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On the Degree and Consequences of Talent Misallocation for the United States

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On the Degree and Consequences of Talent Misallocation for the United States*

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Abstract

We develop a search and matching model linking unequal access to employment with wage gaps, labor misallocation, and income losses. We then use microeconomic data for millions of individuals across the United States over the period from 1960 to 2017, to explore the misallocation effects arising due to frictions related to race and gender and to quantify their impact on aggregate economic outcomes. We systematically find that women and non-whites receive lower wages compared to their counterparts with similar individual characteristics. Within our theoretical model, such wage gaps coexist with talent misallocation due to the presence of workers that are underprivileged as a result of their gender or race. State-level misallocation implied by our estimated wage gaps is negatively related to productivity and output at the state level over the period under study. Furthermore, calibrating the theoretical model to match the US economy, we find that a fall in white privilege has a sizeable positive effect on aggregate income.

Keywords: Economic growth; inefficiencies; wage gaps; race; gender.

JEL Classification: O4, O51, E0, J31

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1 Introduction

Input misallocation can have adverse effects on productivity and economic growth. In particular, labor market frictions in the form of barriers for some or privileged treatment for others could result in significant output losses (e.g., Murphy et al., 1991). In this paper, we develop a search and matching model of the labor market (e.g., Mortensen and Pissarides, 1994) in which there are two groups of workers facing different opportunities for employment. Our model links unequal access to employment with wage gaps, labor misallocation, and income losses. We then use microeconomic data across the United States over the period from 1960 to 2017, in order to detect wage gaps and implied misallocation effects related to gender and race, and to quantify their impact on aggregate economic outcomes. Finally, calibrating our model to match US data, we assess the income losses associated with the degree of unequal access to employment consistent with our microdata-based estimates of the conditional wage gaps.

The novel model environment we propose to study wage gaps and misallocation differs from the related existing literature which is based on the Roy (1951) model of occupational choice. In our theoretical model, wage gaps and misallocation are both generated by the unequal opportunities for employment that equally talented workers have, depending on whether they are "privileged" or "underprivileged". These differences can arise from the lack of connectivity or the presence of social norms, prejudice, and so on. In our context, "underprivileged" will refer to workers that due to barriers related to race and gender find it more difficult to be employed in the market as compared to other individuals that otherwise share their economic characteristics. Both types of workers search for employment in both low- and high-productivity jobs but underprivileged types face a disadvantage in the high-productivity sector's labor market.[1] In this environment, we show that underprivileged workers will be paid less compared to privileged ones, despite being equally talented.[2]

[1]Our assumption here is consistent with Hsieh et al. (2019) who find that women and African-Americans in the US have historically been poorly represented in high-skilled occupations, with 94 percent of doctors and lawyers in 1960 being white males.

[2]Our model relates to Borowczyk-Martins et al. (2018) who develop a search and matching model

Our study stems from the branch of the growth literature which assigns a central role to total factor productivity (TFP) as an explanation for economic growth and cross-country income differences.[3] Hsieh and Klenow (2009) provide quantitative evidence on the potential impact of resource misallocation on aggregate output. Using plant-level data from China and India, they measure marginal products and find that if capital and labor were reallocated towards US levels this would increase TFP by 30 to 50 percent in China and 40 to 60 percent in India.

Our work is related to the literature on talent misallocation going back to Becker (1957) and Murphy et al. (1991).[4] Gradstein (2019) shows that barriers to skill acquisition and other barriers which make it more difficult for certain population groups to enter skilled occupations, can have large economic costs. Bentolila et al. (2010) investigate labor misallocation through the prism of a standard search model. In their model, misallocation in the economy is generated as agents base their occupational choice on factors other than their comparative advantages, e.g. on social contacts, which leads to a fall in aggregate net income. Bello and Morchio (2020) develop an occupational choice model with search frictions to study the link between labor misallocation and intergenerational occupational persistence. In their model, labor misallocation arises as parents help their offspring find a job faster in their own occupation, which is not necessarily where their offspring's comparative advantage lies.

According to the closely related work by Hsieh et al. (2019) who investigate the allocation of talent in the US, the significant convergence in the occupational distribution during the last few decades has resulted in large productivity gains explaining 20 to 40 percent of growth in output per worker. They argue that as innate talent among

with skill heterogeneity and employer taste-based discrimination to explain the existence of a wage gap associated with race, and to Acemoglu (2001) who develops a search and matching model where wage differentials for identical workers emerge. It also relates to work by Chassamboulli and Palivos (2014), Liu et al. (2017) and Chassamboulli and Peri (2018) among others, that develop search and matching models to explain wage gaps between domestic and foreign workers.

[3]For an overview of this literature see Caselli (2005) and Jones (2016).

[4]Becker (1957) was the first to explore the economic effects of discrimination in the labor market due to race, gender, social class and so on. Restuccia and Rogerson (2013, 2017) provide reviews of the literature on misallocation as a potential source of aggregate productivity differences across countries.

members of a group is unlikely to have changed over time, the initial occupational distribution in 1960 likely reflected misallocation of talent due to labor market discrimination, barriers to forming human capital, and social norms.[5] Related work showing gender gaps can have large macroeconomic consequences includes Cavalcanti and Tavares (2016) who develop a growth model with endogenous fertility. Calibrating this to the US economy, they find large increases in *per capita* income related to reduced barriers to female labor market participation in the form of a wage gap: a 50 percent fall in the wage gap leads to a 35 percent rise in *per capita* income. Cuberes and Teignier (2016) calibrate an occupational choice model for 33 OECD countries for 2010 and find that gender wage gaps cause an average income *per capita* loss of 15 percent.

Our paper also draws inspiration from the large body of work documenting the relation between individual economic outcomes and race or gender.[6] That body of work shows that despite reductions in the level of gender and racial discrimination in the US relative to the 1960s, gender and race continue to matter for economic outcomes to this day. Blau and Kahn (2017) provide empirical evidence on the extent of and trends in the gender wage gap using microdata from 1980 to 2010. Lang and Lehmann (2012) report that labor market outcomes of black Americans, particularly males,[7] continue to be significantly worse than those of white Americans. Bertrand and Mullainathan (2004) perform a field experiment and find significant racial inequality in the US labor market: African American-sounding names are 50 percent less likely to receive callbacks for interviews compared to white-sounding names.[8] Kline and Walters (2020) use three different experimental datasets to detect discrimination by employers using correspondence experiments that send fictitious resumes to real job openings, and find that callback probabilities differ by race and sex. Bayer and Charles (2018) explore black-white earning differences among men in the US for the past seven decades and

[5]Bell et al. (2018) also show that occupational decisions in the US have mainly been driven by individuals' exposure to opportunities provided by their environment rather than by inherited abilities.

[6]Neumark (2018) reviews the literature on labor market discrimination due to gender and race.

[7]This shows up as a positive female-African American interaction term in our Table B7.

[8]This agrees with Edelman et al. (2017), that conduct an experiment in an online marketplace and find that Airbnb applications from guests with distinctively African American names are 16 percent less likely to be accepted relative to identical guests with distinctively white names.

report that between 1940 and the mid-1970s these were reduced but only to rise again.[9]

Using microeconomic data on wages and individual characteristics across the United States over the period from 1960 to 2017, we systematically find that women and non-whites receive lower wages as compared to their counterparts with otherwise similar observable characteristics. Considering the relation of our estimated misallocation measure with Technical Efficiency, TFP, and GDP per worker for each state over time, we find a negative relation between our microdata-based measure and these aggregate measures, consistent with an important role of talent misallocation for macroeconomic outcomes. Calibrating our theoretical model to match the US economy over the most recent period used in our estimation, 2010-2017, we find that a 50 percent reduction in the wage gap between African-Americans and whites increases net income by more than 0.4 percent per month, and that eliminating the white privilege results in a substantially larger increase in net income of around 4 percent per month. This suggests important aggregate effects arising from talent misallocation in the United States over this period.

The rest of the paper is organized as follows. Section 2 describes our theoretical model. Section 3 presents the data, summary statistics, and our empirical methodology. Section 4 presents the results of our estimation, while section 5 relates talent misallocation to aggregate economic outcomes. The last section briefly concludes.

2 The Model

We develop a search and matching model of the labor market (e.g., Mortensen and Pissarides, 1994) in which there are two groups of workers facing different opportunities for employment. These differences can arise from the limited connectivity of certain groups of workers or from the presence of social norms and phenomena such as prejudice against certain groups of workers. No matter what the underlying cause of unequal

[9] We observe a similar pattern for the conditional wage gap, falling substantially between 1960 and 1980 but then rising until 2010.

access to employment, we show that it can lead to wage gaps and to talent misallocation.

2.1 Main Assumptions

Time is continuous and the economy consists of a continuum of workers and a continuum of firms. The measure of workers is normalized to one, whereas the measure of firms is determined endogenously. All agents are risk neutral and discount the future at a constant interest rate $r > 0$. There are two types of workers indexed by $j \in \{P, U\}$. A fraction $\mu \in (0, 1)$ of them are underprivileged (U) and the remaining $1 - \mu$ are privileged (P). However, all workers are equally talented or skilled.

There are also two types of jobs/sectors: low-productivity (L) and high-productivity (H) jobs, indexed by $i \in \{L, H\}$. We assume that each firm has at most one position and use the terms firms, jobs, and positions interchangeably. A firm must decide the type of job that it will create before entering the labor market. We assume that creating either type of job is costless and entry is free. There is, however, a flow hiring cost c, which is paid until the vacancy is filled. In principle, each vacancy can be filled by a worker of either type. A match between a low- (high-) productivity job and a worker results in output y_L (y_H), where $y_H > y_L$. Thus, the productivity of a job does not depend on the type of worker that occupies it. Furthermore, since each firm can create at most one position and the cost of it is zero, profit maximization and free entry amount to an expected-zero-profit condition for firm entry and exit. Such a condition endogenously determines the number of firms.

Unemployed workers of both types search for employment in both high- and low-productivity markets. During unemployment they receive a flow of income b, which captures the opportunity cost of employment, e.g., the value of home production, leisure and unemployment benefits. As we show later, to ensure that some production takes place it suffices to assume that $y_H > y_L > b$.

2.2 Matching

Unemployed workers and vacant positions are brought together in each sector via a stochastic matching technology. Both types of workers search for employment in both markets. In particular, the matching function in the low-productivity sector

$$M_L = M(v_L, u_P + u_U), \tag{1}$$

gives the total flow of contacts within a short interval dt, as a function of the stock of low-productivity vacancies searching for workers, v_L, and the total stock of unemployed workers looking for work in the low-productivity sector, $u_P + u_U$, where u_j is the mass of unemployed workers of type $j = P, U$. We assume that the function $M(\cdot)$ is of constant returns to scale, has positive first-order and negative second-order partial derivatives, and satisfies standard Inada conditions. We define labor market tightness as $\theta_L \equiv v_L/(u_P + u_U)$. The rate then at which a firm meets a worker is $q(\theta_L) = M_L/v_L$, where $q'(\theta_L) < 0$, and the rate at which a worker finds a job is $m(\theta_L) = M_L/(u_P + u_U) = q(\theta_L)\theta_L$.

A similar matching technology is assumed in the high-productivity sector,[10] namely,

$$M_H = M(v_H, u_P + u_U). \tag{2}$$

Nevertheless, workers in the high-productivity sector may differ in terms of the probability of forming a match. Thus, even if the probability of meeting a vacancy among workers is the same, a contact between a high-productivity job and a worker may not be consummated because of the limited connectivity of certain groups of workers or due to the existence of social norms against the presence of underprivileged workers such as women and non-whites in high-productivity jobs. This is in line with the evidence from Hsieh et al. (2019) who report that women and African-Americans have historically been under-represented in high-skilled jobs. More generally, this situation arises

[10] Note that we write $M(\cdot)$, $m(\cdot)$ and $q(\cdot)$ to keep the notation simple. We do not mean to assume that the two matching functions are of the same functional form.

any time certain privileged workers are "connected", i.e., have strong social network connections, and get hired more easily than other (underprivileged) workers who are relatively "disconnected". Thus, the probability of getting hired (the matching rate) for underprivileged workers is $\eta m(\theta_H) < m(\theta_H)$, where $\eta < 1$.[11]

We assume that all matches dissolve at an exogenous rate $\delta > 0$. Whenever a job is destroyed, the worker becomes unemployed and starts looking for a new job while the firm becomes vacant and can either withdraw from the market or open a new position in any of the two sectors.

2.3 Asset Values and Bargaining

We let U_j denote the expected present discounted income of an unemployed worker who is of type j, and E_{ij} denote the expected present discounted income of an employed worker who is of type j and is matched with a job of type i. In steady state:

$$rU_P = b + m(\theta_L)max[(E_{LP} - U_P), 0] + m(\theta_H)(E_{HP} - U_P), \tag{3}$$

$$rU_U = b + m(\theta_L)max[(E_{LU} - U_U), 0] + \eta m(\theta_H)(E_{HU} - U_U), \tag{4}$$

$$rE_{ij} = w_{ij} - \delta(E_{ij} - U_j), \;\; i = L, H, \;\; j = U, P, \tag{5}$$

where w_{ij} is the wage earned by a worker of type j who is matched with a vacancy of type i. The terms $max[(E_{Lj} - U_j), 0]$, $j = P, U$, appear in equations (3) and (4) in order to capture the case where workers do not consider it worthwhile to be employed in low-productivity jobs; such a case, as we will see below, does not arise with regard to high-productivity jobs, as long as $y_H > y_L > b$.

Similarly, letting V_i denote the expected income accrued to a vacant position of type i,

[11] An alternative modeling formulation, to capture a handicap of isolated workers in job search, is to define the matching function in the high-productivity sector as $M_H = M(v_H, u_P + \gamma u_U)$, where the parameter $\gamma \in (0, 1)$ indicates that disconnected workers have a lower number of efficiency units than connected ones. The rate at which the latter find jobs is $m(\theta_H)$, where the effective labor market tightness is defined as $\theta_H \equiv v_H/(u_P + \gamma u_U)$. The corresponding rate for isolated workers is $\gamma m(\theta_H) < m(\theta_H)$. The two approaches yield similar results. We follow the one outlined in the main text as it is somewhat simpler.

and Π_{ij} denote the expected income accrued to a position of type i that is filled with a worker of type j, the asset values associated with the firms are given by:

$$rV_L = -c + q(\theta_L)\{\phi_{LU} max[(\Pi_{LU} - V_L), 0] + (1 - \phi_{LU}) max[(\Pi_{LP} - V_L), 0]\}, \tag{6}$$

$$rV_H = -c + q(\theta_H)\{\eta\phi_{HU}(\Pi_{HU} - V_H) + (1 - \phi_{HU})(\Pi_{HP} - V_H)\}, \tag{7}$$

$$r\Pi_{ij} = y_i - w_{ij} - \delta(\Pi_{ij} - V_i), \;\; i = L, H, \;\; j = U, P, \tag{8}$$

where ϕ_{iU}, $i = L, H$ is the probability that a vacancy of type i meets an underprivileged worker. Thus, a low-productivity vacancy is filled by an underprivileged worker with probability $q(\theta_L)\phi_{LU}$ and by a privileged worker with probability $q(\theta_L)(1 - \phi_{LU})$. Similarly, a high-productivity job is filled by an underprivileged worker with probability $\eta q(\theta_H)\phi_{HU}$ and by a privileged one with probability $q(\theta_H)(1 - \phi_{HU})$. As mentioned above, there is free entry at zero cost and hence, in equilibrium, the expected payoff of posting a vacancy is zero:

$$V_i = 0, \;\; i = L, H. \tag{9}$$

The wage rate is determined according to a generalized Nash bargaining rule, where the worker's bargaining power is captured by $\beta \in (0, 1)$. In other words, the worker receives a share β and the firm $1 - \beta$ of the surplus S_{ij} that is generated from a match:

$$S_{ij} = \Pi_{ij} + E_{ij} - V_i - U_j, \;\; i = L, H, \;\; j = U, P. \tag{10}$$

Hence,

$$\Pi_{ij} - V_i = (1 - \beta)S_{ij}, \tag{11}$$

$$E_{ij} - U_j = \beta S_{ij}. \tag{12}$$

It follows that a match between an unemployed worker of type j and a firm of type i will be consummated if and only if $S_{ij} \geq 0$.

2.4 Equilibrium

The nature of the equilibrium depends on the values assumed by the parameters of the model. There are three cases to consider. The first case is an equilibrium in which workers of both types match with both low- and high-productivity jobs, that is, $S_{ij} \geq 0$ for $i = L, H$, $j = P, U$; we call this an *integrated* equilibrium. The second case is a *partially segregated* equilibrium in which only underprivileged workers find it beneficial to match with low-productivity jobs, that is, $S_{LU} \geq 0, S_{LP} < 0$ and $S_{Hj} \geq 0$, $j = P, U$. Finally, the third case is a *restricted* equilibrium in which only high-productivity firms exist, i.e., $S_{Lj} < 0$ and $S_{Hj} \geq 0$ for $j = P, U$. As we mention in our Quantitative Analysis Section, when we attempt to calibrate the integrated equilibrium of the model for the US, we find that $S_{LP} < 0$. Hence, we calibrate the US economy as if it was at a partially segregated equilibrium. Nevertheless, for the sake of completeness, we analyze and present all three cases. We present the case of the integrated equilibrium in the main text because it is the most general one, and the other two in the Appendix.

Using (5), (8), and (9), equation (10) becomes

$$(r + \delta)S_{ij} = y_i - rU_j. \tag{13}$$

It follows then that a match will be formed if and only if

$$y_i \geq rU_j. \tag{14}$$

Moreover, (5), together with (12) and (13), yields

$$w_{ij} = \beta y_i + (1 - \beta)rU_j. \tag{15}$$

According to (15), the wage is a weighted average of the output of the match and the worker's flow value of unemployment, which is common in this framework.

