The Economic Gains from Equity

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January 19, 2021 – Version 0.0

Conference draft: preliminary and incomplete, do not cite

Abstract

How much is inequity costing us? Using a simple growth accounting framework we apply standard shift-share techniques to data from the Current Population Survey (1990-2019) to compute the aggregate economic costs of persistent educational and labor market disparities by gender and race. We find significant economic losses associated with these gaps. Building on this finding, we consider which disparities generate the largest costs, paying specific attention to differences in employment, hours worked, educational attainment, educational utilization, and occupational allocation. We also examine gaps in the returns on these variables. Our findings suggest that differences in employment opportunities and educational attainment make the largest contributions by race; differences in returns on these variables also contribute materially to the total costs. Differences by gender are primarily driven by gaps in employment and hours. Given the disproportionate impact of COVID-19 on the labor market outcomes of women and people of color, as well as the fact that the U.S. population is increasingly racially diverse, these costs will only increase in the future.

JEL classi ication codes: E24, J7, J15, O4.

Keywords: Economic growth, productivity, labor market gaps, misallocation, equity

Opinions and conclusions herein are those of the authors and do not necessarily represent the views of the Federal Reserve System and the Federal Reserve Bank of San Francisco.

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1 Introduction

A long literature has documented persistent disparities in labor market outcomes by gender and race in the United States [1], [2], [3], [4], [5]. These disparities have persisted despite changes in laws, policies, and programs meant to remove barriers and prevent discriminatory practices [6]. Most strikingly, many of the gaps in outcomes cannot be explained by observable measures of talent or skill, meaning that as of now gender and race remain meaningful predictors of labor market outcomes in our economy [1].

These facts have long been recognized as unfair and inconsistent with the ideals of opportunity and meritocracy that define the American narrative. But there is growing awareness that they are also costly, not just to those that experience them, but to society and the economy as a whole [7], [8]. The persistence of systemic disparities and inequitable opportunities by race, gender, socioeconomic status, and a myriad of other indicators results in a misallocation, or complete sidelining of talent, that ultimately bridles economic growth [9], [10], [11], [12].

In this paper, we focus on disparities by race and gender. We document gaps in opportunities and labor market outcomes, and their evolution over time, using data from the Current Population Survey (CPS) from 1990 to 2019. We find that gaps in employment, hours worked, educational attainment, educational utilization, and occupational allocation have remained relatively constant since 1990. With these facts in hand, we ask: how much have persistent gaps in measured outcomes hindered U.S. economic growth? To answer this question we apply a simple growth accounting framework that allows us to estimate the total aggregate economic losses over time, and decompose these losses into the components that drive them: employment, hours worked, and labor productivity. We estimate these costs using standard shift-share techniques.

We find significant aggregate economic losses associated with persistent disparities; losses measured in trillions of dollars and several tenths of a percentage point on GDP growth. Decomposing these losses we find differences in employment and educational attainment make the largest contributions by race. Differences in returns on these variables also contribute materially to the total costs. Differences by gender are primarily driven by gaps in employment and hours.

Looking ahead, given the disproportionate impact of COVID-19 on the labor market outcomes of women and people of color, as well as the fact that the U.S. population is increasingly racially diverse, the costs of disparities will likely increase. Simple tabulations based on Census population projections, suggest that without significant progress to close these gaps, disparities in labor market outcomes by group could be a major restraining factor on U.S. growth over the next 20 years.

The remainder of the paper is structured as follows. In Section 2 we briefly summarize the related literature. In Section 3 we discuss the historical gaps in the labor market outcomes and educational attainment by race and gender. In Section 4 we describe our framework, data, and methodology. We present the results in Section 5 and provide a concluding discussion in Section 6.

2 Related Literature

A growing research literature demonstrates that the persistent inequities in opportunities and outcomes impose significant costs on the U.S. economy [8]. This is true across a wide variety of measures including employment, earnings, wealth, and innovation. We summarize the key findings of this literature here and provide a more detailed summary in Appendix Table A1.

Starting with employment and earnings, Hsieh et al. [9] estimate that improving the allocation of female and black talent in the economy accounted for between 20% and 40% of growth in U.S. market GDP per person between 1960 and 2010. Turner [11] similarly estimates that closing the racial earnings gap associated with disparities in health, education, incarceration and employment opportunities by 2050 would increase GDP by 22%, for a corresponding gain of $8 trillion. Finally, Truehaft, Scoggins, and Tran [12] estimate that closing racial income gaps in 2012, by way of both increased wages and employment among people of color, would have increased GDP by 14%, or $2.1 trillion, that year.

Looking across a broad array of factors that influence wealth, Peterson and Mann [10] estimate that closing racial gaps in key areas such as wages, higher education, home ownership, and investment would have generated significant additional income for saving, investing, and consumption, leading to a significant increase in aggregate output. Their bottom line estimate is a boost to GDP of $16 trillion over the past 20 years, and an additional $5 trillion over the next five years. Noel et al. [13] similarly estimate that closing the racial wealth gap by 2028 across dimensions such income, tangible investments, and stock-market investments would increase aggregate output by 4-6%.

Studies also demonstrate that systemic inequities cost the economy by holding back innovation. Bell et al. [14] estimate that the U.S. could have many more inventors if women, people of color, and children from low-income families were exposed to innovation at an early age. Cook and Yang [15] estimate that removing barriers for women and blacks in patenting and commercialization would increase per capita GDP. Cook (2014) [16] demonstrates that the rise of hate-related violence against African Americans in the late 19th and early 20th centuries depressed patent activity among African Americans. Collectively, these studies imply that disparities are limiting the potential growth of the U.S. economy far more the simple closing of current gaps would suggest.

