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

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Abstract

Racial discrimination can lead to talent misallocation. We examine the effects of discrimination against African-Americans over the life-cycle. In WW2, the US armed forces trained African-American pilots – the famous Tuskegee airmen. They arguably constituted one of the most highly selected groups of black Americans. The Air Forces' exacting, sophisticated selection procedures and the availability of aptitude test scores enable us to measure ability. We examine later-life outcomes using granular, individual-level data from the census, zip-codes of later-life residences, and income tax data. Comparing black with white pilots, and black pilots returning to high vs low racism locations, we show that pre-war racial discrimination is highly predictive of talent misallocation: Tuskegee airmen who returned to US counties with one standard deviation higher racial discrimination earned one third less in 1950, worked in occupations with markedly lower cognitive requirements in the 1960s, lived in six-percentile cheaper housing in the 1990s, and died in markedly poorer ZIP codes. Using individual-level data on ability scores from a large sample of WW2 recruits (going beyond the Tuskegees) shows that racial discrimination exacted a particularly high price among the most talented African-Americans. Our findings are robust to accounting for various potential confounders, including potential selective migration over racism.

Keywords: Racial Discrimination, Talent Allocation, Tuskegee Airmen, US History, Word War II

The Tuskegee Airmen were probably the most talented group of African-American men ever brought together in one place.
—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, to fulfill its potential, producing talented and highly trained individuals is not enough—the most demanding and rewarding jobs should also go to those most qualified to fill them. Accordingly, a growing literature argues that the better use of human talents contributed to the onset of modern economic growth (Landes, 2003; Mokyr, 2009; Cantoni et al., 2018) and differences in comparative developments (Lucas, 1978; Baumol, 1990; Murphy et al., 1991). Conversely, where prohibitions, frictions and discrimination inhibit efficient talent allocation, human talent is wasted (Ashraf et al., 2022), innovation is sluggish (Cook, 2014; Aghion et al., 2017; Andrews and Rothwell, 2020), productivity and output are lower (Hsieh et al., 2019; Adamopoulos et al., 2022; Hnatkovska et al., 2021), inequality rises (Guner and Ruggieri, 2022), and poverty traps may result (Balboni et al., 2022).

Pinning down the efficiency-reducing effects of talent misallocation is empirically challenging. Human ability is inherently difficult to measure. The existing literature on talent misallocation either assumes that human talent follows the same distribution across groups,[1] or relies on indirect tests at the aggregate level.[2] An ideal experiment would compare the socio-economic outcomes for two groups of individuals with the same ability, assigned randomly to environments with sharply divergent levels of discrimination. Differences in later-life outcomes in matched

[1](Hsieh et al., 2019) examine the effect of discrimination on US economic growth between 1960 and 2010, and assume that the innate ability of all groups follows a similar distribution. For a controversial treatment arguing the opposite, cf. Herrnstein and Murray (1994).

[2]For example, 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 worse gender norms.

pairs of similarly talented people would capture the cost of misallocation to the individuals themselves (abstracting from spillovers in the aggregate).

In this paper, we provide direct, granular evidence of the effect of discrimination on talent misallocation, using a select group of highly talented individuals—the Tuskegee Airmen. The Tuskegees were the first African Americans to fly as military pilots in US history. They trained at US Army Air Forces (USAAF) airfields around Tuskegee, Alabama during WWII. Forced by Presidential Decree to accept black pilots, the AAF started the flight training program in 1941. It used the same, exacting selection standards for blacks as for whites (USAAF Assistant Chief of Air Staff, 1943, p. 21; Du Bois, 1947; Cameron, 1999). In addition to only admitting unusually talented individuals, the AAF training program "washed out" 50-70% of aviation cadets during the one-year long, four-stage training (Pierce, 2013). The Tuskegee pilots were the "cream of the crop" (Haulman, 2015) with "superior aptitudes and abilities" (Homan and Reilly, 2018, p. 31)—or, as the New York Times put it, "*the most talented group of African-American men ever brought together in one place*."

To measure the effect of discrimination, we examine differences in later-life outcomes for matched groups of Tuskegee and white pilots. After 1945, these men returned to either high- or low-discrimination US counties. To fix ideas, consider the contrasting fates of two Tuskegee pilots—John Adams and Lee Archer. Both were born in around 1920 and completed flight training as single-engine pilots at Tuskegee. Both had similar military careers, flying P-51 Mustangs in Europe, battling German planes while on escort duty protecting US bombers. However, Adams hailed from Brown, KS—a county with a history of lynchings, racial segregation, and active discrimination. He failed to find a lucrative job in his hometown after his discharge, despite applying to numerous positions as a commercial airline pilots or as an aircraft mechanic. Instead, he became a mail carrier for the US postal office. He lived in a modest home from 1958 onwards According to the *Kansas City Directory* of 1958, he lived at 3133 N 38th St, Kansas City, KS 66104, a three-bedroom, two-bathroom, 1,572-square-feet house. By July 2022, the market value of the residence was $179,000 according to Zillow. He died in a ZIP code where the yearly per capita income in 2018 averaged $34,800. Contrast his post-war career with that of fellow Tuskegee airman Lee Archer, who originally came from Westchester, NY. After the war, he returned to New York and joined the General Fruit Company, where he became the first African-American Vice President of a major US corporation. He later became an entrepreneur, founding a venture capital firm. The estimated value of his residence was $\$1,346,000$ in July 2022,[3] eight times more than John Adams'. At the time of his death, he lived in a ZIP code where the 2018 annual personal income, on average, was $\$252,400$.

Comparing post-war outcomes for black pilots returning to high- vs. low-discrimination counties may overstate the degree of talent misallocation if high-discrimination areas in general are poorer. We sidestep this issue by using WWII white AAF pilots as a control group. In this way, we can measure both a within-location black-white gap (where the underlying assumption is that black and white pilots are similarly highly selected) and an across-location gap (where we assume that black pilots that made the USAAF "cut" from high-discrimination counties are similarly talented as those from low-discrimination ones).

We collect data on pilots' post-war economic outcomes throughout the life cycles. In 1950, when pilots were in their thirties, we collect their income data from the newly available non-anonymous *1950 US Census*. For pilots in their forties, we use their occupational information from *City Directories*. In the 1990s, we measure their home's market value. At the time of their death, we use their death ZIP codes' average personal income. To measure county-level racism, we construct a racial discrimination index by combining historical lynchings, residential segregation, the 1960s race riots, and support for segregationist candidates Strom Thurmond and George Wallace in 1948 and 1968 presidential elections. ++cite standard papers using these measures++

In our baseline results, one standard deviation increase in racial discrimination (e.g., moving from Floyd, VA to Roanoke, VA with doubled residential segregation in 1930 and a half increase in votes for George Wallace in the 1968 presidential election) resulted in an annual income decline of $\$1,000$ in 1950, which is equivalent to one third of mean pilot income, or approximately $\$12,000$ in 2022 (++converted at CPI? which source++). However, this startling talent misallocation did not disap-

[3] Archer lived in a four-bedroom, three-bathroom, 3,246-square-feet house (221 Paine Ave, New Rochelle, NY 10804) according to *US Public Records Index*. Its market value was estimated at $\$1,346,000$ in July 2022 on Zillow.

pear after the 1960s, when the Civil Rights Movement eventually bore fruit, Jim Crow segregation was finally abolished, and racial discrimination was legally forbidden. From the 1960s to the 2000s, if Tuskegee Airmen were exposed to one standard deviation higher racism, they worked in an occupation with 3% lower median income, lived in six-percentile cheaper housing, and died in ten percent poorer ZIP codes. Crucially, black pilots talents were systematically wasted in the labor market after 1945. They systematically sorted into jobs with lower cognitive requirements. The effects are big – a standard deviation increase in racial discrimination reduced the cognitive requirements of jobs taken by black airmen by 0.465-0.491, roughly equivalent to the difference between an economist and a service manager.