Substituting (12) and (13) in (3) and (4), we obtain the reservation values of the two types of workers:

$$rU_P = \frac{(r+\delta)b + \beta[m(\theta_L)y_L + m(\theta_H)y_H]}{r+\delta+\beta[m(\theta_L)+m(\theta_H)]}, \tag{16}$$

$$rU_U = \frac{(r+\delta)b + \beta[m(\theta_L)y_L + \eta m(\theta_H)y_H]}{r+\delta+\beta[m(\theta_L)+\eta m(\theta_H)]}. \tag{17}$$

Each measure of unemployed workers, u_P and u_U, satisfies the steady-state condition that the flow of new hires equals the flow of layoffs:

$$[m(\theta_L) + m(\theta_H)]u_P = \delta(1-\mu-u_P), \tag{18}$$

$$[m(\theta_L) + \eta m(\theta_H)]u_U = \delta(\mu-u_U). \tag{19}$$

The probabilities that each type of vacancy meets an underprivileged worker are equal:

$$\phi_{LU} = \phi_{HU} = \phi = \frac{u_U}{u_P+u_U}. \tag{20}$$

Using (11), (13), (16), and (17), we can rewrite the free entry conditions (9), $V_i = 0$ $i = L, H$, as

$$\frac{(r+\delta)c}{q(\theta_H)(1-\beta)} = [1-\phi(1-\eta)]y_H - \eta\phi rU_U - (1-\phi)rU_P, \tag{21}$$

$$\frac{(r+\delta)c}{q(\theta_L)(1-\beta)} = y_L - \phi rU_U - (1-\phi)rU_P, \tag{22}$$

where rU_P and rU_U are given by equations (16) and (17), respectively. Equations (21) and (22) are the free and costless entry conditions in the high- and low-productivity sector, respectively.

We are now in a position to define the *integrated* steady-state equilibrium:

Definition. An *integrated* steady-state equilibrium consists of a set of value functions U_j, E_{ij}, V_i, Π_{ij}, and S_{ij} that satisfy (3) – (13) and a vector $\{\theta_L, \theta_H, \phi, v_P, v_U\}$, such that all matches produce a non-negative surplus, i.e., inequality (14) holds, and the vector

$\{\theta_L, \theta_H, \phi, v_P, v_U\}$ satisfies *a*) the free-entry conditions (21) and (22); *b*) the steady-state conditions (18) and (19) regarding the stocks of unemployed workers of each type and *c*) equation (20), which defines the probability that a firm finds an underprivileged worker.

Solving (18) and (19), we find

$$u_P = \frac{\delta(1-\mu)}{\delta + m(\theta_L) + m(\theta_H)}, \tag{23}$$

$$u_U = \frac{\delta\mu}{\delta + m(\theta_L) + \eta m(\theta_H)}. \tag{24}$$

Substituting (23) and (24) in equation (20) we find

$$\phi = \frac{\mu[\delta + m(\theta_L) + m(\theta_H)}{\delta + m(\theta_L) + (\mu + \eta - \mu\eta)m(\theta_H)}. \tag{25}$$

Equations (21) and (22), where rU_P and rU_U are given by equations (16) and (17) and ϕ by equation (25), determine a unique pair of (θ_H, θ_L). Once this pair has been determined, we can obtain unique values for all other variables. First, consider the following proposition:

Proposition 1. If $y_L \geq \frac{(r+\delta)b+\beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)}$ and c and η are sufficiently high, then an integrated steady-state equilibrium exists and is unique.

Proof. All proofs are presented in the Appendix.

The existence of an integrated steady-state equilibrium requires that the surplus generated by each match is non-negative. From equations (14), (16) and (17), we see that if $y_H > y_L > b$, then $S_{Hj} \geq 0$ for every $j = U, P$, i.e., the two surpluses in the high-productivity sector are always non-negative. Both types of workers always find it beneficial to work in the high-productivity sector. On the other hand, the condition specified in Proposition 1 regarding the size of y_L is necessary and sufficient for privileged workers to accept jobs in the low-productivity sector. It follows that if privileged workers accept jobs in the low-productivity sector, so do the underprivileged ones, since the latter face worse prospects in the high-productivity sector and, as shown below, have a lower reservation value.

Using (13), (16) and (17), we find that the *partially segregated* equilibrium, in which only underprivileged workers find it beneficial to match with low-productivity jobs, that is, $S_{LU} \geq 0$ and $S_{LP} < 0$, occurs when $\frac{(r+\delta)b+\beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)} > y_L \geq \frac{(r+\delta)b+\beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)}$. Finally, the *restricted* equilibrium in which only high-technology firms exist, i.e., $S_{Li} < 0$ for $i = P, U$, occurs when $\frac{(r+\delta)b+\beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)} > y_L$.

We note that from (23) and (24), the unemployment rate among privileged workers $(= v_P/(1-\mu))$ is lower than the one among underprivileged since the former have a higher probability of getting matched in one of the two sectors, namely, the high-productivity sector. For the same reason, the probability that a vacancy of either type meets an underprivileged worker is greater than the share of underprivileged workers in the general population, that is, $\phi > \mu$.

Proposition 2. Privileged workers have a higher reservation wage: $rU_P > rU_U$. Moreover, in each sector, privileged workers receive a higher wage than the underprivileged: $w_{HP} > w_{HU}$ and $w_{LP} > w_{LU}$. In addition, workers of each type in the high-productivity sector receive a higher wage than their counterparts in the low-productivity sector: $w_{HP} > w_{LP}$ and $w_{HU} > w_{LU}$.

Privileged workers have better prospects in one of the two markets and hence the minimum wage at which they will accept a job (rU_P) is higher than the one for the underprivileged (rU_U). For the same reason, privileged workers in each sector are in a better bargaining position and hence receive a higher wage. This is so despite the fact that both types of workers are equally skilled. Moreover, workers in the high-productivity sector receive a higher wage than their counterparts in the low-productivity sector simply because the match in which they participate is more productive $(y_H > y_L)$.

Proposition 3. As parameter η goes up, the search conditions for workers in the high-productivity sector improve (θ_H increases) and in the low-productivity sector deteriorate (θ_L decreases). Moreover, the probability that a vacancy of either type meets an underprivileged worker (ϕ) decreases and asymptotically, as η approaches one, becomes equal to the share of underprivileged workers in the general population, μ. Naturally, as η approaches one, wages of privileged and underprivileged workers in each sector as well as unemployment rates converge.

As η increases, the probability that a match between a high-productivity position and an underprivileged worker (who, as you may recall, receives a lower wage) is consummated, also goes up. This increases expected profits temporarily, spurs entry in the high-productivity sector, and raises the wage for underprivileged workers. At the same time, it induces exit from the low-productivity sector since the better prospect of underprivileged workers raises their wage and decreases temporarily expected profitability in that sector. Hence, θ_H goes up and θ_L down. Moreover, the percentage change in the measure of unemployment among privileged workers is higher than that among underprivileged, $(du_P/d\eta)/u_P > (du_U/d\eta)/u_U$. That is why the share of underprivileged workers among the unemployed goes down and eventually, as η approaches one, becomes equal to their share in the general population. Moreover, as η approaches one, all barriers for underprivileged workers are eliminated and wages of workers in the same sector as well as unemployment rates become equal.

Finally, we note that as η increases, it becomes more likely that the condition regarding the size of y_L for the existence of an integrated equilibrium, stated in Proposition 1, ceases to hold; namely, the term $\frac{(r+\delta)b+\beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)}$ increases with η and may become higher than y_L, in which case the economy jumps to a partially segregated equilibrium where only the underprivileged work in the low-productivity sector. As η increases further, then even the term $\frac{(r+\delta)b+\beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)}$ may become higher than y_L. In that case, the economy moves to a restricted equilibrium, where any talent mismatch disappears; the low-productivity sector shuts down since no worker finds it worthwhile to work there. The equations describing each of these two types of equilibria are given in Appendix A.

3 Empirically investigating talent misallocation

We recall that in our theoretical model, wage gaps and misallocation are both generated by the unequal opportunities for employment that different types of workers have in the labor market so that the higher the degree of unequal treatment for underprivileged workers, the higher will be the wage gap relative to privileged workers and the higher the degree of misallocation in the economy. Given this theory-based link, we can estimate implicit measures of talent misallocation present in each state based on the conditional wage gaps associated with each state.

3.1 Data

We use cross-sectional data at the individual level by the U.S. Decennial Censuses covering the period from 1960 to 2000 and the 2010 and 2017 waves of the annual American Community Survey (ACS) to construct a total of seven samples. Summary statistics for these samples are shown in Table 1. The 1960, 1980, 1990, and 2000 decennial census samples each have more than eight million observations, while for the 1970 sample we have about four million and for the 2010 and 2017 samples around three million observations. These data are provided for all fifty states and the District of Columbia.[12]

Our main objective is to investigate talent misallocation across the United States focusing on individuals' gender and race. In particular, we will investigate whether being a female or non-white has explanatory power for wages beyond that explained by individual characteristics. The dependent variable in our analysis is the log of hourly income. This is defined as annual income divided by the number of months worked, multiplied by weekly hours of work times 4.2. Annual income is given by income earned from wages or a person's own business or farm for the previous year.[13]

[12]The data are also available for 1950 but we did not use it since the sample is not as comparable to other decades, with the number of observations much lower, 506,318 as compared to several million, and only a limited number of states included.

[13]As annual income is available from 1990 onward, we folloq Ruggles et al. (2019) and derive a

We use a broad definition of race taking into account all races and identifying them as whites versus non-whites. That is, we treat African-Americans, Hispanics, American Indians, Alaska Natives, Asians, and mixed race individuals, as non-white. This is supported by our preliminary analysis which showed large positive wage differentials for whites relative to each of the above race categories, suggesting that all non-white groups may have some sort of disadvantage in the labor market.

The distinction between private and public sector employment is based on information provided by the variable "class of worker" in the ACS database. This indicates whether an individual worked for someone else or whether they worked in their own enterprise. A public sector employee is defined as an individual that works for the local, state, or federal government, while the rest are defined as private sector employees. We also utilize the "Occupational Education Score" provided by this database. This is derived using educational attainment information and indicates the percentage of people in the respondent's occupational category that completed one or more years of college, relying on the modified version of the 1990 occupational classification scheme.

In addition, we use state-level data for GDP per worker, Technical Efficiency and TFP. Data regarding real GDP and total employment by state are from the Bureau of Economic Analysis (BEA). Real GDP data start from 1977. Until 1997 these are based on the Standard Industrial Classification (SIC) and from 1997 onward they are based on the North American Industry Classification System (NAICS). Data regarding technical efficiency are from Sharma et al. (2007).[14] As for the state-level TFP data, these are available from 1980 to 2000 (also from Sharma et al. (2007)) and we extend these for the 2000 and 2010 waves using data provided by Cardarelli and Lusinyan (2015).

Our final sample for each wave includes both employees and the self-employed,[15] irre-

similar measure for previous years by adding several components provided separately in the database. Moreover, there are cases where the weeks someone worked during the previous year are provided in intervals. If so, we transform this into a continuous variable by taking the average for each interval.

[14] They apply the stochastic frontier production model to 48 US states for 1977-2000 to decompose the sources of TFP growth into changes in technical efficiency, technological progress and changes in economies of scale.

[15] The latter are included as we have no reason to believe there is severe non-declaration of income.

spective of whether they work full-time or part-time, along with the unemployed. We exclude individuals below 25 and above 64, soldiers, and family workers.

3.2 Summary Statistics

Our final sample consists of millions of individuals across states and over time. As shown in Table 1, the number of observations for our regression samples ranges between 1.4 to 6.3 million depending on the year. Females comprise 41 to 49 percent of the total depending on the sample year, while non-whites comprise 13 percent in 1960 and 32 percent for the most recent available year. Historically, the majority of individuals work in the private sector (more than 80 percent) and are married (59.1 to 79.6 percent). Moreover, around 33.5 percent in 1960 worked part-time, while by 2017 only 12.9 percent were in part-time occupations. As expected, we observe a reduction in the percentage of individuals with low educational levels and a significant rise in the share of high-educated individuals over time.[16] As for the age groups, from Table 1 it can be observed that a high fraction consists of ages 25 to 54, with the percentage of the age group 55-64 rising however after year 2000 to about one quarter of our sample.

Table 1 shows median hourly earnings by gender, race, and employment sector. We observe that in 1960, women's median hourly earnings were \$8.77 compared with \$14.05 for men, with the resulting 62 percent female to male ratio implying a 38 percent unconditional gender gap. The latter gap has been falling over the years, with the female to male ratio wage ratio rising to 83 percent by 2017, but has yet to vanish.[17] With regard to race, the median hourly earnings in 1960 for non-whites were \$8.43 compared with \$12.80 for whites, with the resulting ratio of 65.9 climbing to a high of 82.4 by 2000 and then falling to 78.6 percent by 2017, implying again a persistent race-related wage gap. Viewed together, the above earning differentials may reflect that

[16] In 1960, 20% of our sample had completed at least one year of college. By 2017, this reached 61%.

[17] An alternative measure of the unconditional wage gap is derived from the female to male ratio of median annual earnings for full-time workers provided by the U.S. Census Bureau. From Figure B.1, we see that these measures follow a similar pattern and clearly indicate that the unconditional gender wage gap has persisted throughout the period under study.

white men maintained a relative privilege in the labor market throughout this period.

Finally, comparing the median hourly earnings of private-sector to public sector employees, we see that while the former are paid relatively less, this particular earnings ratio has historically been higher than the earning ratios for females and non-whites discussed above. The median hourly earnings for private-sector employees were \$12.08 compared with \$13.48 for public sector employees in the 1960's implying a private to public earnings ratio of about 90 percent and an unconditional wage gap of about ten percent. The implied unconditional wage gap for private sector employees reached a low of 7.7 percent in the 1980s as compared to a gender gap of nearly 40 percent and a race gap of about 19 percent at that time. It had nevertheless risen to 16.6% by 2017.

3.3 Empirical Specification

Having examined the unconditional wage differentials in the previous subsection, we now turn to the estimation of conditional wage gaps. Based on our theoretical model, wage gaps and misallocation are both generated by the unequal opportunities for employment that different types of workers have in the labor market. Thus, conditional wage gaps between privileged and underprivileged workers can serve as an implicit measure of talent misallocation. Our main empirical objective here will then be to estimate wage gaps related to race and gender, conditioning on a broad set of individual characteristics. To achieve this, we consider a Mincer-type wage regression.

To correct for selectivity bias, we first use the Heckman method by estimating the following probit equation:

$$T_{ij} = 1(\delta \mathbf{X}_{1ij} + \alpha_j + e_{ij} > 0) \tag{26}$$

where T_{ij} is a binary dependent variable with zero indicating being out of the labor force and unity indicating being in the labor force, and α_j and e_{ij} are state-fixed effects and an error term, respectively. X_{1ij} is a vector of covariates that includes dummy variables such as $Female_{ij}$ indicating the gender of individual i in state j, and $Nonwhite_{ij}$

denoting whether the individual is of a race other than white, i.e., African-Americans, Hispanics, American Indians, Alaska Natives, Asian, or "mixed race" individuals. Vector X_{1ij} also includes the binary variable $Private_{ij}$ that indicates employment sector, along with three controls for education (L= until 8^{th} grade, S=between 9^{th} to 12^{th} grades, and H=higher education), three controls for age, a continuous measure of occupation ($Occupscor$), marital status ($Married$), and a binary variable indicating part-time work.[18] As it is recommended to impose at least one exclusion restriction to avoid collinearity problems in the second stage of Heckit, we include the number of own children under age 5 in the household ($nchild5$) and other income ($other - inc$)[19] as instruments in the probit equation. The intuition is that women with young children are less likely to enter the labor force due to the time they have to dedicate to looking after children. Similarly, receiving earnings from other sources not related to labor income could have an adverse effect on the likelihood to enter the labor force in the first place. Estimating the above regression, we derive the inverse Mills ratio λ for each observation from $\hat{\delta}$.

We then estimate a Mincer-type wage regression as follows:

$$w_{ij} = \beta_0 + \beta_1 Female_{ij} + \beta_2 Nonwhite_{ij} + \beta \mathbf{X}_{2ij} + \gamma_1 \lambda(\hat{\delta}\mathbf{X}_{1ij}) + \alpha_j + \epsilon_{ij} \tag{27}$$

where w_{ij} is the logarithm of hourly earnings of individual i in state j, female is a binary variable that takes a value of unity if the individual is a female and zero otherwise, and nonwhite is a binary variable that takes a value of unity if the individual is non-white and zero otherwise.[20] X_{2ij} is a vector of covariates that includes variables from vector X_{1ij} such as education, age, occupation, marital status and part-time work, α_j are state-specific effects, and ϵ_{ij} is the error term. We also consider interactions for the

[18]The binary variable $Part - time$ is constructed following Hsieh et al. (2019), defining part-time workers as those who usually work up to thirty hours per week.

[19]This includes income from public assistance programs, estate or trust, interest, dividends, royalties, and rents received.

[20]Although country of birth is also available, race appears in Tables B8 and B9 in appendix B to be much more relevant than country origin in determining wages in this US sample, thus we followed Hsieh et al. (2019) in focusing on race and gender.

employment sector with education, female with education, non-white with education, female with marital status, female with part-time job, female with non-white, female with private sector, and private sector with non-white. Using the above wage regression, we estimate wage differentials between female versus male and non-white versus white with β_1 and β_2 capturing respectively the gender wage gap and the earning differential associated with race.

We first estimate the parameters for the US as a whole for each decade to assess the overall plausibility of our empirical model. Next, we allow the coefficients of $Female_{ij}$ and $Nonwhite_{ij}$ to differ for each state in both stages of the estimation. This provides the means for us to create a measure that indicates the overall misallocation effects for each state arising from these wage differentials. The state-level measure that we create focuses on misallocation related to race and gender.[21] Finally, we investigate the relationship of this estimated misallocation measure with Technical Efficiency, TFP, and GDP per worker at the state-level to assess the degree to which our microdata-based estimated misallocation proxy is related with macroeconomic outcomes.

4 Results

Table 2 reports the results from estimating equation (26), where unity indicates paid employment or unemployment and zero indicates being out of the labor force. This table summarises the results for the probit estimation for each decennial census starting from 1960 to 2000, and the annual surveys 2010 and 2017. The results indicate that for 1960 and 1970 being a female reduces the likelihood of being in the labor force. However, there have been significant changes throughout the decades regarding the probability of being in the labor force. For instance, from the 1980s onward we observe that women are more likely to enter the labor force. A similar pattern is also observed for those working in the private sector. By contrast, being of a race other than white is associated with

[21] While we control for the employment sector, we will show in the next section that, unlike in European countries, in the US there is no apparent misallocation problem related to this.

a lower likelihood of being in the labor force starting in the 1980s, with the exception of the 2017 sample. Higher education consistently increases the probability of being in the labor force. On the other hand, currently working part-time, having children of age under 5 and receiving other income, are associated with reduced likelihood of being in the labor force.