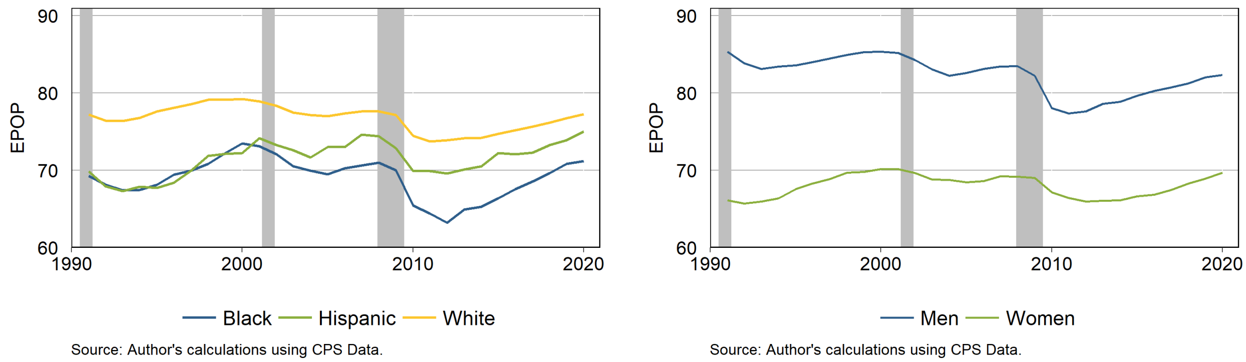
Although we do not investigate the causes of persistent gaps in race and gender outcomes, we recognize that a long literature has linked these gaps to the presence of structural factors embedded in the institutions and practices of society. For example, explicitly racialized policies such as Jim Crow laws and redlining have had long lasting effects on residential segregation and wealth accumulation [17], [18], [19], which continue to create inequitable economic opportunities across racial and ethnic groups. These "opportunity gaps" influence a range of outcomes such as educational attainment and employment that ultimately shape labor market disparities. As Williams and Wilson [2] demonstrate, even when black workers do attain a college degree, they are more likely than their white counterparts to work in jobs that typically do not require a college degree, meaning their talent is systematically underutilized. We recognize that while hard to measure individually, a range of macro and micro systems have greatly contributed to the racialized outcomes we observe. Gee and Ford [20], building on the work of Powell [21], define this collection of forces as structural racism or, "macro-level systems, social forces, institutions, ideologies, and processes that interact with one another to generate and reinforce inequities among racial and ethnic groups." Notably, structural racism has been codified by policy, custom, and practice, therefore it perpetuates inequities whether or not racism occurs at the interpersonal level [22]. But in fact, numerous studies document ongoing labor market discrimination at the individual level, including Bertrand and Mullainathan [23] and Pager, Bonikowski, and Western [24], suggesting that both structural and interpersonal racism influence labor disparities.

A long literature also has demonstrated disparate labor market outcomes by gender, including differences related to occupational segregation, labor force participation, and wages [25], [4], [26], [5]. There are many factors that contribute to these differences, including structural impediments to full economic participation, such as limited policies for paid parental leave and a lack of affordable child care. These impediments have significant implications for broader economic growth [27].

Importantly, the intersection of race and gender creates compounding labor market challenges for women of color, particularly black and Hispanic women, who face discrimination associated with overlapping socially marginalized identities, as evidenced by a growing body of literature [28], [3], [29], [30]. For example, in an exploration of the wage gap between black women and white men, Paul et al. [31] estimate that the unexplained portion of the wage gap is larger than the sum of the two individual penalties of gender and race, suggesting the intersection of these identities creates a wage penalty greater than the additive components of measured race and gender penalties in isolation. In the context of COVID-19, Gezici and Ozay [32] find that after controlling for education, age, and industry and occupation effects, women are more likely to be unemployed compared to men, and black and Hispanic women are more likely to be unemployed than white women.

3 Outcome and Opportunity Gaps

To get a sense of the potential gains to the economy from closing labor market outcome and opportunity gaps it is useful to review a few illustrative examples of the differences by race, ethnicity, and gender. Figure 1 plots the employment to population ratios (EPOP) from 1990-2019 for black, white, and Hispanic and individuals ages 25-64 (left panel) and for men and women (right panel). Several things stand out in these charts. First, whites and men have higher employment rates than other groups throughout the sample. The average gap between whites and blacks is about eight percentage points. The average gap between whites and Hispanic individuals is just over five percentage points. The gaps by gender are larger, averaging about 14 percentage points over the sample. The second thing to notice is the cyclicality of EPOP for all groups. EPOP goes down during and after recessions, and comes back up as the economy recovers and expands. Finally, while there is some evidence that gaps narrow during expansions, particularly for blacks and Hispanics, the narrowing is insufficient to close gaps completely [33].

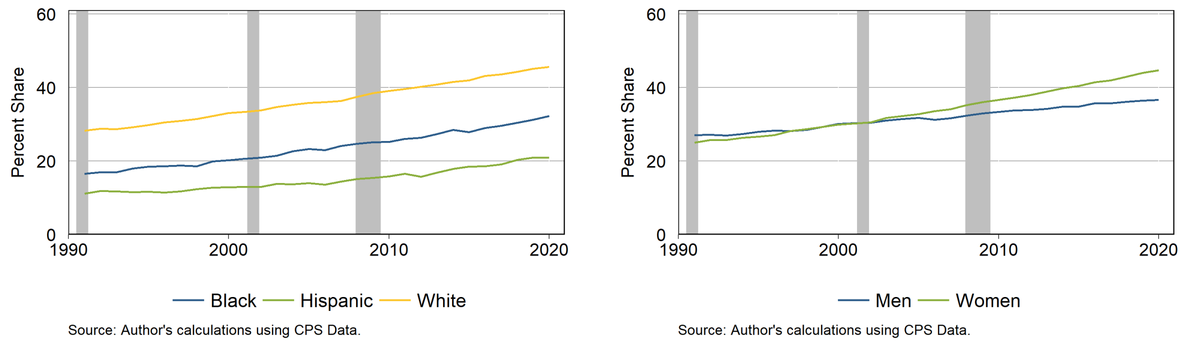


(a) Employment to Population Ratio, Race

(b) Employment to Population Ratio, Gender

Figure 1: **Trends in Employment (25-64)**

One of the key inputs to labor market success is educational attainment. Figure 2 shows the percent share of working-age individuals with a bachelor's degree or higher by race and ethnicity (left panel), and gender (right panel). Again, several things stand out in these plots. A far larger share of whites have a BA or more than do blacks or Hispanics. These gaps have grown over time. In 2019, the share of whites with a BA or higher was 45.6, compared to 32.3 for blacks, and 21.0 for Hispanics. The patterns by gender are quite different. In the early part of our sample, educational attainment was nearly equivalent for men and women. This changed in the early 2000s when the share of women with a BA or more began to rise steadily. In 2019, 44.7 percent of women had a BA or more compared to 36.6 of men. Notably, we find these patterns are insensitive to the age range of the sample (not shown), suggesting that these facts are not the result of differences carried forward by older cohorts.