Selective migration due to racial discrimination is not driving our results—the ablest black pilots did not flee more racist regions like the Deep South, nor did white pilots at the upper end of ability distribution move into these places. There is a flat relationship between pilots' ability proxies and racial discrimination. We use data from the Army General Classification Test (AGCT) – an early intelligence test,[4] and nonparametrically estimate its relationship with racial discrimination. There is neither a downward sloping AGCT-racism pattern for blacks nor an upward sloping one for whites. Alternatively, we proxy pilots' ability by their military productivity—the number of enemy planes they shot down during WWII. There is also no correlation between aerial victories and racism.

The second exercise of testing the sorting is through randomization tests (Young, 2019). We randomly reshuffle pilots' post-war residence counties and create the level of *randomized* discrimination exposed to pilots. Comparing the predictive power of AGCT and aerial victories on the randomized locational racism to the *realized* one, these ability proxies are not more predictive of actual racism than simulated racism, indicating that sorting is limited.

Finally, if the selective migration concern were true, controlling for ability would attenuate our estimates. However, adding AGCT or aerial victories to our baseline

[4]The AGCT is the precursor of the Armed Forces Qualification Test (AFQT), which captures cognitive ability (Ferrie et al., 2012; Aaronson and Mazumder, 2011; Feyrer et al., 2017) and is predictive of labor market outcomes (Neal and Johnson, 1996; Lang and Manove, 2011). The similar aptitude tests are extensively used in other settings and countries such as Sweden (Dal Bó et al., 2017; Besley et al., 2017; Lindqvist and Vestman, 2011).

regressions does not result in a decrease in our estimates, supporting that the sorting does not exist.

The results are also robust after controlling for the other additional variables. For example, by comparing pilots with the same education level, we still find the same level of talent misallocation as our baseline. The baseline results still hold after considering their social networks.

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 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 utilization 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 neighborhood effect on socioeconomic outcomes. 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.[5]

Finally, it is related to the literature using military personnel to study key economic questions. Angrist (1990) pioneered the use of military draft lotteries to identify the effects of career disruptions on labor market outcomes.[6] Ager et al. (Forthcoming) study peer rivalry among WWII Nazi fighter pilots. Voth and Xu (2022) examine the

[5]For example, Bayer and Charles (2018) find a rapid convergence of top black-white earnings gap. From 1940 to today, the richest blacks (i.e., the top 10%)'s rank in the white income distribution rose from the median to the 75th percentile.

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

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 USAAF's exacting selection of pilots, which created a cohort of similarly talented individuals.

The remainder of the paper is organized as follows: Section 3 briefly provides historical background on the Tuskegee Airmen. Section 4 present our data sources. Section 5 demonstrate our estimate strategy and results. Finally, we conclude in Section 7.

2. Higher Costs of Talent Misallocation for Highly Skilled Individuals

Talent misallocation supposedly imposes higher costs on the more skilled workers, as they tend to possess higher levels of education and training, which can translate into higher earning potential and more job opportunities. If misallocated in positions that do not fully utilize their skills and abilities, these workers may experience lower job satisfaction, reduced income, and slower career advancement, resulting in significant aggregate costs. However, a lack of reliable measure of human ability has hindered the exploration of this conjecture.

To address this, we utlize a sample of ?? WWII Army recruits for whom we have reliable AGCT scores (Ferrie et al., 2012; Aaronson and Mazumder, 2011; Feyrer et al., 2017). We link these individuals to the 1940 census and the NUMIDENT dataset, and use this information to construct their earnings in 1940 and death ZIP code-level average income in 2019.

Figure 1 illustrates our findings that the costs of talent misallocation for black recruits increase with AGCT test scores. In the bottom quintile of AGCT distribution, the average earnings of white recruits in 1940 were \$??, white the figure for blacks was \$??, resulting in a racial gap of \$??. However, as skills increase, this earning gap widens, reaching a maximum of \$??? in the top 20%. A similar pattern is also observed in death ZIP code's average income, with the racial gap in the top quintile being twice(?) that of the bottom quintile.

To formally test how talent misallocation varies with skills, we run a regression analysis with the following equation:

$$y_i = \beta AGCT_i * Black_i + \Gamma X_i + \epsilon_i \quad (1)$$

where y_i represents either earnings in 1940 or the income per capita of the death ZIP code of recruit i. $AGCT_i$ is the AGCT score, $Black_i$ is a dummy for blacks, and X_i includes controls. If the burden of talent misallocation falls disproportionately on highly skilled individuals, we would expect β to be positive.

From Column 1 of Table 1, white individuals on average earned ??? more than blacks in 1940. However, one additional unit of AGCT increases this gap by ?? percentage points. That said, moving from the the minimum AGCT of 39 to the maximum of 163 increases the racial earning gap from ?? to ??. Even when we control for fixed effects such as residence county, education, age, and birth state (as shown in Column 2), the magnitude of the coefficient does not change significantly.

When the outcome measure is the average income of the death ZIP code, one additional unit of AGCT widens the outcome gap by ??percentage points. This effect accumulates to a ??percentage point increase in the gap when moving from the bottom to the top of the AGCT distribution, according to Columns 3 and 4.

These findings highlight the importance of addressing talent misallocation among highly skilled workers. The Tuskegee Airmen, a group of highly skilled black pilots selected on the basis of both observables such as health, education, and cognitive ability test scores, as well as *unobservables*, offer a unique opportunity to delve deeper into this matter.

3. Historical Background

In this section we provide historical background on the Tuskegee Airmen. We describe the process by which Army recruits could join the US Army Air Forces (USAAF), eventually qualifying as pilots. We also discuss the professional trajectories of Tuskegee Airmen's after WWII life.

3.1 The Tuskegee Airmen

The Tuskegee Airmen were an elite group of African-American pilots who fought in World War II. They were the first black military aviators in the United States Armed Forces, training at Tuskegee Army Air Field in Alabama. The Army Air Corps did not accept African-Americans as pilot trainees until 1940, when Franklin D. Roosevelt ordered the creation of squadrons manned by black pilots. The AAF started its black pilot training program at segregated airfields around Tuskegee, Alabama in July 1941 (Haulman, 2015). In addition to airmen, the program trained navigators, mechanics, bombardier, and other support staff.

The first all-black unit to see combat was the 99th Pursuit Squadron, activated in 1943 in North Africa. By 1944, four black squadrons were active, making up the 332nd Fighter Group, stationed in Italy. Initially equipped with P-40 planes, the group was upgraded to the P-51 Mustangs. They were mainly used as escorts for heavy bombers flying into Germany from Foccia, Italy.

Tuskegee Airmen flew over 15,000 missions during WWII, claiming 36 aerial victories. While the claim that they never lost a bomber to German fighters is a myth, Tuskegee Airmen's loss rates of bombers was relatively low (but their rate of aerial victories was lower than for white units, too). By the end of the war, 66 Tuskegees were killed and 32 taken prisoner.

3.2 Selection of Pilots

The USAAF used sophisticated methods to select aircrew during WWII (USAAF Assistant Chief of Air Staff, 1943; USAAF Historical Office, 1946; Cameron, 1999). These included stringent physical and academic prerequisites including academic performance, exacting classification tests (Du Bois, 1947; Flanagan, 1948), and rigorous flight training (Pierce, 2013). These screening devices jointly guaranteed that those who managed to get their wings were among "the best physical and mental specimens the country produces" (Steinbeck, 2009).

As early as during WWI, two years of college education were the minimum required to apply for flight training application (USAAF Assistant Chief of Air Staff, 1943,

p. 3). As the war intensified, the AAF needed to recruit more pilots. The education standard was lowered to include accredited high-school graduates who "rank in the upper half of the class, and have a minimum of one and one-half mathematics credits" (USAAF Historical Office, 1946, p. 66). High school graduates also had to attend college-level pre-flight training programs and pass a special education test to demonstrate their academic abilities (Haulman, 2015, p. 3; USAAF Assistant Chief of Air Staff, 1943, p. 21; US Army Air Forces, 1943, p. 11).

