Red Tails, Broken Wings: Talent Misallocation Among America's Most Talented African Americans

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Abstract

This paper examines how racial discrimination affected talent allocation of African Americans who were part of the Greatest Generation. Leveraging Army intelligence test scores of WWII recruits to measure cognitive ability and linking them to decennial censuses, IRS tax returns, and social security data, we show that Black veterans earned substantially less and were employed in occupations with lower cognitive requirements compared to their white counterparts, even after controlling for cognitive ability. This finding contrasts with Neal and Johnson (1996). We further show that talent misallocation was more pronounced among Black veterans with higher cognitive scores. To explore this, we focus on the Tuskegee Airmen—the first Black military pilots. The Air Force applied a uniformly high bar, resulting in a highly selected group with exceptional cognitive and non-cognitive abilities. Their later-life outcome shows evidence of persistent talent misallocation. We compare Black versus white pilots, and Black pilots living in high- versus low-discrimination counties. Tuskegee Airmen in higher-discrimination counties earned less and worked in occupations with lower cognitive demands (1950-90), resided in less valuable housing (1990s), and ultimately died in poorer ZIP codes. We exploit a mover design and the quasi-random assignment of wingmen to provide evidence that these effects are causal.

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> The Tuskegee airmen were probably the most talented group of African-American men ever brought together in one place.
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> — *The New York Times*, 7 May 1995

1. Introduction

Human capital plays a key role in modern economic growth (Romer, 1990; Gennaioli et al., 2013; Jones, 2021). However, the availability of high-ability individuals alone is not enough—the most talented people should also fill the most demanding and rewarding jobs. A growing literature argues that talent misallocation can reduce economic performance (Hsieh et al., 2019): Better use of human talents may have contributed to the onset of modern economic growth and shaped comparative development (Mokyr, 2009; Cantoni et al., 2018; Lucas, 1978; Baumol, 1990; Murphy et al., 1991). Conversely, where prohibitions, frictions and discrimination inhibit efficient talent allocation, technology and productivity stagnate (Aghion et al., 2017; Andrews and Rothwell, 2020; Goldberg et al., 2025; Adamopoulos et al., 2022; Hnatkovska et al., 2021), inequality widens (Guner and Ruggieri, 2022), and poverty traps emerge (Balboni et al., 2022).

Estimating the efficiency costs of talent misallocation is empirically challenging. Human ability is multidimensional. The existing literature typically either assumes that talent is distributed identically across groups or relies on indirect, aggregate tests.[1] An ideal experiment would compare the socioeconomic outcomes of individuals with the same underlying ability, but suffering different levels of discrimination. Differences in later-life outcomes between matched pairs of similarly talented people would then reflect the private cost of misallocation, which may be compounded by spillovers.

In this paper, we provide direct, individual-level evidence on the effect of racial discrimination on talent misallocation among the Greatest Generation in

[1] Hsieh et al. (2019) assume that the innate ability distribution is similar across all groups. For a controversial treatment arguing the opposite, see Herrnstein and Murray (1994). Olivetti and Petrongolo (2008) and Ashraf et al. (2022) use the negative correlation between female labor force participation and gender pay gaps to indirectly diagnose female talent misallocation in countries with unequal gender treatment.

the US. In the first part of the paper, we analyze a unique dataset of 446,400 WWII Army recruits for whom cognitive test scores are available. The Army designed the Army General Classification Test (AGCT) to assess a wide range of cognitive abilities, including verbal, quantitative, and spatial reasoning (Bingham, 1944). We link recruits to decennial census records, confidential income tax returns, and social security data. This linkage allows us to track their pre- and post-war outcomes, from education to socioeconomic status (SES), including income, occupation, and neighborhood quality.

We find evidence of substantial talent misallocation among Black members of the Greatest Generation. First, Black recruits have approximately 20 percent lower AGCT scores at enlistment, controlling for years of education, age, county of origin, and enlistment characteristics. In contrast to claims about the ethnic and hereditary origins of ability score gaps (Herrnstein and Murray, 1994), which imply stable differentials over time and space, we find that measured AGCTs correlate with measures of racial discrimination in the location of origin.[2] In particular, the racial AGCT gap is substantially larger in counties with higher racial discrimination levels based on our measure. In Shelby County, Tennessee—in the South—the gap is 30 percent relative to the mean. In contrast, in a northern county like Clark County, Ohio, the gap is less than 10 percent.

Second, Black recruits have significantly lower post-war SES, even conditional on AGCT scores. This finding contrasts with Neal and Johnson (1996), who find that the racial earnings gap disappears after controlling for cognitive ability. Our results instead point to labor market inefficiency: Black individuals with cognitive abilities similar to their white peers are placed in lower-paying occupations that do not match their skills. These findings suggest both systemic and direct discrimination, concepts recently formalized by Bohren et al. (2025). The formation of cognitive ability itself is unequal, which impacts earnings (systemic discrimination). Furthermore, conditional on cognitive ability, Black individuals still experience lower earnings and worse outcomes (direct discrimination).

Talent, however, has more than one side. Cognitive ability is relevant to labor market outcomes, but it is not the only driver of productivity (Kautz et al., 2014; Heckman, 1995). Other factors, such as social skills, resilience, and grit, could differ systematically between white and Black recruits. These unobserved

[2]This echoes the findings in Reardon et al. (2024); Card and Rothstein (2007).

differences may also contribute to the post-war SES gaps we observe.

To overcome this challenge, in the second part of the paper, we focus on a group of exceptionally talented recruits: military pilots. The Army Air Forces (AAF) sought "the best physical and mental specimens the country produces" to fly fighter planes and bombers, or to act as navigators or flight engineers (Steinbeck, 2009). This selection was enforced through stringent prerequisites (including at least two years of college and high AGCT scores) and high wash-out rates (30–50%) during the 27-week training program (USAAF Assistant Chief of Air Staff, 1943; Du Bois, 1947; Flanagan, 1948; Harrell, 1992; Pierce, 2013).[3] This demanding process ensures that pilots were recruited from the extreme upper tail of the talent distribution. Compared to the full sample of Army recruits, these pilots are not only highly talented but also more homogeneous in their abilities.

Beginning in 1941, the AAF trained Black pilots in Tuskegee, Alabama. The same standards were applied to Black and white air cadets (USAAF Assistant Chief of Air Staff, 1943, p. 21). These Tuskegee Airmen were the first African Americans to fly as military pilots in American history. Contemporaries described them as the "cream of the crop" (Haulman, 2015; Homan and Reilly, 2018) or, as the *New York Times* put it, "the most talented group of African-American men ever brought together in one place."

Our baseline analysis compares differences in post-war outcomes for Black versus white pilots, as a function of a county's level of racial discrimination. To fix ideas, consider the contrasting fates of two Tuskegee pilots: Terry Bailey and Lee Archer. Both were highly skilled. Bailey returned to his parents' home in Richmond, Virginia—a place with a history of discrimination against African Americans. Despite his qualifications, he became a US Postal Service mail carrier. Compare his career with that of fellow Tuskegee Airman Lee Archer, who came from Westchester, New York. Archer returned to New York and eventually became the first African-American vice president of a major US corporation.[4] These divergent outcomes are not simply due to Westchester being richer overall. For whites, postwar outcomes could be remarkably similar across locations: John Whiteman from Westchester owned a billboard company, and his Eighth Air Force fellow pilot Noah Tipton from Richmond did not fare worse—he owned three companies,

[3] Approximately 5.5% of the population had at least two years of college education in 1940.
[4] See Bailey's story here and Archer's here.

including a commercial airline.[5]

We collect comprehensive data on pilots' post-war economic outcomes. We gather income and occupation from the 1950 Census, occupations from 1960–1990 City Directories, and income from three-year IRS tax returns (1969, 1974, and 1979). We also use the Index to Public Records and the Social Security Death Index to track neighborhood quality in 1990 and at the time of death.

We find evidence of talent misallocation for Tuskegee Airmen throughout their lives. Compared to white pilots, one standard deviation (SD) increase in county-level discrimination—about one-third of the difference between Westchester and Richmond—is associated with 30 percent lower income in 1950 and ■ percent lower income in the 1970s. This gap is not driven purely by wage differentials for the same job. Rather, consistent with Bailey's experience, Tuskegee Airmen in counties with higher discrimination levels are sorted into occupations with lower requirements for cognitive ability, leadership, and social skills.

One concern with our baseline results is that Black and white pilots may not be perfectly comparable. The selection share of pilots from the Black population was lower than the share from the white population. Assuming similar underlying talent distributions, this implies the Tuskegee Airmen may have been, on average, even more highly selected than their white counterparts. If so, our baseline estimates would represent a *lower bound* on the true extent of talent misallocation. We address this by using Coarsened Exact Matching (CEM) (Iacus et al., 2012) to create comparable samples based on observable proxies for ability, including education and aerial victories (a proxy for military productivity). Our results hold within this matched sample.

A second concern is selective sorting: the most talented Tuskegee Airmen might have sorted into counties with lower discrimination levels, which would bias our estimates. To address this, we exploit the quasi-random geographical origins of a pilot's wingmen as an alternative strategy to address potential endogenous sorting. We define a pilot's wingmen as pilots who served in the same AAF flight squadron. The military prioritized rapid mobilization and faced high training attrition rates. Consequently, assignment to flight squadrons was random conditional on race and birth state. Upon discharge, pilots were significantly

[5]See Tipton's story here and Whiteman's here.

more likely to settle in localities where their former wingmen originated.[6] Leveraging these factors, we create an instrument using the weighted average racial discrimination of the birth counties of a pilot's wingmen. We find this instrument is strongly associated with the discrimination level of the pilot's residence in 1950. The 2SLS estimates confirm our main results. Relative to white pilots, Black pilots experienced significantly worse economic outcomes in counties with higher discrimination levels.

While the peer origin instrument predicts locational choices in 1950, it lacks predictive power for locational choices in later periods. This stems from the high mobility of pilots. Compared to their 1950 county of residence, fewer than one third of pilots lived in the same county during the 1960–90 period. This mobility undermines the relevance of the peer origin instrument for later outcomes.

To address this limitation, we employ a mover design as a complementary strategy (Finkelstein et al., 2016; Chetty et al., 2013). We exploit our panel data to track pilots who moved between 1950 and 1960–90. This approach allows us to account for time-invariant individual characteristics, both observed and unobserved. We compare the socioeconomic *change* of Black pilots who move to more (or less) discriminatory areas with the change of white pilots who make similar moves. We find that Black pilots who moved to counties with higher discrimination experienced a decline in occupational status. Conversely, those moving to counties with lower discrimination saw improvements. We observe no such pattern for white pilots.

This paper is structured as follows. Section 2 reviews the literature, Section 3 provides historical context and describes the data, Section 4 includes the conceptual framework, Section 5 and Section 6 present the main results, and Section 7 concludes.

2. Literature Review

This paper speaks to three strands of existing literature. The key contribution of this paper is to provide granular, well-identified individual-level evidence on talent misallocation. The macroeconomic literature has highlighted the role of

[6] Green (2025) shows the similar geographic mobility patterns for WWII Naval sailors.

allocations of capital and labor across firms in the aggregate economy (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2017). Recently, there has been a growing literature that argues that the frictions in the use of human talents caused by discrimination and social norms have serious macroeconomic consequences (Hsieh et al., 2019; Hnatkovska et al., 2021). The literature, however, fails to measure "talent" precisely and instead assumes a specific distribution of "talent." We complement the scholarship by measuring "talent" among a group of similarly talented individuals.

Our findings are also related to the literature on the determinants of Black-white life-cycle outcomes, and on the neighborhood effect on socio-economic outcomes. Bayer and Charles (2018) find a rapid convergence of top Black-white earnings gap. From 1940 to the 1970s, Black men's median earnings rapidly converged with white male's earnings; thereafter, progress stalled or even reversed. Ferrara (2022) argues that WW2 played a particular role in the convergence of labor market outcomes after 1945 because higher casualty rates among white soldiers resulted in significant increases in the share of Black men entering semi-skilled occupations. Aizer et al. (2020) argue that reduced labor market discrimination and increased hiring of Black men in industrial jobs had an important effect on race pay gaps, spilling over into higher high school graduation rates and further downstream improvements. Collins and Zimran (2025) show that the GI Bill led to large gains in Black veterans' educational attainment. Neal and Johnson (1996) found that earnings gaps largely disappear once differences in cognitive ability are controlled for. Chetty and Hendren (2018a) study the role of childhood environments in intergenerational mobility and find large variations across counties (Chetty and Hendren, 2018b). According to Bell et al. (2019), exposure to inventors when one is a child increases the likelihood of filing a patent later in life. There is a large locational fixed effect on mortality found by Finkelstein et al. (2021). This study supports these findings and confirms the place-based effect even for a highly talented group, thus rejecting the "cream-always-rising-to-the-top" hypothesis.[7]

Finally, our paper is related to the literature using military personnel to study key economic questions. Angrist (1990) pioneered the use of military draft lot-

[7]For example, Bayer and Charles (2018).

teries to identify the effects of career disruptions on labor market outcomes.[8] Ager et al. (2021) study peer rivalry among WWII Nazi fighter pilots. Voth and Xu (2022) examine the 18th-century Royal Navy ship captains to study the beneficial effects of discretion on selection. We solve the "talent" measurement issue of talent misallocation literature by exploiting the AAF's exacting selection of pilots, which created a cohort of similarly talented individuals.

3. Historical Background and Data

3.1 Historical Background

3.1.1 Mobilization in WWII

The manpower mobilization for WWII was the largest in US history. The Army was the largest branch of the military and included the Army Air Forces (AFF), which became an independent branch in 1947. Approximately 9 million individuals served in the Army, of whom about 835,000 (9%) were Black Americans.[9] The Army was racially segregated. Black soldiers served in separate units and used separate facilities. This segregation limited their combat opportunities; they were often assigned to labor-intensive service positions. After the war, the Army discharged the majority of its recruits, including Black soldiers, within two years. In 1945, the Army had approximately 8.3 million recruits; by July 1947, this number had fallen to about 694,000 recruits (The National WWII Museum, 2020).

3.1.2 Recruitment of the Army Personnel

The WWII Army recruited personnel from both volunteers and draftees. Upon entry, all recruits proceeded through several stages: reception, sorting, and training. An individual's military career typically began at an induction center, which conducted initial physical and psychological examinations. Successful candidates advanced to a reception center. At this center, recruits underwent further physical examinations, an interview, and the Army General Classification Test

[8] There is a recent literature estimating the effect of military service on income, including Angrist et al. (2011) and Greenberg et al. (2022).

[9] Based on the calculations using our data.

(AGCT). The results of these procedures were used to determine recruits' job assignments. Following this classification, recruits received basic training and were assigned to a specific Army unit (Gatzemeyer, 2021).

The Army designed the AGCT to assess a wide range of cognitive abilities among new recruits, including verbal, quantitative, and spatial reasoning (Bingham, 1944). AGCT scores were scaled with a mean of 100 and a standard deviation of 20, with scores ranging from 39 to 163. It is the precursor to the present-day Armed Forces Qualification Test (AFQT), which the literature uses to measure cognitive abilities (e.g., Neal and Johnson (1996) and Lang and Manove (2011)). Maier and Sims (1986) find that AGCT score percentiles strongly overlap with those of the Armed Services Vocational Aptitude Battery (ASVAB). The ASVAB itself shows performance comparable to formal intelligence tests (Uriell, 2023).

3.1.3 Pilot Selection in the Army Air Forces

The AAF sought to select "the best physical and mental specimens the country produces" for flying tasks (Steinbeck, 2009). This selection was enforced through stringent pre-training prerequisites and high wash-out rates during the training itself (Du Bois, 1947; Flanagan, 1948; Pierce, 2013).

To be eligible for the AAF flight training program, Army recruits were required to have at least two years of college education and an AGCT score of 100 or higher (USAAF Assistant Chief of Air Staff, 1943; Harrell, 1992).

Once admitted, aviation cadets proceeded through primary, basic, and advanced phases. Each stage lasted approximately nine weeks. Cadets faced the constant pressure of being washed out. Consequently, the program had a high wash-out rate: only about 30–50% of aviation cadets completed the training to become pilots (Pierce, 2013).

3.1.4 The Tuskegee Airmen

The AAF did not accept Black men as pilots before WWII. Under pressure from civil rights activists, Congress passed legislation in 1939 designating funds for training Black pilots. In 1941, the AAF established its Black pilot training program at segregated airfields near Tuskegee, Alabama (Haulman, 2015). Pilots who completed this training became known as the "Tuskegee Airmen." In total, 1,007 men

graduated from the program.

The AAF applied the same highly exacting selection and training requirements to Black cadets as it did to white cadets (USAAF Assistant Chief of Air Staff, 1943, p. 21). About half of the Black cadets completed flight training—a completion rate comparable to the AAF average (see Section 3.1.3).[10]

The 99th Pursuit Squadron, the first all-Black unit, was activated in 1943 and saw combat in North Africa. By 1944, four Black squadrons formed the 332nd Fighter Group, stationed in Italy. Their primary role was escorting heavy bombers flying from Foggia, Italy, into Germany. The Tuskegee Airmen flew over 15,000 missions during WWII and claimed 36 aerial victories. A second all-Black unit, the 477th Bombardment Group, completed training but was not deployed overseas before the war ended. After the war, like the majority of Army recruits, these Black pilots were largely discharged.