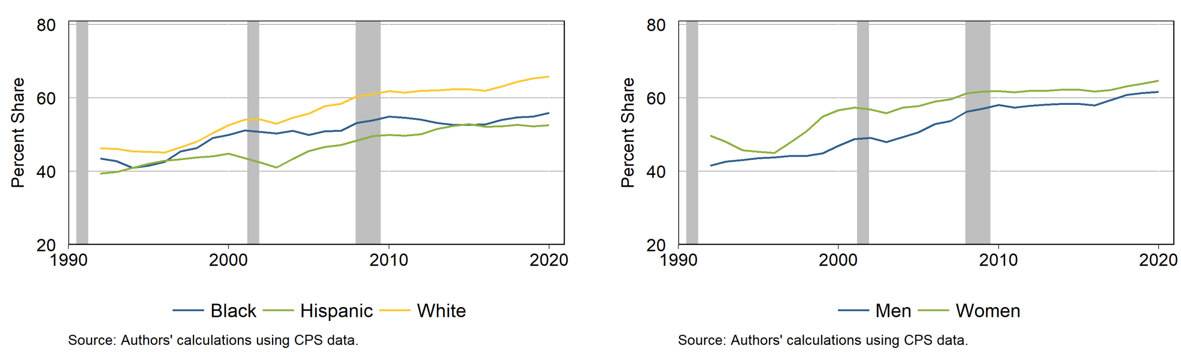


(a) Share of population with a BA or higher, Race (b) Share of population with a BA or higher, Gender

Figure 2: **Trends in Educational Attainment (25-64)**

Research has shown that even when women and people of color acquire a BA degree, they are not always in jobs that fully utilize their skills [2]. This results in an under utilization of resources for these individuals and for the economy as a whole. Figure 3 plots the degree to which worker skills are utilized by group, following the classification used by Williams and Wilson [2]. The figure shows the share of BA degree holders who are in BA jobs by race and gender. Several things stand out. First, over the course of the sample, utilization rates are always higher for whites. Second, the gaps in utilization between whites, blacks, and Hispanics have grown over time. In 2019, the last year of our sample, the utilization gap between whites and both blacks and Hispanics stood around 10 percentage points.

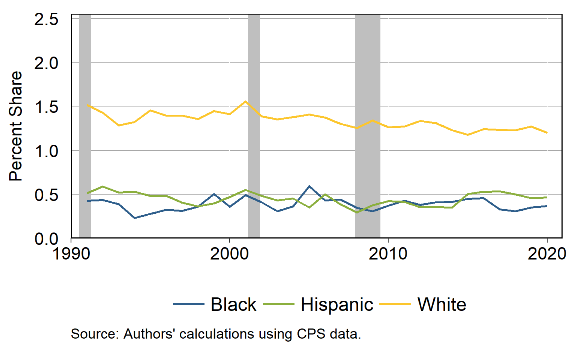
Notably, the pattern is completely different by gender. Women are consistently better utilized than their male counterparts with the same level of education. The utilization gap between women and men has narrowed over time.



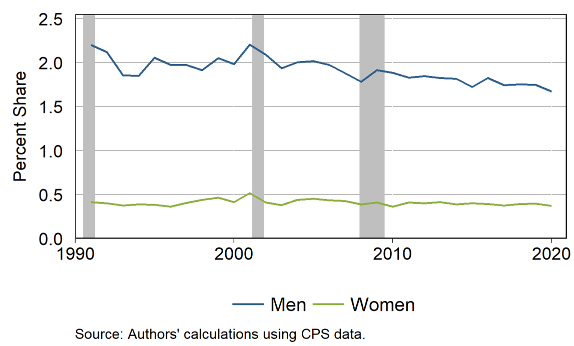
(a) Share of BA+ degree holders in BA+ jobs, Race (b) Share of BA+ degree holders in BA+ jobs, Gender

Figure 3: **Trends in Educational Utilization (25-64)**

The final gap we highlight is in the differences in employment opportunities across industries and occupations by race and gender. Since capital input and productivity vary by industry and occupation, these disparities matter, showing through to gaps in earnings. Figure 4 shows the share of whites, blacks, and Hispanics and men and women who have a professional occupation in the durable manufacturing sector. In the manufacturing sector these are among the highest paid workers. As the figure shows, whites and men are much more likely to hold these jobs than are blacks, Hispanics, or women. In 2019, for example, whites were more than twice as likely to be in this sector than other racial groups. The gap by gender was even larger; in 2019 the share of men in this industry-occupation category was more than three times that of women.



(a) Share of prof in durable good manu, Race



(b) Share of prof in durable goods manu, Gender

Figure 4: **Trends in Industry - Occupation Allocation (25-64)**

These trends document large and persistent disparities in the labor market and skill building opportunities in the U.S. We now turn to estimating the costs of these gaps to aggregate output and growth.

4 Estimating the Cost of Gaps

As highlighted in the literature review, there are many ways to assess the costs of persistent racial and gender disparities on the U.S. economy. In this study, we focus on computing the aggregate cost over time and then decomposing that aggregate into the specific factors that drive it. We frame our analysis through the lens of simple GDP accounting and complete the empirical work using standard shift-share techniques. Our framework, methodology, and data are described below.

4.1 Basic Growth Accounting

Aggregate output in the economy at any point in time can be written as:

$$Y = A \times F(K, L) \tag{1}$$

Where (Y) is aggregate output, (K) is physical capital, (L) is labor input, and (A) is aggregate productivity.

For this study we focus only on the labor contributions to aggregate output,[1] considering both the quantity of labor input and the productivity of labor inputs. Further decomposing labor input into its component parts, the labor component of aggregate output Y_L can be written as:

$$Y_L = \left(N \times \frac{H}{N}\right) \times LP \tag{2}$$

Where N is the number of workers, $\frac{H}{N}$ is hours worked per worker, and LP is labor productivity. Labor productivity is determined by a number of factors including the skills of workers, the extent to which workers' skills are utilized, and the amount of capital workers use in production, which varies by job and industry. These factors can be proxied by educational attainment, the degree to which workers' jobs utilize their education, and the industry and occupational distribution in the economy. Taking these factors into account we can further expand equation 2 to:

$$Y_L = \left(N \times \frac{H}{N}\right) \times F(e, u, io) \tag{3}$$

Where (e) is educational attainment, (u) is the degree of skill utilization, and (io) is selected industry/occupation groups. This simple expression frames our analysis.

4.2 Shift-Share Methodology

To estimate the costs of disparities to aggregate growth, we imagine a counterfactual world in which gaps in labor market outcomes and opportunities do not exist. We conduct these experiments using standard shift-share techniques, which allow us to adjust the inputs to growth and calculate the impact the changes have on aggregate output. Applying these techniques, we ask how much larger would U.S. aggregate output (Y) have been if racial and gender gaps in labor input and labor productivity were eliminated.