Second, the AAF relied on aptitude tests to screen applicants. Before the introduction of the AAF specific aptitude tests (the Aviation Cadet Qualifying Examination (ACQE) and STAINE tests in January 1942), the air forces relied on the Army General Classification Test (AGCT) to select cadets. The AGCT test was designed by Army psychologists in 1941 to measure a serviceman's "capacity to learn" (Bingham, 1944). It is the precursor to the present-day Armed Forces Qualification Test (AFQT). The AAF required aviation cadets to score at least 100 in AGCT (Harrell, 1992). When the more specific and demanding ACQE was introduced, AAF psychologists found that a passing mark of 90 on the ACQE was equivalent to 119 in AGCT (USAAF Office of Air Surgeon, 1942, p. 18).

If selected based on academic merit, having passed the AGCT/AFQT, recruits would become aviation cadets, training to fly. As in other air forces, flight training consisted of primary, basic, and advanced phases, each of which lasted approximately nine weeks. Aviation cadets were "washed out" at every stage. During the WWII, 50% – 70% of aviation cadets did not complete flight training (Pierce, 2013).[7] Only the most capable young servicemen became pilots. The AAF used the same, highly exacting requirement of pilot selection for colored applicants as for white ones (USAAF Assistant Chief of Air Staff, 1943, p. 21).

[7]Daniel L. Haulman, the world's leading authority on the Tuskegee Airmen at the Air Force Historical Research Agency, mentioned that "about half of the Black flight cadets who entered the flight training completed that training" when he was interviewed by the National WWII Museum on July 14, 2020. The interview's transcripts can be find here (https://www.nationalww2museum.org/war/articles/tuskegee-airmen-interview-daniel-haulman).

3.3 Racial Discrimination after WWII

Tuskegee Airmen either served in the European Theater during WWII, or remained state-side, waiting for their unit to be activated. After the end of the war, the AAF sharply reduced the number of active squadrons. The majority of pilots—both black and white—were demobilized. Of the African-Americans who remained in the Air Force, several attained high ranks (including the first black American General, and the first black four-star general).

Many demobilized white pilots joined the booming post-war airline industry, becoming commercial pilots. Despite having the same training and experience, Tuskegee Airmen faced severe discrimination in the labor market. It was only in 1964 that a commercial carrier in the US hired the first black pilot.[8] Transitioning to other jobs in the airline industry, even as mechanics, was similarly fraught with difficulty. Many Tuskegees sorted into low-paying jobs, where their ability and talent went unused.

4. Data

This paper studies the cost of talent misallocation caused by racial discrimination among Tuskegee Airmen. This requires individual-level data on post-WWII economic conditions and exposure to racial discrimination. To account for confounders associated with both racism and economic outcomes, we need WWII USAAF white pilots as a comparison group and pilots' ability measures. We glean such a granular dataset by combining administrative and publicly available records with meticulous genealogical research.

4.1 Roster of Tuskegee Airmen

We download the roster of all 1,007 Tuskegee Airmen from the CAF RISE ABOVE, with their names, flight training class numbers, graduation dates, ranks, and home-

[8] David Harris was the first black pilot to work for a US passenger carrier, following the 1963 supreme court case brought by another black pilot, Marlon Dewitt Green.

towns. We conduct genealogical searches on *Ancestry* for each Tuskegee pilot based on the information available from the roster and were eventually able to locate the birth year and place of 849 pilots. The matching rate is approximately 84%, which is significantly higher than the standard automated record linking rate in the literature (Abramitzky et al., 2021).

We conduct a similar genealogical search for white pilots. Since the USAAF trained up to one hundred thousand white pilots during WWII (USAAF Office of Statistical Control, 1945) and there is no comparable roster of white pilots available, we focus instead on those who served in the 8th Air Force during WWII. We have compiled a list of 5,142 pilots based on various sources (see Appendix Section A.1) and found 3,761 (73%) pilots' birth year and place on *Ancestry*.

4.2 Later-Life Economic Outcomes

We can measure Tuskegee Airmen's post-war economic situations at various critical stages of their life cycle.

Income in 1950. We use the newly-released *1950 Census* to find their income. We find 349 Tuskegee Airmen and 2,102 white pilots in the 1950 census. Since only one fifth of the population was asked to report their income in 1950, we are only able to locate 52 black and 368 white pilots with reliable income information. To the best of our knowledge, we are the first to use the newly declassified 1950 census data.

Occupations in the 1960s. We collect pilots' occupations from the *US City Directories* on *Ancestry*. We find 127 black and 940 white pilots at this source, and the median observed year is 1960 (see Figure ??(a) in the Appendix Section A.2). We manually classify these occupations by the 1950 census classification system (Census Bureau, 1950) and assign each occupation a score representing its median income in 1950 by state and race (Saavedra and Twinam, 2020).

Market Values of Residences in the 1990s. We construct the *percentile* of pilots' residence prices by combining the *US Public Records Index* from *Ancestry*, Zillow's *Zestimate*, and the Federal Housing Financial Agency (FHFA)'s house price index. The *US Public Records Index* records the exact addresses of 477 black pilots and 2,351 white pilots in the 1990s.[9] We collect each address's house price estimate from Zillow and extrapolate it to when the pilot was living there by using FHFA's ZIP code level house price index. To determine the rank of pilots' residences in the national real estate market, we randomly scraped 100 property prices of 10% of ZIP codes from Zillow.

Death ZIP Codes' Average Income in the 2000s. Following Suandi (2021), we collect pilots' death ZIP codes from the publicly available *Death Master File* (DMF) of the Social Security Administration. We find 425 black and 2,278 white pilots' death ZIP codes, and 56 percent of them died in the 2000s. Merging it with IRS' *Individual Income Tax Statistics*, we can calculate the *percentile* of these ZIP codes' average income at the time of pilots' deaths.

4.3 Racial Discrimination Index

We consider the level of racial discrimination that Tuskegee Airmen experienced as that of their post-WWII residence counties. This is in line with the literature on the importance of locational environments for intergerational mobility (Chetty and Hendren, 2018a,b) and health (Finkelstein et al., 2021). We use the principal component analysis and construct an index of county-level racial discrimination by combining historical lynchings, residential segregation in 1930 and 1940, support for segregationist candidates Strom Thurmond and George Wallace in the 1948 and 1968 presidential elections, and the 1960s race riots. The distribution of the racism index across counties can be found in Figure ??, and it is strongly correlated with its constituent elements (see Figure ???).

4.4 Controls

To address the concern of selective migration over exposed racial discrimination, we collect ability measures such as Army General Classification Test (AGCT) scores and aerial victories.

[9] 80% of them are in the 1990s. See Figure ??(b) in the Appendix Section A.2.

AGCT Scores. Following Ferrie et al. (2012), Aaronson and Mazumder (2011), and Feyrer et al. (2017), we recover the AGCT scores of 461,480 WWII Army recruits from the *WWII Army Enlistment Records*. To have full sample coverage, we use LASSO to predict AGCT scores for all WWII Army servicemen based on a rich set of variables. The LASSO algorithm performs extremely well, with R^2 0.60, correlation of 0.77, and almost recovering the distribution (see Appendix Figure ???). See Appendix Section A.4 for details.

Aerial Victories. We also measure each pilot's ability by the number of aerial victories that he achieved during WWII—a transparent measure of military productivity. We collect the data from USAAF Historical Research Agency (1978). However, we can only collect the information of fighter pilots who were deployed to the front. In the end, we have aerial credit data for 682 Tuskegee Airmen and 3,262 white pilots. Consistent of the finding of Ager et al. (Forthcoming) for WWII German pilots, the distribution of aerial credits is highly skewed (see Appendix Figure **??**).

4.5 Summary Statistics

Table ?? displays summary statistics of primary variables used for estimation in Section 5. On average, Tuskegee Airmen earned approximately 2,200 dollars annually in 1950, worked in an occupation with a median income of 2,500 dollars a year in the 1960s, lived in housing properties in the middle of the market in the 1990s, and died in ZIP codes in the top 33% in terms of personal income.

5. Discrimination and Talent Misallocation

We first examine how racial discrimination caused the inefficient use of Tuskegee Airmen's talents. To measure the misallocation of black talent, we examine differences in occupational outcomes between black and white pilots. If the USAAF did not discriminate against blacks entering pilot training, and imposed the same, demanding standards on pilots irrespective of their racial background, we will be ablet to recover the effect of discimination directly: By comparing the career trajectories and occupational characteristics of jobs for black and white pilots, we can measure the effect of systemic barriers or biases directly.