3.1.5 Racial Discrimination after WWII

The period from the end of WWII to the passage of the Civil Rights Act and Voting Rights Act in the 1960s was characterized by widespread discriminatory practices against Black Americans in the US. In the South, Jim Crow laws enforced legal segregation between Black and white individuals. In the North, Black individuals faced severe discrimination in various aspects of life, including education, employment, and housing.

This era coincided with the return of demobilized WWII veterans, including Black recruits, who were beginning their post-war careers. Historical accounts suggest that Black veterans particularly struggled to find employment commensurate with their skills (Homan and Reilly, 2018). The divergent fates of white and Black AAF pilots illustrate this disparity. Many demobilized white pilots entered the booming post-war airline industry, securing positions as commercial pilots and commanding high salaries. However, commercial airlines in the US refused to hire Black individuals as pilots before 1963.[11] Consequently, almost no Tuskegee Airmen secured the lucrative pilot jobs available to their white peers.

[10] See Daniel Haulman's interview by the National WWII Museum. The interview transcript is available at this link.

[11] David Harris became the first Black pilot for a US passenger carrier, following the 1963 Supreme Court case initiated by another Black pilot, Marlon Dewitt Green.

Some Black veterans even struggled to find other jobs in the airline industry, such as mechanic positions. As a result, many highly skilled Black pilots sorted into low-paying jobs, leaving their abilities and talents underutilized.

3.2 Data

3.2.1 Enlistee Dataset

We follow Ferrie et al. (2012) and use the NARA Army Enlistment Records (NARA-AER) to obtain AGCT scores for approximately 534,000 Army recruits from WWII. Ferrie et al. (2012) found that the "weight" variable in the NARA-AER was used to store the AGCT scores for enlistees admitted during March–May 1943. We drop observations with implausible birth years, female recruits, or those with missing birthplaces. Our final sample, which we refer to as the "enlistee dataset," comprises approximately 446,400 recruits. In addition to AGCT scores, birth year, and state of birth, this dataset provides variables for name, race, residence county upon enlistment, enlistment date, and enlistment station.

We use the algorithm developed by Abramitzky et al. (2021) to link the enlistee dataset to other data sources. First, we link the enlistees to the IPUMS 1950 Census. This linkage allows us to measure their residence county, income and occupations in 1950. We link using name, age, race, and state of birth. This procedure successfully links 224,958 enlistees. To measure occupational characteristics, we use two sets of measures. We draw occupational income and prestige scores from IPUMS. We use data from Autor et al. (2003) to assign cognitive ability requirements to each occupation. We also use O*NET data to assign scores for leadership and social skills (Deming, 2017). These measures allow us to rank occupations based on median income, prestige, or their requirements for cognitive, leadership, and social skills.

Second, we link the dataset to IRS 1040 data for 1969, 1974, and 1979. [redacted]

Third, we link the dataset to the public NARA Numerical Identification Files (NUMIDENT). The NUMIDENT dataset contains records for individuals with a verified death or who would have been over 110 years old by December 31, 2007. We link using name, age, and state of birth, which yields 131,190 linked enlistees. Using their death ZIP code from NUMIDENT, we merge this with the 2022 IRS Individual Income Tax ZIP Code data. This IRS dataset—which provides to-

tal income and the number of returns per ZIP code—allows us to measure the percentile of income per return for each enlistee's death ZIP code.

Table 1 presents summary statistics for the enlistee sample. The average birth year is approximately 1920. 11% of the sample are Black. The average AGCT score is 97.7, and the average years of schooling at enlistment are 10.6. In 1950, their average income is $2,838.91. At the time of death, the average income percentile of their zip code is 52.24.

3.2.2 Pilot Dataset

We construct our sample of Black pilots starting from a complete roster of all 1,007 Tuskegee Airmen, which includes their names and hometowns, sourced from CAF RISE ABOVE. Using genealogical searches on Ancestry, we find the birth year and birthplace for 903 of these pilots. This linkage rate of approximately 90% is substantially higher than those typically achieved through standard automated record-linking procedures in the literature (Abramitzky et al., 2021).

We construct a comparable dataset for white pilots using a similar genealogical search methodology. Since the AAF trained up to 100,000 white pilots during WWII and a comprehensive roster is unavailable, we focus on pilots who served in the 8th Air Force (USAAF Office of Statistical Control, 1945). The 8th Air Force was the largest AAF unit in the war; it flew more sorties than all other air force units combined. We compile a list of 5,142 white pilots and subsequently identify the birth year and birthplace for 4,655 (91%) of them via Ancestry. The resulting "pilot dataset," combining the linked Black and white samples, contains 5,558 pilots in total.

We also manually link the pilot dataset to other data sources. First, we link these pilots to the 1950 Census. We successfully locate the 1950 census questionnaires for 2,857 pilots. These data provide their county of residence, occupation, and income in 1950. Similar to our procedure for the enlistee data, we also rank occupations based on median income, prestige, or their requirements for cognitive, leadership, and social skills.

Second, we link the pilots to IRS 1040 data [redacted]

Third, we identify occupations for approximately 2,579 pilots from City Direc-

tories for 1960–90. We classify these occupations using the 1950 census occupational system and assign occupational rankings using the same methodology as for the 1950 census data.

Fourth, we identify the exact address for 2,764 pilots using the Index to Public Records of Ancestry for the 1990s. We use these addresses to obtain Zillow's valuation estimate for each property as of January 2022. For comparison, we also scrape Zillow's estimates for a 10% random sample of properties nationwide for the same period. This allows us to measure the nationwide percentile of each pilot's address valuation. We note that the city directories do not indicate whether the pilot owned the property.

Finally, we find the death ZIP code for 2,579 pilots from NUMIDENT. Following the same procedure as for the enlistees, we use the IRS Individual Income Tax ZIP Code data to measure the income-per-return percentile for each pilot's death ZIP code.

Table 2 summarizes the characteristics of the pilots. Their average birth year is 1920, and 17% are Black. Their average years of schooling is 11.34 in 1940, rising to 13.08 at the time of enlistment. We also report several economic outcomes. In 1950, their average income is $3,022, and their average occupational income score (measured by occupational median income) is $2,883. This occupational income score is $2,925 in the 1960–1990 City Directories. Later in life, their average house value percentile is 48.95 in the 1990s Index to Public Records, and their average ZIP code income percentile at death is 61.47.

3.2.3 County-Level Racial Discrimination

The discrimination that Black recruits faced before and after the war was heavily rooted in their local environments. Because we can observe their counties of residence at different stages of their lives, we construct a county-level measure to proxy for the level of discrimination to which Black veterans were exposed. For example, if Queens County, New York, has a lower discrimination score than Brown County, Kansas, we assume that a veteran residing in the former faced less local discrimination than a veteran residing in the latter.

We follow Qian and Tabellini (2024) and construct a composite measure of historical racial discrimination at the county level. This index is constructed by

performing Principal Component Analysis (PCA) on six county-level indicators: average Democratic vote share in congressional and presidential elections (1900–1930) (Clubb et al., 2006), lynching counts until 1941 (Bailey et al., 2008; Seguin and Rigby, 2019), KKK presence from the "Mapping the Second Ku Klux Klan, 1919-1940" Project, as well as Black residential isolation (1930 and 1940) and white-Black education gap (1940) based on the complete censuses. Prior to PCA, these variables are scaled, and missing data are handled using iterative imputation. The resulting first principal component is then normalized to have a mean of 0 and a standard deviation of 1.

Figure 1 presents a choropleth map visualizing this composite index. The map shows a stark geographic concentration of high racial discrimination across the South, particularly in states such as Mississippi, Alabama, Georgia, South Carolina, and Louisiana. In contrast, most counties in the Northeast, Midwest, and West show markedly lower index values.

4. Methodological Framework

To analyze the sources of the post-war income gap between white and Black WWII veterans, we adapt the systemic discrimination framework of Bohren et al. (2025). We model a two-stage system where a veteran's innate ability is first converted into a measurable skill, which is then compensated in the labor market. This allows us to decompose the total income gap into components attributable to *direct discrimination* in the labor market versus *systemic discrimination* arising from pre-labor market factors.

4.0.1 Model Setup

Let the population consist of veterans belonging to a group $i \in \{b, w\}$ for Black and white, respectively. We define a two-step system, which maps a veteran's innate ability, y_i^0, into income.

- Step 1: Skill Formation. The first step represents the process of skill formation, where innate ability is converted into a measurable skill. In our context, the "output" at this step, y_i^1, is the veteran's Army General Classification Test (AGCT) score. This result is determined by a group-dependent

conversion rule $A_i^1 : \mathcal{Y}_i^0 \to \mathcal{Y}_i^1$ that maps the veteran's innate ability to an AGCT score, $y_i^1 = A_i^1(y_i^0)$. The set $\mathcal{Y}_i^1$ represents all possible AGCT scores for group i. A_w^1 and A_b^1 captures all pre-army factors, such as the schooling quality, that may cause individuals with the same innate ability to achieve different test scores.

- Step 2: Labor Market. The second step is the post-war labor market. Here, the veteran's AGCT score y_i^1 serves as the primary input, and the "output", y_i^2, is the veteran's income. Income is determined by a labor market conversion rule $A_i^2 : \mathcal{Y}_i^1 \to \mathcal{Y}_i^2$ that maps the veteran's AGCT score into an income level, $y_i^2 = A_i^2(y_i^1)$. $\mathcal{Y}_i^2$ is the set of possible income.

4.0.2 Bohren-Hull-Imas Decomposition

Given this two-step system, we can define three forms of discrimination precisely. In our deterministic model, a veteran with innate ability level y_*^0 can get the income of $A_i^2(A_i^1(y_*^0))$.

Total Discrimination. Total discrimination (Δ^T) is the full difference in income between white and Black veterans with the same innate ability y_*^0.

$$\Delta^T(y_*^0) \equiv A_w^2(A_w^1(y_*^0)) - A_b^2(A_b^1(y_*^0)) \tag{1}$$

Direct and Systemic Discrimination. Following Bohren et al. (2025), we decompose this total gap into a systemic and a direct component.

Direct discrimination (Δ^D) is the portion of the income gap resulting from the labor market applying different conversion rules to veterans with the same skill (AGCT score). Using the Black veterans' skill distribution as the reference, average direct discrimination is:

$$\Delta^D(y_*^0) \equiv A_w^2(A_b^1(y_*^0)) - A_b^2(A_b^1(y_*^0)) \tag{2}$$

where $A_w^2(A_b^1(y_*^0))$ is the counterfactual income for a white veteran with the Black group's skill level. This term captures differential returns to the same AGCT score in the labor market.

Systemic discrimination (Δ^S) is the portion of the income gap caused by racial differences in skills (AGCT scores) for veterans with the same innate ability, evaluated under the same labor market returns. Using the white veterans' labor market conversion rule as the reference, it is:

$$\Delta^S(y_*^0) \equiv A_w^2(A_w^1(y_*^0)) - A_w^2(A_b^1(y_*^0)) \tag{3}$$

where $A_w^2(A_b^1(y_*^0))$ is the counterfactual income for a Black veteran under the white group's labor market conversion rule. This systemic component functions like a toxin accumulating through a food chain. An initial disadvantage introduced at step 1 (skill formation) is "ingested" by the next stage, the labor market. There, the effect of this initial "poison" is concentrated, ultimately producing a significant earnings gap even if the labor market itself – step 2 – is free from direct discrimination.

These components perfectly decompose the total income gap:

$$\Delta^T(y_*^0) = \Delta^S(y_*^0) + \Delta^D(y_*^0) \tag{4}$$

4.0.3 Relation to Oaxaca-Blinder

This Bohren-Hull-Imas decomposition is analogous to the Kitagawa-Oaxaca-Blinder decomposition (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973) under linearity. Assume the conversion rules are linear: $A_i^n(y_i^{n-1}) = a_i^n * y_i^{n-1}$. Here, a_i^n represents the effectiveness of converting y_i^{n-1} into y_i^n.

The direct discrimination component becomes:

$$\begin{aligned} \Delta^D(y_*^0) &= a_w^2 \cdot a_b^1 \cdot y_*^0 - a_b^2 \cdot a_b^1 \cdot y_*^0 \\ &= a_w^2 \cdot y_b^1 - a_b^2 \cdot y_b^1 \\ &= (a_w^2 - a_b^2) \cdot y_b^1 \end{aligned} \tag{5}$$

This is the combination of "coefficient effect" and "interaction effect" of the Kitagawa-Oaxaca-Blinder decomposition, measuring the gap in returns to skills ($a_w^2 - a_b^2$) valued at the Black veteran's level of skill (y_b^1).

The systemic discrimination component becomes:

$$\begin{aligned}\Delta^S(y_*^0) &= a_w^2 \cdot a_w^1 \cdot y_*^0 - a_w^2 \cdot a_b^1 \cdot y_*^0 \\ &= a_w^2 \cdot y_w^1 - a_w^2 \cdot y_b^1 \\ &= a_w^2 \cdot (y_w^1 - y_b^1)\end{aligned} \tag{6}$$

This is the "endowment effect" of the Kitagawa-Oaxaca-Blinder decomposition, capturing the gap in skill endowments ($y_w^1 - y_b^1$) valued at the white veteran's returns (a_w^2). It captures how pre-market skill differences affect the total income gap.

5. Talent Misallocation in the Greatest Generation

We begin by documenting racial gaps in AGCT scores among WWII recruits. We examine how these differences vary with the level of racial discrimination in the county of residence at the time of enlistment. Next, we analyze the racial gap in postwar socioeconomic outcomes. We show that these gaps correlate with the level of racial discrimination in the county of residence when outcomes are measured. This association persists even after we control for AGCT scores.

5.1 Racial Gaps in AGCT Scores

To quantify the difference in AGCT scores between Black and white recruits, we estimate the following linear regression model:

$$Y_i = \alpha + \beta \cdot \text{Black}_i + \gamma_{c(i)} + \delta_{b(i)} + \lambda_{m(i)} + \theta_{p(i)} + \varepsilon_i \tag{7}$$

where Y_i denotes the AGCT score for recruit i. The indicator Black_i takes the value of one if the recruit is Black and zero otherwise. To compare individuals with similar local characteristics, we include $\gamma_{c(i)}$, a vector of fixed effects for the county of residence at enlistment. We also include birth-year fixed effects, $\delta_{b(i)}$, to account for age-based differences in cognitive development. Finally, we add fixed effects for the year-month of enlistment, $\lambda_{m(i)}$, and the place of enlistment, $\theta_{p(i)}$, to address potential differences in testing timing and conditions. Standard errors are clustered at the enlistment county level. The coefficient β captures the

conditional racial gap in AGCT scores.

Table 3, Panel A, Column 1 reports the estimates from Equation 7. On average, Black recruits score 26 points lower than white recruits. This gap corresponds to approximately one SD of the AGCT score distribution.

To ensure we compare observationally equivalent individuals, we employ Coarsened Exact Matching (CEM) as a pre-processing step (Iacus et al., 2012). This procedure generates weights, w_i, that balance the empirical distributions of the baseline covariates—county of residence when enlistment, birth year, enlistment year-month, and enlistment place—between Black and white recruits. We assign $w_i = 1$ for Black recruits. For white recruits, w_i is proportional to the ratio of Black to white counts within each exact matching stratum. Unmatched observations receive a weight of zero. This procedure drops 56% of observations that lack a suitable match. We then estimate the racial gap on the matched sample using weighted least squares:

$$Y_i = \alpha + \beta_{\text{CEM}} \cdot \text{Black}_i + \nu_i \tag{8}$$

where observations are weighted by w_i. Table 3, Panel B, Column 1 presents the results. The estimate is similar to that of the OLS specification: Black recruits score 26 points lower on average.

We next examine racial differences in educational attainment. We replace the dependent variable in Equation 7 and Equation 8 with indicators for completing at least 9, 12, or 14 years of schooling at the time of enlistment.

Columns 3–5 of Table 3 report these results. Column 3 indicates that Black recruits are 20 percentage points less likely than white recruits to complete 9 years of schooling, a gap representing approximately one-third of the sample mean. We observe a similar disparity for high school completion. While the average completion rate is 41%, Black recruits are 23 percentage points less likely to graduate (Column 4). This pattern persists for higher education. The average rate of completing at least two years of college is approximately 7–8 percent, but Black recruits are 6 percentage points less likely than white recruits to reach this level (Column 5).

We further assess the extent to which educational differences drive the racial gap in AGCT scores. When we include fixed effects for years of schooling in Equa-

tion 7, the racial gap reduces from 26 to 18 points (Panel A, Column 2). Similarly, when we add years of schooling to the CEM matching covariates and generate new weights for Equation 8, the gap decreases from 26 to 18 points.