4.2.1 Computing the data matrix

We start by mapping the elements of equation 3 to publicly available data. We use data from the Current Population Survey (CPS) from 1990-2019. The CPS contains the full set of demographic, educational, and

[1] We hold capital fixed at its realized value.

labor market information required to complete our analysis. We limit our sample to the outgoing rotation groups from the CPS basic monthly files.

We focus on non-institutionalized adults ages 25-64 and divide them into mutually exclusive groups defined by age, gender, and race.[2] We construct four race groups: white, black, Hispanic, and other, based on self-reported designations. Because we need our groups to be mutually exclusive we assign race such that all non-Hispanic white individuals are classified as white, all black individuals are classified as black, regardless of their Hispanic ethnicity, all non-Hispanic Asian individuals are classified as Asian, all Hispanic white or Hispanic Asian individuals are classified as Hispanic, and all other groups are classified as other. For the purpose of this analysis we combine Asian and other individuals into a single group labeled other. We use 10 year age groups given by: (25-34, 35-44, 45-54, 55-64). This leaves us with 32 analysis groups for a baseline sample. The next step in our analysis is to compute the input variables that make up equation 3, for each of our 32 groups. We briefly describe them here and provide a full data guide in Appendix B.

Starting with the quantity of labor input, we define employment (N) using responses to the CPS monthly question: were you employed last week, either at work or off. We aggregate these responses over our sample and compute the average number of employed individuals by group on an annual basis. We exclude individuals who are self-employed. We define hours worked (H/N) as usual weekly hours worked over all jobs, and similarly average this value over our sample and on an annual basis. We exclude individuals who have zero, negative, or missing hours, regardless of their employment status. This leaves us with two labor input variables for each of our 32 groups: the fraction employed and average usual hours worked. These variables are computed separately for each year of our sample.

With labor input in hand we turn to labor productivity. We measure educational attainment for each of our sample members using four distinct categories: high school degree or less, associates degree, bachelors degree, and graduate degree. We then compute the fraction of individuals in each of our 32 groups who fall into these education categories in each year. This gives us the distribution of educational attainment for each age/gender/race group.

Next we confront aspects of labor productivity related to how workers are utilized and allocated in the economy. We first consider how well worker skills are utilized. Following Williams and Wilson [2], we use the CPS data to compute the educational requirements for each 4-digit occupation category. Specifically, we examine whether 50 percent or more of people in that occupation have an associates degree, or less education. If they do, we mark that occupation as requiring those degrees. All remaining occupations are characterized as requiring more education. We then compare the educational attainment of each individual to what is required and determine whether their skills are appropriately or under-utilized. Using this methodology we compute the shares of each of our 32 groups that are appropriately or under utilized.

[2] For the remainder of this paper we will use the term race to characterize both race and ethnicity

Finally, we complete our calculations of the determinants of labor productivity by considering how workers' skills are allocated in the economy. Previous studies have shown that barriers to entry for women and people of color have resulted in a misallocation of talent across industry and occupation [9], [4]. This miss-sorting matters because different jobs have different levels of labor productivity, primarily related to the amount of capital that workers use in production. To quantify how misallocation impacts aggregate labor productivity we divide the economy into 24 industry-occupation job types and compute the industry-occupation distribution for each of our 32 groups. These 24 industry-occupation pairs were constructed from combining 11, 2-digit occupation codes and 14, 2-digit industry codes into 4 occupation groups and 6 industry groups. A more detailed description of how we constructed these groups can be found in Appendix B. We exclude individuals who are not employed and those who do not list an industry and/or occupation.

So far we have described the determinants of the quantity of labor input and labor productivity as given in equations 2 and 3. We need one final element, average hourly earnings (AHE), to compute the value of (Y_L). Following previous research, we use (AHE) as a measure of the productive value of a single unit of labor input.

We define AHE for each individual as usual weekly earnings divided by usually weekly hours, averaged over the year. A well known fact in doing analysis on AHE with CPS data is that the top-coded value has a large, discrete jump in 1998. To address this, we re-calculate top-coded earnings in each year using a lognormal distribution following methods developed by the Center for Economic Policy Research [34]. To reduce noise in our sample, we remove the top and bottom 1% of earnings after we top-code the data. We adjust the earnings value for inflation using the PCEPI deflator. Values are in 2019 dollars. We exclude individuals who have zero, negative, or missing AHE, regardless of their employment status. Finally, we compute measures of AHE for all the separate groupings we use in the analysis. These include: AHE for the entire sample; AHE by age, race, gender, and education; AHE by age, race, gender, and utilization; AHE by age, race, gender, and industry-occupation, and finally AHE by age, race, gender, education, utilization, and industry-occupation.

This leaves us with a complete data matrix that is 32x447x30, reflecting the 32 age, race, and gender groups required to perform a complete shift-share analysis for equation 3, for each of the 30 years in our sample. Table A2 provides an illustration of our analysis data set for year 2019.

It is important to recognize that equipped with our constructed data matrix and the equation 3 we can recover the actual labor contribution to aggregate output. This would entail summing over our age/gender/race groups the elements of the equation relating to the labor input, and computing the group share weighted average of the labor productivity inputs from equation 3.

Below we describe how we use this data matrix and method to perform our counterfactual analyses.

4.2.2 Counterfactual analysis

With the data matrix in hand we turn to the specifics of our shift-share counterfactual exercises. Here we will describe our counterfactual exercises in which we shift by race and gender. In section 5 we will show results adjusting for race and gender individually as well as adjusting for race and gender simultaneously. We start by asking what would happen to the quantity of labor input if women and people of color had the same employment and hours opportunities as white males. White males are the default group in our analysis as they have historically faced fewer systemic barriers in the labor market and as a result have had better labor outcomes relative to women, blacks, and Hispanics.[3]

Given our data matrix this is straight forward to compute. We simply replace the employment rates and hours worked of women and people of color with those of white males for each of our age groups and recompute labor input using the following equation:

$$ {Y_H}^C = \sum_{a,g,r} \left({N_{a,g,r}}^C \times \frac{{H_{a,g,r}}^C}{{N_{a,g,r}}^C} \right) \tag{4} $$

Where $({Y_H}^C)$ is the counterfactual quantity of labor, or total hours worked per week across all workers, $({N_{a,g,r}}^C)$ is the total number of workers in a given age, gender, race group, and $({H_{a,g,r}}^C/{N_{a,g,r}}^C)$ is usual weekly hours worked for a given age, gender, race group. The difference in the actual output and this counterfactual output is the economic gain from having a more equitable distribution of employment and hours by gender and race.