To quantify and analyze the observed disparities in occupational outcomes, analyze the cognitive requirements as derived from ONET occupational scores. The use of ONET scores provides an objective and standardized measure to assess the skill requirements of jobs. We estimate two variants

$$S_{ic} = \beta Black_i + \gamma X_{ic} + \pi_s + \epsilon_{ic} \tag{2}$$

$$S_{ic} = \beta_1 Racism_{ic} + \beta_2 Black_i + \beta_3 Racism_{ic} \times Black_i + \gamma X_{ic} + \pi_s + \epsilon_{ic} \tag{3}$$

$$\begin{aligned} S_{ic} = {} & \beta_1 Racism_{ic} + \beta_2 Black_i + \beta_3 AFQT_i \\ & + \beta_4 Racism_{ic} \times Black_i + \beta_5 Racism_{ic} \times AFQT_i \\ & + \beta_6 Racism_{ic} \times Black_i \times AFQT_i + \gamma X_{ic} + \pi_s + \epsilon_{ic} \end{aligned} \tag{4}$$

where the parameters of interest are β in equation (1), $\beta_1 + \beta_2 + \beta_3$ in equation (2), and the sum of all β in equation (3). In the first equation, we simply examine how much lower the cognitive requirements in jobs of average black pilots are, compared to white pilots. In eq. (2), we compare black with white pilots, and ask if cognitive requirements in each job are systematically lower for blacks in places with more discrimination.

6. Discrimination and Earning Divergence

We examine how racial discrimination worsened the income, occupation, housing, and neighborhood environment of Tuskegee Airmen at different life stages after World War II. Figure 3 summarizes our main findings. We generate four binned scatterplots relating racial discrimination in a Tuskegee Airman's county of residence to their (A) income in 1950, (B) occupational scores in the 1960s, (C) house price percentiles of residence in the 1990s, and (D) death ZIP code's average personal income rankings. Despite having met the same, exacting AAF's selection and training standards as white pilots, living in a region with greater racial discrimination substantially worsened the gap between black and white pilots.

The negative outcome-racism gradient of Tuskegee Airmen arguably reflects two forces: (1) distortions caused by racial discrimination leading to lower aggregate output, which may adversely affect both discriminated and privileged groups, and (2) disadvantages specific to blacks. To pinpoint the second channel, we compare the slope of the outcome-racism gradient across black and white pilots. White pilots' individual socioeconomic outcome may be lower in racist regions, even if they were not discriminated against, reflecting other economic distortions in aggregate.[10] The outcome-racism gradient of black pilots is markedly steeper than that of white pilots from 1950 to the early 21st century. This slope *differential* demonstrates the direct economic disadvantage imposed on Tuskegee airmen as a result of racial discrimination.

6.1 Estimation

To go beyond the visual evidence, we estimate the effect of racial discrimination on individual-level outcomes by running the following regressions:

$$y_{ic} = \beta Racism_{ic} \times Black_i + \gamma X_{ic} + \pi_s + \epsilon_{ic} \tag{5}$$

where y_{ic} denotes an economic outcome of pilot i residing in county c after WWII, $Racism_{ic}$ is the racial discrimination level of county c, and $Black_i$ indicates whether pilot i is black. X_{ic} is a vector of controls which we will include to address identification concerns. We also include state fixed effects π_s to exploit intrastate variation in racial discrimination.

β is the key parameter of interest, which captures the direct penalties racial discrimination inflicted upon Tuskegee Airmen, absent of racially neural economic distortions. We expect it to be negative. The higher the absolute value of β, the more detrimental racial discrimination to Tuskegee Airmen. To account for spatial correlation, we adjust standard errors by Conley (1999).

Table 6 presents our results based on individual-level outcomes during different phases of pilots' adult lives. When Tuskegee Airmen were in their thirties, a one

[10] The only exception is that white pilots earned more in racist counties in 1950. In fact, it strengthens rather than weakens our argument.

standard deviation increase of additional racial discrimination resulted in their annual earnings dropping by 1,000 dollars in 1950 (i.e., approximately half of the black pilot sample mean $2,200, or $12,000 in 2022). This would be equivalent to moving from Floyd, VA to Roanoke, VA, where the 1930 residential segregation was twice as high and the segregationist George Wallace received a 1.5 times higher vote share than in Floyd in 1968.

During their peak earning years (in the 1960s), an average former black pilot worked in an occupation with a median income of $2,500, 1,300 dollars more than the average black worker. However, they earned 23% percent less than the average white pilot, and the difference is markedly greater the higher the level of racial discrimination: every standard deviation of additional racism in their county of residence lowered their earnings by an additional 125 dollars, and widened the gap with white pilots by 100 dollars.

By the 1990s, startling differences remained in the 1990s. Half a century after the end of World War II, and some 25 years after the Civil Rights Act, Tuskegee Airman still lived in housing that was, on average, four percent cheaper than that of white pilots. For every standard deviation increase in racial discrimination, the value of a dwelling occupied by a Tuskegee dropped by 12 percentiles.

For the decade starting in 2000, we can also examine the locations where Tuskegees died, and examine the average income in the corresponding ZIP code. While in low-discrimination counties, there was on average no statistically significant difference between incomes in the zip codes of black and white pilots, the same is not true in high-discrimination counties. In the counties in the top 5% of racial discrimination, white pilots died in locations where incomes were more than 1.5 times those of areas where black pilots died.

In combination, our results document statistically and economically significant, persistent costs of racial discrimination for Tuskegee pilots. Despite being similarly talented to white pilots, they sorted into less attractive occupations, earning lower wages, lived in cheaper housing, and died in zip codes with lower average incomes. ++ can you produce a chart with 3 lines // three charts, side-by-side// showing a bar chart of the percentile gap in outcomes over time, using all our measures, black-white, for the lowest 10%, median, and highest 10% of discrimination counties, where they lived generated divergent economic circumstances. ++ The adverse effects of racial discrimination are persistent and linger throughout their lifespans.

6.2 Selective Migration

Our identification assumption is that there is no systematic correlation between pilots' ability and the level of racism to which they are exposed in the place where they live after 1945. As we discussed in Section 3, the stringent, multi-stage screening and training procedures used by the AAF resulted in the creation of highly homogeneous group. However, one might worry that the most capable Tuskegee Airmen might have migrated to low-discrimination counties (or, less probably, that the ablest whites would have chosen to live in high-discrimination counties). If such selection was substantial, our baseline estimates in Table **??** would exaggerate the magnitude of economic costs that racial discrimination imposed on Tuskegee Airmen.

Figure 5 illustrates the relationship between pilots' cognitive ability, as measured by LASSO-predicted AGCT test scores, and racial discrimination levels in counties where they lived in 1950, the 1960s, the 1990s, and the 2000s. We draw scatterplots for each race and smooth them nonparametrically using kernel-weighted local polynomial regressions. The flat local polynomial lines across races and decades show that pilots did not sort into high or low-discrimination counties as a function of talent. This should alleviate the concern of selective migration.

We also use pilots' aerial victories during WWII—the most transparent measure of their productivity in the military—to proxy their ability. We scatterplot their victory credits versus our racism index and overlay them with local polynomial smoothings in Figure 5. Consistent with our findings in Figure 5, we do not observe any relationship between outcomes and county-level racism.

To quantify the extent to which pilots' ability predicts their exposure to racial discrimination, we compare ability measures' predictive power for *realized* locational racism to that for the *randomized* racism through a permutation exercise (Young, 2019) in Figure ?. The actual F-statistics, regardless of samples across races and decades, all fall into the left or middle part of the hypothetical F-statistics distributions. This means that we cannot reject the hypothesis that pilots' ability does not predict the level of racial discrimination they experienced after WWII. It is also true if we examine each measure of ability separately (Appendix Figures ? and ?).