Tables 3 and 4 present estimates from the wage regression specified in equation (27) for the 1960 decennial sample and for year 2017 respectively. Results for the decennial samples from 1970 to 2000 and year 2010 are presented in Tables B1 to B5 in the appendix. We observe that the correlation coefficient between the error term in the Probit and the wage equation *athrho*, is significantly different from zero, indicating that our sample selection correction is indeed necessary[22]. Moreover, we note that the impact of the included covariates on hourly wages in the United States generally has the expected sign: workers with low education receive lower hourly wages as compared to workers with secondary education, those with high education receive higher wages as compared to those with only secondary education, age as a proxy for experience has a positive impact on wages for all age groups, individuals with higher occupational education scores have higher wages, and those that do part-time work have lower wages since the 1990s.

Importantly, our estimates overall suggest that being a female and of a race other than white exert a negative impact on earnings beyond that explained by individual economic characteristics. Our basic findings apply consistently over time, and results are robust to adding a number of covariates to the baseline wage regression.

As shown in Figure 1 and in the abovementioned Tables, the conditional gender wage gap appears to be a persistent phenomenon in the U.S. throughout the decades even if

[22]To test whether the instruments are relevant, we perform an F-test on the coefficients of instruments in the first-stage regression, regressing the endogenous variable on two instruments and all the exogenous variables. We reject the null hypothesis that the coefficients of the two instruments are equal to zero, in support of the hypothesis that our instruments are not weak. We also perform a likelihood ratio test to investigate the validity of our exclusion restrictions by comparing the model with an over-identified version with two exclusion restrictions to one which is just-identified, and find that the included instruments result in a statistically significant improvement in model fit.

declining from 1960 up until around 2010. Between 1960 and 1980, women were paid around 50 percent less than men, as shown in Tables 3, B1 and B2. Wage differentials related to gender were reduced considerably to 18 percent by 2010 as shown in Table B5, but were up to 24 percent in 2017 in Table 4 according to the most complete specification with interaction effects shown in column (5) of each Table.

Looking at the impact of race on the wage gap relative to whites, it stands out that being non-white affects hourly wages negatively and strongly so, controlling for a number of other individual-specific covariates such as education level and occupation. For instance, in the 1960s, non-white workers were paid 27.1 to 29.1 percent less compared to white ones, as shown in Table 3. Conditional wage differentials were about half this size but still present by 2017, with non-white workers being paid 11.2 to 12.5 percent less than their white counterparts.[23]

Race appears to be a more important factor in determining wages as compared to the country of birth. Tables B8 and B9 in the appendix show estimates from a wage regression that accounts for the country of birth, *Migrant*, in addition to race, for 1960 and 2017. The results clearly show that, other than a small and non-robust negative effect on wages in the 1960's, migrants are not paid less than native-born workers in the US conditional on their individual characteristics. This is consistent with the US being a dynamic country that historically welcomed new immigrants, unlike many European countries as shown, e.g., in Gramozi et al. (2020). On the other hand, race seems to be quite important for the U.S. as it is harder for non-whites to be integrated into the labor market, putting them at a disadvantage as compared to white workers.

We also find wage differentials between private and public sector employees, but these are much lower compared to those associated with gender or race and are reversed by the end of our sample period. More specifically, by 2017, private sector employees

[23]We also consider wage gaps between each of the different types of non-whites relative to whites in Tables B6 and B7 for 1960 and 2017. We find that African-American, Hispanic, American Indian, Alaska Native, Asian and mixed race individuals are systematically paid less then whites. While wage gaps vary across these races, they remain consistently negative suggesting it is reasonable to distinguish non-whites from white workers in estimating wage gaps in our baseline given also our focus.

were paid around 4.1 to 5.8 percent more compared to public sector ones controlling for their characteristics, depending on the specification in Table 4. This contrasts with European countries where on average, private-sector employees were paid systematically less compared to public sector employees as shown in Gramozi et al. (2020). Thus, unlike most European countries, the US does not appear to have a misallocation problem associated with the public sector.

In all Tables of results, we consider interactions of our main variables with a number of covariates. More specifically, we consider the interaction of education with gender, race, and sectoral affiliation, as well as the interaction of gender with part-time job status, and marital status. Moreover, we consider the interaction of gender with race and sectoral affiliation, and the interaction of the latter with race. These interaction terms often suggest different wage impact of certain variables for females as compared to males, and for non-whites as compared to whites. The interaction of female with education indicates high education consistently reduces gender wage gaps in all samples from 1960 to 2017 as shown in Tables 3, B1-B5, and 4. Interestingly, while high education also served to reduce race-related earning differentials throughout 1960 to 2000, this is no longer the case in our 2010 and 2017 samples. We also observe that wage differentials associated with race are consistently lower for females, consistent with Lang and Lehmann (2012)'s finding that wage gaps between black and white women have been historically lower than for males. Moreover, race-related wage gaps have consistently been higher in the private-sector as compared to the public sector, and the same goes for gender wage gaps except for year 2010. Finally, since 1990, part-time work consistently serves to reduce wage differentials between men and women.

Estimation without exclusion restrictions

So far, we have included instruments such as number of children in the household under age 5 and other income (comprised of income from public assistance programs, estate or trust, interest, dividends, royalties, and rents received). To examine whether our results are sensitive to imposing exclusion restrictions, we consider here the case where we do not include any instruments in the probit equation in the first stage. For the sake of brevity, we provide results of the Mincer-type wage regression for 1960 and 2017 in Tables B10 and B11 respectively, with Figure B.2 summarizing the results of the average conditional wage gaps derived without the exclusion restrictions for all the years in our sample. Overall, results are similar to those obtained by imposing exclusion restrictions. Being a female or non-white exert negative impact on hourly wages beyond that explained by their economic characteristics, and this impact is typically quite similar irrespective of whether we impose the above exclusion restrictions or not.

5 Macroeconomic Implications

5.1 Misallocation and macroeconomic outcomes

We now estimate regression specifications that allow the estimated coefficients related to gender and race to be state-specific. We include our complete set of explanatory variables and interactions as in the specifications reported in the last column of Tables 3, 4, and B1-B5.[24] This allows us to compute state-specific wage gaps based on these individual-level data, and to consider a ranking of all states for each period based on the wage gaps characterizing each state. Tables 5 and 6 present state-specific results for 1960 and 2017 respectively, while appendix Tables B12 to B16 show our results for the in-between decades from 1970 to 2010.

The average of our estimated misallocation measure across the United States was relatively large in the early decades. This was 69.3 percent in the 1960s but gradually declined to about half that value by 2017. In the 1960s, South Carolina, Alabama, Louisiana, Mississippi, and Georgia had the highest estimated misallocation values, while Vermont, Nebraska, Iowa, Minnesota, and Wisconsin had the lowest, as shown in Table 5. In 2017, Louisiana, Alaska, South Dakota, Mississippi, and West Virginia were the five states with the highest misallocation values, with Georgia and South Carolina having improved somewhat over these six decades, and New Hampshire, Oregon,

[24] This specification has the better goodness of fit as shown at the end of Tables 3, 4, and B1-B5.

Main, Kentucky, and Nevada now emerging as the five states with the lowest level of misallocation.[25] As we can see in these Tables, the gender wage gap is systematically the main contributor to the overall misallocation measure. In the 1960s, the average gender wage gap was around 46 percent while the wage differential related to race was around 23 percent. Despite the significant reduction for both wage gaps, in 2017 we still saw an average gender wage gap of around 24 percent, about twice the value of the race-related wage gap.

Our theoretical model implies that our estimated wage gap is closely related to (and thus can proxy for) talent misallocation. If this relation holds, we would expect that our estimated misallocation proxy would have adverse effects on observed economic outcomes in each state. To assess this hypothesis, we investigate here the relation between our micro-based estimated talent misallocation measure in each state and state-level economic outcomes. More specifically, we compute Pearson correlations of our estimated misallocation measures with aggregate outcome measures such as real GDP per worker, TFP and Technical Efficiency. In all cases, we find a significant negative relation between our misallocation measure and these macroeconomic outcomes as shown in Table 7. These results are in line with Hsieh et al. (2019) who show the important role that labor misallocation plays for U.S. economic outcomes.

As shown in Figure 2 and Table 7, for 1980 to 2017 the correlation between real GDP per worker and our estimated misallocation measure is equal to -0.605, significant at the 1% level. A negative correlation is also found for our talent misallocation measure and TFP. As illustrated in Figure 3 and Table 7, for 1980 to 2000 the correlation coefficient is equal to -0.293, significant at the 1% level. Extending this period by using data from Cardarelli and Lusinyan (2015) covering 2000 to 2010, we find again a negative correlation coefficient of -0.390, significant at the 1% level, as shown in Figure 4. Thus, using data from two different databases for different periods, we find a robustly significant negative relationship between state-level productivity and our

[25] Given the large number of states and years, Figures B.3 to B.11 where we group the states according to regions, serve to provide a clearer picture of our estimated misallocation measure and its decomposition for each state over the period under study.

state-level talent misallocation estimate based on microeconomic data. Finally, Figure 5 and Table 7 show a negative relation between the Technical Efficiency component of TFP and our misallocation measure for 1980 to 2000. The correlation coefficient is equal to -0.173, significant at the 10% level.

Labor Force Weighted Measure

So far, we have constructed the talent misallocation measure by simply adding the coefficients of gender and race. We now construct the aggregate misallocation measure for each state, taking into account the fact that the share of non-whites and females in the labor force differs across states. Using external data from the U.S. Census Bureau for the number of females and non-whites that are part of the labor force in each state for the period under study, we weight each factor by multiplying with the corresponding number of female or non-white workers and then dividing by the labor force as follows:

$$Misallocation = \beta_f \frac{n_f}{N} + \beta_{nw} \frac{n_{nw}}{N}.$$

where n_f is the number of active females in each state and period, n_{nw} is the number of active individuals of non-white race, and $N = n_f + n_{nw}$.

Having constructed the talent misallocation measure weighted with the labor force for each state and period, we compute again Pearson correlations with state-level economic outcomes. The second row of Table 7 presents the results of the correlation between our talent misallocation measure and aggregate measures such as GDP, TFP, and Technical Efficiency. Once again, we find a negative relationship between our micro-based estimated misallocation measure and these aggregate outcomes. The correlation coefficient between the misallocation measure thus constructed and GDP per worker equals -0.741, significant at the 1% level. The respective correlations with TFP and Technical Efficiency over the period 1980-2000 are -0.349 and -0.389, also strongly significant beyond the 1% level. All three of these correlations are higher than the ones using the equally weighted measure as can be seen by comparing the first and second rows of Table 7. Finally, the correlation of talent misallocation with TFP over the period 2000-2010 is

-0.317 and is again strongly significant beyond the 1% level.

The findings in this subsection seen together are in line with the hypothesis that input misallocation can have negative effects for aggregate economic outcomes. Noting that our goal is not to identify a causal link, we argue that the negative relation found here between aggregate economic outcomes and our misallocation measure estimated using microeconomic data, is suggestive of a potentially important role played by talent misallocation in determining aggregate outcomes across states and over time.

5.2 Quantitative Analysis

Having provided some empirical evidence pointing to a negative relationship between our micro-based talent misallocation measure and state-level economic outcomes, we now proceed to provide some quantitative evidence regarding the impact of talent misallocation on total surplus based on our theoretical model.

We calibrate this model to match the US economy over the most recent period used in our estimations: 2010-2017.

The flow of total surplus in the economy is given by

$$\text{Total Surplus 1} \equiv (e_{LP} + e_{LU})y_L + (e_{HP} + e_{HU})y_H - c(v_L + v_H),$$

where e_{LP} and e_{LU} are employment in the low-productivity sector for privileged and underprivileged workers respectively, e_{HP} and e_{HU} are employment in the high-productivity sector for privileged and underprivileged workers respectively, y_L and y_H stand for productivity of a worker in the low- and high-productivity sectors respectively, c is a flow hiring cost, and v_L and v_H are respectively the stock of low- and high-productivity vacancies searching for workers. An alternative measure we compute takes into account the value of leisure. In this case the flow of total surplus in the economy is

$$\text{Total Surplus 2} \equiv (e_{LP} + e_{LU})y_L + (e_{HP} + e_{HU})y_H + b(u_P + u_U) - c(v_L + v_H),$$

where the term b is a flow of income received during unemployment that captures the opportunity cost of employment, and u_P and u_U are the stock of the privileged and the underprivileged unemployed, respectively. One period in the model represents one month; thus, all relevant parameters are interpreted monthly.

To illustrate the relevance of talent misallocation on aggregate economic outcomes quantitatively within the setting of our theoretical model, we apply our model in relation to race focusing in particular on African Americans as compared to whites. That is, based on the jargon of our theoretical model, we identify as potentially "privileged" and "underprivileged" the white and African-American workers, respectively.

We use Cobb-Douglas functional forms for both matching functions. (see Blanchard and Diamond, 1990). Next, we need to determine parameters such as the interest rate r, productivity parameter (y_L, y_H), the unemployment elasticity of the matching function, the separation rate δ, workers' bargaining power β, the share of blacks in the labor force μ, the value of leisure b, the vacancy cost c, and the connectivity parameter η.

According to the literature,[26] we set the unemployment elasticity of the matching function and the workers' bargaining power parameter β equal to 0.5, while for the value of leisure we follow Shimer (2005) and set it to $b = 0.4$. The productivity parameter in the low-productivity sector is normalized to one. Using the Federal Reserve Economic Data (FRED), we compute the real interest rate as the difference between the 10-year government bond and the growth rate of the Consumer Price Index. We compute a value 0.763% for the monthly real interest rate. As for the separation rate δ, we follow the method explained by Shimer (2005) and find it to be equal to 0.0199. Using data from the Current Population Survey (CPS) of the Bureau of Labor Statistics, we calculate the average share of African-Americans in the labor force to be 12.04% over the period from 2010 to 2017. In addition, we calibrate the remaining parameters to match targets such as the unemployment rate among African-Americans which equals 11.93%, the unemployment rate among whites which equals 6.04%, and wage differen-

[26]For example, Mortensen et al. (2003), Petrongolo and Pissarides (2001)

tials between African-Americans relative to whites which is equal to 22.3% from our estimation shown in Table B7.

We calibrate the equilibrium as a partially segregated one since the integrated equilibrium is not satisfied. The resulting values of the calibrated parameters are $y_H = 1.446$, $c = 8.374$, $\eta = 0.177$, and the matching rates in the high- and low-productivity sector are $m_H = 0.31$ and $m_L = 0.092$, respectively. This is our benchmark case. Table 8 presents the effect of a fall in white privilege, i.e., an increase in parameter η in the US. The numbers indicate percentage changes relative to the benchmark.

An increase in parameter η corresponding to a 50% decrease in the wage gap related to race, reduces first the matching rates in both sectors. The reduction in the matching rate in the low-productivity sector is larger as compared to the high-productivity one. As a result, the profitability in the low-productivity sector decreases and this induces job exit. Regarding employment, more underprivileged workers are employed in the high-productivity sector (e_{HU}), which results in higher output (Y_H) and higher surplus ($= Y_H - cV_H$). Moreover, the unemployment rate among privileged workers increases, and the same goes for the underprivileged. However, the unemployment rate for the underprivileged is larger as a result of the job exit in the low-productivity sector. As parameter η increases further, the matching rate in the high-productivity sector increases. This increases expected profitability in the high-productivity sector and spurs job entry, i.e., V_H and θ_H increase. Both types of workers are now in a better bargaining position (their reservation values, rU_P and rU_U, increase), which leads to higher wages (w_{HP} and w_{HU}). In addition, employment in the high-productivity sector (e_{HP} and e_{HU}), output ($Y_H = (e_{HP} + e_{HU})y_H$) and surplus ($= Y_H - cV_H$) increase in that sector. The low-productivity sector shuts down. Interestingly, as one sector gradually expands and the other vanishes, the unemployment rate among underprivileged workers first increases and then declines. Finally, both measures of net income, i.e., Total Surplus 1 and Total Surplus 2, go up.

Calibrating our model using values that mimic the US economy over the period 2010-

2017, our simulation exercise suggests that a 50 percent decrease in the wage gap between African-Americans and whites, for instance, increases both measures of net income relative to the benchmark case. Specifically, the percentage change is 0.4 per month for Total Surplus 1, and 0.7 for Total Surplus 2 as shown in Table 8. In addition, if we eliminate the white privilege completely, the increase in net income is much larger, with the percentage change equal to 3.9 and 3.5 for Total Surplus 1 and Total Surplus 2 respectively.

6 Conclusion

We have used individual data across the United States over an extended period from 1960 to 2017, to provide quantitative evidence about the misallocation effects arising due to barriers related to race and gender. Our empirical findings indicate that being a female or of a race other than white is associated with lower wages for individuals with otherwise identical observed economic characteristics, and that such wage gaps are associated with adverse aggregate outcomes.

Our state-level talent misallocation measure based on microeconomic data has a strong negative relation with state-level productivity and GDP per worker over time. Calibrating our theory model for the US economy for the period 2010 to 2017, we find that a reduction of 50 percent in the wage gap between African-Americans and whites is associated with an increase of net income of about 0.4 percent per month or 0.7 percent per month taking into account the value of leisure, and that if the wages of African-Americans and whites converged completely this would increase net income by nearly 4 percent per month.

Overall, having linked wage gaps to talent misallocation within a search model of the labor market, we have shown that talent misallocation matters for aggregate economic outcomes. Our work thus has clear implications about the aggregate economic importance of policies that address any remaining existing labor market barriers applying to specific population groups for the United States but possibly even more so for other economies across the world. As such gaps remain in a large number of countries across the globe, our work suggests that the efficiency and economic growth gains that can be realized in such economies via this channel are substantial.