We next turn to labor productivity again asking how much larger would it be if women and people of color had the same opportunities for educational attainment, skill utilization, and industry-occupation allocation as white males. While slightly more complicated than our calculation for adjusted employment and hours, given our data matrix, this is also straight forward to compute.

We begin by simply giving women and people of color the same distribution (shares) of educational attainment, utilization, and industry-occupation of white males. For now, we assume that only the shares of opportunities change, holding the returns on the opportunities, AHE, constant at the prevailing rate for each age/gender/race/labor productivity group (e.g., the share of black college educated men out of black men would change to be the share of white college educated men out of white men, but black educated men would still maintain the AHE for college educated black men).

The following equation maps this logic and illustrates our calculation for eliminating gaps in educational attainment.

[3] Our analysis only adjusts groups when they are worse off than white males. This primarily affects adjustments for the “other” group, where employment and educational attainment are frequently higher for Asian Americans than for white males.

$$Y_{LP}^{C,Educ} = \sum_{a,g,r} \Big[\alpha_{a,g,r}\big(\alpha_{a,g,r}^{C,hs} \times AHE_{a,g,r}^{hs} + \alpha_{a,g,r}^{C,ac} \times AHE_{a,g,r}^{ac} + \alpha_{a,g,r}^{C,ba} \times AHE_{a,g,r}^{ba} + \alpha_{a,g,r}^{C,gd} \times AHE_{a,g,r}^{gd}\big)\Big] \tag{5}$$

Where ($Y_{LP}^{C,Educ}$) is the contribution of labor productivity to overall output, ($\alpha_{a,g,r}$) is the share of the population that belong to a given age, gender, race group, ($AHE_{a,g,r}^{hs}$) is the average hourly earnings for individuals with a high school diploma or less in a given age, gender, race group, and ($\alpha_{a,g,r}^{C,hs}$) is the share of individuals with a high school diploma in a given age, gender, race group, etc. The difference in the actual output and this counterfactual output is the economic gain from having a more equitable distribution of educational distribution across gender and race.

We can perform a similar exercise for our utilization and industry-occupation variables by repeating this exercise by shifting utilization shares and industry-occupation shares for women and people of color to that of white males.

Putting this all together, we complete the shares part of this exercise by defining very fine groups that adjust simultaneously for educational attainment, utilization, and industry-occupation. This is equivalent to adding rows to our baseline data matrix. Again, we hold AHE at the value of the treated group.

Our final experiments consider changes in the returns on opportunity, or AHE, by group as well as by changes in the shares. Looking back to equation 5, these experiments change the AHE values by age/gender/race to be the counterfactual values, which in our experiments are the values for equivalent white males. We do two separate experiments. The first holds the returns of opportunities constant, changing only the shares. The second changes both the shares and the returns. We compute these experiments for each labor productivity variable separately and for them all together.

5 Results

In this section we report on the results of our experiments. We begin by discussing the impact of making labor market opportunities more equal. We then turn to examining the impact of making returns to those opportunities more equal.

Throughout this section we display tables showing our counterfactual inputs of labor, calculated from changes to shares as well as changes to returns for our age/gender/race groups. We also include tables showing overall counterfactual labor output constructed from these inputs for each decade in our sample 1990-2019. Each table contains first a row with the actual value of the given variable we are adjusting, then the counterfactual when adjusting by race only, then the counterfactual when adjusting by gender only, and then the counterfactual when adjusting by race and gender. Given recent research focusing on the costs of systemic barriers for black Americans we also compute results considering changes in opportunities and returns for blacks alone [10].

5.1 Equalizing Shares

We start by showing how each of the individual components of labor output in equation 3 change through our shift share analysis, and then relate this to its effect on labor output gaps.

5.1.1 Labor Input

We begin by asking how much more output would the U.S. economy have had if historical gaps in employment and hours opportunities by race and gender had been closed. Table 1 shows the values for employment to population ratios (EPOP) and usual weekly hours as well as the counterfactual adjustments by race, gender, and race/gender together.

	EPOP (%)				**Weekly Hours**			
	1990	2000	2010	2019	1990	2000	2010	2019
Actual	75.47	77.50	71.81	75.89	40.12	41.08	40.17	40.75
Adj by Race	77.43	79.30	74.17	77.94	40.38	41.37	40.60	41.16
Gain by Race	1.96	1.80	2.36	2.04	0.27	0.29	0.42	0.41
Adj by Gender	85.10	84.99	77.15	82.17	42.66	43.39	42.19	42.52
Gain by Gender	9.63	7.50	5.34	6.28	2.54	2.31	2.02	1.77
Adj by Race Gender	87.06	86.63	79.30	83.90	43.15	43.89	42.91	43.14
Gain by Race Gender	11.58	9.14	7.49	8.01	3.03	2.81	2.74	2.38
Black only:								
Adj by Race	76.40	78.24	72.99	76.79	40.25	41.19	40.30	40.85
Gain by Race	0.93	0.74	1.19	0.89	0.13	0.10	0.13	0.10
Adj Race Gender	77.56	79.18	73.68	77.62	40.53	41.46	40.56	41.10
Gain Race Gender	2.09	1.69	1.87	1.73	0.41	0.38	0.39	0.35

Table 1: Impact on Employment and Hours of more Equitable Opportunities

Note: All adjustments use granular age/gender/race groups and are shifted by the group listed in the leftmost column. i.e. Adjusting by race holds age and gender groups constant.

Starting with race (line 2), giving people of color the EPOP of whites in their age/gender group increases overall employment in the economy by about two percentage points.[4] Abstracting from modest business cycle variability this increase occurs consistently for all years in our sample. The hours adjustments have more modest effects.

The picture for gender is different.[5] The gains to equalizing EPOP between women and men are large, 9.6 percentage points at the beginning of the sample and 6.3 percentage points at the end of the sample. Adjustments to hours also have a larger impact, adding about two hours per week to average weekly hours across the sample.

[4]For example, this exercise gives black females age 25-34 the EPOP of white females age 25-34.

[5]This exercise, for example, gives black females age 25-34 the EPOP of black males age 25-34.

The final rows in the table repeat the analysis for race and gender together.[6] The results show sizeable gains to employment and hours from eliminating race and gender gaps. Although the gains have declined somewhat over time, in 2019, closing these gaps would have increased the annual employment rate of the working age population by eight percentage points and added over two hours to the average work week.