We account for the slight ability heterogeneity, despite the lack of a systematic correlation with locational racial discrimination, by including ability proxies as controls in Equation 5. As shown in Panels A-B of Table 6, our baseline results remain unchanged when controlling for either predicted AGCT or aerial victories, and the magnitude of the estimates is even larger than the baseline.[11] This confirms our aforementioned tests on the absence of selective migration over racial discrimination. We would have smaller estimates by controlling for abilities, had the most talented Tuskegee Airmen migrated to racially friendly regions or the ablest white pilots chosen to exploit their status as privileged groups in racist places.

6.3 Robustness of Results

To address concerns that could affect the interpretation of our baseline results, we conduct a number of additional robustness checks.

Education. After World War II, education was increasingly rewarding, particularly college degrees (Bayer and Charles, 2018). Even if there is no systematic sorting over ability, there is still a possibility that pilots were able to move to more hospitable places if they were more educated. In Panel C of Table 6, we nonparametrically control the education level of pilots by including education-level fixed effects and still find significant costs of talent misallocation associated with racial discrimination.[12]

Social networks. The decision of which city to live in after demobilization might depend on the location of their social connections. A stronger social network can cushion the blow of hostile environments and helps career development, thus attracting pilots to migrate to places with various social contacts. Using kinship networks as a proxy for social networks (References), we restrict our sample to pilots who returned to their birth counties. In Panel D of Table 6, we find doubled

[11]except the specification of the 1960s OCCSCORE as outcome and aerial victories as control.

[12]The education variable is divided into ten categories, ranging from grammar school, one year of high school, to four years of college, and post-graduate study.

estimates of talent misallocation costs from 1950 to the 2000s, compared to our baseline. Combined with our evidence on how racial discrimination hindered the road to Tuskegee in Figure ???, the implication is startling: an average black young man from the Deep South had to overcome formidable obstacles to develop high abilities and pass the AAF pilot selection threshold; however, once he decided to return to the Deep South after discharge, his efforts of human capital accumulation and skill development might be in vain, as he was unable to rise as far as he talents would take him.

7. Conclusion

How can we cleanly 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 one third less in 1950, worked in 3% fewer gainful occupations in the 1960s, lived in six-percentile cheaper housing in the 1990s, and died in six-percentile poorer ZIP codes in the 1990s if experiencing one standard deviation higher racial discrimination. 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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Tables and Figures

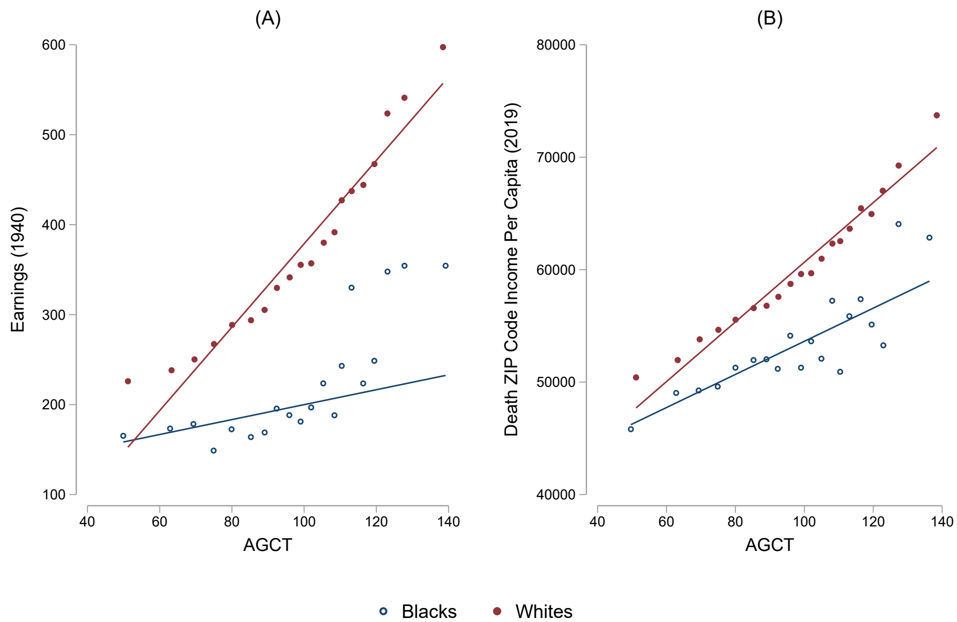

Figure 1: ability and racial outcome gaps

Notes: These binned scatterplots demonstrate talent misallocation disproportionately falling on talented individuals, by showing that WWII Army enlistees' racial gaps increase with AGCT. The x-axes are AGCT. The y-axes denote earnings (1940) (A) and per capita income of death ZIP codes (2019) (B). See Section 4 and Appendix Section A for data sources and variable construction.

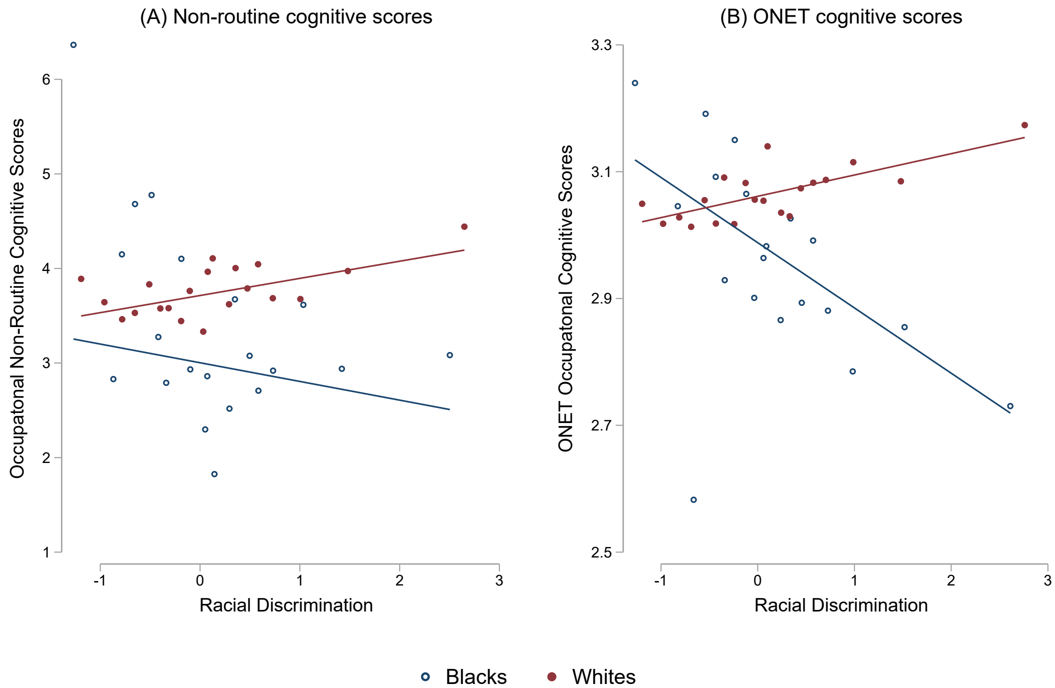

Figure 2: discrimination and talent misallocation

Notes: These binned scatterplots demonstrate the associations between racial discrimination and talent misallocation for Tuskegee Airmen (blue) and comparable white pilots (red). The x-axes are racial discrimination of pilots' 1950 residence county. The y-axes denote cognitive requirements of pilots' 1950 occupations, which are measured by metrics from Autor et al. (2003) (A) and from O*NET (B). See Section 4 and Appendix Section A for data sources and variable construction.