Table 1: Summary statistics from the final sample

Wave	1960	1970	1980	1990	2000	2010	2017
Sample composition:							
Female(%of total)	40.88	44.12	45.26	48.01	48.55	49.36	49.08
Non-white(%of total)	12.78	14.23	17.77	19.65	26.10	28.86	31.66
Private(%of total)	87.02	83.55	81.38	83.67	84.35	83.27	84.47
Low-education(%of total)	31.60	20.00	10.29	5.27	4.31	3.34	2.95
Middle-education(%of total)	48.67	54.91	51.21	42.97	46.01	38.78	35.66
High-education(%of total)	19.73	25.09	38.50	51.76	49.68	57.87	61.38
Age 25-34(%of total)	29.44	29.50	37.14	34.35	27.23	23.18	24.65
Age 35-44(%of total)	29.14	25.59	24.63	30.71	31.61	24.69	23.43
Age 45-54(%of total)	24.58	25.61	20.81	20.30	26.27	28.97	25.85
Age 55-64(%of total)	16.85	19.30	17.42	14.64	14.90	23.16	26.06
Part-time(%)	33.48	35.00	21.45	20.76	20.06	25.20	22.41
Married(%)	79.60	78.34	72.74	68.37	63.87	61.73	59.14
Children under age 5(%)	26.03	20.31	16.87	17.41	15.41	13.56	12.88
Earnings:							
Median Female	8.77	11.24	10.91	11.20	12.02	12.73	12.98
Median Male	14.05	18.10	18.15	16.29	15.81	15.73	15.64
Female-Male Ratio	62.44	62.10	60.11	68.75	76.03	80.93	82.99
Median Nonwhite	8.43	11.87	12.14	11.63	12.02	11.98	11.98
Median White	12.80	16.13	14.94	14.22	14.58	14.98	15.24
Nonwhite-White Ratio	65.86	73.59	81.26	81.79	82.44	80	78.61
Median Private	12.08	15.40	14.26	13.23	13.46	13.48	13.58
Median Public	13.48	17.11	15.45	15.53	16.06	16.69	16.28
Private-Public Ratio	89.61	90	92.30	85.19	83.81	80.77	83.42
Number of states	51	51	51	51	51	51	51
Total observations	8,965,606	4,060,019	11,343,120	12,501,046	14,081,466	3,061,692	3,190,040
Observations in regressions	3,105,144	1,461,597	4,397,316	5,492,116	6,353,277	1,391,357	1,390,390

Data are from the US decennial census and the annual ACS. The samples include employees, the unemployed, self-employed and individuals working in full-time and part-time occupations aged between 25 to 64. Earnings are converted to constant 1999 dollars using the CPI, which render them comparable across time.

Table 2: Probit selection equation results for the waves from 1960 to 2017

Variables	(1960)	(1970)	(1980)	(1990)	(2000)	(2010)	(2017)
Female	-0.750***	-0.556***	0.105***	0.176***	0.223***	0.083***	0.173***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Non-white	0.215***	0.080***	-0.050***	-0.120***	-0.142***	-0.019***	0.004
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.006)
Private	-0.063***	0.024***	0.024***	0.024***	0.006*	0.165***	0.235***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
Educ L	0.015***	-0.091***	-0.133***	-0.079***	-0.110***	0.041***	0.033**
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.011)	(0.013)
Educ H	0.013***	0.030***	0.162***	0.180***	0.169***	0.151***	0.185***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
Age 35-44	0.190***	0.185***	0.063***	0.014***	0.001	0.002	-0.012*
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.007)	(0.007)
Age 45-54	0.192***	0.159***	-0.077***	-0.107***	-0.078***	-0.056***	-0.061***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.008)
Age 55-64	-0.053***	-0.110***	-0.426***	-0.482***	-0.429***	-0.506***	-0.512***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Occupscor	0.001***	0.002***	0.003***	0.003***	0.002***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.124***	-0.045***	0.012***	0.046***	0.029***	0.025***	-0.017***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Part-time	-2.111***	-2.323***	-2.843***	-3.016***	-3.686***	-3.791***	-4.075***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.015)	(0.065)	(0.083)
nchild5	-0.176***	-0.217***	-0.327***	-0.272***	-0.234***	-0.237***	-0.259***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
other_inc			-0.013***	-0.015***	0.005***	-0.010***	-0.014***
			(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	2.512***	2.631***	3.147***	3.360***	3.968***	4.419***	4.543***
	(0.011)	(0.015)	(0.013)	(0.013)	(0.019)	(0.069)	(0.087)
Observations	3,105,144	1,461,597	4,397,346	5,492,170	6,353,335	1,391,379	1,390,418
Number of states	51	51	51	51	51	51	51
State-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: Selection-corrected hourly wage regression for the period 1960, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.469***	-0.447***	-0.470***	-0.306***	-0.097***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Non-white	-0.291***	-0.284***	-0.267***	-0.132***	-0.120***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Private	-0.034***	-0.038***	-0.035***	0.052***	0.054***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.186***	-0.190***	-0.178***	-0.168***	-0.163***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.146***	0.150***	0.114***	0.128***	0.136***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.100***	0.090***	0.091***	0.091***	0.087***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.094***	0.087***	0.087***	0.087***	0.080***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.058***	0.061***	0.060***	0.059***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.151***	0.151***	0.150***	0.274***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		0.123***	0.123***	0.124***	0.109***
		(0.002)	(0.002)	(0.002)	(0.002)
Female *Educ L			0.039***	0.047***	0.030***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.063***	0.020***	0.006**
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			-0.048***	-0.035***	-0.036***
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.057***	0.013***	0.019***
			(0.004)	(0.005)	(0.004)
Private *Educ L			-0.017***	-0.031***	-0.030***
			(0.003)	(0.003)	(0.003)
Private *Educ H			0.016***	0.013***	0.007**
			(0.003)	(0.003)	(0.003)
Private *Female				-0.188***	-0.198***
				(0.003)	(0.003)
Private *Non-white				-0.164***	-0.165***
				(0.004)	(0.004)
Female *Non-white				0.012***	-0.024***
				(0.003)	(0.003)

Female *Married					-0.284***
					(0.002)
Female *Part-time					0.088***
					(0.002)
athrho	0.032***	0.016***	0.016***	0.019***	0.004
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.408***	-0.414***	-0.415***	-0.416***	-0.420***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.855***	0.723***	0.725***	0.651***	0.548***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.469***	-0.447***	-0.446***	-0.449***	-0.459***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.291***	-0.284***	-0.271***	-0.277***	-0.283***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Total effect Private	-0.034***	-0.038***	-0.037***	-0.068***	-0.072***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.235	0.245	0.245	0.247	0.253
Observations	3,105,144	3,105,144	3,105,144	3,105,144	3,105,144

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Selection-corrected hourly wage regression for the period 2017, ACS

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.334***	-0.257***	-0.277***	-0.297***	-0.225***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Non-white	-0.125***	-0.112***	-0.123***	-0.094***	-0.086***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Private	0.041***	0.058***	-0.032***	0.005	0.013**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.067***	-0.082***	-0.132***	-0.148***	-0.144***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.201***	0.194***	0.067***	0.073***	0.061***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.248***	0.191***	0.191***	0.191***	0.186***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.321***	0.254***	0.254***	0.253***	0.249***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.319***	0.278***	0.277***	0.276***	0.270***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.013***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.212***	0.212***	0.214***	0.290***
		(0.002)	(0.002)	(0.002)	(0.002)
Part-time		-0.431***	-0.432***	-0.430***	-0.585***
		(0.002)	(0.002)	(0.002)	(0.004)
Female *Educ L			0.061***	0.019*	0.026***
			(0.009)	(0.010)	(0.010)
Female *Educ H			0.029***	0.036***	0.058***
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			0.019*	0.032***	0.026**
			(0.011)	(0.011)	(0.011)
Non-white *Educ H			0.018***	0.002	0.003
			(0.003)	(0.003)	(0.003)
Private *Educ L			0.022	0.051**	0.045**
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.123***	0.118***	0.116***
			(0.005)	(0.005)	(0.005)
Private *Female				-0.016***	-0.036***
				(0.004)	(0.004)
Private *Non-white				-0.079***	-0.077***
				(0.005)	(0.005)
Female *Non-white				0.096***	0.073***
				(0.003)	(0.003)

Female *Married					-0.172***
					(0.003)
Female *Part-time					0.254***
					(0.004)
athrho	0.090***	0.007**	0.007**	0.007**	0.016***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
lnsigma	-0.145***	-0.169***	-0.169***	-0.170***	-0.173***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.094***	2.135***	2.227***	2.206***	2.174***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Total effect Female	-0.334***	-0.257***	-0.257***	-0.258***	-0.240***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.125***	-0.112***	-0.112***	-0.112***	-0.113***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	0.041***	0.058***	0.044***	0.046***	0.043***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.203	0.237	0.238	0.238	0.243
Observations	1,390,418	1,390,418	1,390,418	1,390,418	1,390,418

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: Misallocation Measure and its decomposition across the United States for the period 1960

State	Female	Nonwhite	Misallocation Measure
South Carolina	0.362***	0.651***	1.014***
Alabama	0.503***	0.501***	1.004***
Louisiana	0.517***	0.474***	0.991***
Mississippi	0.326***	0.640***	0.966***
Georgia	0.411***	0.540***	0.951***
Texas	0.511***	0.374***	0.886***
Arkansas	0.394***	0.475***	0.869***
Delaware	0.522***	0.335***	0.857***
Virginia	0.434***	0.418***	0.853***
Alaska	0.509***	0.343***	0.852***
West Virginia	0.629***	0.219***	0.849***
Arizona	0.534***	0.282***	0.816***
Oklahoma	0.491***	0.320***	0.811***
Tennessee	0.406***	0.396***	0.802***
Florida	0.485***	0.315***	0.800***
Maryland	0.492***	0.304***	0.796***
North Carolina	0.288***	0.505***	0.793***
New Mexico	0.517***	0.270***	0.787***
Kentucky	0.427***	0.329***	0.756***
Montana	0.513***	0.234***	0.748***
District of Columbia	0.364***	0.375***	0.739***
North Dakota	0.425***	0.289***	0.714***
Utah	0.587***	0.123***	0.711***
Ohio	0.530***	0.164***	0.693***
New Jersey	0.456***	0.230***	0.685***
Pennsylvania	0.496***	0.170***	0.666***
Rhode Island	0.421***	0.244***	0.665***
Michigan	0.500***	0.165***	0.664***
Washington	0.497***	0.167***	0.664***
Illinois	0.468***	0.177***	0.645***
Oregon	0.533***	0.102***	0.636***
Missouri	0.435***	0.199***	0.634***
California	0.468***	0.165***	0.633***
Nevada	0.493***	0.134***	0.628***
Connecticut	0.448***	0.164***	0.612***
Wyoming	0.517***	0.095	0.612***
New York	0.394***	0.217***	0.611***
Colorado	0.479***	0.131***	0.611***
Idaho	0.463***	0.145***	0.608***
Hawaii	0.493***	0.102***	0.595***

Massachusetts	0.437***	0.157***	0.594***
Kansas	0.497***	0.060***	0.557***
Indiana	0.515***	0.041***	0.556***
Main	0.441***	0.083	0.523***
South Dakota	0.379***	0.141***	0.520***
New Hampshire	0.423***	0.065	0.488***
Wisconsin	0.453***	0.003	0.456***
Minnesota	0.402***	0.049*	0.451***
Iowa	0.439***	-0.031	0.408***
Nebraska	0.388***	-0.063**	0.325***
Vermont	0.352***	-0.094	0.258***
Average	0.460	0.233	0.693

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Misallocation Measure and its decomposition across the United States for the period 2017

State	Female	Nonwhite	Misallocation Measure
Louisiana	0.341***	0.191***	0.532***
District of Columbia	0.143***	0.333***	0.476***
Alaska	0.136***	0.336***	0.472***
South Dakota	0.325***	0.139***	0.464***
Mississippi	0.328***	0.130***	0.457***
West Virginia	0.256***	0.194***	0.450***
Wyoming	0.302***	0.139***	0.441***
Texas	0.288***	0.133***	0.421***
Alabama	0.313***	0.097***	0.410***
New Jersey	0.245***	0.151***	0.397***
South Carolina	0.259***	0.134***	0.393***
Montana	0.208***	0.184***	0.392***
New Mexico	0.241***	0.136***	0.377***
Georgia	0.242***	0.126***	0.368***
Ohio	0.235***	0.131***	0.365***
Oklahoma	0.308***	0.052***	0.359***
Connecticut	0.195***	0.163***	0.358***
North Carolina	0.246***	0.110***	0.356***
California	0.208***	0.144***	0.352***
Illinois	0.258***	0.093***	0.351***
Indiana	0.284***	0.065***	0.349***
Florida	0.225***	0.124***	0.349***
Pennsylvania	0.254***	0.095***	0.348***
Arizona	0.217***	0.129***	0.346***
Utah	0.274***	0.067***	0.340***
Virginia	0.242***	0.092***	0.334***
Hawaii	0.296***	0.036	0.332***
North Dakota	0.259***	0.070	0.328***
Wisconsin	0.263***	0.064***	0.327***
Michigan	0.244***	0.080***	0.324***
Minnesota	0.215***	0.108***	0.323***
Iowa	0.273v	0.049*	0.323***
Missouri	0.253***	0.069***	0.323***
Arkansas	0.263***	0.059***	0.322***
Maryland	0.202***	0.113***	0.315***
Vermont	0.158***	0.150**	0.309***
Kansas	0.273***	0.033	0.306***
Washington	0.250***	0.055***	0.304***
Massachusetts	0.192***	0.111***	0.303***
Colorado	0.229***	0.072***	0.301***

Idaho	0.273***	0.021	0.294***
Rhode Island	0.170***	0.122***	0.292***
Nebraska	0.266***	0.025	0.292***
Delaware	0.187***	0.096***	0.283***
New York	0.194***	0.089***	0.283***
Tennessee	0.235***	0.045***	0.280***
Nevada	0.198***	0.082***	0.280***
Kentucky	0.249***	0.020	0.269***
Main	0.219***	0.041	0.260***
Oregon	0.193***	0.057***	0.250***
New Hampshire	0.224***	-0.018	0.206***
Average	0.242	0.105	0.347

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Correlations between the micro-data based talent misallocation estimate with macroeconomic outcomes at the state level

	$GDP_{perworker}$	TFP	TFP	Technical Efficiency
Talent Misallocation Measure	-0.605***	-0.293***	-0.390***	-0.173*
Talent Misallocation $Measure_{weighted}$	-0.741***	-0.349****	-0.317***	-0.389***
Period	1980-2017	1980-2000	2000-2010	1980-2000
Observations	255	141	102	144

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: The effects of an increase in parameter η signifying a fall in the wage gap in the United States

Decrease in wage gap related to race	50%	100%
High-Productivity Sector	1	2
$m(\theta_H)$	-0.4	5.6
w_{HP}	-0.0	0.3
w_{HU}	1.7	14.1
e_{HP}	-0.0	0.4
e_{HU}	130	182.5
Y_H	63	8.9
Surplus	5.9	9.5
V_H	15.5	2.2
Low-Productivity Sector		
$m(\theta_L)$	-97.0	—
w_{LP}	—	—
w_{LU}	2.0	—
e_{LP}	—	—
e_{LU}	-98.6	—
Y_L	-98.6	—
Surplus	-98.5	—
V_L	-100.0	—
Aggregate Variables		
$\frac{u_P}{1-\mu}$	0.4	-5.6
$\frac{u_U}{\mu}$	73.4	-52.2
Total Surplus 1	0.4	3.9
Total Surplus 2	0.7	3.5

Notes: The numbers indicate percentage changes from the benchmark case: Wage gap = 22.3%.

1. Partially segregated equilibrium
2. Restricted equilibrium

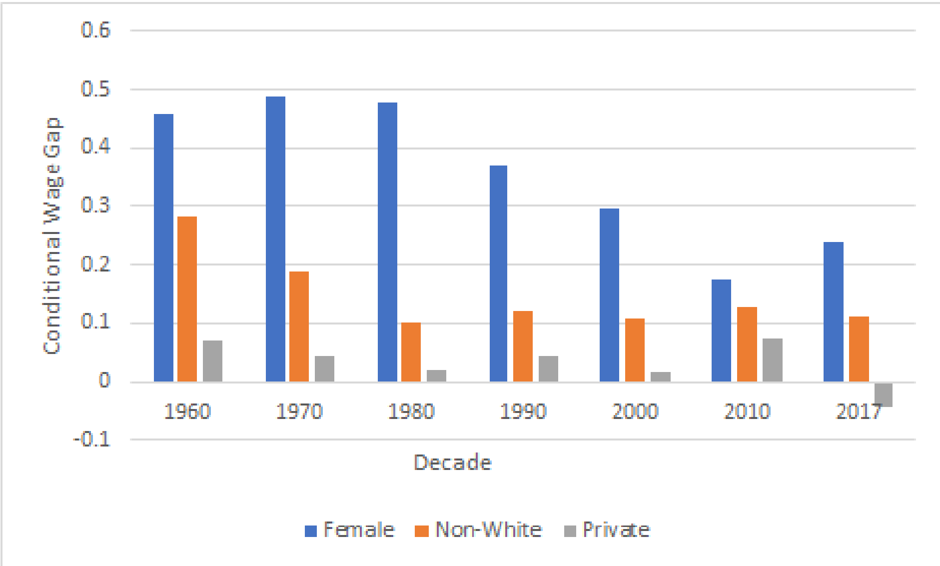

Figure 1: Conditional wage differentials in the US over time

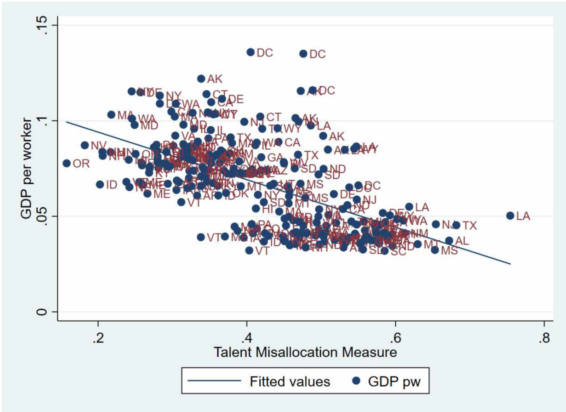

Figure 2: Correlation of real GDP per worker with the talent misallocation measure for 1980-2017.

Figure 3: Correlation of TFP with the talent misallocation measure for 1980-2000.

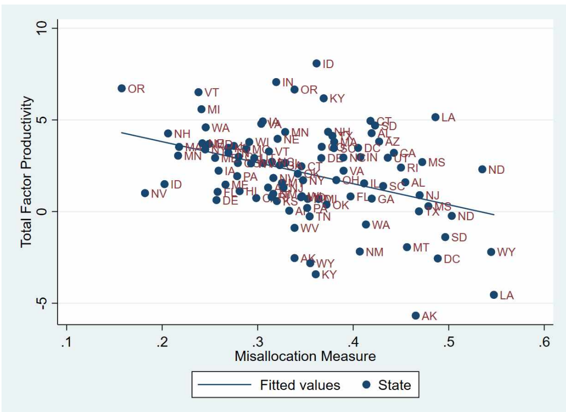

Figure 4: Correlation of TFP with the talent misallocation measure for 2000-2010.