The dollar value of closing each of these gaps is shown in Table 2.[7] As the numbers highlight, eliminating gaps in employment and hours opportunities produces meaningful economic benefits. Equalizing employment across race and gender would have boosted measured GDP in 2019 by 0.63 trillion 2019 dollars. Adjusting hours by race and gender also has an impact, increasing GDP in 2019 by 0.37 trillion 2019 dollars. These gains are not unique to 2019; they are consistently significant across the sample.

	EPOP ($Trillions)				**Hours ($Trillions)**			
	1990	2000	2010	2019	1990	2000	2010	2019
Actual	4.07	5.54	5.97	6.97	4.07	5.54	5.97	6.97
Adj by Race	4.16	5.64	6.13	7.13	4.10	5.57	6.03	7.04
Gain by Race	0.08	0.10	0.16	0.15	0.02	0.03	0.05	0.06
Adj by Gender	4.47	5.96	6.34	7.47	4.29	5.81	6.25	7.25
Gain by Gender	0.39	0.42	0.37	0.49	0.22	0.27	0.28	0.28
Adj by Race Gender	4.55	6.05	6.49	7.60	4.33	5.86	6.34	7.35
Gain by Race Gender	0.48	0.52	0.52	0.63	0.26	0.33	0.36	0.37
Black only:								
Adj by Race	4.11	5.58	6.05	7.04	4.09	5.55	5.99	6.99
Gain by Race	0.04	0.05	0.08	0.07	0.01	0.01	0.02	0.01
Adj by Race Gender	4.16	5.63	6.10	7.10	4.11	5.58	6.02	7.02
Gain by Race Gender	0.08	0.10	0.13	0.13	0.03	0.04	0.05	0.05

Table 2: Adjusted Output by Labor Quantity Shares

Note: All adjustments use granular age/gender/race groups and are shifted by the group listed in the leftmost column. i.e. Adjusting by race holds age and gender groups constant.

5.1.2 Labor Productivity Determinants

In Table 3 we turn to productivity. For each experiment we show the impact on measured labor productivity (AHE) from changing education alone and education, utilization and allocation simultaneously. The key things to note from table 3 are that changing the determinants of productivity changes aggregate AHE only slightly. This is true whether we consider race, gender, or race and gender together. This owes in part to the fact that people of color make up a smaller share of the population than whites and the gaps in education are

[6]This exercise, for example gives black females age 25-34 the EPOP of white males age 25-34.

[7]Recall from Section 4.2.1 we value the gains to output by multiplying our adjusted labor input quantities by labor productivity (measured as group specific AHE) as described in equation 2.

not existent by gender, ie., by 2019 the gains from equalizing education by gender are zero. Importantly however, the gains from equalizing these determinants by race are rising over the sample as the population share of people of color increases.

	Education ($)				**All ($)**			
	1990	2000	2010	2019	1990	2000	2010	2019
Actual	20.23	22.88	24.51	25.59	20.23	22.88	24.51	25.59
Adj by Race	20.50	23.31	25.16	26.28	20.47	23.30	25.25	26.40
Gain by Race	0.27	0.43	0.65	0.69	0.24	0.43	0.74	0.82
Adj by Gender	20.38	22.96	24.55	25.59	20.48	23.07	24.60	25.60
Gain by Gender	0.15	0.08	0.03	0.00	0.25	0.19	0.09	0.02
Adj by Race Gender	20.66	23.39	25.14	26.13	20.69	23.47	25.21	26.20
Gain by Race Gender	0.42	0.51	0.63	0.54	0.46	0.59	0.70	0.62
Black only:								
Adj by Race	20.35	23.04	24.69	25.78	20.33	23.02	24.70	25.81
Gain by Race	0.12	0.16	0.18	0.19	0.10	0.15	0.18	0.22
Adj by Race Gender	20.37	23.04	24.67	25.70	20.31	23.02	24.62	25.71
Gain by Race Gender	0.14	0.16	0.16	0.11	0.08	0.14	0.11	0.12

Table 3: Impact on Productivity of more Equitable Opportunities

Note: All adjustments use granular age/gender/race groups and are shifted by the group listed in the leftmost column. i.e. Adjusting by race holds age and gender groups constant. All values in this table are in terms of average hourly earnings.

Valuing these adjustments as we did in table 2, table 4 computes the gains to GDP from equalizing the determinants of productivity. The results show that removing the gaps in educational attainment, education utilization, and industry-occupation allocation by race and gender would have increased GDP in 2019 by 0.17 trillion 2019 dollars.

	Education ($Trillions)				All ($Trillions)			
	1990	2000	2010	2019	1990	2000	2010	2019
Actual	4.07	5.54	5.97	6.97	4.07	5.54	5.97	6.97
Adj by Race	4.13	5.64	6.12	7.16	4.12	5.64	6.15	7.19
Gain by Race	0.05	0.10	0.15	0.19	0.05	0.10	0.18	0.22
Adj by Gender	4.10	5.55	5.98	6.97	4.12	5.58	5.99	6.98
Gain by Gender	0.03	0.02	0.01	0.00	0.04	0.04	0.02	0.00
Adj by Race Gender	4.15	5.66	6.12	7.12	4.16	5.67	6.14	7.14
Gain by Race Gender	0.08	0.12	0.15	0.15	0.09	0.14	0.17	0.17
Black only:								
Adj by Race	4.10	5.58	6.01	7.02	4.09	5.57	6.01	7.03
Gain by Race	0.02	0.04	0.04	0.05	0.02	0.03	0.04	0.06
Adj by Race Gender	4.10	5.58	6.01	7.00	4.09	5.57	6.00	7.01
Gain by Race Gender	0.03	0.04	0.04	0.03	0.02	0.03	0.03	0.03

Table 4: Adjusted Output by Labor Productivity Shares

Note: All adjustments use granular age/gender/race groups and are shifted by the group listed in the leftmost column. i.e. Adjusting by race holds age and gender groups constant.

5.2 Equalizing Returns

The final component of our counterfactual exercise acknowledges that differences in labor inputs and the observable determinants of productivity are only part of the disparities observed in the economy. In particular, differences in the rates of return AHE earned by individuals vary by race and gender in ways not fully explained by differences in skills, utilization, industry-occupation other measurable variables [6].

To account for these differences our final experiments keep the determinants of productivity fixed at actual values and adjust the returns earned by race and gender. For example, when adjusting by race only, we hold the distribution of educational attainment at its actual values and substitute the wages of white equivalents into the calculation of productivity.[8]

We report the results in table 5. The findings are striking. Eliminating the gaps in returns earned by whites versus people of color and women versus men on measured skills, utilization, and industry-occupation allocation would have increased aggregate economic output in 2019 by 0.94 trillion 2019 dollars. This is over 5 times the impact of adjusting the determinants while leaving the returns at their actual values.