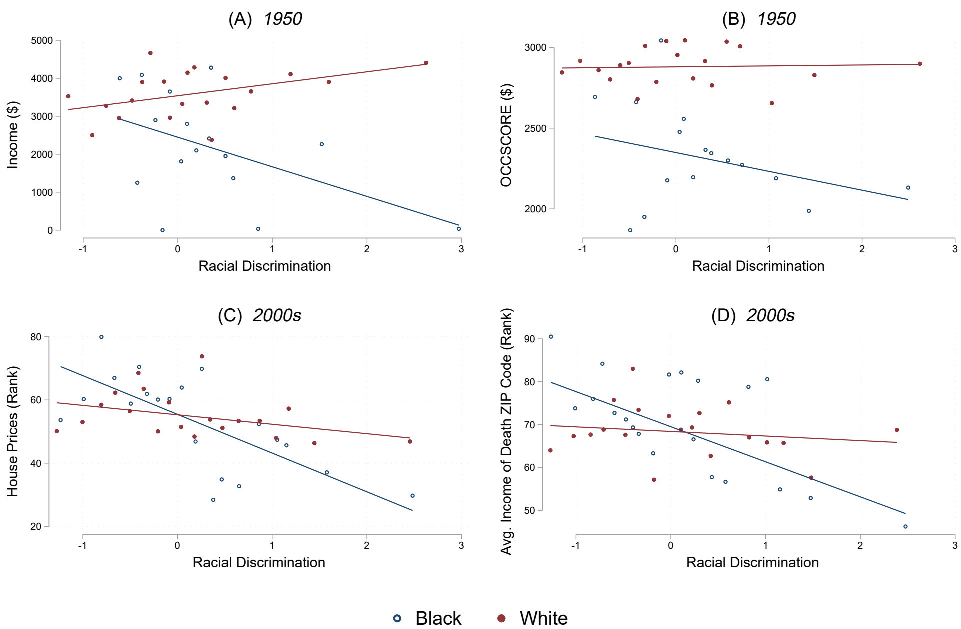

FIGURE 3: DISCRIMINATION AND RACIAL OUTCOME GAPS

Notes: These binned scatterplots demonstrate the associations between racial discrimination and later-life outcomes for Tuskegee Airmen (blue) and comparable white pilots (red). The x-axes are racial discrimination of pilots' residence county. The y-axes denote earnings in 1950 (A), occupational scores in 1950 (B), ranks of death ZIP's house prices (C), and ranks of death ZIP's average income (D). See Section 4 and Appendix Section A for data sources and variable construction.

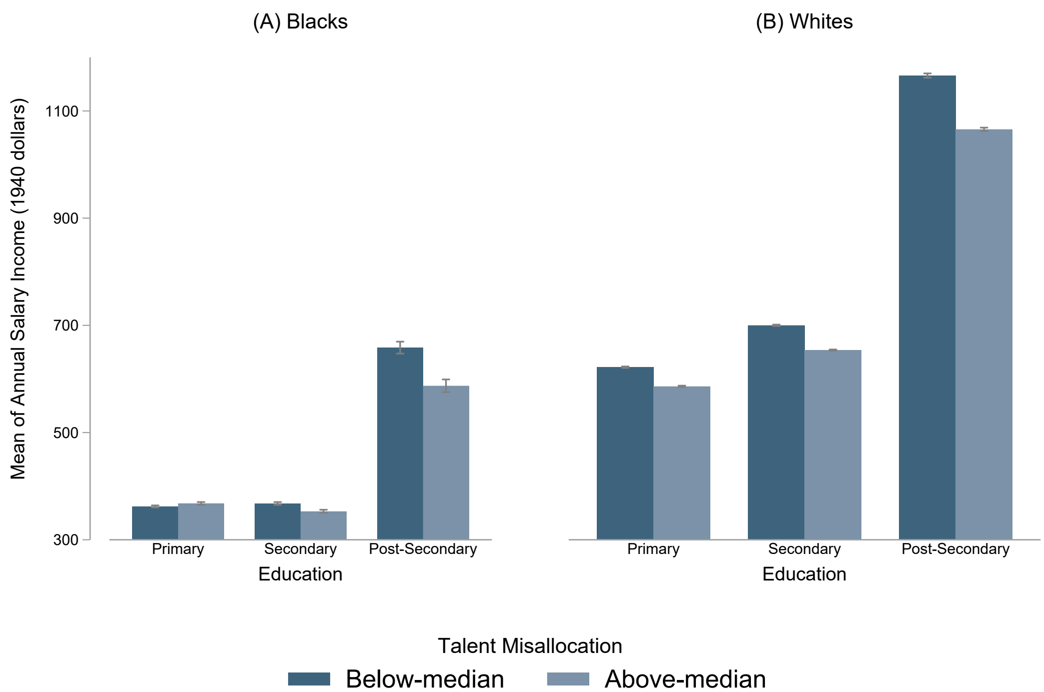

Figure 4: tuskegee airmen's and aggregate talent misallocation

Notes: These histograms demonstrate how counties that used Tuskegee Airmen's talent inefficiently rewarded human capital deferentially. They show the mean earnings in 1940 by education and residence county' talent misallocation level. Sub-figure (A) is for black individuals who reported earnings in the 1940 census, while (B) focuses on whites. County-level talent misallocation level is the mean difference of occupational cognitive scores (Autor et al., 2003) between white pilots and Tuskegee Airmen in a given county. Deep blue bars are for counties with below-median misallocation levels, while light blue bars are for the above-median counties. See Section 4 and Appendix Section A for data sources and variable construction.

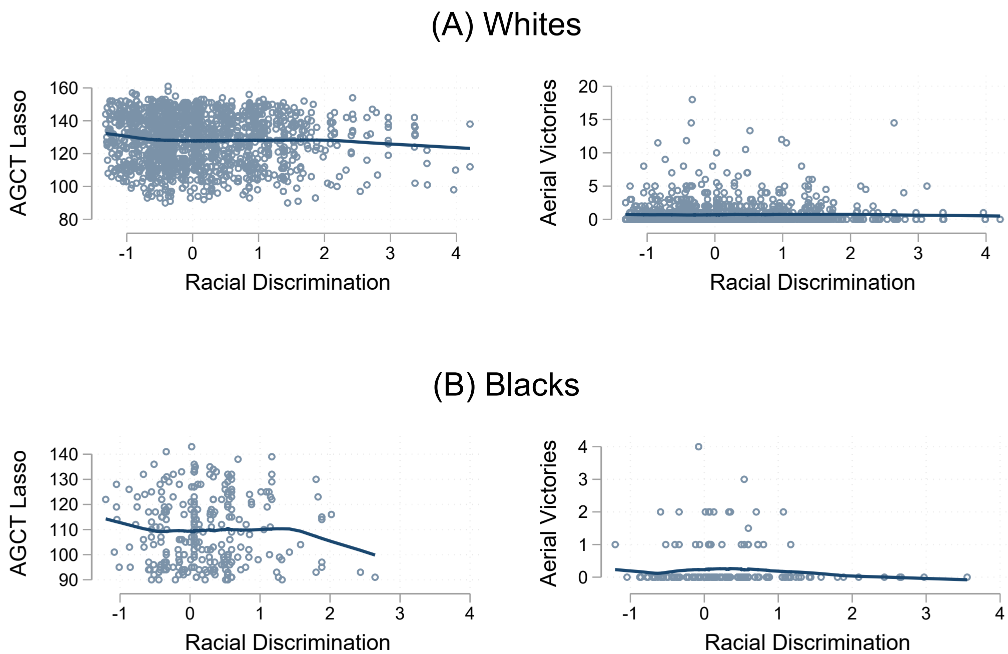

FIGURE 5: ABILITY AND DISCRIMINATION

Notes: These figures are scatter plots (red) with their local polynomial fitted lines (blue) between pilots' ability measures and racial discrimination of their 1950 residence county. Abilities are measured by AGCT scores (left) and WWII aerial victories (right). (A) are for white pilots, and (B) are for Tuskegee Airmen. See Section 4 and Appendix Section A for data sources and variable construction.