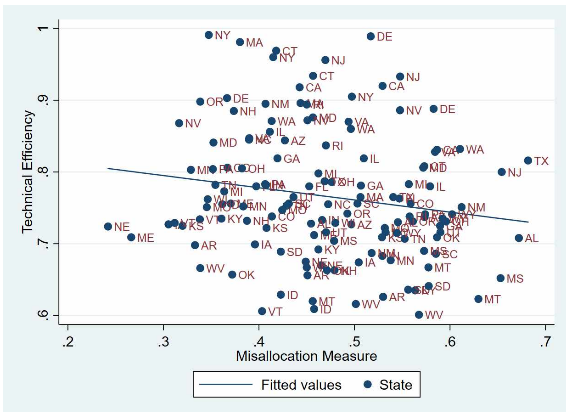

Figure 5: Correlation of Technical Efficiency with the talent misallocation measure for 1980-2000 (Data cleared from outliers, thus North Dakota excluded here).

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A Appendix

A.1 Proofs of Propositions

Proof of Proposition 1. First, we show that equations (21) and (22) yield a unique pair of (θ_H, θ_L). Having shown the existence of such a pair, we can obtain unique values for the variables u_P, u_U, and ϕ by substituting in equations (23), (24) and (25), respectively.

Let (21) and (22) define two functions $\theta_L = f_H(\theta_H)$ and $\theta_L = f_L(\theta_H)$, respectively. It follows that $f_H(0) = \infty > f_L(0)$. Also, simple differentiation of (25), (16) and (17) yields

$$\frac{d\phi}{d\theta_L} < 0, \frac{d\phi}{d\theta_H} > 0, \frac{d(rU_P)}{d\theta_H} > 0, \frac{d(rU_U)}{d\theta_H} > 0.$$

Moreover, if $y_L \geq \frac{(r+\delta)b+\beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)}$, then

$$\frac{d(rU_P)}{d\theta_L} > 0, \frac{d(rU_U)}{d\theta_L} > 0$$

As shown in Proposition 2, $rU_P > rU_U$. Simple differentiation then of each of (21) and (22) shows that, for a sufficiently high value of η, $f'_H < f'_L < 0$. It follows that the graphs of the two functions intersect at most once. For a sufficiently high value of c, they intersect in the positive orthant. ■

Proof of Proposition 2. Comparing (16) and (17), we see that $rU_P > rU_U$. Using this and equation (15), yields the remaining of the results. ■

Proof of Proposition 3. Denote equations (21) and (22) as $F(\theta_H, \theta_L, \eta) = 0$ and $G(\theta_H, \theta_L, \eta) = 0$, respectively. At least for sufficiently high η the following hold: $F_{\theta_H} > 0, F_{\theta_L} > 0, F_\eta < 0, G_{\theta_H} > 0, G_{\theta_L} > 0, and F_\eta > 0$. Applying Cramer's rule, it follows that $(d\theta_H/d\eta) > 0$ and $(d\theta_L/d\eta) < 0$. Next, differentiate (18) and (19) to show that $(du_P/d\eta)/u_P > (du_U/d\eta)/u_U$ and hence ϕ decreases. Finally the limiting values of ϕ,

w_{ij} and $u_j, i = L, H$ and $j = P, U$ as η approaches 1, follow easily by substitution in (16), (17), (15), (18), (19) and (20). ■

A.2 Partially Segregated Equilibrium

In a partially segregated equilibrium $S_{LP} < 0$ and hence priviledged workers do not occupy high-productivity jobs. Following the same steps as before, equation (16) becomes

$$rU_P = \frac{(r+\delta)b + \beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)}. \tag{A.1}$$

The equation that sets the flow of newly hired privileged workers with the flow of of layoffs (equation 18) becomes:

$$m(\theta_H)]u_P = \delta(1-\mu-u_P). \tag{A.2}$$

Solving for u_P yields

$$u_P = \frac{\delta(1-\mu)}{\delta + m(\theta_H)}, \tag{A.3}$$

which replaces equation (23) in the main text. Furthermore, since privileged workers do not work at low-productivity jobs, $\phi_{LU} = 1$ and, using equation (A.3) to substitute away u_P in equation (20), we have

$$\phi_{HU} = \frac{\mu[\delta + m(\theta_H)]}{\delta + (1-\mu)m(\theta_L) + (\mu+\eta-\mu\eta)m(\theta_H)}. \tag{A.4}$$

Finally, the free-entry condition in the low-productivity sector (equation 22) becomes

$$\frac{(r+\delta)c}{q(\theta_L)(1-\beta)} = y_L - rU_U. \tag{A.5}$$

(Recall that low-productivity jobs match only with underprivileged workers and hence $\phi_{LU} = 1$).

A.3 Restricted Equilibrium

In a restricted equilibrium $S_{LP} < 0$ and $S_{LU} < 0$. Hence, no worker, no matter whether privileged or underprivileged, is employed at a low-productivity job. The reservation value of privileged workers is still given by (A.1), whereas that of underprivileged workers simplifies to

$$rU_U = \frac{(r+\delta)b + \beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)}. \tag{A.6}$$

The measure of privileged unemployed workers is still given by (A.3), whereas that of the underprivileged ones is

$$u_U = \frac{\delta\mu}{\delta + \eta m(\theta_H)}. \tag{A.7}$$

Moreover, equation (A.4) becomes

$$\phi_{HU} = \frac{\mu[\delta + m(\theta_H)]}{\delta + (\mu + \eta - \mu\eta)m(\theta_H)}. \tag{A.8}$$

Finally, there is only one free-entry equilibrium condition, that for the high-productivity sector, which is still given by equation (21).

B Appendix

Table B1: Selection-corrected hourly wage regression for the period 1970, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.492***	-0.477***	-0.502***	-0.379***	-0.172***
	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)
Non-white	-0.205***	-0.195***	-0.187***	-0.152***	-0.143***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Private	-0.039***	-0.039***	-0.041***	0.039***	0.039***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Educ L	-0.172***	-0.170***	-0.193***	-0.180***	-0.175***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Educ H	0.150***	0.153***	0.116***	0.136***	0.141***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Age 35-44	0.105***	0.096***	0.097***	0.097***	0.095***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.113***	0.107***	0.108***	0.109***	0.104***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.076***	0.078***	0.078***	0.079***	0.067***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.119***	0.120***	0.119***	0.249***
		(0.002)	(0.002)	(0.002)	(0.002)
Part-time		0.084***	0.084***	0.085***	0.087***
		(0.002)	(0.002)	(0.002)	(0.003)
Female *Educ L			0.034***	0.032***	0.017***
			(0.004)	(0.004)	(0.004)
Female *Educ H			0.075***	0.046***	0.036***
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			-0.054***	-0.038***	-0.039***
			(0.004)	(0.004)	(0.004)
Non-white *Educ H			0.048***	0.033***	0.037***
			(0.005)	(0.005)	(0.005)
Private *Educ L			0.026***	0.010*	0.010*
			(0.005)	(0.005)	(0.005)
Private *Educ H			0.008**	-0.004	-0.008**
			(0.004)	(0.004)	(0.004)
Private *Female				-0.155***	-0.161***
				(0.004)	(0.004)
Private *Non-white				-0.084***	-0.083***
				(0.005)	(0.005)

Female *Non-white				0.073***	0.046***
				(0.004)	(0.004)
Female *Married					-0.269***
					(0.003)
Female *Part-time					0.031***
					(0.003)
athrho	0.032***	0.006**	0.006**	0.007**	0.002
	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
lnsigma	-0.414***	-0.418***	-0.418***	-0.419***	-0.423***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	1.274***	1.166***	1.174***	1.111***	1.003***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Total effect Female	-0.492***	-0.477***	-0.476***	-0.480***	-0.488***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.205***	-0.195***	-0.186***	-0.189***	-0.190***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.039***	-0.039***	-0.034***	0.041***	0.044***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.238	0.244	0.244	0.246	0.251
Observations	1,461,597	1,461,597	1,461,597	1,461,597	1,461,597

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B2: Selection-corrected hourly wage regression for the period 1980, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.465***	-0.450***	-0.481***	-0.415***	-0.144***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Non-white	-0.108***	-0.093***	-0.100***	-0.160***	-0.149***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Private	-0.027***	-0.027***	-0.030***	0.040***	0.039***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.199***	-0.194***	-0.239***	-0.221***	-0.225***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Educ H	0.132***	0.135***	0.101***	0.112***	0.117***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age 35-44	0.171***	0.156***	0.156***	0.155***	0.149***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.215***	0.199***	0.199***	0.199***	0.188***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.212***	0.205***	0.204***	0.203***	0.180***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.007***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.124***	0.124***	0.125***	0.296***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		0.023***	0.024***	0.031***	0.199***
		(0.001)	(0.001)	(0.001)	(0.002)
Female *Educ L			0.093***	0.058***	0.060***
			(0.003)	(0.003)	(0.003)
Female *Educ H			0.058***	0.047***	0.033***
			(0.002)	(0.002)	(0.002)
Non-white *Educ L			-0.033***	-0.006**	-0.004
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.032***	0.033***	0.034***
			(0.002)	(0.002)	(0.002)
Private *Educ L			0.026***	0.012***	0.011**
			(0.004)	(0.004)	(0.004)
Private *Educ H			0.005**	-0.006***	-0.005**
			(0.002)	(0.002)	(0.002)
Private *Female				-0.115***	-0.118***
				(0.002)	(0.002)
Private *Non-white				-0.038***	-0.036***
				(0.003)	(0.003)
Female *Non-white				0.183***	0.143***
				(0.002)	(0.002)

Female *Married					-0.334***
					(0.002)
Female *Part-time					-0.191***
					(0.003)
athrho	0.067***	0.023***	0.024***	0.023***	0.013***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.261***	-0.264***	-0.264***	-0.266***	-0.271***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.613***	1.529***	1.545***	1.501***	1.370***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.465***	-0.450***	-0.449***	-0.451***	-0.480***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.108***	-0.093***	-0.091***	-0.096***	-0.101***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Private	-0.027***	-0.027***	-0.025***	0.020***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.171	0.176	0.176	0.179	0.187
Observations	4,397,346	4,397,346	4,397,346	4,397,346	4,397,346

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B3: Selection-corrected hourly wage regression for the period 1990, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.415***	-0.367***	-0.400***	-0.344***	-0.143***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Non-white	-0.133***	-0.118***	-0.132***	-0.163***	-0.151***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Private	-0.047***	-0.044***	-0.072***	-0.003	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.178***	-0.171***	-0.160***	-0.147***	-0.147***
	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
Educ H	0.172***	0.174***	0.102***	0.108***	0.107***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age 35-44	0.166***	0.147***	0.148***	0.147***	0.140***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.234***	0.210***	0.211***	0.210***	0.198***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.223***	0.220***	0.220***	0.218***	0.198***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.143***	0.143***	0.145***	0.284***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		-0.187***	-0.187***	-0.181***	-0.192***
		(0.001)	(0.001)	(0.001)	(0.002)
Female *Educ L			0.111***	0.059***	0.060***
			(0.003)	(0.004)	(0.004)
Female *Educ H			0.053***	0.050***	0.048***
			(0.001)	(0.001)	(0.001)
Non-white *Educ L			-0.039***	-0.015***	-0.014***
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.036***	0.025***	0.027***
			(0.002)	(0.002)	(0.002)
Private *Educ L			-0.031***	-0.033***	-0.034***
			(0.006)	(0.006)	(0.006)
Private *Educ H			0.046***	0.041***	0.040***
			(0.002)	(0.002)	(0.002)
Private *Female				-0.102***	-0.111***
				(0.002)	(0.002)
Private *Non-white				-0.056***	-0.052***
				(0.002)	(0.002)
Female *Non-white				0.165***	0.124***
				(0.002)	(0.002)

Female *Married					-0.285***
					(0.002)
Female *Part-time					0.046***
					(0.002)
athrho	0.079***	0.011***	0.011***	0.010***	0.009***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.237***	-0.244***	-0.244***	-0.245***	-0.249***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.969***	1.913***	1.953***	1.906***	1.812***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.415***	-0.367***	-0.367***	-0.368***	-0.369***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.133***	-0.118***	-0.115***	-0.119***	-0.122***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Private	-0.047***	-0.044***	-0.050***	-0.043***	0.045***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.198	0.208	0.208	0.210	0.216
Observations	5,492,170	5,492,170	5,492,170	5,492,170	5,492,170

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B4: Selection-corrected hourly wage regression for the period 2000, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.345***	-0.304***	-0.331***	-0.307***	-0.170***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Non-white	-0.120***	-0.107***	-0.124***	-0.121***	-0.113***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Private	-0.014***	-0.010***	-0.072***	-0.016***	-0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.190***	-0.187***	-0.184***	-0.190***	-0.190***
	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)
Educ H	0.176***	0.178***	0.059***	0.065***	0.061***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age 35-44	0.167***	0.147***	0.146***	0.145***	0.141***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.215***	0.189***	0.190***	0.189***	0.183***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.225***	0.215***	0.215***	0.214***	0.202***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.150***	0.150***	0.152***	0.255***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		-0.196***	-0.197***	-0.192***	-0.252***
		(0.001)	(0.001)	(0.001)	(0.002)
Female *Educ L			0.041***	-0.010***	-0.008**
			(0.004)	(0.004)	(0.004)
Female *Educ H			0.050***	0.052***	0.057***
			(0.001)	(0.001)	(0.001)
Non-white *Educ L			0.018***	0.036***	0.036***
			(0.004)	(0.004)	(0.004)
Non-white *Educ H			0.034***	0.023***	0.025***
			(0.002)	(0.002)	(0.002)
Private *Educ L			-0.023***	-0.004	-0.004
			(0.007)	(0.007)	(0.007)
Private *Educ H			0.100***	0.095***	0.093***
			(0.002)	(0.002)	(0.002)
Private *Female				-0.063***	-0.073***
				(0.002)	(0.002)
Private *Non-white				-0.067***	-0.063***
				(0.002)	(0.002)
Female *Non-white				0.118***	0.088***
				(0.002)	(0.002)

Female *Married					-0.218***
					(0.001)
Female *Part-time					0.103***
					(0.002)
athrho	0.051***	0.003**	0.004**	0.003*	0.009***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.207***	-0.214***	-0.214***	-0.215***	-0.217***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.223***	2.175***	2.245***	2.208***	2.144***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Total effect Female	-0.345***	-0.304***	-0.304***	-0.305***	-0.298***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.120***	-0.107***	-0.106***	-0.107***	-0.109***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Private	-0.014***	-0.010***	-0.023***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.180	0.191	0.192	0.193	0.197
Observations	6,353,335	6,353,335	6,353,335	6,353,335	6,353,335

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B5: Selection-corrected hourly wage regression for the period 2010, ACS

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.313***	-0.203***	-0.212***	-0.264***	-0.230***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)
Non-white	-0.143***	-0.129***	-0.134***	-0.089***	-0.080***
	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)
Private	-0.085***	-0.051***	-0.169***	-0.160***	-0.142***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.076***	-0.079***	-0.176***	-0.200***	-0.192***
	(0.005)	(0.005)	(0.024)	(0.024)	(0.024)
Educ H	0.215***	0.211***	0.059***	0.064***	0.054***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.234***	0.179***	0.179***	0.178***	0.173***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.287***	0.221***	0.219***	0.219***	0.215***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.258***	0.232***	0.232***	0.231***	0.228***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Occupscor	0.013***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.208***	0.207***	0.208***	0.267***
		(0.002)	(0.002)	(0.002)	(0.003)
Part-time		-0.658***	-0.658***	-0.657***	-0.900***
		(0.003)	(0.003)	(0.003)	(0.004)
Female *Educ L			0.041***	0.005	-0.003
			(0.010)	(0.010)	(0.010)
Female *Educ H			0.012***	0.020***	0.046***
			(0.004)	(0.004)	(0.004)
Non-white *Educ L			0.056***	0.068***	0.059***
			(0.012)	(0.012)	(0.012)
Non-white *Educ H			0.007*	-0.007*	-0.005
			(0.004)	(0.004)	(0.004)
Private *Educ L			0.050**	0.086***	0.085***
			(0.023)	(0.023)	(0.023)
Private *Educ H			0.166***	0.160***	0.153***
			(0.005)	(0.005)	(0.005)
Private *Female				0.036***	0.003
				(0.005)	(0.005)
Private *Non-white				-0.085***	-0.080***
				(0.005)	(0.005)
Female *Non-white				0.066***	0.042***
				(0.004)	(0.004)

Female *Married					-0.147***
					(0.004)
Female *Part-time					0.410***
					(0.004)
athrho	0.070***	0.007**	0.007**	0.007***	0.014***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
lnsigma	-0.002***	-0.041***	-0.041***	-0.042***	-0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.041***	2.123***	2.230***	2.231***	2.215***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Total effect Female	-0.313***	-0.203***	-0.203***	-0.204***	-0.176***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.143***	-0.129***	-0.128***	-0.129***	-0.127***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.085***	-0.051***	-0.071***	-0.072***	-0.073***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.172	0.232	0.232	0.233	0.239
Observations	1,391,379	1,391,379	1,391,379	1,391,379	1,391,379

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B6: Selection-corrected hourly wage regression for the period 1960. Race decomposition.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.467***	-0.446***	-0.469***	-0.307***	-0.098***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
African-Americans	-0.326***	-0.320***	-0.314***	-0.155***	-0.138***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
Hispanic	-0.178***	-0.174***	-0.116***	-0.052***	-0.051***
	(0.003)	(0.003)	(0.005)	(0.009)	(0.009)
American Indian/Alaska Native	-0.309***	-0.313***	-0.255***	-0.082***	-0.076**
	(0.011)	(0.011)	(0.018)	(0.030)	(0.030)
Asian	-0.227***	-0.207***	-0.164***	-0.093***	-0.081***
	(0.007)	(0.007)	(0.009)	(0.017)	(0.017)
Mixed races	-0.212***	-0.206***	-0.153***	-0.059	-0.053
	(0.017)	(0.017)	(0.024)	(0.036)	(0.036)
Private	-0.035***	-0.039***	-0.036***	0.052***	0.053***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.187***	-0.191***	-0.180***	-0.171***	-0.165***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.147***	0.150***	0.116***	0.132***	0.140***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.102***	0.092***	0.092***	0.092***	0.088***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.096***	0.089***	0.089***	0.089***	0.082***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.060***	0.063***	0.062***	0.062***	0.048***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.149***	0.149***	0.148***	0.273***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		0.125***	0.125***	0.126***	0.111***
		(0.002)	(0.002)	(0.002)	(0.002)
Female *Educ L			0.040***	0.046***	0.029***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.061***	0.019***	0.004*
			(0.003)	(0.003)	(0.003)
African-Americans *Educ L			-0.030***	-0.013***	-0.016***
			(0.003)	(0.003)	(0.003)
African-Americans *Educ H			0.091***	0.021***	0.030***
			(0.005)	(0.006)	(0.006)
Hispanic *Educ L			-0.103***	-0.092***	-0.090***
			(0.006)	(0.006)	(0.006)