5.1.1 Racial Gaps in AGCT Scores and Racial Discrimination

We also investigate the relationship between the racial AGCT gap and the level of racial discrimination in the recruit's county of residence at enlistment. We first estimate the Black-white AGCT gap separately for each county by regressing individual-level AGCT scores on the interaction between a Black indicator and county fixed effects. The marginal effects of the Black indicator represent the estimated racial gap for each county. To ensure reliable estimates, we exclude counties with fewer than 50 Black or 50 white individuals. In total, we are able to estimate the Black-white ability gap for 200 counties.

Figure 2 plots these estimated gaps against our index of county-level racial discrimination. The figure displays a negative correlation: as the level of discrimination increases, the Black-white ability gap widens. For example, in Clark County, Ohio, which has one of the lowest discrimination scores, Black recruits score less than 10 points lower than their white peers. In contrast, in Shelby County, Tennessee, where discrimination is one of the highest based on our index, Black recruits score approximately 30 points lower than their white counterparts.

To formally test this relationship, we estimate an interaction model:

$$Y_i = \alpha + \beta \cdot (\text{Black}_i \times \text{Discrimination}_{c(i)}) + \beta_1 \cdot \text{Black}_i + \beta_2 \cdot \text{Discrimination}_{c(i)} + \mathbf{X}_i' \Gamma + \varepsilon_i \tag{9}$$

where $\text{Discrimination}_{c(i)}$ represents the racial discrimination index in recruit i's county of residence when enlistment. The control vector $\mathbf{X}_i$ includes the fixed effects defined in Equation 7 (birth year, enlistment timing, and place), with the exception that we replace county fixed effects with state fixed effects, $\gamma_{s(i)}$, to identify the effect of county-level discrimination. Standard errors are clustered at the enlistment state level. The coefficient β captures how the conditional racial gap changes with a one SD increase in $\text{Discrimination}_{c(i)}$.

Table 4, Panel A, Column 1, reports the results. A one SD increase in the racial discrimination index is associated with a widening of the racial AGCT gap by 4 points. Column 2 adds fixed effects for years of schooling; although the coeffi-

cient decreases, the interaction effect remains statistically significant at 2 points.

We verify these findings using the CEM approach. We construct weights to balance covariates—state of residence when enlistment, birth year, enlistment timing, and place—and estimate the following weighted regression:

$$Y_i = \alpha + \beta_{\text{CEM}} \cdot (\text{Black}_i \times \text{Discrimination}_{c(i)}) + \nu_i \tag{10}$$

The results in Table 4, Panel B, Column 1, confirm a similar increase in the racial AGCT gap associated with higher local discrimination.

Finally, we examine whether local discrimination correlates with racial gaps in educational attainment. We replace the dependent variable in Equation 9 and Equation 10 with our education indicators. As the discrimination level in the county of residence increases by one SD, the Black-white gap in the probability of completing at least 9, 12, and 14 years of schooling widens by approximately 9, 4, and 1 percentage points, respectively (Panel A, Columns 3–5). Weighted estimates using CEM yield similar results (Panel B).

5.2 Racial Gaps in Postwar Socioeconomic Outcomes

To quantify racial gaps in postwar socioeconomic outcomes, we estimate the following specification:

$$Y_i = \alpha + \beta \cdot \text{Black}_i + \mathbf{X}_i'\Gamma + \varepsilon_i \tag{11}$$

where Y_i denotes the postwar socioeconomic status for veteran i. The dependent variables include income in 1950 and several measures of occupational standing in 1950. These measures include median income, prestige scores, and requirements for cognitive, leadership, and social skills. We construct a summary SES index from all 1950 proxies by using structural equation modeling with full information maximum likelihood. We also examine income reported on tax returns (1969–1979) and the income percentile of the veteran's ZIP code at the time of death.

The variable Black_i is an indicator for Black veterans. To ensure a robust comparison, we include a rich set of fixed effects. These include the county of residence (at the time of observation and at enlistment), birth year, years of educa-

tion, month of enlistment, and place of enlistment. We cluster standard errors by county of residence at the time of outcome measurement. The coefficient β captures the conditional racial gap in socioeconomic outcomes.

Panel A of Table 5 presents the results. We find that Black veterans earned $684 less than their white counterparts in 1950 (Column 1). This difference represents approximately 20% of the average income for all veterans in the sample ($2,942).

This racial gap appears across occupational rankings as well. Black veterans held occupations with median incomes that were $577 lower (21% of the mean) and prestige scores that were 8.3 points lower (23% of the mean). Their occupations also had lower requirements for cognitive skills (0.4 SD), leadership (0.3 SD), and social skills (0.5 SD). The overall 1950 SES index indicates a racial gap of 0.6 SD. Finally, we observe differences at the end of the life cycle. Black veterans died in ZIP codes where the average income rank was 10 percentile points lower than the ZIP codes of white veterans.

5.2.1 Are Racial SES Gaps Explained by Ability?

In an influential study, Neal and Johnson (1996) analyze young adults from the National Longitudinal Survey of Youth (NLSY). They show that the Black-white income gap is largely explained by ability gaps. They document a large raw gap, which declines by 70% after controlling for cognitive ability as measured by AFQT scores. They conclude that the Black-white income gap among young adults at that time primarily reflected an ability gap present before labor market entry. Because we have similar data on a cognitive ability measure (AGCT), we can test whether this finding holds in our sample. In Panel B of Table 5, we additionally control for AGCT scores.

We find a contrasting result. Controlling for cognitive ability shrinks the racial income gaps, but not substantially. After accounting for AGCT scores, Black veterans still earn 568 dollars less than whites (Panel B, Column 1). Controlling AGCT scores reduces the racial income gap by 17%, in contrast to the 70% documented by Neal and Johnson (1996).

5.2.2 Racial SES Gaps and Discrimination

We next investigate whether racial SES gaps widen with the level of racial discrimination in the veteran's post-war environment. To test this, we estimate the following equation:

$$\begin{aligned} Y_{ics} = \alpha &+ \beta_1 \text{Black}_i + \beta_2 \text{Discrimination}_{c(i)} + \beta_3 \text{AGCT}_i \\ &+ \beta_4(\text{Black}_i \times \text{Discrimination}_{c(i)}) + \beta_5(\text{Black}_i \times \text{AGCT}_i) \\ &+ \beta_6(\text{Discrimination}_{c(i)} \times \text{AGCT}_i) \\ &+ \beta_7(\text{Black}_i \times \text{Discrimination}_{c(i)} \times \text{AGCT}_i) + \delta_s + \varepsilon_{ics} \end{aligned} \tag{12}$$

In this specification, Y_{ics} represents the socioeconomic outcome for veteran i residing in county c and state s. The variable Black_i is an indicator equal to one if the veteran is Black and zero otherwise. $\text{Discrimination}_{c(i)}$ denotes the measure of racial discrimination in the veteran's county of residence at the time of observation, and AGCT_i is the veteran's AGCT score. The model includes all two-way interactions and the triple interaction. δ_s represents state fixed effects.

Table 6 reports the results based on Equation 12. We use the Black-white difference in the marginal effect of county-level discrimination to capture the relative cost of discrimination for Black veterans. Column 1 shows that a one-SD increase in county discrimination is associated with an income that is 181 dollars lower in 1950 for Black veterans relative to whites. This difference is approximately 8% of the average income for all veterans in the sample ($2,934). Columns 2–6 show the Black-white difference in the marginal effects of the discrimination index on occupational rankings in 1950. Although the differences in requirements for cognitive ability and leadership skills are statistically insignificant, all estimates indicate relatively negative effects of discrimination on occupational rankings. When we combine income and occupational rankings into a standardized 1950 SES index (Column 7), we find that a one-SD increase in the discrimination index is associated with a 0.05-SD reduction in the SES index. Column 9 indicates that this same increase in discrimination is associated with a 3 percentile point reduction in the income percentile of the ZIP code at death.

We also estimate county-level racial gaps in the 1950 SES index and examine whether these gaps correlate with the level of discrimination in the county.

Specifically, we regress the SES index on the interaction between a Black indicator and indicators for the 1950 county of residence. This regression controls for the AGCT score and includes fixed effects for county of residence at enlistment, birth year, years of education, enlistment year-month, and enlistment place. The coefficient on the interaction term for each county provides the county-level Black-white SES gap. To ensure reliable estimates, we exclude counties with fewer than 50 Black or white veterans. This procedure yields estimates of the racial SES gap for 47 counties.

Figure A.1 plots these county-level racial SES gaps against our measure of county discrimination. Counties with higher levels of discrimination display larger Black-white SES gaps. For example, Shelby County, Tennessee, has one of the highest discrimination levels according to our measure; its Black-white SES gap is 0.7 SD. In contrast, San Francisco County, California, has one of the lowest discrimination levels, and its Black-white SES gap is only 0.1 SD.

5.2.3 Does Discrimination Disproportionately Harm High-Ability Black Veterans?

We also investigate whether the racial gap in SES varies by ability level. For this analysis, we interact the Black indicator with the AGCT score. Panel C of Table 5 reports these results. For all outcomes, ranging from 1950 income to the death ZIP code income percentile, the coefficients on the interaction term between the Black indicator and the AGCT score are negative. Although the coefficient is statistically insignificant when the outcome is 1950 income, these results point in the same direction: the Black-white SES gaps are larger for higher-ability individuals.

Figure A.2 visualize the same pattern by plotting the marginal effects of the Black indicator at AGCT scores ranging from 40 to 160. At the lowest AGCT level of 40, the racial SES gap in 1950 is approximately 0.2 SD. As the AGCT level increases, the gap widens. At an AGCT score of 160, the racial SES gap is exceeds 0.8 SD, four times the magnitude of the gap observed at the lowest AGCT score. This pattern indicates that the racial penalty is larger for higher-ability Black veterans. This finding motivates our focus on the Tuskegee Airmen, a group of highly talented Black Americans.

6. Talent Misallocation in the Tuskegee Airmen

> "A fighter pilot is a combination of a mathematician, an athlete, a scientist, and a sharpshooter."
>
> Ronald Reagan, in *Wings for this Man.*

Our findings so far suggest that ability differences do not explain the Black-white income gaps of the "Greatest Generation." We also find that these gaps widen with talent. However, using the AGCT score as a proxy for ability has limitations. Although relevant to labor market outcomes, other factors, such as non-cognitive skills, could differ systematically between white and Black recruits, potentially explaining some or all of the observed income gap.

To sidestep this issue, we focus on a group of highly talented soldiers: pilots. Since the advent of aviation, pilots have been highly selected. Before flying complicated and valuable equipment in combat, every air force since WWI examined pilots for their physical fitness, character, non-cognitive skills, and mental ability. Aerial combat was not only extremely demanding physically; it also required concentration, skill, fast thinking, and intuitive mastery of a complex and fragile flying machine under life-and-death conditions. Air forces routinely "washed out" 50-70% of pilot cadets, despite the highly selected nature of the pool.

The US AAF in WWII began recruiting Black pilots, holding them to the same demanding standards as all other groups. This creates a unique historical experiment. We can examine the effects of racial discrimination and talent misallocation by comparing outcomes for Black and white soldiers whose exceptional ability was vetted by the most rigorous procedures. We first document the stark difference in later-life outcomes between Black and white pilots, which supports our earlier finding that the cost of discrimination is highest for the most talented. To sharpen our analysis, we use the dose-response pattern identified in the preceding section—in counties with high discrimination, the gaps are markedly wider. Remarkably, we find that in low-discrimination parts of the US, Black pilots faced substantially less discrimination—and in some cases, even experienced better outcomes than their white peers.

6.1 The Road to Tuskegee

The AAF applied uniform standards to its airmen. We can therefore examine the likelihood of young Black male enlistees "making it to Tuskegee"—being selected into the elite group of the first Black military aviators. If racial discrimination in each county prejudiced the chances of young Blacks, we should expect that the share of Army recruits joining the AAF will be inversely correlated with our measure of discrimination.

We condition on the number of Black Army recruits in each county, by calculating the ratio of young Black recruits who successfully became AAF aviators. The average rate was 0.17%; the highest rates occasionally exceeded 6%, but such cases were rare and occurred with small absolute cohorts. Three quarters of counties produced no Tuskegees, and at the 90th percentile of Tuskegee transition probability, only 0.53% young Black recruits made the cut.

The likelihood of doing so was strongly influenced by racial attitudes and practices. Average acceptance rates were approximately 0.5% in the most favorable counties, but quickly plummet to less than 0.2% as discrimination rises. Figure 3 shows binscatters (with state fixed effects) confirming the pattern.

The stark gradient—with higher discrimination associated with a sharply lower chance to "reach Tuskegee"—suggests a form of "pre-market" discrimination; the more adverse racial conditions in a county were, the lower the chances for young Black recruits to reach the uniformly high bar of the AAF for aviators. While ability differences across counties are not logically impossible, it seems implausible that they correlate with discrimination to this extent.

6.2 Discrimination and Postwar Socioeconomic Outcomes

6.2.1 SES in 1950

We draw our first measures of pilot SES from the 1950 US Census, which provides data on income and occupation. We construct a SES index using Structural Equation Modeling with full information maximum likelihood. The model combines five components—occupational income score, cognitive score, prestige score, leadership score, and social skill score—into a standardized latent fac-

tor representing each pilot's SES.[12]

Figure 4A plots the binscatterplot of the pilots' SES index against the discrimination level of their 1950 residence county, by race. The patterns are starkly different for Black and white pilots. For white pilots, the SES index shows no correlation with the county's discrimination level. For Black pilots, in contrast, the SES index declines by 0.85 standard deviations for each one-SD increase in county-level discrimination. Notably, in low-discrimination counties, the SES index of Black pilots is higher than that of white pilots.

To rigorously test the visual pattern, we estimate the following regression:

$$y_i = \beta Black_i \times Discrimination_{c(i)} + \alpha_1 Black_i + \alpha_2 Discrimination_{c(i)} + \theta X_i + \epsilon_i \quad (13)$$

where y_i is a proxy for post-WWII SES for pilot i. $Black_i$ is an indicator variable for Black pilots. $Discrimination_{c(i)}$ is a measure of discrimination in pilot i's county of residence c at the time y_i is measured (e.g., 1950 or 1970). X_i is a vector of controls, including state fixed effects. We cluster standard errors at the state level. The key coefficient of interest, β, captures the effect of discrimination on the SES of Tuskegee Airmen.

Columns (1)–(7) of Panel A, Table 7 report the regression results from Equation 13 using log income in 1950, the constituent variables of the SES index, and the SES index itself as dependent variables. Relative to the change for white pilots, a one-SD increase in discrimination is associated with a 22% lower income, 43% lower occupational income score, 36% lower occupational prestige score, 0.64 SD lower occupational cognitive score, 0.25 SD lower occupational leadership score, 0.7 SD lower occupational social skills score, and 0.82 SD lower SES index.

6.2.2 Income and Occupations in 1970s

To trace the pilots' long-term outcomes, we analyze their income twenty years later, using 1970s tax returns. This captures their income at their prime age. Figure 4B illustrates the relationship between this 1970 income and the discrimination level of their residence county. The figure shows that as the discrimination

[12] We do not use income to construct the SES index because the income data have a relatively high share of missing values, which causes the FIML algorithm to fail.

level increases, the income gap between Black and white pilots widens.

Panel A of Table 8 reports the regression results. Relative to the change for white pilots, a one-SD increase in discrimination is associated with a 14% decline in adjusted gross income for Black pilots and a 17% decline in wages and salaries. Although we do not find an effect on interest income, the overall decline in earned income associated with one-SD-higher discrimination is 15%.[13]

The 1960–90 City Directories also document the pilots' occupations during their prime age. Column 8 of Table 7 shows that, relative to the change for white pilots, a one-SD increase in discrimination is associated with a 0.26-SD decline in occupational rankings. These rankings are measured in terms of median income, prestige, requirements for cognitive ability, leadership, and social skills.

6.2.3 House Valuation in 1990

We continue to trace the pilots' economic trajectories by examining their house valuations in 1990. We obtain the pilots' exact addresses in 1990 and use Zillow's estimate for the price of the house at each address. A limitation of this measure is that we do not know whether the pilots owned these houses. Figure 4C shows the relationship between their 1990 house's valuation (as a nationwide percentile) and the discrimination level of their residence county. Pilots of both races lived in lower-valued houses as their county's discrimination level increases. However, the pattern differs by race: Black pilots lived in more expensive houses in low-discrimination counties, but the decline in house prices is steeper for them as discrimination increases. Regression estimates (Column 1, Table 9) show that a one-SD increase in discrimination is associated with a 6.3–point decline in the national house price percentile for Black pilots, relative to white pilots.

6.2.4 Income of Death ZIP Code

As a final measure of lifetime economic standing, we examine the average income of the ZIP code where each pilot died. Figure 4D shows the relationship between pilots' death ZIP code rankings by average income and the discrimination level of their death county. Although white pilots in high-discrimination counties

[13] We define earned income as the maximum of (AGI minus interest income) and (wage and salaries).

died in slightly more expensive ZIP codes, Black pilots died in less expensive zip codes if they lived in more racist counties. Regression results (Column 2, Table 9) show that, relative to the change for white pilots, a one-SD increase in discrimination is associated with a 9.4-point decline in the national percentile of their death zip code's average income.