[8] For example, for all black women age 25-34 with a BA degree we assign the AHE of white women age 25-34 with a BA degree.

	Education ($Trillions)				All ($Trillions)			
	1990	2000	2010	2019	1990	2000	2010	2019
Actual	4.07	5.54	5.97	6.97	4.07	5.54	5.97	6.97
Adj by Race	4.19	5.75	6.21	7.28	4.18	5.73	6.19	7.26
Gain by Race	0.12	0.21	0.24	0.31	0.11	0.20	0.22	0.28
Adj by Gender	4.51	6.12	6.51	7.58	4.48	6.10	6.51	7.58
Gain by Gender	0.44	0.58	0.54	0.61	0.41	0.56	0.54	0.60
Adj by Race Gender	4.68	6.40	6.83	7.97	4.63	6.35	6.77	7.91
Gain by Race Gender	0.60	0.86	0.86	1.00	0.56	0.81	0.80	0.94
Black only:								
Adj by Race	4.13	5.62	6.06	7.10	4.12	5.61	6.05	7.09
Gain by Race	0.06	0.08	0.09	0.13	0.05	0.08	0.08	0.11
Adj by Race Gender	4.19	5.70	6.14	7.20	4.18	5.69	6.12	7.18
Gain by Race Gender	0.11	0.16	0.16	0.23	0.10	0.15	0.15	0.21

Table 5: Adjusted Output by Labor Productivity Returns

Note: All adjustments use granular age/gender/race groups and are shifted by the group listed in the leftmost column. i.e. Adjusting by race holds age and gender groups constant.

5.3 Putting it All Together

To return to our original question: what are the economic gains from equity, our final experiment closes all gaps: those in labor inputs, determinants of productivity, and returns on those determinants. The results are reported in Table 6.

The bottom line from our analysis is that the U.S. economy would have had about 2.6 trillion 2019 dollars more output in 2019 if gaps in labor market opportunities and returns were eliminated. The table also shows that the gains to eliminating gaps have been rising over time as the U.S. population becomes more racially diverse while disparities remain.

Adding the costs up over the length of the sample, we estimate the gains to equalizing labor market opportunities is 34.4 trillion 2019 dollars. If we equalize labor market opportunities and returns we estimate gains of 70.8 trillion 2019 dollars. This is similar in magnitude to findings by Truehaft, Scoggins, and Tran [12] who estimate that raising the average incomes in 2012 of people in each major racial/ethnic group to the average incomes of non-Hispanic whites would generate an additional $2.1 trillion in GDP annually, and Peterson and Mann [10] who estimate that closing black-white gaps in wages, housing, higher education, and business investment would have added $16 trillion to GDP over the past twenty years.

	Shares ($Trillions)				Returns ($Trillions)				Total ($Trillions)			
	1990	2000	2010	2019	1990	2000	2010	2019	1990	2000	2010	2019
Actual	4.07	5.54	5.97	6.97	4.07	5.54	5.97	6.97	4.07	5.54	5.97	6.97
Adj by Race	4.24	5.79	6.39	7.43	4.24	5.81	6.27	7.36	4.41	6.06	6.68	7.82
Gain by Race	0.17	0.25	0.42	0.46	0.17	0.27	0.30	0.38	0.33	0.52	0.71	0.84
Adj by Gender	4.81	6.34	6.68	7.80	4.73	6.35	6.71	7.82	5.48	7.15	7.42	8.65
Gain by Gender	0.74	0.81	0.71	0.83	0.66	0.81	0.74	0.84	1.40	1.62	1.45	1.67
Adj by Race Gender	5.01	6.63	7.12	8.24	5.00	6.75	7.15	8.33	5.94	7.84	8.30	9.60
Gain by Race Gender	0.94	1.09	1.15	1.27	0.93	1.21	1.18	1.36	1.87	2.30	2.33	2.62
Black only:												
Adj by Race	4.15	5.64	6.12	7.13	4.15	5.65	6.09	7.13	4.23	5.75	6.25	7.29
Gain by Race	0.08	0.10	0.15	0.15	0.08	0.11	0.12	0.16	0.16	0.21	0.28	0.31
Adj by Race Gender	4.22	5.72	6.19	7.20	4.26	5.77	6.23	7.28	4.41	5.96	6.44	7.51
Gain by Race Gender	0.15	0.19	0.22	0.23	0.18	0.24	0.26	0.31	0.33	0.42	0.47	0.54

Table 6: Labor Output Adjusted by All Terms: Changing Shares and Returns

Note: All adjustments use granular age/gender/race groups and are shifted by the group listed in the leftmost column. i.e. Adjusting by race holds age and gender groups constant.

6 Conclusion

The opportunity to participate in the economy and to succeed based on ability and effort is at the foundation of our nation and our economy. Unfortunately, structural barriers and embedded inequities in policies and practices have persistently disrupted this narrative for many Americans.

We have shown that the resulting disparities in economic opportunity constrain our national economic output and leave the talents of millions of Americans underutilized or on the sidelines all together. The effects are cumulative, limiting innovation, invention, and entrepreneurship which set the foundation for growth today and growth in the future [14] [35].

With considerable pressures weighing on U.S. economic potential in coming decades, eliminating disparities in labor market opportunities and outcomes will be critical to producing faster growth and maintaining global competitiveness.

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A Extended Literature Review Summary

Authors	Experiment	Data Sources	Estimate
Gaps in earnings, wages, or income			
Hsieh, Hurst, Jones, Klenow (2019) [9]	Effect on aggregate productivity of the convergence in the occupational distribution between 1960 and 2010 through the prism of a Roy model.	Synthetic panel data on occupations and wages of women and black men relative to white men from 1960 to 2010; data from the decennial Censuses and the 2010-2012 American Community Surveys	Across various specifications, between 20% and 40% of growth in aggregate market output per person can be explained by the improved allocation of talent.
Turner (2018) [11]	Estimate the potential gain in GDP by closing the racial earnings gap resulting from disparities in health, education, incarceration, and employment opportunities.	Population estimates from U.S. Census Bureau; GDP estimates from U.S. BEA; consumer spending from BLS National Consumer Expenditure Survey; earnings from PolicyLink/PERE National Equity Atlas and American Community Survey; incarceration rates from the Sentencing Project; health inequality data from LaVeist, Gaskin, and Richard (2009).	Closing the earnings gap by 2050 would increase GDP by 22%, equivalent to increasing the long-term growth rate by half a percentage point to 2.5% per year. The corresponding gain in 2050 GDP would be $8 trillion.
Truehaft, Scoggins, and Tran (2014) [12]	Calculates what total earnings and economic output would have been in 2012 if racial differences were eliminated and all groups had similar average incomes as non-Hispanic whites. The analysis does not assume that everyone has the same income, rather that the income distributions do not differ by race and ethnicity	GDP from Bureau of Economic Analysis (2012); average annual income and hours of work from American Community Survey (2008-2012)	2012 GDP would have been 14% higher, or $2.1 trillion, in the absence of racial differences in incomes. The analysis also shows that the largest 150 metros, which are the most diverse, would have experienced total GDP gains of 24%.

