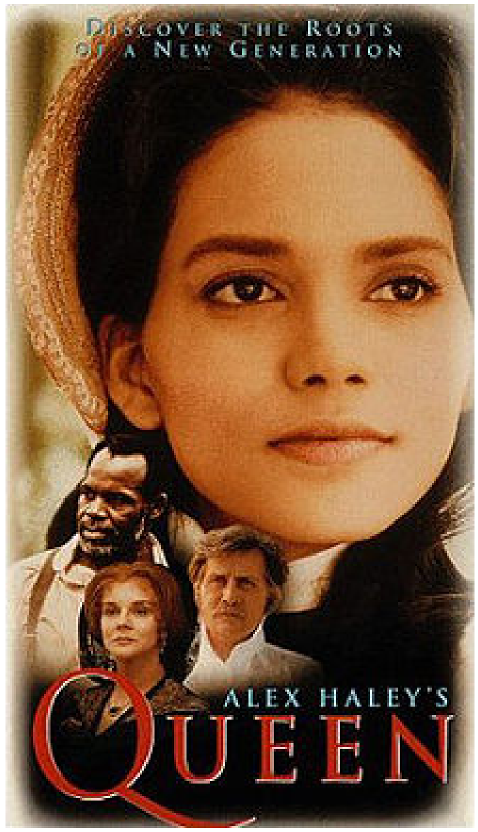
(a) Wentworth Miller



(b) Wentworth Miller with his uncle and father

Figure A.6: Racial Appearance can Vary for the Same Individual

(a) Halle Berry plays Queen, who passes and reverse passes



(b) Rashida Jones (Young)

(c) Rashida Jones (Adult)

Figure A.7: The Percentage of Individuals Excluded from the Using Sample by Age

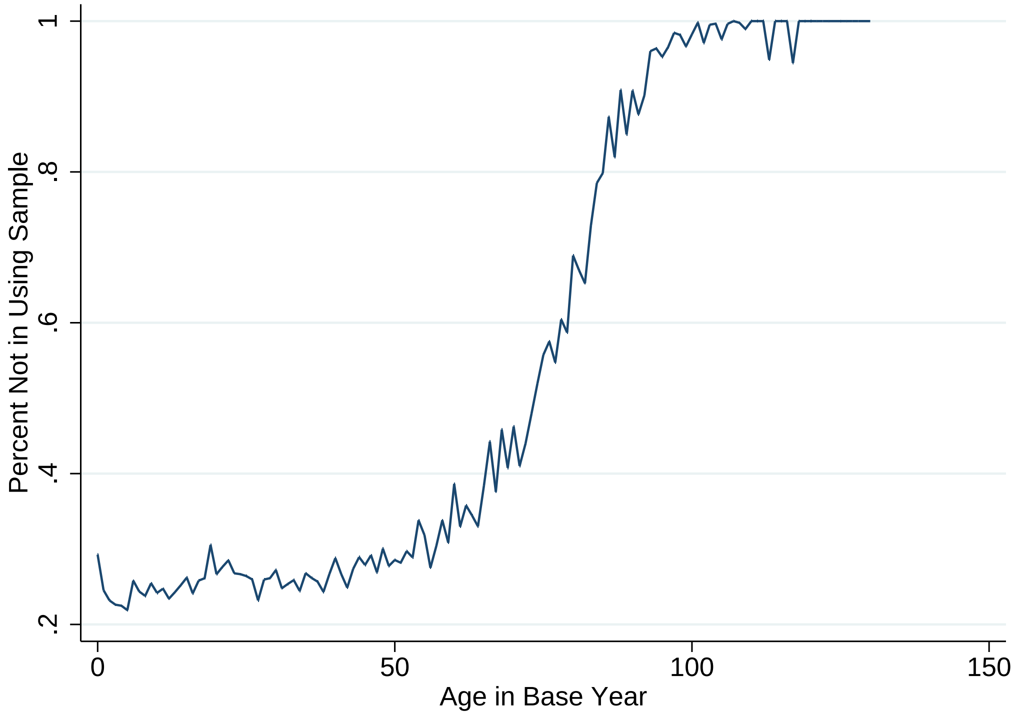


Figure A.8: Average Number of Potential Matches

Population in Year *t**

↓

Phonex Matches: 3,229 matches per person

↓

Within Age Bandwidth Matches: 350 matches per person

↓

Birth State Matches: 247 matches per person

↓

Parental Birth State Matches: 230 matches per person

↓

If there is a Perfect Match, drop all imperfect matches: 77 Matches per person

↓

“Using Sample” of Potential Pairs of Individuals in Years *t* and *t+1***

↓

Perfect Matches: 2 per person, JW Matches: 4 per person, Ferrie Matches: 5 per person

↓

Restrict to Closest Age Matches: Perfect Matches: 0.64 per person, JW Matches: 1.02 per person, Ferrie Matches: 1.17 per person

* Averages reported for 3 robustness states (Georgia, Louisiana, and South Carolina) matching from 1900 to 1910.
** Below this point average matchers per person are computed for those within the using sample.

Figure A.9: Match Rates by Census Interval and Matching Method

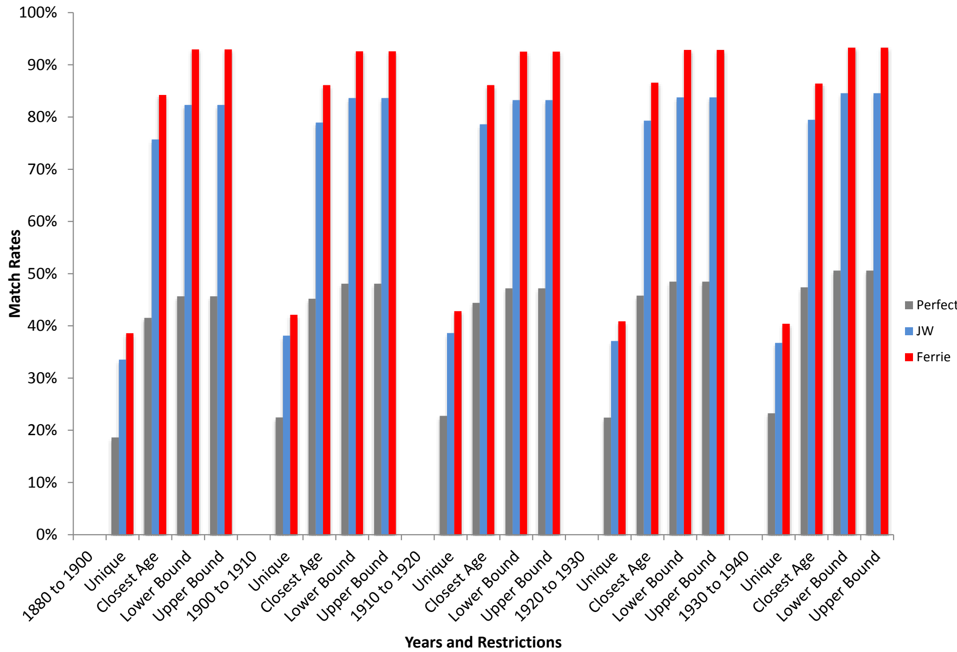


Figure A.10: Pass Rates by Census Interval and Matching Method