6.2.5 Robustness

Selective Sorting. The results in Table 7–Table 9 could be driven by selective sorting: more talented Black pilots might be more likely to live in less racist counties, *relative to white pilots*. To test this, we regress the discrimination level of each pilot's residence county on their talent proxy, an indicator for Black pilots, and an interaction term between the two. If this sorting pattern holds, the coefficient on the interaction term should be negative. We use three proxies for talent: years of schooling from the 1940 Census, years of schooling at the time of enlistment, and the number of aerial victories. We examine the discrimination level of the residence county associated with each of our outcome data sources: the 1950 Census, 1960–1990 City Directories, 1970s Tax Returns, 1990 Index to Public Records, and NUMIDENT.

Table A.1 reports the results of this test. We find that in most combinations of talent proxies and data sources, more talented Black pilots do not selectively sort into less racist counties relative to white pilots. The only two exceptions appear in the 1950 Census data. In this sample, when using years of schooling at enlistment, a one-year increase in schooling is associated with Black pilots living in counties with a 0.061 SD lower discrimination level ($p = 0.01$), relative to white pilots. Similarly, when using the number of aerial victories, one additional victory credit is associated with Black pilots living in counties with a 0.044 SD lower discrimination level ($p = 0.004$).

Coarsened Exact Matching. The baseline regression in Equation 13 faces two potential issues. First, it compares white and Black pilots in different residence counties, so long as those counties have similar measured discrimination levels. A more rigorous approach would compare pilots strictly within the same county. Second, and more importantly, the estimates may be biased by post-war

locational sorting. Pilots of both races might have had different preferences and constraints influencing their post-war settlement choices. If, for instance, high-ability Black pilots systematically avoided high-discrimination counties while high-ability white pilots did not, our estimate of the $Black_i \times Discrimination_i$ interaction term would be biased. This specific sorting pattern would artificially inflate the measured Black–white SES gap in high-discrimination areas.

To address these concerns, we employ Coarsened Exact Matching to generate a more comparable sample. We match pilots on three key variables:

1. Residence County: We match pilots exactly on their county of residence at the time each outcome is measured. This directly addresses the first concern by forcing all comparisons to be within-county.
2. Education Level: We match on pre-war education (dichotomized as high school vs. at least one year of college) as a proxy for human capital.
3. Aerial Victories: We match on aerial victory credits (dichotomized as above- or below-median) as a transparent proxy for military productivity and pilot skill.[14]

Matching on education and aerial victories mitigates this selection bias concern. This approach ensures that we compare Black and white pilots who lived in the same county and had similar, observable pre-war abilities.

Panel B of Table 7, Panel B of Table 8, and Columns 3–4 of Table 9 report the regression results using this CEM-matched sample. The findings are qualitatively similar to our baseline estimates: residing in a high-discrimination county is associated with worse post-war socioeconomic outcomes for Black pilots relative to their matched white peers from 1950 to the time of death. The magnitudes differ, but the pattern holds. The estimates for 1950 income, 1950 occupational leadership score, and SES index of the 1960–90 City Directories, however, are no longer statistically significant. This loss of significance is likely attributable to the reduction in statistical power, as the CEM procedure necessarily reduces the regression sample size.

Heterogeneity in Racial SES Gaps: A Causal Forest Approach. Our baseline regression in Equation 13 examines the role of county-level discrimination in explain-

[14] We collect the data from USAAF Historical Research Agency (1978).

ing the racial SES gap. We complement this analysis by identifying the most important determinants of the racial SES gap in a flexible, data-driven manner. To do so, we employ a Generalized Random Forest (GRF) framework (Athey et al., 2019).

We train a causal forest to estimate the Conditional Average Treatment Effect (CATE) of being Black on socioeconomic outcomes. We first account for unobserved state-level heterogeneity. We residualize both the outcome variable and the Black indicator using state fixed effects. We then implement the causal forest on these residuals using a vector of county-level features. These include discrimination, the share of Black residents, education, income, labor force participation, population size, population density, and the share of farmers.

To interpret the model, we calculate the variable importance score for each covariate. This metric reflects the depth-weighted frequency with which a variable splits the trees in the forest. It effectively ranks features by their ability to explain heterogeneity in the racial SES gap without imposing a rigid functional form.

Figure A.3 displays the results. We find that the level of discrimination is a primary driver of differential SES outcomes. This pattern holds across all five data sources (1950 Census, City Directories, 1970s Tax Returns, 1990s Public Records, and NUMIDENT). The county's level of discrimination and the share of the Black population consistently rank as the top two features.

When the outcome is the SES index based on occupational rankings in the 1950 Census (Figure A.3A), discrimination in the 1950 residence county is the single most important determinant. It explains more heterogeneity than any economic fundamental. In later periods (Figure A.3B and Figure A.3E), the share of the Black population often ranks highest. However, discrimination remains a dominant second factor. In all specifications, these two variables have higher predictive power than economic features such as median income, median education, or the share of farmers. These findings suggest that the socioeconomic penalty for Black pilots depends more on the intensity of the racial environment than on local economic conditions.

6.3 Instrumental Variable

The OLS estimate of β in Equation 13 may be biased by endogenous sorting. Specifically, Black pilots with high unobserved ability might possess more resources or information. This could allow them to settle in less racist counties after their discharge. Such sorting would lead OLS to overestimate the true magnitude of the effect (i.e., β would be biased upwards).

To address this concern, we construct an instrument for $Discrimination_{c(i)}$ using the geographic origins of a pilot's wingmen—defined here as the pilots who serve in the same flight group.[15] This strategy relies on two assumptions. First, the assignment of pilots to units is quasi-random. Second, the origin of a pilot's wingmen influences his post-war location choice.

6.3.1 Quasi-Random Geographical Origins of Wingmen

Two institutional features of the AAF during WWII support the assumption of quasi-random assignment. First, the primary objective of the AAF was the rapid assembly of effective combat units. Assignment officers prioritized immediate operational needs and quota fulfillment over individual preferences or demographic characteristics. The military bureaucracy viewed recruits as fungible assets (Van Creveld, 1982); consequently, the system did not sort individuals based on pre-service geographic or social ties.

Second, high attrition rates made the formation of flight groups stochastic in terms of geographical origins. Training spanned four distinct stages. Washout rates were high at every step. As a result, the peer group a pilot started with was rarely the group he finished with. The composition of a graduating class—and the subsequent assignment to flight groups—depended on success throughout this rigorous process rather than on pre-existing social ties. We therefore assume that assignment to flight groups was random conditional on the origin state.[16]

To validate the quasi-random assignment of pilots to flight groups, we conduct permutation tests. We compare the observed sorting of pilots to a counter-

[15] The AAF designated groups by function (i.e., fighter or bombardment), precluding fighter and bomber pilots from serving in the same unit.

[16] This identification assumption mirrors the strategy in Green (2025). She finds that the assignment of Navy sailors to ships was random conditional on the state of enlistment, the first quarter aboard a ship, and ship type.

factual distribution generated by randomly reassigning flight groups 500 times within strata defined by race and state of birth. We focus on four metrics to detect potential non-random clustering: geographic concentration (measured by the birth-county Herfindahl-Hirschman Index and the average share of wingmen from the same county) and assortative matching on background characteristics (measured by regression coefficients of individual education and birth year on wingman averages).

Figure 6 displays the results. The observed statistics in the actual data fall centrally within the distributions simulated under the null hypothesis of random assignment conditional on race and birth state. The resulting two-sided p-values are consistently large. We fail to reject the null hypothesis. This evidence supports the assumption that pilots were not systematically sorted into groups based on individual characteristics other than race and birth state.

6.3.2 Wingmen's Origins and Post-War Location

Upon discharge, some pilots chose to move. Choosing the location of a former wingman was one of the available options. Service with these peers likely provided information about their home towns and established social ties that may have influenced location decisions.

To test the influence of wingmen's origins on post-war residence decisions, we construct a dataset of pilot-county pairs that links every pilot to all counties in the contiguous US. We estimate a linear probability model where the dependent variable is a binary indicator equal to one if the pilot resided in a specific county in 1950 and zero otherwise. The primary explanatory variable is the proportion of a pilot's wingmen who were born in that county.

Table A.7 presents the results. We find a strong, statistically significant positive relationship between wingmen's origins and subsequent location choices across all specifications. In the full sample (Column 1), pilots were 0.629 percentage points more likely to settle in a county if the share of their wingmen from that county was one percentage point higher ($p < 0.01$). When we split the sample by race, we observe that this peer effect is stronger for Black pilots (Column 2), with a coefficient of 0.921, compared to white pilots (Column 3), who have a coefficient of 0.518. These estimates suggest that social ties formed during service

were a substantial determinant of post-war geographic mobility for both racial groups.

6.3.3 2SLS Results

We construct the instrument as the weighted average of discrimination levels in the birth counties of a pilot's wingmen. Formally, we define the instrument Z_i for pilot i as:

$$Z_i = \sum_c \omega_{c,-i} \times Discrimination_c \tag{14}$$

where $Discrimination_c$ denotes the discrimination level of birth county c, and $\omega_{c,-i}$ is the share of pilot i's wingmen born in county c. For Black pilots, we impose a restriction based on migration constraints during the Jim Crow era. We assign a weight of zero to wingmen from Southern states if the focal pilot i was born in a non-Southern state. This adjustment accounts for the low likelihood that Black pilots born outside the South would migrate to the South after the war.[17]

Table 11 presents the results. Column 1 shows the first-stage relationship between the instrument and the level of discrimination in the pilot's 1950 county of residence. The correlation is positive and strong. A one-SD increase in the wingmen-based discrimination instrument is associated with a 0.564-SD increase in the discrimination index of the pilot's 1950 residence. The first-stage F-statistic is 23.647. This is well above conventional thresholds and indicates a strong instrument.

Columns 4 and 5 present the reduced-form estimates. Here, we regress the outcomes directly on the interaction between the Black indicator and the instrument. The coefficients for both outcomes are negative. Relative to white pilots, a one-SD increase in the instrument reduces the 1950 income of Black pilots by approximately 58.5% ($p = 0.087$). It lowers the SES index by 0.679 SDs ($p = 0.028$).

Columns 2 and 3 report the 2SLS estimates. These results suggest a substantial penalty for Black pilots residing in more racist counties. Relative to white pilots, a one-SD increase in local discrimination lowers earnings for Black pilots by approximately 72% ($p = 0.034$). It reduces the SES index by 0.763 SDs

[17] In our sample, only 1.4% of Tuskegee Airmen born outside the South lived in the South in 1950. By comparison, the share of South-born Airmen living in the South is 6.1%.

(p = 0.019). These estimates support a causal interpretation. Exposure to discriminatory environments—instrumented by the quasi-random assignment of wingmen' geographic origins—negatively affects the post-war economic status of Black pilots.

One limitation of this instrumental variable strategy is that it cannot predict the level of discrimination in the residence county of Black pilots for the post-1950 period. Table A.8 tests the predictive power of the instrument defined by Equation 14. We use residence counties from 1960–90 City Directories, 1970s Tax Returns, the 1990s Index to Public Records, and the Social Security Death NUMIDENT file. The results show that the instrument is weak in these later periods. The F-statistics ranges from 1.548 to 7.176, below the conventional thresholds. This result is likely due to residential mobility. Black pilots may have initially co-located with wingmen immediately following their discharge. However, subsequent migration decisions over the following decades likely attenuated this peer influence.

6.4 Mover Design

Despite the near-talent-homogeneity among pilots due to the exact AAF selection and our Coarsened Exact Matching among small observed heterogeneity in terms of aerial victories, the cross-sectional estimates in **??** could still be biased by unobserved time-invariant individual characteristics. For example, a Black pilot with high "ambition" might be systematically more likely to live in a low-discrimination county and earn more in 1950. This sorting on unobservables would bias our $Black_i \times Discrimination_i$ coefficient in Equation 13.

To address this sorting concern, we adopt a "mover design" from Finkelstein et al. (2016) and Chetty et al. (2013). By restricting the sample to Black pilots who move counties between year t and t+1 and analyzing the *change* in their outcomes (Δy_i) as a function of the *change* in their discrimination exposure ($\Delta \text{Discrimination}_i$), we mechanically difference-out all time-invariant individual characteristics, whether observed or unobserved. This design, however, still faces an identification challenge: a simple regression of Δy_i on $\Delta Discrimination_i$ among Black pilots would be biased if the change in discrimination is correlated with other unobserved changes in county characteristics. For instance, moving to a less-racist county

might also mean moving to a county with a local economic boom that increases SES.

To cleanly isolate the causal effect of discrimination change from these confounders, we improve from the classic "difference-in-differences" mover design and utilize a "triple-difference strategy." We add a counterfactual for the outcome trajectory that a Black pilot would have experienced had race been irrelevant to their outcomes. We construct this counterfactual using white pilots who make identical moves.

The intuition of this triple-difference logic can be illustrated as follows. Consider two Black pilots (B1, B2) and two white pilots (W1, W2) from the same origin county. Pilot B1 and W1 make an identical move to Destination A (e.g., lower-discrimination), while B2 and W2 make an identical move to Destination B (e.g., higher-discrimination).

1. The first difference (within-individual, $\Delta y_i = y_{i,t+1} - y_{i,t}$) controls for all time-invariant individual characteristics.
2. The second difference (within-destination) compares the outcome *changes* of the Black and white pilot who made the same move. The difference in outcome change ($\Delta y_{B1} - \Delta y_{W1}$) isolates the race-specific effect of moving to Destination A, netting out any common economic shocks in that location. Similarly, ($\Delta y_{B2} - \Delta y_{W2}$) isolates the race-specific effect for Destination B.
3. The third difference (across-destinations) compares these two race-specific effects: $\left[(\Delta y_{B1} - \Delta y_{W1}) - (\Delta y_{B2} - \Delta y_{W2})\right]$. This final comparison differences-out any race-specific trends common to all movers, isolating the causal effect of the *difference* in discrimination exposure between Destination A and B.

6.4.1 Graphical Evidence

We first examine pilot mobility between the 1950 Census and the 1960–1990 City Directories. Among the 1,756 pilots we observe in both data sources, 72% (1,260) resided in a different county in 1960–1990 than in 1950 (Table A.2). However, more talented pilots, regardless of race, are no more likely to move. This extensive-margin relationship between the probability of moving and talent holds across our three talent proxies: years of schooling in the 1940 Census, years of schooling

in the Enlistment Records, and aerial victories (see columns 1–3 of Table A.4).

Focusing on the sample of movers, we find that moving to higher-discrimination regions reduced the SES of Black pilots. This penalty does not appear for white pilots. Figure 5A plots the SES of mover pilots in the 1950 Census and the 1960–1990 City Directories, categorized by race and the change in county-level discrimination. We find that when Black pilots moved to higher-discrimination counties, their SES generally declined; conversely, their SES improved when they moved to less-racist counties. In stark contrast, the SES of white pilots remains largely unchanged between the two periods, regardless of whether they move to more or less-racist counties. Figure 5B presents this relationship more directly: the change in SES is plotted against the change in the residence county's discrimination level by race. For white pilot movers, this relationship is flat. However, for Black pilot movers, the relationship between the change in discrimination and the change in SES is distinctly negative. This diametrically different pattern between white and Black pilots is consistent with a detrimental effect of discrimination on Black pilots' outcomes.

The pattern in Figure 5B could be driven by selection: more talented Black pilots might sort into lower-discrimination counties, while such sorting did not occur among white pilots. Columns 4–6 of Table A.4 show this is not the case. The relationship between the change in discrimination and talent is flat (or statistically insignificant positive) for both white and Black pilots.

When we compare movement between the 1950 Census and the NUMIDENT data, we find similar patterns on both the extensive and intensive margins. We find that 75% of pilots (1,226 out of 1,756) died in a county different from their 1950 Census county (see Table A.3). However, we do not find that more talented Black pilots were relatively more likely to move. Furthermore, conditional on moving, we do not find that more talented Black pilots were relatively more likely to move to lower-discrimination counties (see Table A.5). This pattern differs from our findings for the full recruit sample. In that sample, Black recruits were less likely to move than white recruits with similar cognitive ability; however, conditional on moving, Black recruits were more likely to move to lower-discrimination counties (columns 1–2 and 4–5 of Table A.6). However, if we focus only on recruits with high cognitive ability (a group comparable to pilots), we find the same extensive and intensive margin patterns as the pilots (columns 3 and 6 of Table A.6).

6.4.2 Regression Results

To rigorously test the graphical evidence, we turn to the triple-difference regression analysis:

$$\Delta y_i = \alpha + \beta(Black_i \times \Delta\text{Discrimination}_i) + \theta X_i + \epsilon_i \tag{15}$$

where Δy_i is the change in the outcome for mover i between $t+1$ and t, and $\Delta\text{Discrimination}_i$ is the discrimination level difference between the destination and origin. We include a full set of origin county fixed effects (to compare pilots from the same origin) and destination county fixed effects (to control for all destination-specific factors). The coefficient of interest, β, captures the causal effect of discrimination on the socioeconomic trajectory of Black pilots relative to their white counterparts who make identical moves.