Authors	Experiment	Data Sources	Estimate
Gaps related to wealth			
Noel, Pinder, Stewart, and Wright (2019) [13]	Estimate the impact of closing the racial wealth gap on U.S. GDP from 2019-2028 using the Oxford model examining income, tangible investments, and stock-market investments as components of wealth.	U.S. Census Bureau 2013-2017 ACS 5-year estimates on home ownership. Bureau of Labor Statistics 2017 Consumer Expenditure Survey. Federal Reserve Board 2016 Survey of Consumer Finances data on stock values.	Real GDP could be 4-6% higher by 2028 if racial wealth gap is closed, translating to an increase of $2,900-$4,300 in GDP per capita.
Peterson and Mann (2020) [10]	Effect of closing four key racial gaps between blacks and whites: wages; education; housing; and investment. Estimated effect on U.S. GDP of closing the gaps 20 years ago. A second experiment estimates impact to GDP over the next five years if those gaps were closed today.	Wages: Bureau of Labor Statistics. Education: College/advanced degree racial gap, National Center for Education Statistics. Housing: Median home price data, National Association of Realtors; Consumer Expenditure Survey, Bureau of Labor Statistics. Investment: Share of black-owned firms, Citi Research.	Closing racial gaps for Blacks 20 years ago could have contributed an estimated $16 trillion to U.S. GDP. Closing the gaps today could add $5 trillion over the next five years, or an average of 0.35 percentage points to U.S. GDP growth per year.
Gaps in innovation			
Bell, Chetty, Jaravel, Petkova, and Van Reenen (2019) [14]	Characterize the factors that determine who becomes an inventor in the United States. Children's chances of becoming inventors vary sharply by race, gender, and parent' socioeconomic class.	Deidentified data on 1.2 million inventors from patent records linked to tax records, New York City school district records 1989-2009.	If women, people of color, and children from low-income families invent at the same rate as white men from high-income families, there would be 4.04 times as many inventors in the U.S.
Cook and Yang (2018) [15]	Identify factors that result in differences in patenting and commercialization among women and African Americans, relative to men and whites. Estimate effect of these differences on GDP per capita.	Data from the 2001, 2003, and 2008 waves of the Survey of Doctoral Recipients to examine the determinants of patent and commercialization activity among PhD-holders and those who commercialize their inventions over time.	GDP per capita could rise by 0.88% to 4.6% with the inclusion of more women and African Americans in the initial stages of the process of innovation.

Authors	Experiment	Data Sources	Estimate
Cook (2014) [16]	This paper uses the rise in mass violence between 1870 and 1940 as an historical experiment for determining the impact of ethnic and political violence on economic activity, namely patenting.	U.S. Patent Office 1900 and 1913 survey conducted by Henry Baker, matched to U.S. Census data along with multiple additional historic data sources. Constructed data set extends from 1870-1940 and includes 726 utility patents granted to African Americans during this period.	The increase of hate-related violence in the late 19th and early 20th centuries depressed patent activity among African Americans by 1% per year, equivalent of a year's worth of African American patent activity.

Table A1: Summary of studies on economic impacts of inequitable opportunity

B Data Appendix

Age, Gender, Race	% Pop	Epop	Hours	% HS	% AC	% BA	% MA	Ahe HS	Ahe AC	Ahe BA	Ahe MA
25-34, male, white	8.9	88.2	42.1	45.1	10.9	32.6	11.4	18.29	21.34	27.14	30.33
25-34, male, black	2.1	78.0	40.9	63.4	9.1	22.2	5.1	15.64	17.18	20.85	25.94
25-34, male, Hispanic	3.1	85.9	41.1	72.8	8.4	14.7	4.1	16.42	19.98	23.67	28.41
25-34, male, other	1.8	83.3	41.0	39.7	7.3	31.9	21.2	17.06	17.99	29.50	32.76
25-34, female, white	7.9	76.9	38.8	15.6	17.2	20.9	25.9	14.66	17.19	23.81	27.02
25-34, female, black	2.2	73.5	38.8	54.1	12.1	23.2	10.6	13.38	14.93	20.41	23.61
25-34, female, Hispanic	2.3	66.7	38.0	57.8	13.3	21.6	7.3	13.74	16.04	21.02	27.07
25-34, female, other	1.6	70.3	38.7	32.9	7.4	35.5	24.2	14.23	17.57	25.08	31.14
...											
55-64, female, other											

Table A2: Example of Our Data Matrix for Education in 2019

We aggregate data from the Current Population Survey (CPS) for years 1990 through 2019 to an annual frequency. The CPS is a long-standing, nationally representative, publicly available data source on earnings and labor market status. Earnings information along with other details of jobs are collected twice during a household survey tenure, once in survey month 4 and again in survey month 16. Survey months 4 and 16 are commonly referred to as the outgoing rotation groups since they are individuals temporarily moving off the sample frame or permanently retiring from the survey. The matched samples of these outgoing rotation groups are known as the MORG files. As such, we restrict our sample to the outgoing rotation groups. We also restrict our sample to prime-age (25-64 years old) civilians who are not self-employed.

We construct our own measure for average hourly earnings so that we can include both salaried and hourly workers.

We create our industry-occupation categorization from harmonized industry and occupation codes. The coarsest standard breakdown of industry and occupation codes includes 14 industry and 11 occupation groups. Making these into industry-occupation pairs creates 154 industry-occupation pairs which is too fine a disaggregation for our analysis to support. Given this, we took the average hourly earnings of the 11 harmonized occupation groups across all years in our sample and kept the 3 occupations with the highest average hourly earnings as their own occupation groups, and then made a 4th occupation group that combined all other 8 occupation groups into one. We did a similar exercise by industry and chose the 5 industries with the highest average hourly earnings, grouping the remaining 9 larger industry groups into one. We then combined these groups into 24 industry-occupation groups.