Hispanic *Educ H			-0.034***	-0.039***	-0.037***
			(0.009)	(0.009)	(0.009)
American Indian/Alaska Native *Educ L			-0.129***	-0.092***	-0.088***
			(0.024)	(0.024)	(0.024)
American Indian/Alaska Native *Educ H			0.069*	0.031	0.039
			(0.041)	(0.041)	(0.041)
Asian *Educ L			-0.068***	-0.041***	-0.020
			(0.013)	(0.013)	(0.013)
Asian *Educ H			-0.072***	-0.078***	-0.076***
			(0.015)	(0.015)	(0.015)
Mixed races *Educ L			-0.045	-0.035	-0.029
			(0.036)	(0.036)	(0.036)
Mixed races *Educ H			-0.154***	-0.169***	-0.150***
			(0.041)	(0.042)	(0.041)
Private *Educ L			-0.017***	-0.030***	-0.028***
			(0.003)	(0.003)	(0.003)
Private *Educ H			0.016***	0.012***	0.006**
			(0.003)	(0.003)	(0.003)
Private *Female				-0.187***	-0.197***
				(0.003)	(0.003)
Private *African-Americans				-0.193***	-0.195***
				(0.004)	(0.004)
Private *Hispanic				-0.104***	-0.101***
				(0.009)	(0.009)
Private *American Indian/Alaska Native				-0.254***	-0.249***
				(0.029)	(0.029)
Private *Asian				-0.128***	-0.123***
				(0.016)	(0.016)
Private *Mixed races				-0.137***	-0.130***
				(0.035)	(0.034)
Female *African-Americans				0.009***	-0.035***
				(0.003)	(0.003)
Female *Hispanic				0.090***	0.077***
				(0.006)	(0.006)
Female *American Indian/Alaska Native				0.063**	0.041
				(0.026)	(0.026)
Female *Asian				0.117***	0.103***
				(0.013)	(0.013)
Female *Mixed races				0.040	0.025
				(0.034)	(0.034)
Female *Part-time					0.090***
					(0.002)
Female *Married					-0.286***
					(0.002)
athrho	0.032***	0.015***	0.015***	0.018***	0.002

	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.408***	-0.415***	-0.415***	-0.417***	-0.421***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.855***	0.724***	0.726***	0.653***	0.549***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.467***	-0.446***	-0.444***	-0.450***	-0.457***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect African-American	-0.326***	-0.320***	-0.306***	-0.319***	-0.322***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Hispanic	-0.178***	-0.174***	-0.156***	-0.142***	-0.143***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect American Indian/Alaska Native	-0.309***	-0.313***	-0.282***	-0.300***	-0.297**
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)
Total effect Asian	-0.227***	-0.207***	-0.199***	-0.185***	-0.167***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Total effect Mixed races	-0.212***	-0.206***	-0.198***	-0.206***	-0.194***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
Total effect Private	-0.035***	-0.039***	-0.038***	0.054***	0.057***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,105,144	3,105,144	3,105,144	3,105,144	3,105,144

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B7: Selection-corrected hourly wage regression for the period 2017. Race decomposition.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.331***	-0.255***	-0.275***	-0.300***	-0.224***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
African-Americans	-0.219***	-0.171***	-0.172***	-0.115***	-0.092***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.008)
Hispanic	-0.108***	-0.116***	-0.091***	-0.039***	-0.036***
	(0.003)	(0.002)	(0.004)	(0.007)	(0.007)
American Indian/Alaska Native	-0.228***	-0.189***	-0.183***	-0.185***	-0.163***
	(0.009)	(0.009)	(0.012)	(0.020)	(0.020)
Asian	0.005	-0.011***	-0.110***	-0.114***	-0.115***
	(0.003)	(0.003)	(0.007)	(0.012)	(0.012)
Mixed races	-0.119***	-0.091***	-0.105***	-0.103***	-0.089***
	(0.006)	(0.006)	(0.010)	(0.017)	(0.017)
Private	0.032***	0.052***	-0.038***	0.006	0.015***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.084***	-0.088***	-0.137***	-0.158***	-0.153***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.198***	0.191***	0.072***	0.084***	0.073***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.247***	0.192***	0.192***	0.191***	0.187***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.322***	0.256***	0.257***	0.256***	0.251***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.321***	0.280***	0.281***	0.279***	0.274***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.013***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.206***	0.205***	0.207***	0.284***
		(0.002)	(0.002)	(0.002)	(0.002)
Part-time		-0.431***	-0.431***	-0.428***	-0.581***
		(0.002)	(0.002)	(0.002)	(0.004)
Female *Educ L			0.063***	0.038***	0.038***
			(0.009)	(0.010)	(0.010)
Female *Educ H			0.030***	0.036***	0.057***
			(0.003)	(0.003)	(0.003)
African-Americans *Educ L			0.016	0.029	0.035
			(0.022)	(0.022)	(0.022)
African-Americans *Educ H			-0.000	-0.034***	-0.034***
			(0.005)	(0.006)	(0.005)
Hispanic *Educ L			-0.001	0.008	0.003
			(0.012)	(0.012)	(0.012)

Hispanic *Educ H			-0.054***	-0.069***	-0.065***
			(0.005)	(0.005)	(0.005)
American Indian/Alaska Native *Educ L			0.146**	0.161**	0.161**
			(0.067)	(0.067)	(0.067)
American Indian/Alaska Native *Educ H			-0.030*	-0.049***	-0.047***
			(0.017)	(0.017)	(0.017)
Asian *Educ L			-0.018	-0.010	-0.010
			(0.019)	(0.019)	(0.019)
Asian *Educ H			0.131***	0.125***	0.124***
			(0.008)	(0.008)	(0.008)
Mixed races *Educ L			0.044	0.055	0.060
			(0.044)	(0.044)	(0.044)
Mixed races *Educ H			0.020*	0.004	0.004
			(0.012)	(0.012)	(0.012)
Private *Educ L			0.025	0.051**	0.047**
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.122***	0.112***	0.110***
			(0.005)	(0.005)	(0.005)
Private *Female				-0.012***	-0.034***
				(0.004)	(0.004)
Private *African-Americans				-0.150***	-0.147***
				(0.007)	(0.007)
Private *Hispanic				-0.087***	-0.086***
				(0.007)	(0.007)
Private *American Indian/Alaska Native				-0.048***	-0.045**
				(0.018)	(0.018)
Private *Asian				-0.048***	-0.046***
				(0.010)	(0.010)
Private *Mixed races				-0.053***	-0.050***
				(0.015)	(0.015)
Female *African-Americans				0.160***	0.109***
				(0.005)	(0.005)
Female *Hispanic				0.064***	0.049***
				(0.005)	(0.005)
Female *American Indian/Alaska Native				0.102***	0.056***
				(0.017)	(0.017)
Female *Asian				0.100***	0.105***
				(0.006)	(0.006)
Female *Mixed races				0.109***	0.076***
				(0.011)	(0.011)
Female *Part-time					0.251***
					(0.004)
Female *Married					-0.174***
					(0.003)
athrho	0.086***	0.007**	0.007**	0.007**	0.015***

	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
lnsigma	-0.146***	-0.170***	-0.170***	-0.171***	-0.174***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.112***	2.152***	2.239***	2.213***	2.179***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Total effect Female	-0.331***	-0.255***	-0.255***	-0.256***	-0.239***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect African-American	-0.219***	-0.171***	-0.172***	-0.184***	-0.183***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect Hispanic	-0.108***	-0.116***	-0.124***	-0.122***	-0.124***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Total effect American Indian/Alaska Native	-0.228***	-0.189***	-0.197***	-0.200***	-0.198***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Total effect Asian	0.005	-0.011***	-0.031***	-0.029***	-0.026***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Total effect Mixed races	-0.119***	-0.091***	-0.092***	-0.091***	-0.090***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Total effect Private	0.032***	0.052***	0.037***	0.040***	0.038***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,390,418	1,390,418	1,390,418	1,390,418	1,390,418

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B8: Selection-corrected hourly wage regression for the period 1960. Race and country of origin.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.468***	-0.447***	-0.470***	-0.307***	-0.097***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Non-white	-0.291***	-0.285***	-0.266***	-0.133***	-0.121***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Migrant	0.013***	0.015***	-0.010***	-0.016**	-0.012*
	(0.002)	(0.002)	(0.003)	(0.007)	(0.007)
Private	-0.034***	-0.038***	-0.034***	0.052***	0.053***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
1.Educ	-0.187***	-0.191***	-0.183***	-0.173***	-0.168***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.146***	0.150***	0.117***	0.130***	0.138***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.100***	0.090***	0.091***	0.091***	0.087***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.094***	0.087***	0.088***	0.087***	0.080***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.057***	0.060***	0.058***	0.058***	0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.151***	0.151***	0.150***	0.275***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		0.122***	0.124***	0.124***	0.110***
		(0.002)	(0.002)	(0.002)	(0.002)
Female *1.Educ			0.038***	0.045***	0.029***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.063***	0.021***	0.006**
			(0.003)	(0.003)	(0.003)
Non-white *1.Educ			-0.049***	-0.035***	-0.036***
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.063***	0.018***	0.025***
			(0.004)	(0.005)	(0.005)
Migrant *1.Educ			0.082***	0.083***	0.085***
			(0.004)	(0.004)	(0.004)
Migrant *Educ H			-0.078***	-0.069***	-0.068***
			(0.005)	(0.005)	(0.005)
Private *1.Educ			-0.020***	-0.034***	-0.033***
			(0.003)	(0.003)	(0.003)
Private *Educ H			0.020***	0.016***	0.010***
			(0.003)	(0.003)	(0.003)

Private *Female				-0.187***	-0.197***
				(0.003)	(0.003)
Private *Non-white				-0.162***	-0.164***
				(0.004)	(0.004)
Female *Non-white				0.014***	-0.022***
				(0.003)	(0.003)
Migrant *Private				0.001	0.003
				(0.006)	(0.006)
Migrant *Female				0.013***	0.003
				(0.004)	(0.004)
Female *Married					-0.286***
					(0.002)
Female *Part-time					0.086***
					(0.002)
athrho	0.032***	0.016***	0.016***	0.018***	0.004*
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.409***	-0.415***	-0.416***	-0.417***	-0.421***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.855***	0.722***	0.723***	0.650***	0.545***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.468***	-0.447***	-0.446***	-0.450***	-0.460***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.291***	-0.285***	-0.269***	-0.275***	-0.281***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Total effect Migrant	0.013***	0.015***	0.010	0.003	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,091,603	3,091,603	3,091,603	3,091,603	3,091,603

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B9: Selection-corrected hourly wage regression for the period 2017. Race and country of origin.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.333***	-0.257***	-0.277***	-0.298***	-0.225***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Non-white	-0.149***	-0.124***	-0.133***	-0.104***	-0.089***
	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)
Migrant	0.072***	0.034***	0.030***	0.038***	0.018**
	(0.002)	(0.002)	(0.004)	(0.008)	(0.008)
Private	0.036***	0.056***	-0.035***	0.003	0.012**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.092***	-0.094***	-0.134***	-0.153***	-0.145***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.200***	0.194***	0.066***	0.072***	0.060***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.244***	0.190***	0.190***	0.189***	0.185***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.317***	0.253***	0.253***	0.252***	0.247***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.316***	0.277***	0.276***	0.275***	0.270***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.013***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.210***	0.210***	0.212***	0.288***
		(0.002)	(0.002)	(0.002)	(0.002)
Part-time		-0.431***	-0.431***	-0.429***	-0.584***
		(0.002)	(0.002)	(0.002)	(0.004)
Female *Educ L			0.061***	0.028***	0.024**
			(0.009)	(0.010)	(0.010)
Female *Educ H			0.030***	0.037***	0.059***
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			0.032**	0.044***	0.045***
			(0.014)	(0.014)	(0.014)
Non-white *Educ H			0.015***	-0.003	-0.003
			(0.004)	(0.004)	(0.004)
Migrant *Educ L			-0.031**	-0.034***	-0.039***
			(0.013)	(0.013)	(0.013)
Migrant *Educ H			0.009*	0.013***	0.016***
			(0.005)	(0.005)	(0.005)
Private *Educ L			0.025	0.053**	0.048**
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.123***	0.117***	0.116***
			(0.005)	(0.005)	(0.005)

Private *Female				-0.014***	-0.036***
				(0.004)	(0.004)
Private *Non-white				-0.086***	-0.084***
				(0.005)	(0.005)
Female *Non-white				0.107***	0.072***
				(0.004)	(0.004)
Migrant *Private				0.008	0.009
				(0.007)	(0.007)
Migrant *Female				-0.026***	0.005
				(0.005)	(0.005)
Female *Married					-0.172***
					(0.003)
Female *Part-time					0.253***
					(0.004)
athrho	0.089***	0.007**	0.006**	0.007**	0.015***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
lnsigma	-0.145***	-0.169***	-0.169***	-0.170***	-0.173***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.095***	2.137***	2.229***	2.208***	2.175***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Total effect Female	-0.333***	-0.257***	-0.257***	-0.253***	-0.241***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.149***	-0.124***	-0.123***	-0.125***	-0.125***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Migrant	0.072***	0.034***	0.035***	0.041***	0.037
	(0.002)	(0.002)	(0.004)	(0.008)	(0.008)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,390,325	1,390,325	1,390,325	1,390,325	1,390,325

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B10: Selection-corrected hourly wage regression without exclusion restrictions for the period 1960.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.461***	-0.447***	-0.470***	-0.306***	-0.098***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Non-white	-0.291***	-0.284***	-0.267***	-0.132***	-0.120***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Private	-0.033***	-0.038***	-0.035***	0.052***	0.054***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.186***	-0.190***	-0.178***	-0.168***	-0.163***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.146***	0.150***	0.114***	0.128***	0.136***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.099***	0.090***	0.091***	0.091***	0.087***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.092***	0.087***	0.087***	0.087***	0.080***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.057***	0.061***	0.060***	0.060***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.151***	0.151***	0.150***	0.274***
		(0.001)	(0.001)	(0.001)	(0.001)
Part-time		0.123***	0.123***	0.124***	0.107***
		(0.002)	(0.002)	(0.002)	(0.002)
Female *Educ L			0.039***	0.047***	0.030***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.063***	0.021***	0.006**
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			-0.048***	-0.035***	-0.036***
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.057***	0.013***	0.019***
			(0.004)	(0.005)	(0.004)
Private *Educ L			-0.017***	-0.031***	-0.030***
			(0.003)	(0.003)	(0.003)
Private *Educ H			0.016***	0.013***	0.007**
			(0.003)	(0.003)	(0.003)
Private *Female				-0.188***	-0.198***
				(0.003)	(0.003)
Private *Non-white				-0.164***	-0.165***
				(0.004)	(0.004)
Female *Non-white				0.012***	-0.024***
				(0.003)	(0.003)

Female *Married					-0.284***
					(0.002)
Female *Part-time					0.087***
					(0.002)
athrho	0.010*	0.015***	0.015***	0.018***	0.007***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
lnsigma	-0.408***	-0.414***	-0.415***	-0.416***	-0.420***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.857***	0.723***	0.725***	0.651***	0.548***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.461***	-0.447***	-0.446***	-0.449***	-0.460***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.291***	-0.284***	-0.271***	-0.277***	-0.283***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Total effect Private	-0.033***	-0.038***	-0.037***	0.068***	0.072***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,105,144	3,105,144	3,105,144	3,105,144	3,105,144

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B11: Selection-corrected hourly wage regression without exclusion restrictions for the period 2017.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.331***	-0.257***	-0.277***	-0.296***	-0.224***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Non-white	-0.125***	-0.112***	-0.123***	-0.094***	-0.086***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Private	0.040***	0.058***	-0.032***	0.006	0.013***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.068***	-0.083***	-0.132***	-0.148***	-0.144***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.200***	0.195***	0.067***	0.073***	0.061***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.247***	0.192***	0.192***	0.191***	0.187***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.320***	0.255***	0.255***	0.253***	0.249***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.324***	0.278***	0.277***	0.276***	0.271***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.013***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married		0.212***	0.212***	0.214***	0.290***
		(0.002)	(0.002)	(0.002)	(0.002)
Part-time		-0.430***	-0.430***	-0.429***	-0.584***
		(0.002)	(0.002)	(0.002)	(0.004)
Female *Educ L			0.062***	0.020**	0.026***
			(0.009)	(0.010)	(0.010)
Female *Educ H			0.029***	0.036***	0.058***
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			0.019*	0.032***	0.026**
			(0.011)	(0.011)	(0.011)
Non-white *Educ H			0.018***	0.002	0.004
			(0.003)	(0.003)	(0.003)
Private *Educ L			0.022	0.050**	0.045**
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.123***	0.117***	0.116***
			(0.005)	(0.005)	(0.005)
Private *Female				-0.017***	-0.037***
				(0.004)	(0.004)
Private *Non-white				-0.079***	-0.077***
				(0.005)	(0.004)
Female *Non-white				0.096***	0.072***
				(0.003)	(0.003)

Female *Married					-0.172***
					(0.003)
Female *Part-time					0.254***
					(0.004)
athrho	0.032***	0.004	0.004	0.004	0.012***
	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
lnsigma	-0.145***	-0.169***	-0.169***	-0.169***	-0.172***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.104***	2.136***	2.227***	2.206***	2.174***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Total effect Female	-0.331***	-0.257***	-0.258***	-0.258***	-0.211***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.125***	-0.112***	-0.112***	-0.109***	-0.111***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	0.040***	0.058***	0.040***	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,400,027	1,400,027	1,400,027	1,400,027	1,400,027

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B12: Misallocation Measure and its decomposition across the United States for the period 1970.