First, consistent with Figure 5, we focus on pilots who moved between 1950 and the period 1960–1990. In both years, we measure the pilots' SES using the standard occupational ranking index.

The results are reported in Table 10. Column (1) shows that, among all pilots and controlling for origin county fixed effects, moving to more-racist counties is associated with a smaller SES increase. In Column (2), we examine the differential effect by race. Compared to white pilots making the same move, Black pilots moving to a county with one SD higher discrimination experience a 0.6 SD decline in their change in SES. In the most stringent specification, Column (3) additionally controls for destination county fixed effects, leading to an estimated effect magnitude of 0.4 SD. Columns (1)–(3) cluster standard errors at the origin county level. Column (4) demonstrates the robustness of the standard errors when clustering at both the origin and destination county levels.

Next, we study movers observed between 1950 and their year of death. In 1950, we use the nationwide percentile of their occupation based on median income; for the year of death, we use the percentile of their death ZIP code based on average income. We find patterns similar to the 1950-to-1960/90 movers. In the most demanding specification (Column 8), we find that compared to white pilots, a one-SD change in the discrimination level is associated with a 19.5 percentile point lower increase in this broader socioeconomic outcome.

7. Conclusion

How can we identify talent misallocation? One needs to measure individual ability and compares the outcomes of similarly able individuals under different levels of discrimination. Building on the literature on talent misallocation and growth (Baumol, 1990; Murphy et al., 1991; Hsieh et al., 2019; Hnatkovska et al., 2021), we provide granular individual-level evidence on talent allocation by examining the Tuskegee airmen, a similarly high-talented cohort of USAAF pilots trained during WWII. By measuring ability using the Army aptitude test scores and aerial victories, we find a significant cost that racial discrimination imposed throughout their lives. They earned less throughout their life span compared to their white counterparts. More importantly, their jobs cannot fully utilize their high cognitive abilities. These results remain unchanged after addressing various concerns, including sorting over racial discrimination.

Our findings have implications for propagating the role of human capital in development. Getting the population educated is crucial to explain aggregate economic development (Gennaioli et al., 2013; Goldin and Katz, 2001) and individual income growth (Duflo, 2001). However, the importance of human capital for growth lies not only in its "production" but also in its "consumption." An efficient policy on human capital should promote both the education of the population and their placement in the appropriate position based on their abilities.

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Figures

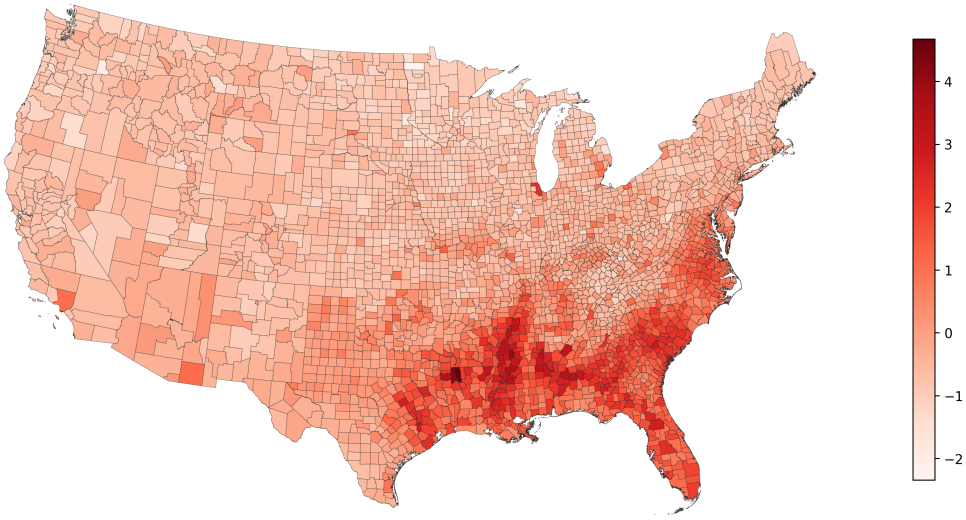
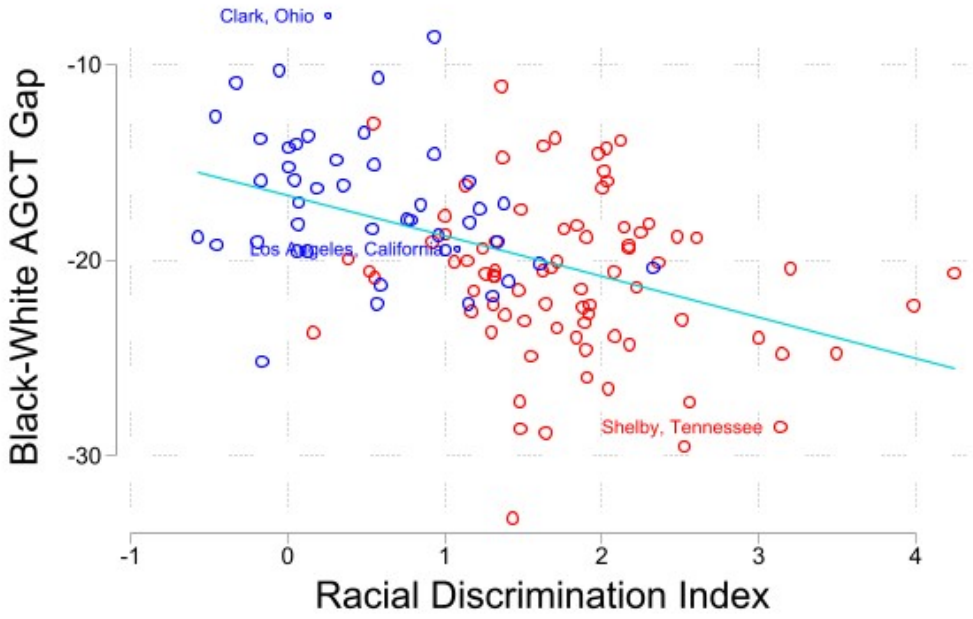


FIGURE 1: Racial Discrimination Index

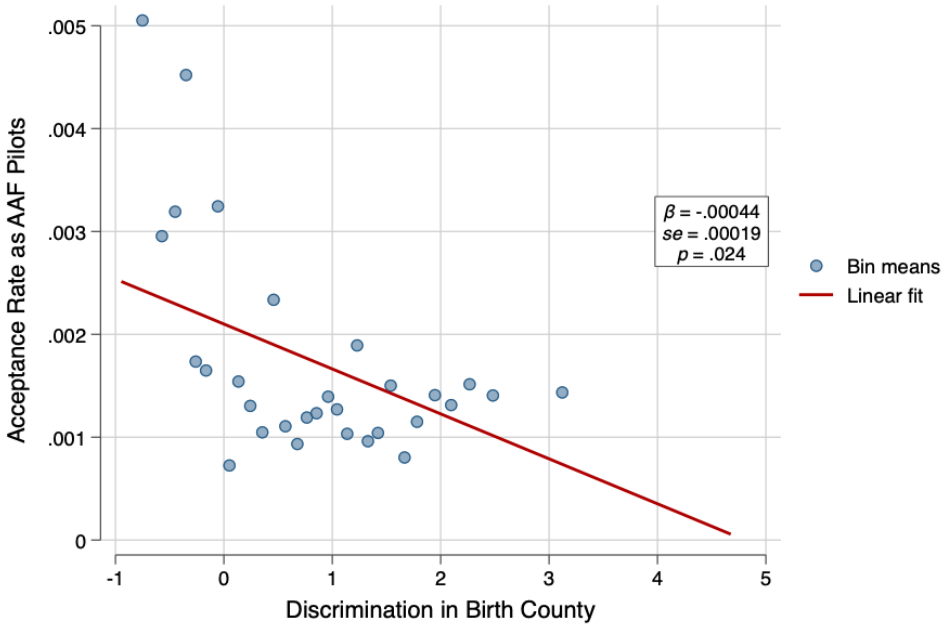
Notes: This map displays a county-level racial discrimination index. The index is the normalized first principal component derived from six historical indicators of racial discrimination, with missing data handled via iterative imputation. Darker shades indicate higher levels of the index.

FIGURE 2: County-Level Racial Discrimination and the Black-white AGCT Gap



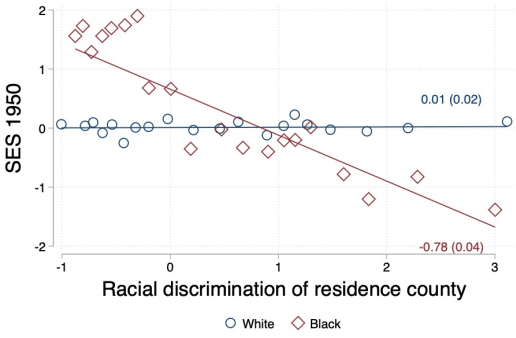
Notes: This figure shows the relationship between the racial discrimination level of residence county when enlistment (*x*-axis) and the estimated Black-white gap in the AGCT score (*y*-axis). The Black-white AGCT gap estimates are the marginal effects of the Black indicator, derived from a regression of the AGCT score on an interaction between a Black indicator and county indicators, with fixed effects for years of education, birth year, enlistment year-month, and enlistment place. The figure plots these county-specific AGCT gaps against the county-level racial discrimination index. The plot includes a linear best-fit line. Counties with fewer than 50 Black or 50 white recruits are excluded from the analysis. Red (blue) dots are for counties from former Confederate (non-Confederate) states.

FIGURE 3: Racial Discrimination and Acceptance Rate for Black Recruits as AAF Aviators

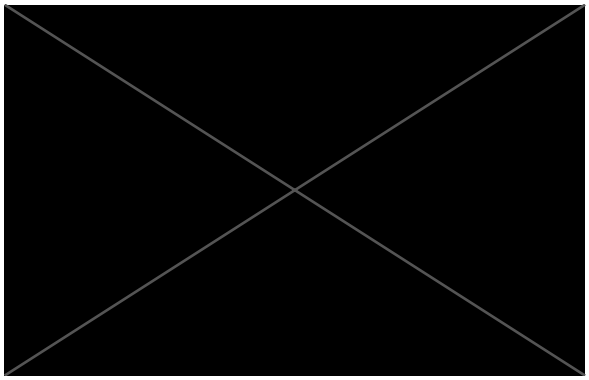


Notes: This figure plots a binscatter of acceptance rates for Black Army recruits as WWII AAF pilots against the level of racial discrimination in their county of birth. We define the acceptance rate as the number of Tuskegee Airmen born in a county divided by the number of Black Army recruits from that county who fall within the same age range as the AAF pilots in our sample. The data are at the county level. We exclude counties with 30 or fewer Black Army recruits. The specification includes state fixed effects. Standard errors are clustered at the state level.

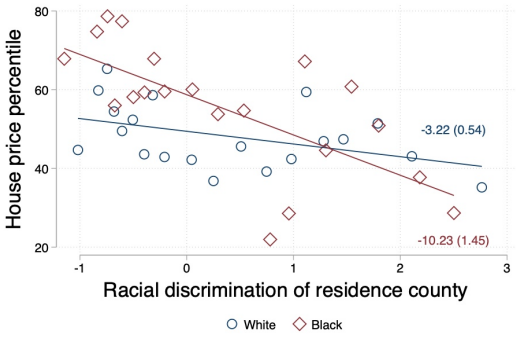
Figure 4: Racial Discrimination in Residence County and Pilot Outcomes by Race



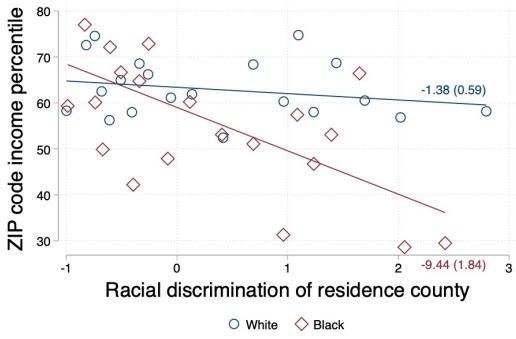
(A) SES (1950)



(B) Income (1970)



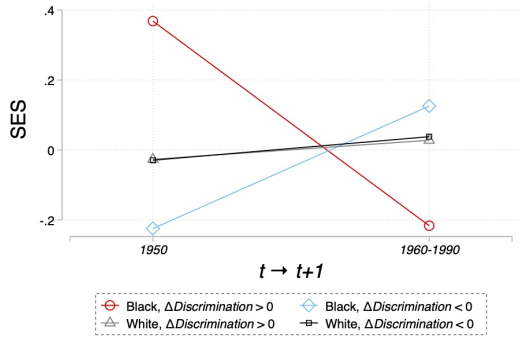
(C) House price percentile (1990)



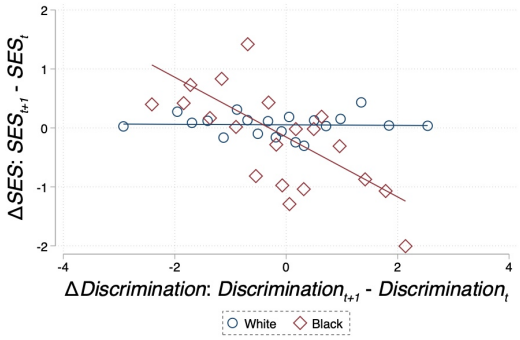
(D) ZIP code income percentile (death)

Notes: This figure shows binned scatterplots illustrating the relationship between county-level racial discrimination and individual outcomes observed at different stages of life, separated by Black and white individuals. Panel A uses the SES index in 1950, a standardized latent factor derived using Structural Equation Modeling with full information maximum likelihood from 1950 occupational income score, cognitive score, prestige score, leadership score, and social skill score. Panel B uses the income in the 1970 tax returns. Panel C uses the price percentile of their house listed in the 1990 city directory. Panel D uses the income percentile of their death ZIP code. Each panel also displays the regression coefficient and standard error from a separate regression of the outcome on the discrimination measure for each racial group.

Figure 5: Mover Design



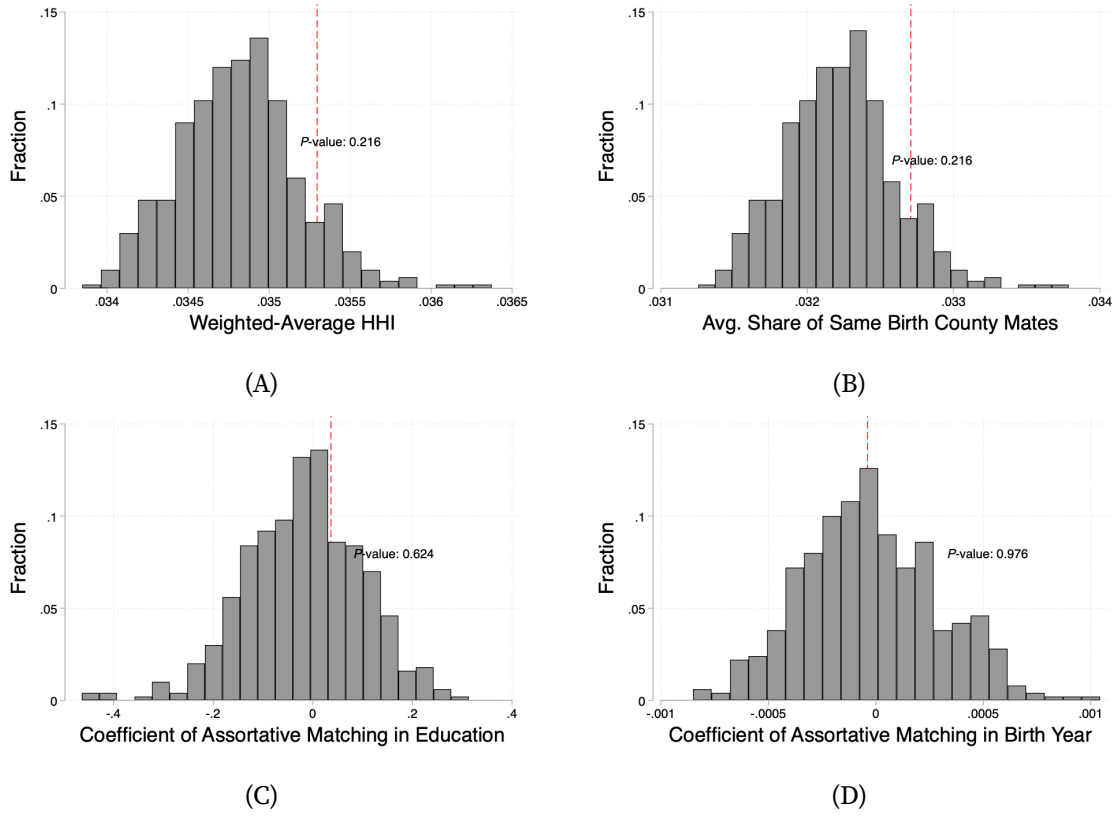
(A) Change in SES for Movers by ΔDiscrimination and Race



(B) ΔDiscrimination and ΔSES, by Race

Notes: A: This figure shows the change in average SES for pilots who moved between counties from the initial observation period t (1950 Census) to the subsequent observation period $t + 1$ (1960-1990 City Directories) ("movers"). It compares movers' SES outcome at time t (1950) and time $t + 1$ (1960-1990) by: race and whether the difference in racial discrimination between the destination county and the origin county to the destination county (i.e., ΔDiscrimination = $\text{Discrimination}_{t+1} - \text{Discrimination}_t$) was positive or negative. The SES index is a standardized latent factor derived using Structural Equation Modeling with full information maximum likelihood from occupational income score, cognitive score, prestige score, leadership score, and social skill score. B: This figure is the binned scatter plot between ΔDiscrimination (x-axis) and ΔSES (i.e., $\text{SES}_{t+1} - \text{SES}_t$; y-axis) by race.