Table 1: ability and racial gaps

	Earnings			Death ZIP Income		
	(1)	(2)	(3)	(4)	(5)	(6)
AGCT * Black	-3.70***	-1.11***	-1.12***	-0.12***	-0.14***	-0.13***
	(0.54)	(0.21)	(0.21)	(0.03)	(0.02)	(0.02)
AGCT	4.19***	1.43***	1.42***	0.27***	0.11***	0.10***
	(0.46)	(0.13)	(0.13)	(0.03)	(0.01)	(0.01)
Black	253.77***	11.73	10.20	4.76**	8.11***	5.56***
	(34.31)	(16.57)	(16.28)	(2.31)	(1.24)	(1.48)
Adj. R-squared	0.03	0.49	0.50	0.04	0.11	0.21
Observations	72295	72277	72225	124554	84745	84445
Black	5862	5858	5850	11541	6758	6745
White	66433	66419	66375	113013	77987	77700
Mean DV	265.49	265.48	265.46	59.72	60.02	59.98
Black	141.84	141.83	141.68	49.42	49.34	49.30
White	276.40	276.39	276.37	60.78	60.95	60.91
Birth County FEs	N	Y	Y	N	Y	Y
Residence County FEs	N	N	Y	N	N	Y

Notes: This table shows results of estimation by Equation (1). The sample consists of WWII Army enlistees with AGCT scores. y_i is either earnings in 1940 or death ZIP's average income in 2019. Standards errors clustered at the birth county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: discrimination and talent misallocation

(a) Panel A: Non-Routine Cognitive Scores

	All Sample		100km Restriction		50km Restriction	
	(1)	(2)	(3)	(4)	(5)	(6)
Racial Discrimination * Black	-0.15*	-0.20**	-0.14	-0.24**	-0.21**	-0.28***
	(0.08)	(0.08)	(0.11)	(0.10)	(0.10)	(0.10)
Adj. R-squared	0.01	0.02	0.01	0.04	0.02	0.03
Observations	2138	2138	1027	1025	894	890
Black	280	280	126	126	123	123
White	1858	1858	901	899	771	767
Mean DV	-0.00	-0.00	-0.00	-0.00	0.00	-0.00
Black	-0.28	-0.28	-0.33	-0.33	-0.34	-0.34
White	0.04	0.04	0.04	0.04	0.06	0.05
Residence State FEs	N	Y	N	Y	N	Y

(b) Panel B: ONET Cognitive Scores

	All Sample		100km Restriction		50km Restriction	
	(1)	(2)	(3)	(4)	(5)	(6)
Racial Discrimination * Black	-0.49***	-0.46***	-0.41**	-0.44***	-0.49***	-0.49***
	(0.13)	(0.13)	(0.18)	(0.16)	(0.18)	(0.17)
Adj. R-squared	0.03	0.04	0.04	0.06	0.05	0.05
Observations	1541	1541	738	736	633	629
Black	185	185	83	83	81	81
White	1356	1356	655	653	552	548
Mean DV	0.00	0.00	0.00	0.00	0.00	-0.00
Black	-0.34	-0.34	-0.49	-0.49	-0.49	-0.49
White	0.05	0.05	0.07	0.06	0.08	0.07
Residence State FEs	N	Y	N	Y	N	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The two panels report the coefficient of the interaction between racial discrimination and the black dummy on non-routine cognitive scores (Panel (A)) and ONET cognitive scores. Columns (1)-(2) report the coefficients for all the sample, while column (2)-(3) restrict the sample to only include pilots that resided within 50 km from their birth place. In columns (4)-(5) we perform again this exercise using a 100km buffer.

Table 3: DISCRIMINATION AND OUTCOME DISTORTION

	1950 Income		1950 Occscore		Death ZIP House Price		Death ZIP Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Racial Discrimination * Black	-1094.490***	-840.478	-122.504	-178.847*	-9.253***	-6.168***	-7.108***	-5.534*
	(288.290)	(823.046)	(75.510)	(94.550)	(0.923)	(0.954)	(2.117)	(2.967)
Adj. R-squared	0.066	0.275	0.107	0.165	0.043	0.296	0.008	0.090
Observations	383	337	843	807	5251	4873	1212	1079
Black	46	43	101	101	1322	1239	188	171
White	337	294	742	706	3929	3634	1024	908
Mean DV	3411.909	3430.745	2809.684	2806.846	54.185	53.934	68.193	68.500
Black	2153.304	2156.326	2290.222	2290.222	52.228	52.378	67.660	68.135
White	3583.706	3617.139	2880.392	2880.754	54.843	54.465	68.291	68.568
Birth County FEs	N	Y	N	Y	N	Y	N	Y
Residence State FEs	N	Y	N	Y	N	Y	N	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table reports the coefficient of the interaction between racial discrimination and the black dummy. The independent variable is US Census 1950 income in columns (1)-(2), US Census 1950 occupational score in columns (3)-(4), 2000s death ZIP house price in columns (5)-(6), 2000s death ZIP income in columns (7)-(8).

Table 4: DISCRIMINATION AND OUTCOME DISTORTION: SAMPLE LIVING WITHIN 50KM FROM THE BIRTHPLACE

	1950 Income		1950 Occscore		Death ZIP House Price		Death ZIP Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Racial Discrimination * Black	-1313.093	-1770.089**	-90.760	-153.074	-14.471***	-9.556***	-10.547***	-10.426
	(972.069)	(846.543)	(83.144)	(119.402)	(1.588)	(1.927)	(3.648)	(6.983)
Adj. R-squared	0.131	0.347	0.125	0.207	0.061	0.449	0.011	0.295
Observations	134	85	565	534	1092	1078	243	200
Black	21	16	81	80	247	247	37	32
White	113	69	484	454	845	831	206	168
Mean DV	2045.429	1909.313	2272.817	2269.306	43.113	43.113	67.108	70.563
Black	3290.230	3446.623	2865.479	2866.746	48.503	48.735	71.539	73.530
White	N	Y	N	Y	N	Y	N	Y
Birth County FEs	N	Y	N	Y	N	Y	N	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table reports the coefficient of the interaction between racial discrimination and the black dummy for the sample of pilots who resided within 50km from their birthplace. The independent variable is US Census 1950 income in columns (1)-(2), US Census 1950 occupational score in columns (3)-(4), 2000s death ZIP house price in columns (5)-(6), 2000s death ZIP income in columns (7)-(8).

Table 5: TUSKEGEE AIRMEN'S TALENT MISALLOCATION AND AGGREGATE CONSEQUENCES

(A) Panel A: All

	Log(Wage)	Non-Routine Cognitive Scores	ONET Cognitive Scores
Above Median	-0.046***	-0.005***	-0.024***
	(0.001)	(0.001)	(0.001)
N	4385158	5117325	5109724
Mean DV	6.714	0.000	0.002

(B) Panel B: Blacks

	Log(Wage)	Non-Routine Cognitive Scores	ONET Cognitive Scores
Above Median	-0.041***	-0.046***	-0.050***
	(0.005)	(0.006)	(0.007)
N	326981	393206	396754
Mean DV	6.177	-0.002	-0.003

(C) Panel C: Whites

	Log(Wage)	Non-Routine Cognitive Scores	ONET Cognitive Scores
Above Median	-0.046***	-0.004***	-0.022***
	(0.001)	(0.001)	(0.001)
N	4036822	4696014	4684940
Mean DV	6.759	0.000	0.002

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The three panels are shown separately for all, white, and black individuals. In all three panels, the independent variable is a dummy representing whether the residence county is characterized by an above-median pilot talent misallocation. The dependent variables are the logarithm of 1940 income, non-routine cognitive scores, and ONET cognitive scores. Robust standard errors.

Online Appendix

to

"Discrimination and Talent Allocation: Evidence from Tuskegee Airmen"

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A. Data

A.1 White Pilots Roster

The USAAF trained more than 100,000 white pilots during the WWII (USAAF Office of Statistical Control, 1945). To the best of our knowledge, a comprehensive of list of all these pilots does not exist. Instead, we manually collect a representative sample of these pilots—those who served in the 8th Air Force during the WWII. Because of Miller (2001)'s work on the 8th AF personnel history, we get access to a complete list of figher pilots in the 8th AF. Unfortunately, the Miller list does not contain additional information other than names and document bombing pilots, neither. Instead, we use the following public available sources to identify 5,142 pilots from 8 fighter groups and 3 bomb groups, and locate 3,761 (73.1%) pilots on the *Ancestry*.