State	Female	Nonwhite	Misallocation Measure
Louisiana	0.541***	0.349***	0.890***
Alabama	0.505***	0.382***	0.887***
South Carolina	0.432***	0.404***	0.836***
Mississippi	0.432***	0.400***	0.831***
Georgia	0.462***	0.369***	0.831***
Delaware	0.559***	0.266***	0.825***
North Dakota	0.480***	0.312***	0.792***
Texas	0.526***	0.264***	0.790***
District of Columbia	0.439***	0.320***	0.759***
Virginia	0.465***	0.288***	0.752***
Wyoming	0.585***	0.161*	0.745***
West Virginia	0.576***	0.148***	0.724***
Montana	0.564***	0.159**	0.723***
Maryland	0.497***	0.223***	0.719***
Arkansas	0.434***	0.274***	0.708***
Florida	0.483***	0.215***	0.698***
New Mexico	0.551***	0.146***	0.697***
Nevada	0.504***	0.191***	0.696***
New Jersey	0.518***	0.176***	0.694***
Tennessee	0.426***	0.261***	0.687***
Oklahoma	0.481***	0.197***	0.678***
Idaho	0.509***	0.168***	0.677***
Ohio	0.556***	0.120***	0.676***
Kentucky	0.455***	0.219***	0.675***
North Carolina	0.359***	0.311***	0.670***
Connecticut	0.494***	0.157***	0.651***
Illinois	0.508***	0.142***	0.649***
Oregon	0.525***	0.115***	0.640***
Kansas	0.512***	0.125***	0.637***
Rhode Island	0.448***	0.184***	0.632***
Alaska	0.552***	0.078	0.630***
Arizona	0.506***	0.123***	0.629***
Michigan	0.538***	0.089***	0.627***
Washington	0.512***	0.114***	0.626***
Missouri	0.489***	0.131***	0.620***
Indiana	0.536***	0.080***	0.616***
Iowa	0.522***	0.092**	0.614***
California	0.488***	0.124***	0.612***
Main	0.415***	0.188	0.603***
Utah	0.544***	0.058	0.602***

Pennsylvania	0.488***	0.109***	0.597***
Massachusetts	0.454***	0.138***	0.592***
Hawaii	0.583***	0.001	0.584***
New Hampshire	0.450***	0.131	0.581***
Colorado	0.479***	0.098***	0.577***
New York	0.428***	0.147***	0.575***
Wisconsin	0.485***	0.077***	0.561***
South Dakota	0.411***	0.146**	0.557***
Minnesota	0.479***	0.063*	0.541***
Nebraska	0.455***	0.075*	0.530***
Vermont	0.421***	0.064	0.486***
Average	0.491	0.180	0.671

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B13: Misallocation Measure and its decomposition across the United States for the period 1980.

State	Female	Nonwhite	Misallocation Measure
Connecticut	0.504***	0.070***	0.573***
Main	0.390***	0.067	0.458***
Massachusetts	0.438***	0.068***	0.506***
New Hampshire	0.434***	0.045	0.479***
Rhode Island	0.415***	0.143***	0.558***
Vermont	0.367***	0.037	0.403***
Delaware	0.513***	0.070***	0.583***
New Jersey	0.527***	0.127***	0.654***
New York	0.414***	0.083***	0.497***
Pennsylvania	0.492***	0.082***	0.574***
Illinois	0.512***	0.067***	0.579***
Indiana	0.534***	-0.005	0.529***
Michigan	0.494***	0.063***	0.557***
Ohio	0.520***	0.076***	0.596***
Wisconsin	0.464***	-0.013	0.450***
Iowa	0.484***	0.020	0.504***
Kansas	0.496***	0.032**	0.529***
Minnesota	0.448***	0.090***	0.538***
Missouri	0.469***	0.062***	0.532***
Nebraska	0.462***	0.003	0.465***
North Dakota	0.435***	0.161***	0.596***
South Dakota	0.396***	0.160***	0.556***
Virginia	0.473***	0.111***	0.584***
Alabama	0.488***	0.184***	0.672***
Arkansas	0.407***	0.123***	0.530***
Florida	0.459***	0.088***	0.547***
Georgia	0.443***	0.147***	0.590***
Louisiana	0.570***	0.184***	0.754***
Mississippi	0.453***	0.200***	0.653***
North Carolina	0.394***	0.139***	0.533***
South Carolina	0.418***	0.167***	0.585***
Texas	0.535***	0.147***	0.682***
Kentucky	0.468***	0.096***	0.564***
Maryland	0.486***	0.086***	0.572***
Oklahoma	0.492***	0.094***	0.586***
Tennessee	0.446***	0.107***	0.553***
West Virginia	0.523***	0.045**	0.567***
Arizona	0.505***	0.068***	0.573***
Colorado	0.508***	0.050***	0.559***
Idaho	0.441***	0.016	0.458***

Montana	0.427***	0.151***	0.577***
Nevada	0.484***	0.064***	0.548***
New Mexico	0.519***	0.093***	0.612***
Utah	0.527***	0.063***	0.590***
Wyoming	0.585***	0.018	0.602***
California	0.481***	0.106***	0.586***
Oregon	0.474***	0.087***	0.561***
Washington	0.524***	0.087***	0.611***
Alaska	0.454***	0.049**	0.503***
Hawaii	0.561***	-0.040***	0.520***
District of Columbia	0.396***	0.142***	0.538***.
Average	0.473	0.086	0.559

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B14: Misallocation Measure and its decomposition across the United States for the period 1990.

State	Female	Nonwhite	Misallocation Measure
Montana	0.351***	0.279***	0.630***
Louisiana	0.426***	0.192***	0.618***
Wyoming	0.484***	0.109***	0.592***
South Dakota	0.339***	0.239***	0.578***
Mississippi	0.405***	0.168***	0.573***
District of Columbia	0.271***	0.279***	0.550***
New Jersey	0.386***	0.162***	0.548***
Alabama	0.409***	0.137***	0.545***
Texas	0.374***	0.167***	0.541***
California	0.371***	0.158***	0.529***
New Mexico	0.386***	0.132***	0.518***
Delaware	0.381***	0.136***	0.517***
Illinois	0.414***	0.096***	0.510***
Alaska	0.417***	0.092***	0.509***
Georgia	0.379***	0.127***	0.507***
South Carolina	0.381***	0.122***	0.503***
West Virginia	0.420***	0.081***	0.501***
North Dakota	0.337***	0.161***	0.498***
Arizona	0.363***	0.133***	0.497***
Washington	0.403***	0.093***	0.496***
Virginia	0.391***	0.103***	0.494***
Oregon	0.389***	0.104***	0.493***
Wisconsin	0.364***	0.116***	0.480***
Ohio	0.393***	0.083***	0.476***
North Carolina	0.360***	0.112***	0.472***
Oklahoma	0.359***	0.112***	0.471***
Utah	0.412***	0.059***	0.470***
Rhode Island	0.299***	0.171***	0.470***
Indiana	0.420***	0.046***	0.466***
Michigan	0.400***	0.062***	0.462***
Kentucky	0.386***	0.076***	0.462***
Connecticut	0.332***	0.125***	0.457***
Maryland	0.363***	0.094***	0.457***
Florida	0.345***	0.108***	0.453***
Arkansas	0.347***	0.104***	0.451***
Nevada	0.370***	0.081***	0.451***
Nebraska	0.395***	0.054***	0.449***
Massachusetts	0.290***	0.154***	0.444***
Tennessee	0.358***	0.070***	0.429***
Missouri	0.369***	0.055***	0.424***

Idaho	0.399***	0.024	0.423***
New York	0.324***	0.091***	0.415***
Colorado	0.344***	0.069***	0.414***
Hawaii	0.437***	-0.025**	0.412***
Kansas	0.384***	0.024*	0.408***
Pennsylvania	0.352***	0.055***	0.407***
Iowa	0.382***	0.014	0.396***
New Hampshire	0.306***	0.082**	0.387***
Minnesota	0.302***	0.082***	0.384***
Main	0.288***	0.082**	0.370***
Vermont	0.263***	0.075	0.338***
Average	0.369	0.108	0.477

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B15: Misallocation Measure and its decomposition across the United States for the period 2000.

State	Female	Nonwhite	Misallocation Measure
Louisiana	0.390***	0.157***	0.547***
Wyoming	0.406***	0.139***	0.544***
North Dakota	0.293***	0.242***	0.535***
District of Columbia	0.193***	0.296***	0.488***
Mississippi	0.360***	0.118***	0.479***
New Jersey	0.291***	0.178***	0.470***
Texas	0.338***	0.131***	0.469***
Alaska	0.261***	0.205***	0.465***
Montana	0.283***	0.173***	0.456***
Alabama	0.356***	0.099***	0.455***
Rhode Island	0.254***	0.196***	0.450***
California	0.280***	0.162***	0.443***
Utah	0.349***	0.087***	0.436***
South Carolina	0.328***	0.104***	0.431***
Arizona	0.297***	0.130***	0.427***
South Dakota	0.265***	0.158***	0.423***
Georgia	0.315***	0.104***	0.419***
Connecticut	0.266***	0.152***	0.418***
Washington	0.292***	0.121***	0.413***
Illinois	0.329***	0.082***	0.411***
Indiana	0.345***	0.062***	0.407***
New Mexico	0.328***	0.079***	0.407***
Florida	0.287***	0.110***	0.397***
Virginia	0.307***	0.083***	0.390***
North Carolina	0.292***	0.097***	0.390***
Ohio	0.309***	0.074***	0.382***
Massachusetts	0.251***	0.129***	0.380***
New Hampshire	0.281***	0.093***	0.374***
Oklahoma	0.320***	0.052***	0.372***
Colorado	0.303***	0.064***	0.367***
Delaware	0.281***	0.086***	0.367***
Michigan	0.320***	0.044***	0.364***
Idaho	0.312***	0.050***	0.362***
Kentucky	0.322***	0.039***	0.361***
Tennessee	0.314***	0.040***	0.354***
Maryland	0.270***	0.083***	0.352***
Pennsylvania	0.282***	0.069***	0.352***
New York	0.250***	0.098***	0.347***
Wisconsin	0.280***	0.067***	0.346***
Missouri	0.309***	0.037***	0.345***

West Virginia	0.318***	0.021	0.339***
Oregon	0.272***	0.067***	0.339***
Arkansas	0.292***	0.041***	0.333***
Minnesota	0.252***	0.077***	0.329***
Kansas	0.320***	0.000	0.320***
Nevada	0.282***	0.034***	0.316***
Vermont	0.224***	0.088**	0.312***
Iowa	0.288***	0.017	0.305***
Hawaii	0.279***	0.002	0.281***
Main	0.262***	0.004	0.266***
Nebraska	0.285***	-0.043***	0.242***
Average	0.298	0.094	0.392

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B16: Misallocation Measure and its decomposition across the United States for the period 2010.

State	Female	Nonwhite	Misallocation Measure
North Dakota	0.271***	0.232***	0.503***
South Dakota	0.174***	0.323***	0.496***
Louisiana	0.307***	0.179***	0.486***
Mississippi	0.275***	0.197***	0.472***
Alabama	0.248***	0.171***	0.419***
District of Columbia	0.031	0.374***	0.405***
South Carolina	0.232***	0.147***	0.380***
Texas	0.242***	0.136***	0.378***
Kentucky	0.221***	0.149***	0.369***
Wyoming	0.325***	0.030	0.355***
Connecticut	0.174***	0.171***	0.346***
Oklahoma	0.256***	0.086***	0.342***
Alaska	0.109***	0.230***	0.339***
Illinois	0.189***	0.140***	0.329***
New Jersey	0.166***	0.161***	0.327***
Montana	0.168***	0.157***	0.325***
Georgia	0.191***	0.132***	0.323***
Nebraska	0.176***	0.144***	0.321***
Indiana	0.196***	0.124***	0.319***
New Mexico	0.213***	0.104***	0.316***
North Carolina	0.191***	0.124***	0.315***
Rhode Island	0.124***	0.191***	0.315***
Arizona	0.170***	0.141***	0.311***
Arkansas	0.228***	0.078***	0.306***
Virginia	0.203***	0.101***	0.304***
California	0.150***	0.148***	0.299***
Utah	0.198***	0.099***	0.296***
West Virginia	0.243***	0.050	0.293***
Wisconsin	0.145***	0.146***	0.291***
Missouri	0.183***	0.105***	0.288***
Ohio	0.148***	0.132***	0.280***
Colorado	0.170***	0.109***	0.279***
Pennsylvania	0.167***	0.112***	0.279***
Hawaii	0.223***	0.053*	0.275***
Tennessee	0.205***	0.065***	0.269***
Kansas	0.219***	0.051**	0.269***
Iowa	0.218***	0.041	0.259***
Florida	0.148***	0.110***	0.258***
Delaware	0.179***	0.078**	0.257***
Main	0.132***	0.124*	0.255***
Maryland	0.130***	0.119***	0.249***

Washington	0.176***	0.070***	0.246***
New York	0.122***	0.123***	0.245***
Michigan	0.130***	0.111***	0.241***
Vermont	0.152***	0.086	0.238**
Massachusetts	0.108***	0.109***	0.218***
Minnesota	0.155***	0.061***	0.217***
New Hampshire	0.182***	0.024	0.206***
Idaho	0.194***	0.008	0.202***
Nevada	0.129***	0.053***	0.182***
Oregon	0.110***	0.048***	0.158***
Average	0.184	0.123	0.307

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

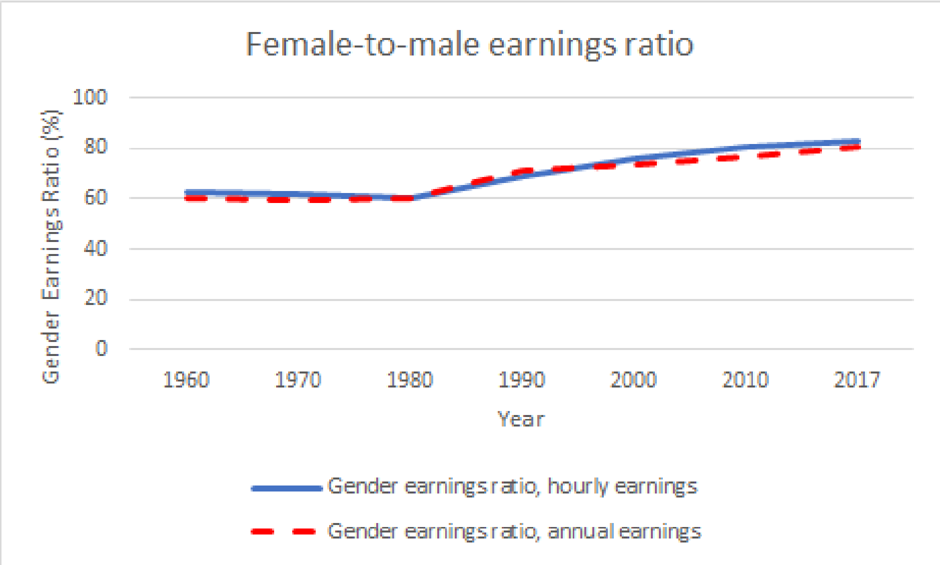

Figure B.1: Female-to-male hourly (annual) earnings ratio

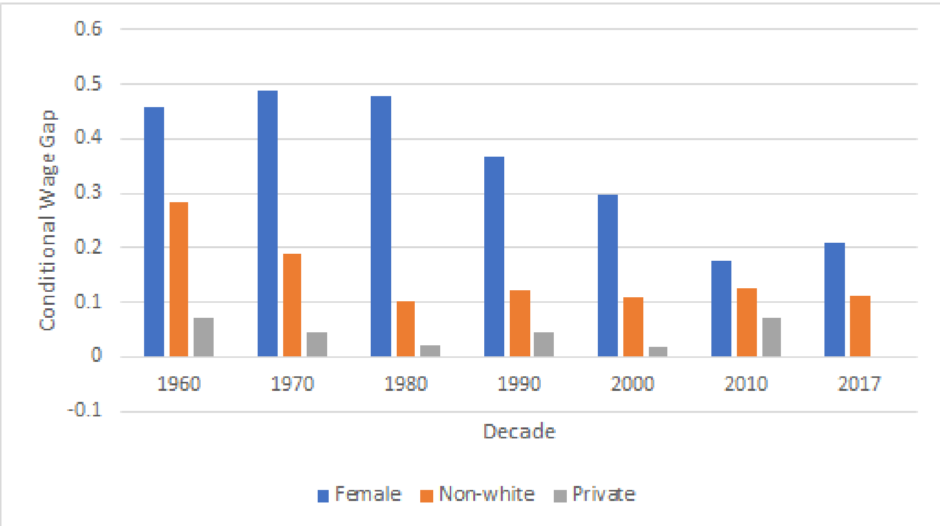

Figure B.2: Conditional wage differentials in the US over time, without instruments

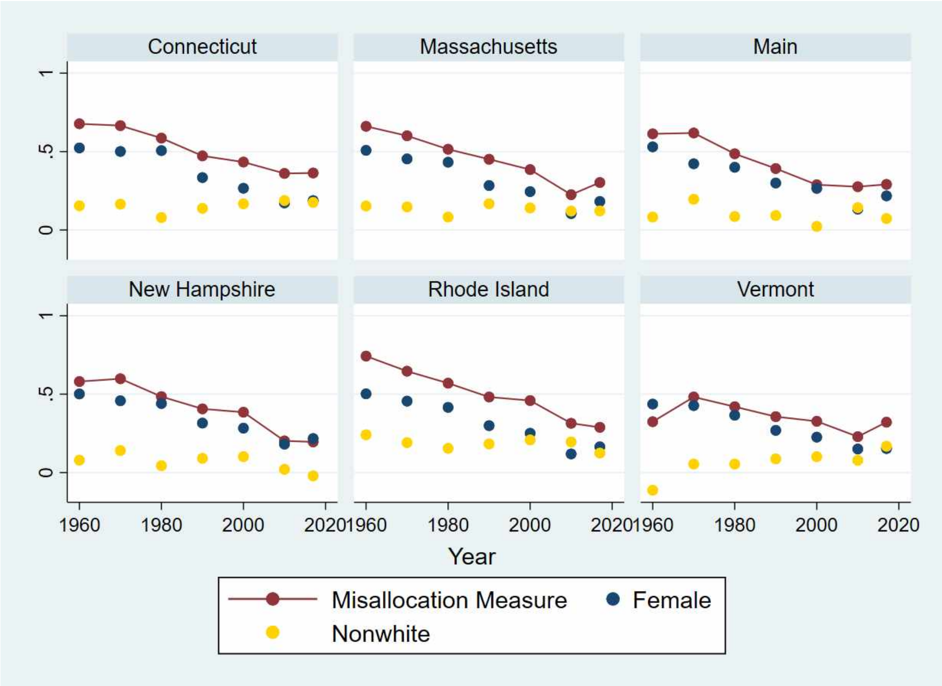

Figure B.3: Misallocation measure and its decomposition for each state of the Northeast Region, New England Division.