Figure 6: Permutation Tests for Random Assignment to Flight Groups



Notes: This figure shows the results of permutation tests assessing whether pilots are randomly assigned to flight groups. Panel A displays the distribution of the weighted average Herfindahl-Hirschman Index (HHI) calculated based on birth counties within groups. Panel B shows the distribution for the average share of wingmen originating from the same birth county. Panels C and D display the distributions of assortative matching coefficients for education and birth year, respectively, where coefficients are derived by regressing an individual's characteristic on the leave-one-out wingman average within the group. In all panels, the histograms represent the distribution of statistics generated by randomly permuting flight group identifiers 500 times, stratified by the Black indicator and the state of birth. The vertical red dashed lines indicate the observed statistics in the actual data. Two-sided p-values are reported.

Tables

Table 1: Summary Statistics for Enlistees

	Black			White		
	Mean	SD	N	Mean	SD	N
Birth year	1919.88	5.11	46,528	1919.71	5.55	395,754
AGCT	70.29	19.65	46,528	100.92	21.90	395,754
Years of schooling (Enlistment Records)	9.47	1.87	46,528	10.74	2.15	395,754
Income ($) 1950	2109.40	1876.22	3,647	2907.96	2049.84	38,530
Occ income score ($) 1950	2159.23	731.04	15,358	2789.49	975.19	175,256
Occ prestige score 1950	28.03	10.90	15,247	37.04	12.23	173,524
Occ cognitive score 1950	-0.41	0.78	15,161	0.04	1.01	174,384
Occ leadership score 1950	-0.29	0.77	15,236	0.03	1.01	173,084
Occ social skill score 1950	-0.49	0.79	15,236	0.04	1.01	173,084
SES index 1950	-0.57	0.77	16,068	0.05	1.00	180,489
Discrimination 1950	1.22	0.93	19,489	0.26	0.92	205,469
ZIP code income percentile death	36.83	32.10	11,568	53.77	30.01	116,008
Discrimination death	1.04	0.98	11,956	0.24	0.94	119,234

Table 2: Summary Statistics for Pilots

	Black			White		
	Mean	SD	N	Mean	SD	N
Birth year	1920.57	2.81	754	1920.43	2.46	3,623
Aerial victories	0.53	1.44	854	0.73	1.61	4,033
Years of schooling (1940 Census)	11.08	2.34	296	11.39	1.78	1,514
Years of schooling (Enlistment Records)	13.72	1.63	226	12.96	1.26	1,163
Income ($) 1950	2841.43	1210.75	77	3052.66	1284.21	464
Occ income score ($) 1950	2846.83	971.67	331	2888.70	1198.34	2,238
Occ prestige score 1950	43.18	15.26	327	43.96	12.90	1,884
Occ cognitive score 1950	-0.02	0.92	315	0.00	1.01	2,237
Occ leadership score 1950	-0.20	1.06	327	0.03	0.98	1,883
Occ social skill score 1950	-0.64	1.06	327	0.11	0.95	1,883
SES index 1950	-0.02	0.90	331	0.00	1.01	2,239
Discrimination 1950	0.88	0.92	418	0.38	1.06	2,439
Occ income score ($) 1960–90	2600.52	1401.90	385	2981.86	1191.95	2,194
Occ prestige score 1960–90	40.05	18.93	373	43.50	16.58	2,159
Occ cognitive score 1960–90	-0.05	1.02	372	0.01	1.00	2,072
Occ leadership score 1960–90	0.10	0.95	368	-0.02	1.01	2,132
Occ social skill score 1960–90	-0.03	0.98	368	0.00	1.00	2,132
SES index 1960–90	-0.14	1.08	385	0.03	0.98	2,194
Discrimination 1960–90	0.65	0.96	385	0.29	1.06	2,194
House percentile 1990s	51.93	32.11	439	48.38	28.04	2,325
Discrimination 1990s	0.66	1.00	439	0.32	1.07	2,325
ZIP code income percentile death	52.76	35.47	385	63.00	29.32	2,194
Discrimination death	0.66	0.95	385	0.28	1.06	2,194

Table 3: Racial Gaps in AGCT Scores and Educational Attainment

	AGCT (1)	AGCT (2)	$\geq$ 9-year schooling (3)	$\geq$ 12-year schooling (4)	$\geq$ 14-year schooling (5)
Panel A: Regressions with FEs					
Black	-25.613***	-18.295***	-0.197***	-0.231***	-0.064***
	(0.412)	(0.241)	(0.010)	(0.006)	(0.005)
Fixed Effects					
Baseline	Y	Y	Y	Y	Y
+ Education	N	Y	N	N	N
Mean DV	97.697	97.697	0.734	0.411	0.076
N	441,684	441,684	441,684	441,684	441,684
R^2	0.293	0.582	0.132	0.087	0.105
Panel B: Regressions with CEM matching					
Black	-25.978***	-17.551***	-0.202***	-0.233***	-0.060***
	(0.644)	(0.392)	(0.013)	(0.009)	(0.005)
Matching Variables					
Baseline	Y	Y	Y	Y	Y
+ Education	N	Y	N	N	N
Mean DV	97.857	94.413	0.768	0.411	0.074
N	192,829	113,453	192,829	192,829	192,829
R^2	0.149	0.094	0.026	0.029	0.006

Notes: Panel A presents results for Equation 7 and Panel B presents results for Equation 8. Columns (1) and (2) use the AGCT score as the dependent variable. Columns (3)-(5) use indicators for schooling of at least 9 years, 12 years, and 14 years, respectively. All specifications in Panel A include fixed effects for residence county when enlistment, birth year, enlistment year-month, and enlistment place. Column (2) additionally includes fixed effects for education level. The matching variables used to generate weights in Panel B correspond to variables in the fixed effects of Panel A. Standard errors, clustered at the enlistment county level, are in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 4: The Effect of Discrimination on Black Enlistees' AGCT Scores and Educational Attainment

	AGCT (1)	AGCT (2)	$\geq$ 9-year schooling (3)	$\geq$ 12-year schooling (4)	$\geq$ 14-year schooling (5)
Panel A: Regressions with FEs					
Black $\times$ *Discrimination*	-4.217***	-2.029***	-0.086***	-0.044***	-0.008**
	(0.521)	(0.251)	(0.018)	(0.008)	(0.004)
Fixed Effects					
Baseline	Y	Y	Y	Y	Y
+ Education	N	Y	N	N	N
Mean DV	98.261	98.261	0.742	0.418	0.079
N	390,539	390,539	390,539	390,539	390,539
Adj. R^2	0.282	0.576	0.118	0.071	0.090
Panel B: Regressions with CEM matching					
Black $\times$ *Discrimination*	-4.222**	-2.460***	-0.110***	-0.049***	-0.006
	(1.610)	(0.902)	(0.027)	(0.017)	(0.006)
Matching Variables					
Baseline	Y	Y	Y	Y	Y
+ Education	N	Y	N	N	N
Mean DV	97.942	94.864	0.752	0.416	0.072
N	288,092	210,630	288,092	288,092	288,092
Adj. R^2	0.124	0.112	0.027	0.023	0.005

Notes: Panel A presents results for Equation 9 and Panel B presents results for Equation 10. Columns (1) and (2) use the AGCT score as the dependent variable. Columns (3)-(5) use indicators for schooling of at least 9 years, 12 years, and 14 years, respectively. All specifications in Panel A include fixed effects for residence state when enlistment, birth year, enlistment year-month, and enlistment place. Column (2) additionally includes fixed effects for education level. The matching variables used to generate weights in Panel B correspond to variables in the fixed effects of Panel A. Standard errors, clustered at the enlistment state level, are in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 5: Racial Gaps in Socioeconomic Outcomes for Veterans

	1950 Census							NUMIDENT
	income	occ income score	occ prestige score	occ cognitive score	occ leadership score	occ social score	SES	ZIP code income percentile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Black	-684.193***	-577.347***	-8.269***	-0.419***	-0.299***	-0.483***	-0.597***	-9.936***
	(57.293)	(12.754)	(0.209)	(0.014)	(0.015)	(0.013)	(0.015)	(0.978)
N	34,494	186,770	186,770	186,770	186,770	186,770	186,770	60,417
R^2	0.057	0.191	0.189	0.142	0.052	0.154	0.180	0.353
Panel B:								
Black	-567.643***	-444.492***	-6.301***	-0.294***	-0.243***	-0.347***	-0.442***	-8.636***
	(58.617)	(12.790)	(0.212)	(0.014)	(0.015)	(0.013)	(0.015)	(0.971)
AGCT	61.528***	72.045***	1.067***	0.068***	0.030***	0.074***	0.084***	0.723***
	(7.660)	(1.877)	(0.025)	(0.002)	(0.002)	(0.002)	(0.002)	(0.086)
N	34,494	186,770	186,770	186,770	186,770	186,770	186,770	60,417
R^2	0.059	0.203	0.206	0.153	0.054	0.166	0.196	0.354
Panel C								
Black	-390.824**	-231.786***	-3.428***	0.203***	0.051	0.037	-0.032	-3.409*
	(162.330)	(35.795)	(0.532)	(0.034)	(0.036)	(0.033)	(0.035)	(2.052)
AGCT	63.156***	73.959***	1.093***	0.073***	0.033***	0.077***	0.087***	0.764***
	(7.839)	(1.946)	(0.025)	(0.002)	(0.002)	(0.002)	(0.002)	(0.088)
Black × AGCT	-22.979	-27.848***	-0.376***	-0.065***	-0.038***	-0.050***	-0.054***	-0.680***
	(18.677)	(4.676)	(0.065)	(0.004)	(0.005)	(0.004)	(0.004)	(0.254)
N	34,494	186,770	186,770	186,770	186,770	186,770	186,770	60,417
R^2	0.059	0.204	0.206	0.154	0.055	0.167	0.196	0.354
Mean DV	2942.087	2758.044	36.354	0.011	0.003	-0.000	0.017	52.687

Notes: This table shows regression results for racial gaps in postwar socioeconomic outcomes for recruits whose AGCT scores are available. Columns (1)-(7) use 1950 Census data: (1) total income ($), (2) occupational income score ($), (3) occupational prestige score, (4) normalized occupational cognitive score, (5) normalized occupational leadership score, (6) normalized occupational social skill score, and (7) a normalized SES index. Column (8) uses the 2022 average income percentile of the individual's ZIP code at death from public-version NUMIDENT. The SES index (Column 7) is a normalized latent factor score derived from a structural equation model using the variables in Columns (1)-(6). Panel A regresses each outcome on a Black indicator, absorbing fixed effects for residence county (at outcome measurement), residence county (when enlistment), birth year, education level, enlistment month, and enlistment place. Panel B additionally includes the AGCT score. Panel C additionally adds an interaction term between the Black indicator and the AGCT score. The AGCT score is the unit of 10 points. Standard errors are clustered by residence county (at outcome measurement). * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 6: The Interaction of Race, Racial Discrimination, and AGCT on SES Outcomes for Veterans

	1950 Census							NUMIDENT
	income (1)	occ income score (2)	occ prestige score (3)	occ cognitive score (4)	occ leadership score (5)	occ social score (6)	SES (7)	ZIP code income percentile (8)
Black-White Difference in Marginal Effects of Discrimination								
Estimate	-229.056	-82.839	-0.502	-0.025	-0.022	-0.050	-0.047	-3.077
P-value	0.000	0.000	0.094	0.196	0.315	0.008	0.020	0.007
Black	-359.951*	201.600***	1.086	0.407***	0.171***	0.289***	0.292***	3.499
	(187.874)	(64.360)	(0.775)	(0.064)	(0.059)	(0.064)	(0.060)	(4.796)
Discrimination	199.027***	98.112**	0.822**	-0.045	-0.044**	0.023	0.018	-4.193***
	(68.834)	(41.635)	(0.360)	(0.029)	(0.020)	(0.024)	(0.028)	(1.463)
AGCT	10.144***	12.501***	0.187***	0.012***	0.006***	0.014***	0.015***	0.198***
	(0.678)	(0.317)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)
Black × Discrimination	150.520	-118.492**	-0.729	0.049	0.027	-0.017	-0.017	-0.906
	(197.125)	(51.842)	(0.881)	(0.057)	(0.046)	(0.052)	(0.062)	(3.273)
Black × AGCT	-0.177	-5.978***	-0.071***	-0.008***	-0.005***	-0.007***	-0.008***	-0.123***
	(2.147)	(0.790)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.043)
Discrimination × AGCT	-0.772	0.441	0.002	0.000	0.000	0.000	0.000	0.041***
	(0.768)	(0.424)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)
Black × Discrimination × AGCT	-3.839	0.360	0.002	-0.001	-0.000	-0.000	-0.000	-0.022
	(2.427)	(0.612)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.032)
Mean DV	2934.475	2757.714	36.359	0.012	0.003	0.001	0.018	52.610
Adj. R^2	0.033	0.128	0.147	0.092	0.029	0.115	0.135	0.128
N	35,562	187,401	187,401	187,401	187,401	187,401	187,401	61,319

Notes: This table shows results from regressions of each SES outcome on a Black indicator, the racial discrimination index at their residence county when the outcome is measured, the AGCT score. The specification includes all main effects, all mutual interactions, and the triple interaction between these three variables. All models include fixed effects for the residence state when the outcome is measured, and standard errors are clustered at the same level. Columns (1)-(7) use 1950 Census data: (1) total income ($), (2) occupational income score ($), (3) occupational prestige score, (4) normalized occupational cognitive score, (5) normalized occupational leadership score, (6) normalized occupational social skill score, and (7) a normalized SES index. Column (8) uses the 2022 average income percentile of the individual's ZIP code at death from public-version NUMIDENT. The SES index (Column 7) is a normalized latent factor score derived from a structural equation model using the variables in Columns (1)-(6). The table reports coefficients, with standard errors in parentheses. The bottom panel reports the Black-white difference in the marginal effect of the discrimination measure and its corresponding *p*-value. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 7: The Effect of Racial Discrimination on Black Pilot Outcomes (1950 Census and 1960-90 City Directories)

	1950 Census							1960-90 City Directories
	income	occ income score	occ prestige score	occ cognitive score	occ leadership score	occ social score	SES	SES
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Regressions								
Black × Discrimination	-971.742***	-998.695***	-12.518***	-0.754***	-0.244*	-0.713***	-0.883***	-0.234***
	(105.625)	(144.894)	(1.492)	(0.096)	(0.135)	(0.080)	(0.094)	(0.068)
Mean DV	3425.051	3176.487	43.942	0.195	-0.001	0.006	0.231	0.000
Adj. R^2	0.136	0.136	0.100	0.089	0.044	0.146	0.116	0.051
N	416	2,186	2,186	2,186	2,186	2,186	2,186	2,579
Panel B: Regressions with CEM								
Black × Discrimination	-274.825	-776.282***	-9.546***	-0.654***	-0.096	-0.663***	-0.706***	-0.359
	(318.114)	(147.381)	(1.586)	(0.123)	(0.142)	(0.065)	(0.091)	(0.231)
Mean DV	3460.641	3157.061	44.536	0.069	-0.183	-0.273	0.160	0.106
Adj. R^2	0.326	0.293	0.181	0.210	0.078	0.343	0.241	-0.004
N	39	524	524	524	524	524	524	170

Notes: This table shows regression results using pilot outcomes from the 1950 Census and 1960-90 City Directories. Panel A: Each column (1-8) presents a separate regression where the dependent variable is listed in the header. The key coefficient reported is for the interaction term between a Black indicator and a continuous measure of racial discrimination of residence county when the outcome was measured. All specifications include fixed effects for residence state and pilot type (fighter or not). Columns (1) through (7) use 1950 Census data: (1) total income ($), (2) occupational income score ($), (3) occupational prestige score, (4) normalized occupational cognitive score, (5) normalized occupational leadership score, (6) normalized occupational social skill score, and (7) a normalized SES index, which is latent factor score derived from a structural equation model using the variables in Columns (2)-(6). Column (8) uses a normalized SES index similar to Column (7), based on the 1960-90 City Directories' occupational rankings. Panel B: Regression results for a sample of Black and white pilots with the same residence county, similar education level at the time of enlistment (high school or college), similar aerial victories (by median) and pilot type with Coarsened Exact Matching. Standard errors (in parentheses) are clustered at the residence state level. * p<0.1, ** p<0.05, *** p<0.01