1. **Fighter Pilots**
    - **The 4th Fighter Group**. Its complete roster of 572 pilots is from the Official Site of the 4th Fighter Group—World War II, which gives each pilot's name, birth date, birth place, death date, death place, etc. We use this website's information to locate pilots in *Ancestry*, and eventually find 328 pilots.
    - **The 55th Fighter Group**. The group has 344 pilots served during WWII according to http://www.55th.org, which provides each pilot's name and hometown. We use the information to locate pilots in *Ancestry*, and eventually find 286 pilots.
    - **The 78th Fighter Group**. It has 437 pilots by Miller (2001). We use *Duxford Diary* by Raymond Shepard to find each pilot's hometown.[1] We use the hometown information to locate pilots in *Ancestry*, and eventually find 364 pilots.
    - **The 339th Fighter Group**. It has 374 pilots by the *Roster of 339th Fighter Group Personnel* of the http://339thfg.com. This website's roster has pilots' name and hometown. We use the information to locate

[1] We thank Curt Shepard for sharing his data with us.

pilots in *Ancestry*, and eventually find 322 pilots.

- **The 353rd Fighter Group**. The group has 409 pilots by Graham Cross, who published his data on https://353rdfightergroup.wordpress.com. This list provides pilots' name and hometown. We use the information to locate pilots in *Ancestry*, and eventually find 340 pilots.
- **The 358th Fighter Group**. It has 294 pilots by the 358th FG Yearbook,[2] which provides pilots' names and hometowns. We use the information to locate pilots in *Ancestry*, and eventually find 221 pilots.
- **The 359th Fighter Group**. It has 365 pilots by a list that we received from Janet Fogg. It has each pilot's name and hometown. We use the information to locate pilots in *Ancestry*, and eventually find 244 pilots.
- **The 364th Fighter Group**. The group has 467 pilots by Miller (2001). We use public available information locate pilots in *Ancestry*, and eventually find 343 pilots.

2. **Bombing Pilots**

- **The 303rd Bombardment Group**. It has 297 (co-)pilots during WWII by the crew list on http://www.303rdbg.com, which provides pilots' name and hometown. We use the information to locate pilots in *Ancestry*, and eventually find 139 pilots.
- **The 384th Bombardment Group**. It has 929 (co-)pilots by a roster we received from Fred Preller, which includes names and hometowns. We use the information to locate pilots in *Ancestry*, and eventually find 673 pilots.
- **The 401st Bombardment Group**. The group has 654 (co-)pilots by the combat personnel list of http://401bg.org. In addition, United States Army Air Forces (1947) provides pilots' address information. We use the information to locate pilots in *Ancestry*, and eventually find 501 pilots.

[2] This book is available on https://www.fold3.com.

A.2 Post-WWII Economic Outcomes

We collect pilots' occupations from the *US City Directories*, their residence addresses from the *the US Public Records Index*, and their death ZIP codes from *Death Master File* (DMF) of the Social Security Administration. Figure ??? illustrates the distribution of observed years of these variables, and shows that these variables are primarily observed in the 1960s, 1990s, and 2000s, respectively.

A.3 Racial Discrimination Index

By combining historical lynchings, residential segregation in 1930 and 1940, support for segregationists Strom Thurmond and George Wallace in the 1948 and 1968 presidential elections, and race riots of the 1960s through principal component analysis, we construct an index of county-level racial discrimination illustrated by Figure ??. Figure ??? shows that the index summarizes the key information of each variable and is strongly correlated with its constituent elements.

The data sources of components are:

- **Historical Lynchings**. We combine lynching datasets from the Lynching Project—which focus on the Southern states—with that from Seguin and Rigby (2019) which has a better coverage of incidents in the non-Southern states.
- **Residential Segregation in 1930 and 1940**. We follow Logan and Parman (2017)'s algorithm and calculate our own indices by using the complete censuses in 1930 and 1940.
- **Support for Strom Thurmond**. It is from variable *V589* of Clubb et al. (2006).
- **Support for George Wallace**. It is from variable *V666* of Clubb et al. (2006).
- **The 1960s Race Riots**. It is from the 1960s Black Riot Data (1964–1971) stored on Harvard Dataverse.

A.4 LASSO Prediction of AGCT Scores

We recover 461,480 WWII Army recruits' AGCT scores from the *weight* variable, following Ferrie et al. (2012), Aaronson and Mazumder (2011), and Feyrer et al. (2017). LASSO selects variables from:

1. Continuous Variables
    - *birth year*

- *enlistment year*
- *enlistment month*

2. Categorical Variables
   - *residence county*
   - *birth state*
   - *enlistment place*
   - *race*
   - *education*
   - *citizenship*
   - *civilian occupation*
   - *marital status*
   - *military grade*
   - *military branch*
   - *conscientious objector*
   - *limited service*
   - *source of Army personnel*
   - *component of the Army*
   - *term of enlistment*
   - *reserve status*
   - *pilot status*
   - *draftee vs. volunteer*
3. Interactions of Continuous and Categorical Variables

The LASSO selects a λ =0.008 and choose the following variables to predict AGCT:

1. Categorical Variables
   - *residence county*
   - *birth state*
   - *enlistment place*
   - *race*

- *education*
- *citizenship*
- *civilian occupation*
- *marital status*
- *military grade*
- *military branch*
- *limited service*
- *source of Army personnel*
- *component of the Army*
- *term of enlistment*
- *pilot status*
- *draftee vs. volunteer*

2. Interactions of Continuous and Categorical Variables

    - *birth state* × *birth year*
    - *birth state* × *enlistment year* × *enlistment month*
    - *civilian occupation* × *birth year*
    - *civilian occupation* × *enlistment year* × *enlistment month*
    - *component of the Army* × *birth year*
    - *component of the Army* × *enlistment year* × *enlistment month*
    - *residence county* × *birth year*
    - *residence county* × *enlistment year* × *enlistment month*
    - *education* × *birth year*
    - *education* × *enlistment year* × *enlistment month*
    - *enlistment place* × *birth year*
    - *enlistment place* × *enlistment year* × *enlistment month*
    - *limited service* × *birth year*
    - *limited service* × *enlistment year* × *enlistment month*
    - *draftee vs. volunteer* × *birth year*
    - *draftee vs. volunteer* × *enlistment year* × *enlistment month*
    - *reserve status* × *birth year*

- *marital status* × *birth year*
- *military branch* × *enlistment year* × *enlistment month*
- *citizenship* × *enlistment year* × *enlistment month*
- *military grade* × *enlistment year* × *enlistment month*
- *race* × *enlistment year* × *enlistment month*
- *source of Army personnel* × *enlistment year* × *enlistment month*
- *term of enlistment* × *enlistment year* × *enlistment month*

The R^2 is 0.60 and the correlation between true AGCT and predicted one in the training sample is 0.77. In addition, as shown in Appendix Figure ??, the LASSO-predicted AGCT satisfactorily recovers the distribution

A.5 Aerial Victory

We collect the number of aerial victories that each pilot obtained during the WWII to measure each pilot's productivity from USAAF Historical Research Agency (1978).[3] Figure ?? demonstrates the distribution of aerial credits by race.

[3]Thanks for the digitalization work by Jan Šafařík.

B. Selective Migration over Racial Discrimination

C. Appendix Tables

Table 6: DISCRIMINATION AND OUTCOME DISTORTION

	1950 Income		1950 Occscore		Death ZIP House Price		Death ZIP Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Racial Discrimination * Black	-1359.136	-1732.336**	-83.650	-144.401	-14.506***	-9.111***	-10.909***	-12.079*
	(897.561)	(847.559)	(81.152)	(113.080)	(1.535)	(1.898)	(3.530)	(6.616)
Adj. R-squared	0.117	0.382	0.114	0.188	0.058	0.434	0.011	0.274
Observations	152	104	625	598	1339	1323	297	252
Black	22	16	83	82	277	277	40	34
White	130	88	542	516	1062	1046	257	218
Mean DV	2084.136	1909.313	2281.444	2278.124	43.664	43.664	67.175	71.706
Black	3264.438	3398.670	2862.587	2862.152	49.638	49.944	71.039	71.950
White	N	Y	N	Y	N	Y	N	Y
Birth County FEs	N	Y	N	Y	N	Y	N	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table reports the coefficient of the interaction between racial discrimination and the black dummy for the sample of pilots who resided within 100km from their birthplace. The independent variable is US Census 1950 income in columns (1)-(2), US Census 1950 occupational score in columns (3)-(4), 2000s death ZIP house price in columns (5)-(6), 2000s death ZIP income in columns (7)-(8).

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