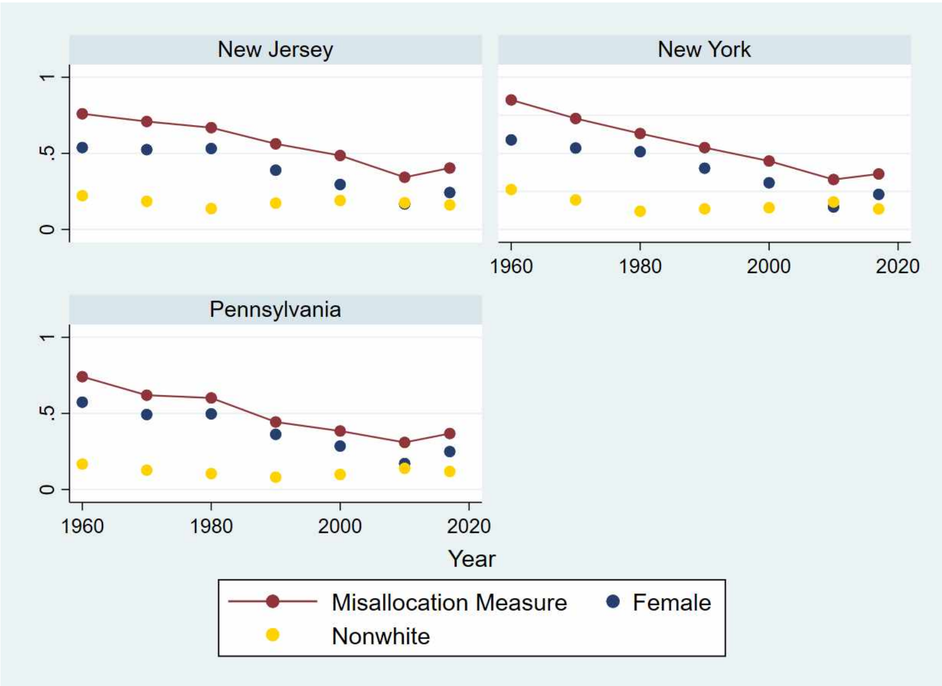

Figure B.4: Misallocation measure and its decomposition for each state of the Northeast Region, Middle Atlantic Division.

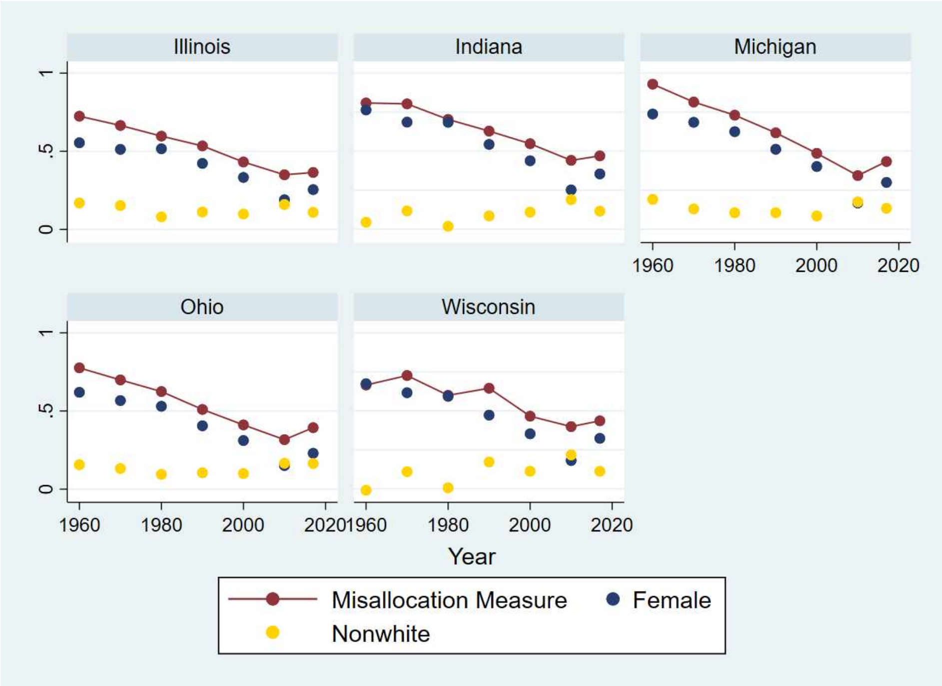

Figure B.5: Misallocation measure and its decomposition for each state of the Midwest Region, East North Central Division.

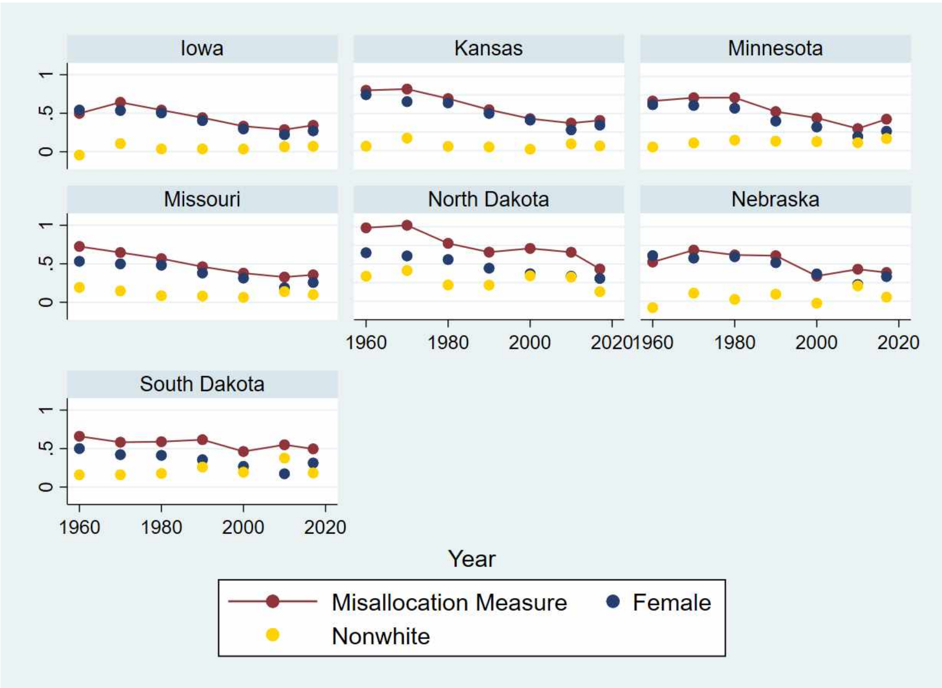

Figure B.6: Misallocation measure and its decomposition for each state of the Midwest Region, West North Central Division.

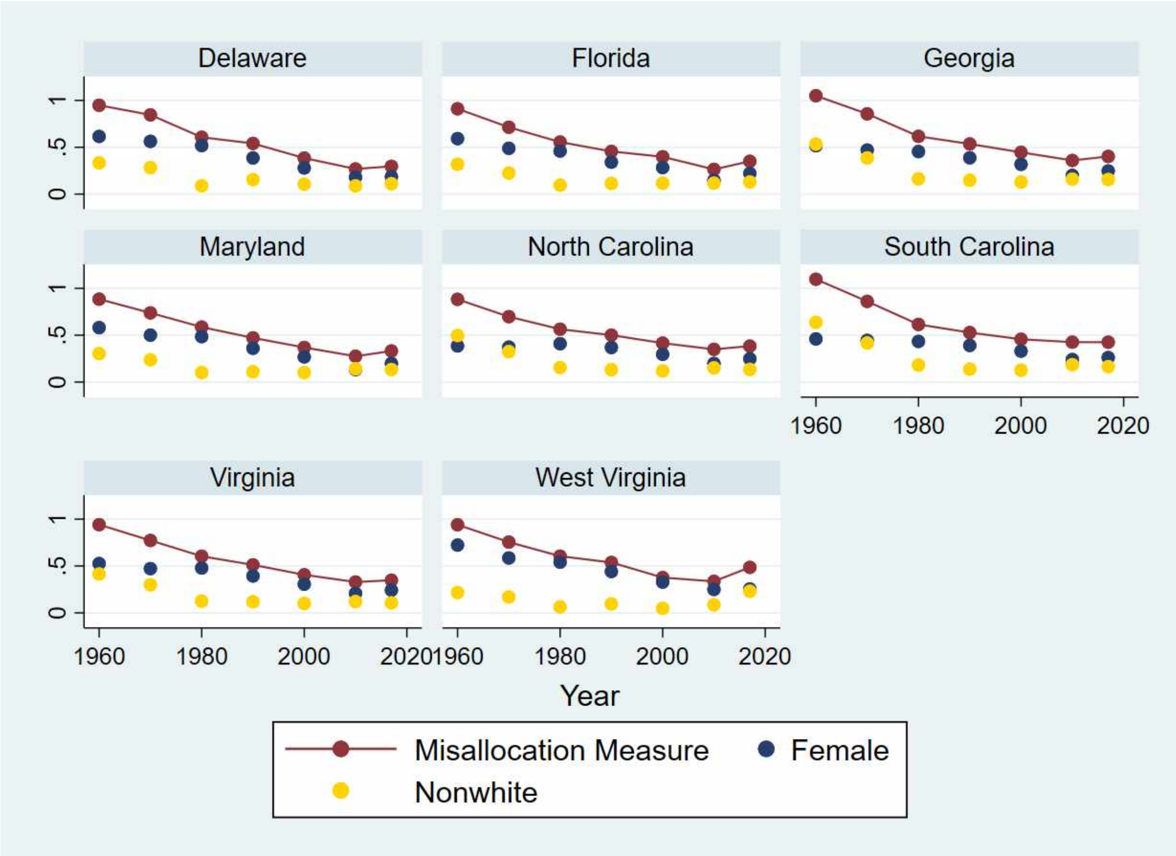

Figure B.7: Misallocation measure and its decomposition for each state of the South Region, South Atlantic Division.

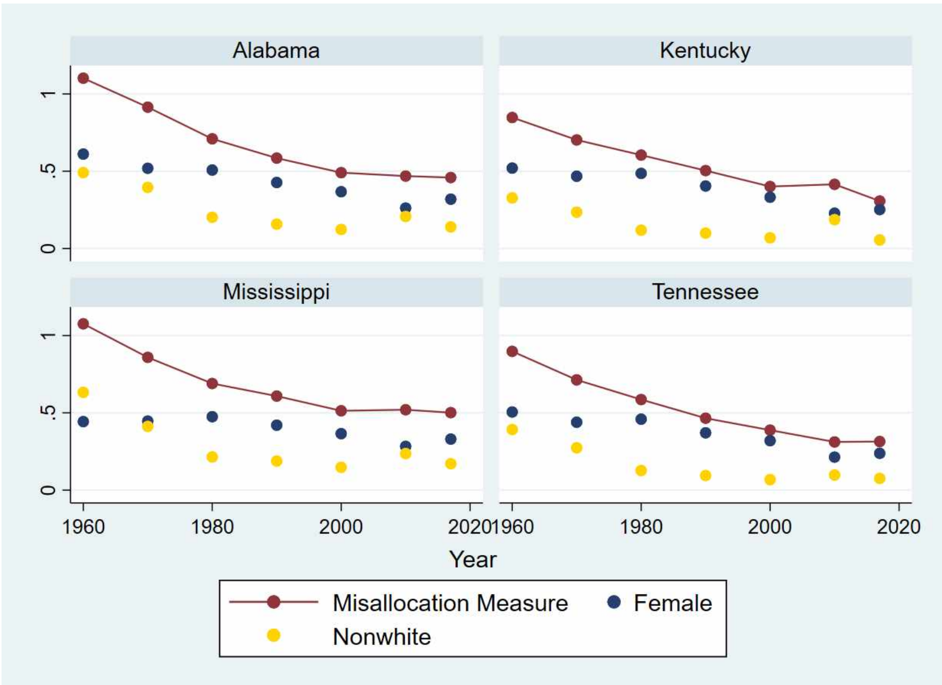

Figure B.8: Misallocation measure and its decomposition for each state of the South Region, East South Central Division.

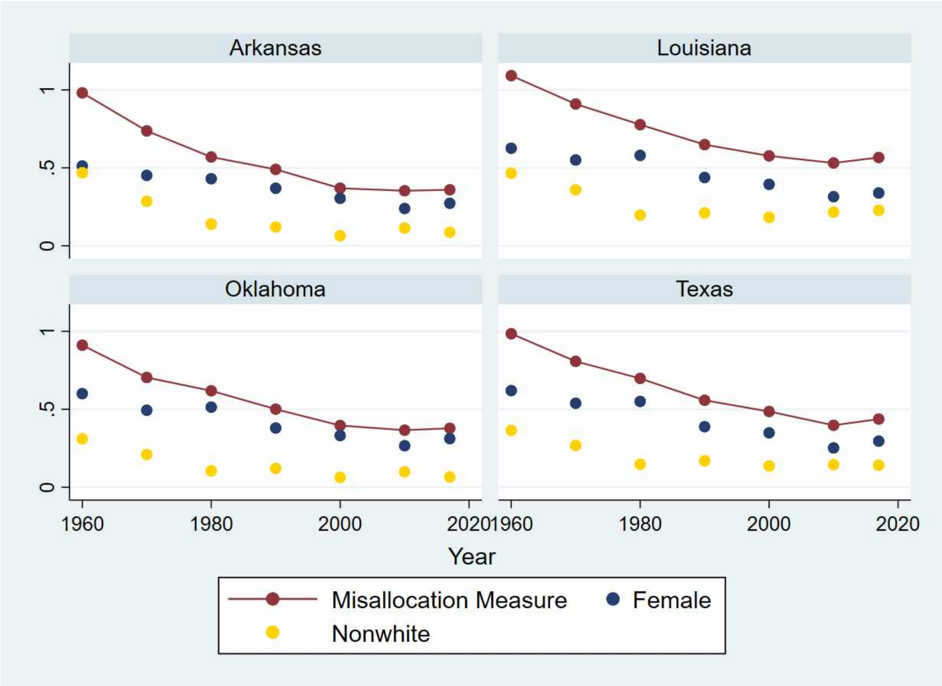

Figure B.9: Misallocation measure and its decomposition for each state of the South Region, West South Central Division.

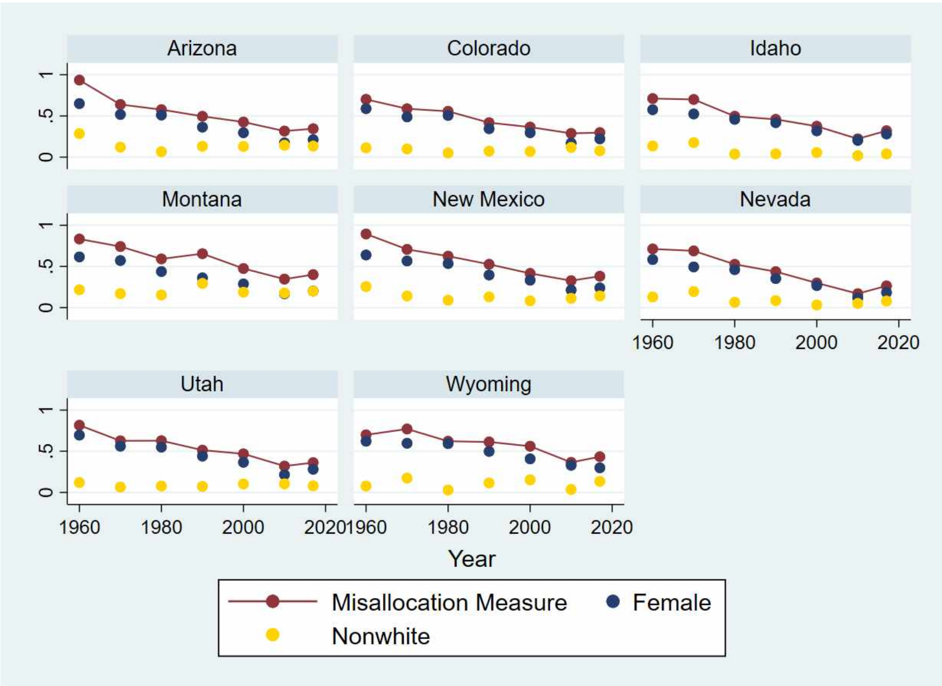

Figure B.10: Misallocation measure and its decomposition for each state of the West Region, Mountain Division.

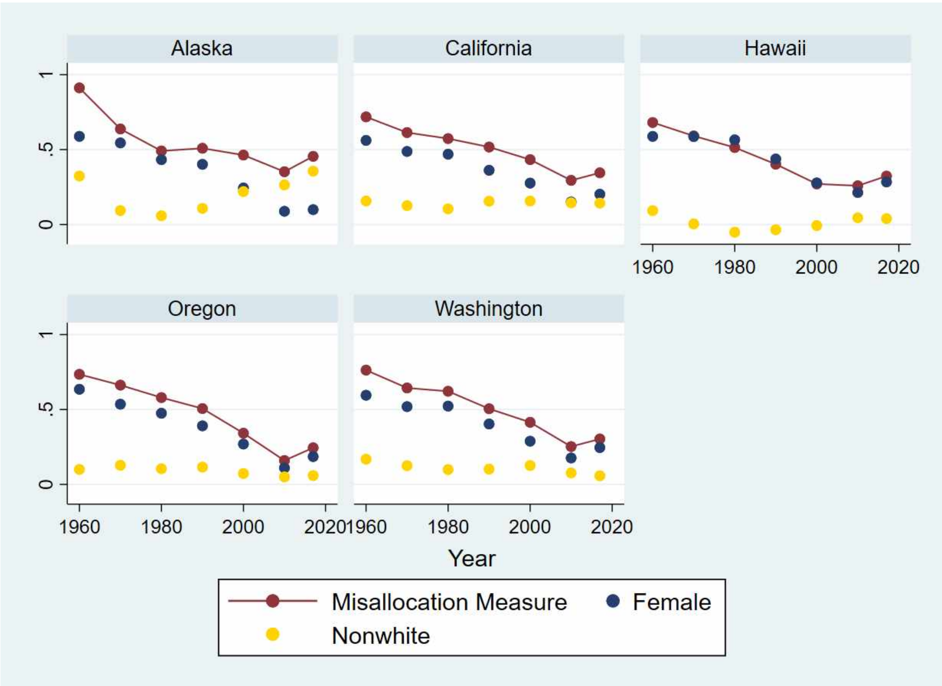

Figure B.11: Misallocation measure and its decomposition for each state of the West Region, Pacific Division.