Table 8: The Effect of Racial Discrimination on Black Pilot Outcomes (Tax Returns in 1969, 1974, and 1979)

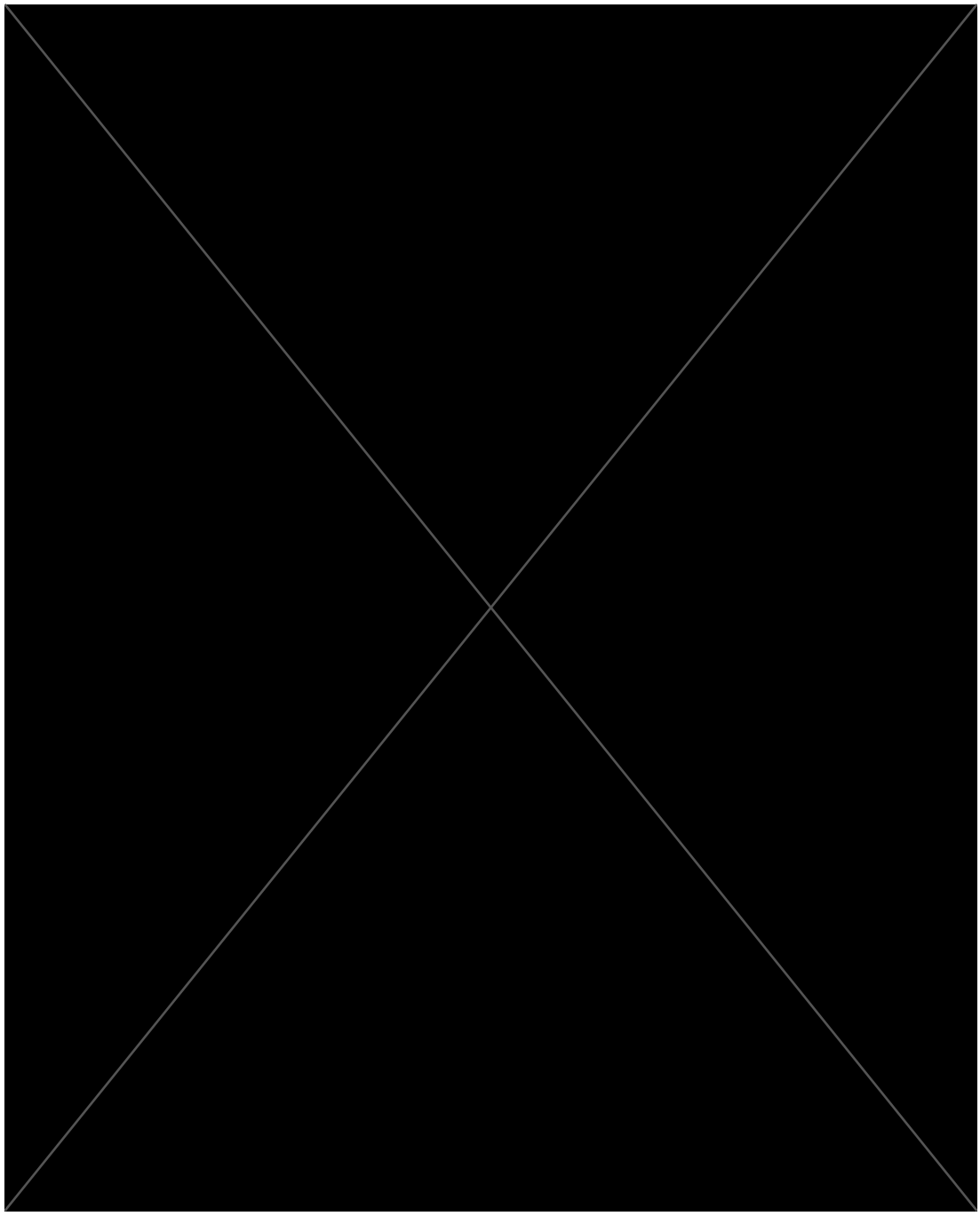


Table 9: The Effect of Racial Discrimination on Black Pilot Outcomes (1990s Index to Public Records and NUMIDENT)

	House percentile (1)	ZIP code income percentile (2)	House percentile (3)	ZIP code income percentile (4)
Black × Discrimination	-5.145***	-9.091***	-3.407**	-9.620***
	(1.665)	(2.043)	(1.253)	(3.061)
	Baseline Reg	Baseline Reg	Reg with CEM	Reg with CEM
Mean DV	48.948	61.472	59.030	63.756
Adj. R^2	0.438	0.116	0.603	0.236
N	2,764	2,579	623	492

Notes: This table shows regression results using pilot outcomes from the 1990s Index to Public Records and NUMIDENT. Columns 1-2: Each column presents a separate regression where the dependent variable is listed in the header. The key coefficient reported is for the interaction term between a Black indicator and a continuous measure of racial discrimination of residence county when the outcome was measured. All specifications include fixed effects for residence state and pilot type (fighter or not). Panel B: Regression results for a sample of Black and white pilots with the same residence county, similar education level at the time of enlistment (high school or college), similar aerial victories (by median), and pilot type with Coarsened Exact Matching. Dependent variables: house price percentile of the address in the 1990s Index to Public Records (Columns 1 and 3), and average income percentile of death ZIP code in NUMIDENT (Columns 2 and 4). Standard errors (in parentheses) are clustered at the residence state level. * p<0.1, ** p<0.05, *** p<0.01

Table 10: The Effect of Change in Racial Discrimination on Change in SES Outcomes for Movers

	Δy: 1950–> 1960-90				Δy: 1950–> Death			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black × *ΔDiscrimination*		-0.490***	-0.350*	-0.350		-15.881***	-16.372***	-16.372**
		(0.137)	(0.203)	(0.217)		(4.190)	(6.156)	(6.738)
ΔDiscrimination	-0.023	0.028			-2.404	-0.440		
	(0.059)	(0.060)			(1.828)	(1.885)		
Origin County FEs	Y	Y	Y	Y	Y	Y	Y	Y
Destination County FEs	N	N	Y	Y	N	N	Y	Y
Double Cluster SE	N	N	N	Y	N	N	N	Y
Mean DV	0.159	0.159	0.341	0.341	6.994	6.994	12.002	12.002
Adj. R^2	0.155	0.166	0.208	0.205	0.206	0.228	0.341	0.339
N	824	824	489	489	798	798	477	477

Notes: Columns (1)-(4) focus on pilots who moved between counties from the initial observation period t (1950 Census) to the subsequent observation period t + 1 (1960-1990 City Directories) ("movers"). $\Delta y = y_{t+1} - y_t$, where y_t (y_{t+1}) is the SES index in period t ($t+1$). The SES index is a standardized latent factor derived using Structural Equation Modeling with full information maximum likelihood from occupational income score, cognitive score, prestige score, leadership score, and social skill score. ΔDiscrimination = $\text{Discrimination}_{t+1} - \text{Discrimination}_t$, where Discrimination_t ($\text{Discrimination}_{t+1}$) is the racial discrimination level of residence county at time t ($t+1$). Columns (5)-(8) focus on pilots who moved between counties from the initial observation period t (1950 Census) to the death year t + 1 (NUMIDENT): y_t is nationwide percentile of occupational income score, whereas y_{t+1} is the nationwide percentile of death ZIP code's average income. Columns (1), (2), (5), and (6) absorb the origin county fixed effects and cluster the standard errors at the origin county level. Columns (3) and (7) absorb both origin and destination county fixed effects and cluster standard errors at the origin county level. Columns (4) and (8) absorb both origin and destination County fixed effects and cluster standard errors at both the origin and destination County levels. Parentheses contain the standard errors. * p<0.1, ** p<0.05, *** p<0.01

Table 11: 2SLS Estimates of the Effects of Racial Discrimination on Pilots' Outcomes from the 1950 Census

	FS	2SLS		RF	
	Discrimination	income	SES	income	SES
	(1)	(2)	(3)	(4)	(5)
Black × Discrimination		-1673.599**	-0.857**		
		(774.082)	(0.335)		
Black × IV				-1859.461	-1.203**
				(1220.422)	(0.462)
IV	0.666***				
	(0.168)				
Birth State FEs	Y	Y	Y	Y	Y
1950 Residence State FEs	Y	Y	Y	Y	Y
Pilot Type FEs	Y	Y	Y	Y	Y
F Statistic	15.775				
N	2,727	505	2,436	505	2,436

Notes: This table shows the first-stage, 2SLS, and reduced-form estimates of the impact of racial discrimination on pilots' outcomes using data from the 1950 Census. The dependent variables are income (Columns 2 and 4) and a SES index (Columns 3 and 5). The SES index is a normalized latent factor score derived from a structural equation model using occupational scores for median income, prestige, cognitive ability requirements, leadership requirements, and social skill requirements. Column 1 reports the first-stage coefficient of the instrument—constructed as a leave-one-out weighted average of peers' birth county racial discrimination—on the racial discrimination level of the pilot's 1950 residence county. Columns 2 and 3 present 2SLS estimates for the interaction between the Black indicator and the residence county racial discrimination measure. Columns 4 and 5 display the reduced-form estimates for the interaction between the Black indicator and the instrument. All specifications include fixed effects for birth state, the state of residence in 1950, and pilot type (fighter or not). Standard errors are clustered at the residence state level and reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Online Appendix

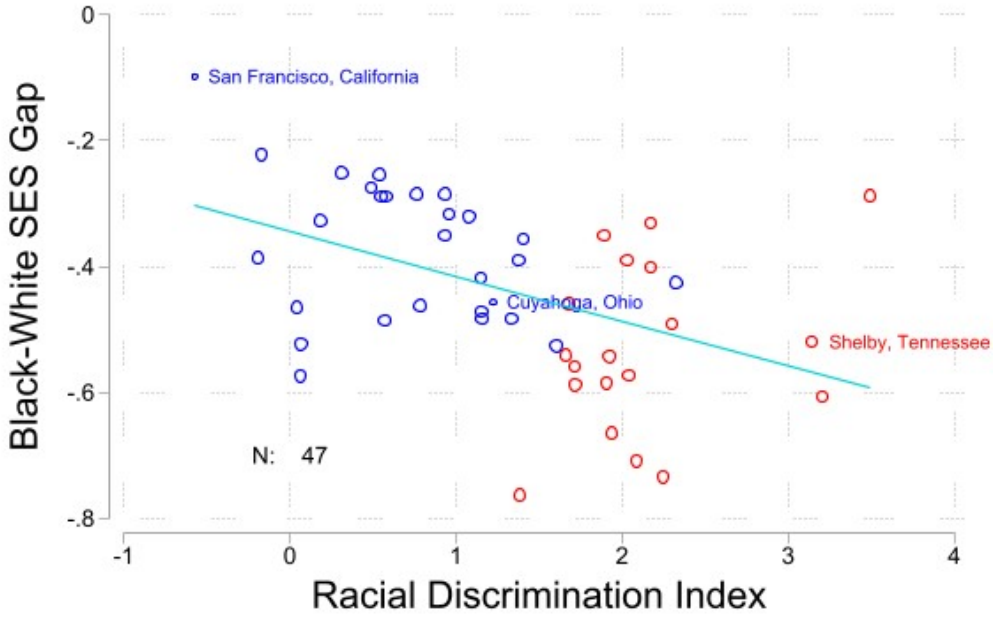
to

Red Tails, Broken Wings: Talent Misallocation Among America's Most Talented African Americans

December 2025

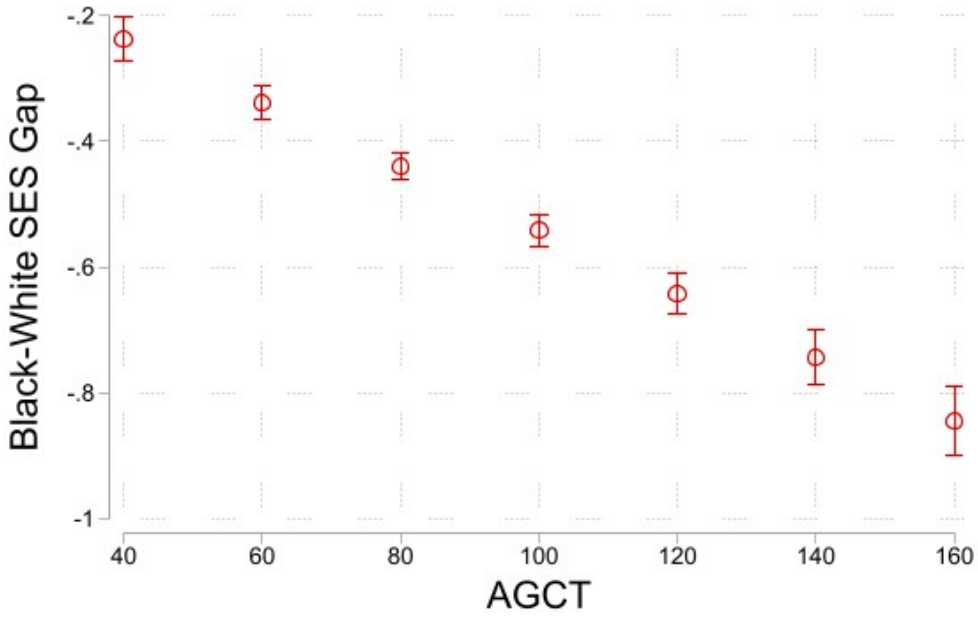
A. Appendix Figures and Tables

FIGURE A.1: County-Level Discrimination and the Black-white SES Gap



Notes: This figure shows the relationship between the racial discrimination level of residence county in 1950 (x-axis) and the estimated Black-white gap in the 1950 SES index (y-axis). The SES index is a standardized latent factor derived using Structural Equation Modeling with full information maximum likelihood from total income, occupational score, occupational cognitive score, prestige score, leadership score, and social skill score. The Black-white SES gap estimates are the effects of the Black indicator for each county, derived from a regression of the SES index on an interaction between a Black indicator and county indicators, controlling for the AGCT score and fixed effects for residence county when enlistment, birth year, education level, enlistment year-month, and enlistment place. The figure plots these county-specific SES gaps against the discrimination measure. The plot includes a linear best-fit line. Counties with fewer than 50 Black or 50 white veterans are excluded from the analysis. Red (blue) dots are for counties from former Confederate (non-Confederate) states.

FIGURE A.2: Racial Gap in 1950 SES by AGCT



Notes: This figure shows how the estimated difference in the 1950 SES index between Black and white veterans changes with AGCT scores. The SES index is a standardized latent factor derived using Structural Equation Modeling with full information maximum likelihood from total income, occupational income score, cognitive score, prestige score, leadership score, and social skill score. First, we regress this SES index against the Black indicator, AGCT score, and their interaction, with fixed effects for 1950 residence county, residence county when enlistment, birth year, education level, enlistment year-month, and enlistment place. Second, we estimate the marginal effects of the Black indicator when the AGCT score changes from 40 to 160. We plot the estimated marginal effect and its 90% confidence interval (y-axis) against the AGCT score (x-axis). Standard errors are clustered by the 1950 county of residence.

Table A.1: Tests on whether more talented black pilots are relatively more likely to live in less racist counties

	Discrimination of Residence County in ...				
	1950 Census	1960-90 City Directories	1970s Tax Returns	1990 Index to Public Records	NUMIDENT
	(1)	(2)	(3)	(4)	(5)
Panel A: Educ is years of schooling (1940 Census)					
Black × *Educ*	-0.013	-0.005		0.006	0.003
	(0.019)	(0.021)		(0.022)	(0.026)
	[0.478]	[0.809]		[0.776]	[0.904]
Educ	0.012	0.003		-0.014	0.003
	(0.012)	(0.008)		(0.013)	(0.010)
	[0.338]	[0.720]		[0.293]	[0.802]
Mean DV	0.442	0.292		0.355	0.292
N	1,305	1,217		1,337	1,217
Panel B: Educ is years of schooling (Enlistment Records)					
Black × *Educ*	-0.077	0.007		-0.052	-0.012
	(0.032)	(0.043)		(0.030)	(0.043)
	[0.022]	[0.868]		[0.093]	[0.785]
Educ	0.041	0.019		0.045	0.022
	(0.014)	(0.013)		(0.024)	(0.015)
	[0.004]	[0.153]		[0.066]	[0.163]
Mean DV	0.454	0.340		0.345	0.326
N	977	955		1,057	955
Panel C: Victory is the number of aerial victories					
Black × *Victory*	-0.062	-0.015		-0.010	-0.020
	(0.025)	(0.023)		(0.025)	(0.024)
	[0.016]	[0.528]		[0.693]	[0.409]
Victory	0.010	0.002		-0.001	-0.000
	(0.011)	(0.009)		(0.009)	(0.008)
	[0.382]	[0.779]		[0.880]	[0.997]
Mean DV	0.457	0.341		0.378	0.341
N	2,857	2,579		2,764	2,579
State FEs	Y	Y	Y	Y	Y

Notes: This table shows regression results examining whether more talented Black pilots are more likely to live in less racist counties, relative to white pilots. The table is divided into three panels by the proxy of talent: years of schooling from the 1940 Census (Panel A), years of schooling from enlistment records (Panel B), and number of aerial victories (Panel C). Each column's dependent variable is the discrimination level based on the county of residence: (1) 1950 Census, (2) 1960-1990 City Directories, (3) 1970s tax returns, (4) 1990s Index to Public Records, and (5) NUMIDENT. All models include a Black indicator, the talent proxy, and their interaction term, as well as residence state fixed effects. Standard errors, clustered at the state level, are shown in parentheses. *P*-values are in brackets.

Table A.2: Comparison of Pilot Talent Proxies by Mover Status and Discrimination Change (1950 –> 1960-90)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Movers				Stayers	Difference			
	Higher Discrimination		Lower Discrimination						
	Black	White	Black	White		(1)–(4) vs (5)	(1)–(2) vs (3)–(4)	(1) vs (3)	(2) vs (4)
Years of schooling	12.240	11.517	11.325	11.444	11.245	0.253	0.154	0.915	0.072
(1940 Census)	(0.470)	(0.113)	(0.406)	(0.099)	(0.116)	[0.065]	[0.305]	[0.154]	[0.632]
Years of schooling	14.375	12.943	13.792	13.026	13.097	0.002	0.004	0.583	-0.083
(Enlistment Records)	(0.254)	(0.083)	(0.356)	(0.087)	(0.103)	[0.983]	[0.976]	[0.189]	[0.496]
Aerial victories	0.713	0.866	0.440	0.667	0.661	0.074	0.214	0.273	0.199
	(0.221)	(0.078)	(0.143)	(0.063)	(0.066)	[0.380]	[0.021]	[0.281]	[0.046]
N	50	515	88	607	496				

Notes: This table shows mean talent proxies (Years of schooling from the 1940 Census, Years of schooling from Enlistment Records, and Aerial victories) comparing stayers and movers. Stayers (Column 5) are defined as individuals residing in the same county in the 1950 Census and the subsequent 1960–90 City Directories. Movers (Columns 1-4) are those who resided in different counties. Movers are disaggregated by the Black indicator and by whether they moved to a county with a higher (Columns 1-2) or lower (Columns 3-4) level of discrimination. Columns (6)-(9) report differences in means from *t*-tests: (6) compares all movers to stayers; (7) compares movers to higher– vs. lower–discrimination areas; (8) and (9) repeat this comparison for Black and white movers, respectively. Standard errors for means are in parentheses, and *p*-values for differences are in brackets. The final row reports the number of observations.

Table A.3: Comparison of Pilot Talent Proxies by Mover Status and Discrimination Change (1950 –> Death)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Movers				Stayers	Difference			
	Higher Discrimination		Lower Discrimination						
	Black	White	Black	White		(1)–(4) vs (5)	(1)–(2) vs (3)–(4)	(1) vs (3)	(2) vs (4)
Years of schooling	12.130	11.504	11.306	11.434	11.297	0.185	0.140	0.825	0.070
(1940 Census)	(0.480)	(0.114)	(0.440)	(0.101)	(0.112)	[0.169]	[0.359]	[0.224]	[0.645]
Years of schooling	14.429	12.948	13.870	13.035	13.087	0.017	-0.018	0.559	-0.088
(Enlistment Records)	(0.281)	(0.086)	(0.363)	(0.087)	(0.099)	[0.881]	[0.887]	[0.236]	[0.478]
Aerial victories	0.738	0.847	0.460	0.691	0.648	0.093	0.175	0.277	0.156
	(0.234)	(0.077)	(0.152)	(0.065)	(0.063)	[0.258]	[0.063]	[0.303]	[0.120]
N	47	507	82	590	530				

Notes: This table shows mean talent proxies (Years of schooling from the 1940 Census, Years of schooling from Enlistment Records, and Aerial victories) comparing stayers and movers. Stayers (Column 5) are defined as individuals residing in the same county in the 1950 Census and the subsequent Social Security Death Index. Movers (Columns 1-4) are those who resided in different counties. Movers are disaggregated by the Black indicator and by whether they moved to a county with a higher (Columns 1-2) or lower (Columns 3-4) level of discrimination. Columns (6)-(9) report differences in means from *t*-tests: (6) compares all movers to stayers; (7) compares movers to higher– vs. lower–discrimination areas; (8) and (9) repeat this comparison for Black and white movers, respectively. Standard errors for means are in parentheses, and *p*-values for differences are in brackets. The final row reports the number of observations.

Table A.4: Change in Discrimination Exposure (1950 Census –> 1960-90 City Directories) vs. Talent for Pilots

	Move			Δ Discrimination		
	(1)	(2)	(3)	(4)	(5)	(6)
Talent	0.009	0.018	-0.002	0.015	0.068	0.039
	(0.012)	(0.018)	(0.009)	(0.035)	(0.061)	(0.021)
	[0.477]	[0.312]	[0.797]	[0.682]	[0.268]	[0.063]
Talent × Black	0.017	0.028	0.026	0.099	0.160	-0.125
	(0.025)	(0.043)	(0.028)	(0.055)	(0.132)	(0.078)
	[0.481]	[0.515]	[0.358]	[0.076]	[0.228]	[0.108]
Talent Proxy	Years of schooling (1940 Census)	Years of Schooling (Enlistment Records)	Aerial Victories	Years of schooling (1940 Census)	Years of Schooling (Enlistment Records)	Aerial Victories
Sample	All	All	All	Movers	Movers	Movers
Mean DV	0.708	0.700	0.726	-0.445	-0.432	-0.294
N	603	434	1,384	381	274	941

Notes: This table shows OLS regressions for the pilots data. Columns (1)-(3) use an indicator for moving (not staying in the same county of the 1950 Census and 1960–90 City Directories) as the dependent variable. Columns (4)-(6) use the change in a discrimination measure (1960–90 value minus 1950 value) as the dependent variable, conditional on moving. The main explanatory variables are a talent proxy, a Black indicator, and their interaction. Three different proxies for talent are used: years of schooling from the 1940 Census (Columns 1 and 4), years of schooling from Enlistment Records (Columns 2 and 5), and aerial victories (Columns 3 and 6). All specifications include 1950 origin county fixed effects. Standard errors, shown in parentheses, are clustered at the origin county level. *p*-values are reported in brackets.

Table A.5: Change in Discrimination Exposure (1950 Census –> Death) vs. Talent for Pilots

	Move			Δ Discrimination		
	(1)	(2)	(3)	(4)	(5)	(6)
Talent	0.008	0.026	-0.001	0.034	0.074	0.034
	(0.011)	(0.018)	(0.009)	(0.034)	(0.058)	(0.021)
	[0.477]	[0.148]	[0.898]	[0.318]	[0.207]	[0.111]
Talent × Black	0.009	0.026	0.033	0.038	0.104	-0.107
	(0.024)	(0.043)	(0.026)	(0.049)	(0.121)	(0.078)
	[0.699]	[0.546]	[0.215]	[0.441]	[0.389]	[0.174]
Talent Proxy	Years of schooling (1940 Census)	Years of Schooling (Enlistment Records)	Aerial Victories	Years of schooling (1940 Census)	Years of Schooling (Enlistment Records)	Aerial Victories
Sample	All	All	All	Movers	Movers	Movers
Mean DV	0.685	0.682	0.707	-0.453	-0.475	-0.302
N	603	434	1,384	365	263	912

Notes: This table shows OLS regressions for the pilots data. Columns (1)-(3) use an indicator for moving (not staying in the same county of the 1950 Census and Social Security Death Index) as the dependent variable. Columns (4)-(6) use the change in a discrimination measure (death value minus 1950 value) as the dependent variable, conditional on moving. The main explanatory variables are a talent proxy, a Black indicator, and their interaction. Three different proxies for talent are used: years of schooling from the 1940 Census (Columns 1 and 4), years of schooling from Enlistment Records (Columns 2 and 5), and aerial victories (Columns 3 and 6). All specifications include 1950 origin county fixed effects. Standard errors, shown in parentheses, are clustered at the origin county level. *p*-values are reported in brackets.

Table A.6: Change in Discrimination Exposure (1950 –> Death) vs. AGCT for Enlistees

	Move			Δ Discrimination		
	(1)	(2)	(3)	(4)	(5)	(6)
log AGCT	0.107	0.129	0.247	-0.027	0.156	0.202
	(0.010)	(0.011)	(0.031)	(0.036)	(0.026)	(0.074)
	[0.000]	[0.000]	[0.000]	[0.457]	[0.000]	[0.006]
log AGCT × Black		-0.203	0.003		-0.319	0.886
		(0.027)	(0.251)		(0.073)	(0.690)
		[0.000]	[0.989]		[0.000]	[0.200]
Sample	All	All	AGCT>100	Movers	Movers	Movers & AGCT>100
Mean DV	0.670	0.670	0.699	-0.023	-0.023	0.009
N	75278	75278	38719	50273	50273	26882

Notes: This table shows OLS regression results for the enlistee data. The dependent variable in columns (1)-(3) is an indicator for moving counties (comparing 1950 Census location to death ZIP code location). The dependent variable in columns (4)-(6) is the change in the discrimination level (death value minus the 1950 value); this sample is restricted to movers only. The main independent variable is the log of the AGCT score. Columns (2)-(3) and (5)-(6) include an interaction term between the log AGCT score and a Black indicator. Columns (3) and (6) further restrict the sample to individuals with a score above 100. All specifications include 1950 county of origin fixed effects. Standard errors, clustered at the 1950 county of origin level, are reported in parentheses, and *p*-values are in brackets.

Table A.7: Impact of Wingmen Origins on 1950 Location Choice

	Indicator for pilot i living in county c in 1950		
	(1)	(2)	(3)
Wingmate share born in county c	0.673	1.198	0.518
	(0.126)	(0.186)	(0.109)
	[0.000]	[0.000]	[0.000]
Sample	All pilots	Black pilots	White pilots
Birth State FEs	Y	Y	Y
R^2	0.003	0.015	0.002
N	8,456,800	1,274,100	7,182,700

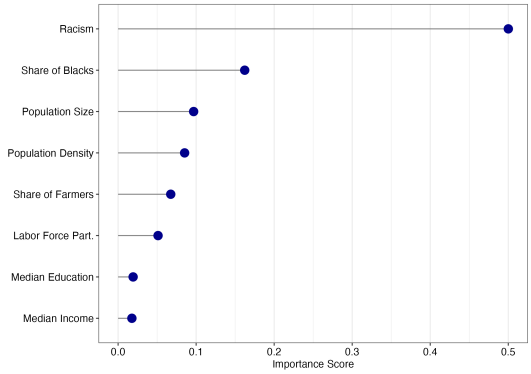
Notes: This table shows the relationship between a pilot's residence county in 1950 and the birth counties of their wingmen. The data are constructed at the pilot-county pair level, where the dependent variable is an indicator equal to one if the pilot lived in a specific county in 1950 and zero otherwise. The key explanatory variable measures the share of a pilot's wingmen who were born in that county. Column 1 reports results for the full sample, while Columns 2 and 3 restrict the sample to Black and white pilots, respectively. All specifications include pilot birth state fixed effects. Standard errors are two-way clustered at the pilot and destination county levels, and p-values are reported in brackets.

Table A.8: Impact of Wingmen Origins on Discrimination of Black Pilots' Residence County after 1950

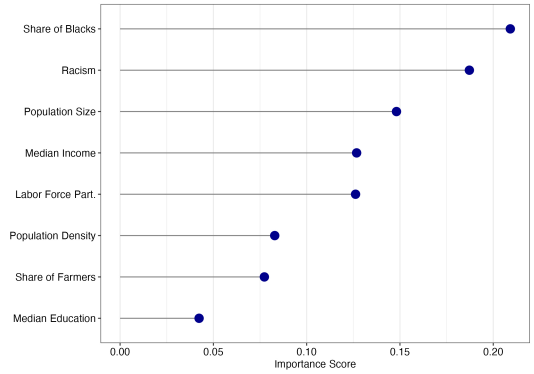
	Discrimination of Residence County			
	1960–90 City Directories	1970s Tax Returns	1990s Index to Public Records	NUMIDENT
	(1)	(2)	(3)	(4)
IV	0.113		0.697	-0.092
	(1.494)	()	(0.583)	(1.125)
	(0.940)	()	(0.241)	(0.935)
Birth State FEs	Y	Y	Y	Y
Residence State FEs	Y	Y	Y	Y
F Statistic	0.006		1.427	0.007
N	371	1,274,100	422	373

Notes: This table shows the relationship between the wingan origin-based instrument and the discrimination level of the Black pilot's county of residence after 1950. The independent variable is a leave-one-out measure calculated as the weighted average of the discrimination level in the birth counties of the pilot's wingmen within the same flight group; for Black pilots born in the North, the measure excludes the influence of peers born in the South. The dependent variables are discrimination indices for the pilot's current residence county derived from 1960–90 City Directories (Column 1), 1970s Tax Returns (Column 2), 1990s Index to Public Records (Column 3), and NUMIDENT (Column 4). All regressions control for birth state and residence state fixed effects. Standard errors are clustered at the residence state level. *P*-values are reported in parentheses.

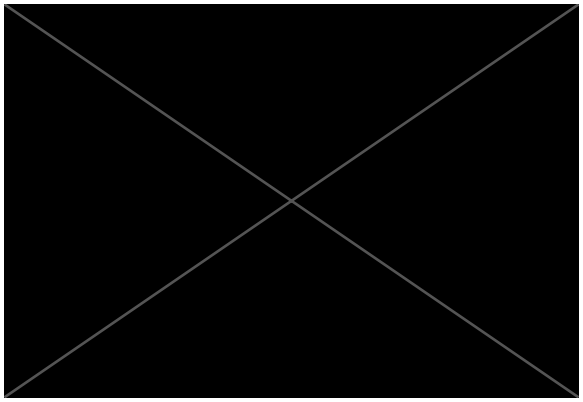
Figure A.3: Variable Importance for Heterogeneous Treatment Effects



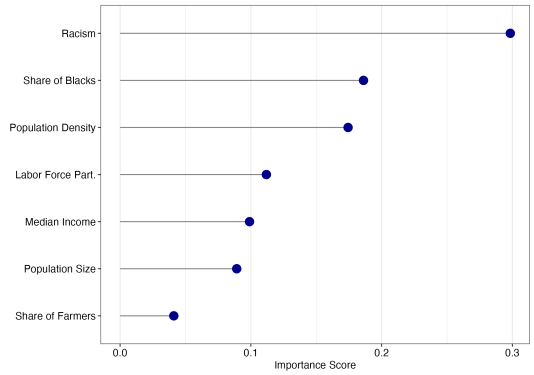
(A) Residence in the 1950 Census



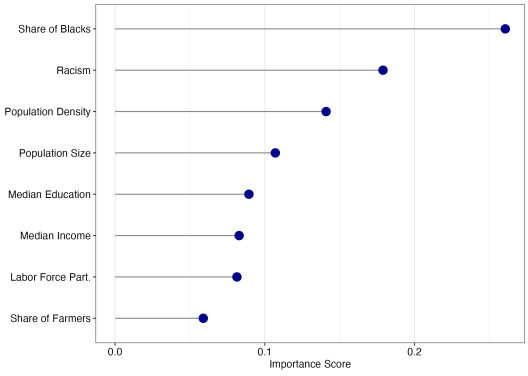
(B) Residence in the 1960–90 City Directories



(C) Residence in the 1970s Tax Returns



(D) Residence in the 1990s Index to Public Records



(E) Residence in the NUMIDENT

Notes: This figure shows the variable importance measures derived from a causal forest algorithm used to estimate the heterogeneous treatment effects of the Black indicator on various socioeconomic outcomes (Athey et al., 2019). The analysis employs a double residualization approach where both the outcome variables and the Black indicator are first orthogonalized with respect to residence state fixed effects. The figure reports the importance score for each county-level covariate, calculated as the weighted frequency with which a variable is used to split nodes across the forest's trees. The covariates include the discrimination index, population size, population density, the share of Blacks, labor force participation, median education, median income, and the share of farmers. Higher values indicate a greater contribution to explaining heterogeneity in the treatment effect. The outcomes correspond to the SES index based on 1950 Census occupational rankings (identical to Column 7, Table 7) in Figure A.3A; the SES index based on 1960–90 City Directories (identical to Column 8, Table 7) in Figure A.3B; income in 1970s Tax Returns in Figure A.3C; the house price percentile from 1990s Public Records (identical to Column 1, Table 9) in Figure A.3D; and the average income percentile of the death ZIP code (identical to Column 2, Table 9) in Figure A.3E.