Technical Change and the Demand for Talent. [*]

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Abstract

Technical change shifts the relative importance of certain economic activities over others, effectively determining the incidence of barriers to the transition of workers across occupations on output and inequality. To what extent has technical change mitigated or exacerbated the incidence of these barriers? We study the link between occupation-specific labor market barriers, as measured in Hsieh *et al.* (2019), and capital-embodied technical change (CETC), as measured in Caunedo *et al.* (2021). We find that CETC mitigated the incidence of labor market barriers on output per worker by 9.1%, between 1984 and 2014. A forecasting exercise over the next 10 years suggests that if the path of CETC follows the one observed during the past 10 years, the gender wage gap should widen by 0.12p.p. per year and the race wage gap should widen by 0.07p.p. per year. The reason is that female and black workers face higher barriers in occupations where CETC rises wages the most. In addition, the model also predicts that absent mitigation policies, the skill-premium should rise at 0.24p.p. per year, twice as fast as the observed change in the last 10 years.

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1 Introduction

To what extent has technical change mitigated or exacerbated the effects of labor market barriers to the transition of workers across occupations? Barriers that hinder worker reallocation across occupations – including social norms and discrimination – determine whether potential gains unleashed by technical change can be fully realized. Technical change shifts the relative importance of certain economic activities over others, effectively determining the incidence of these barriers on output and inequality. In this paper, we study the link between labor market barriers to worker reallocation across occupations, as measured in Hsieh *et al.* (2019), and technical change embodied in capital (CETC), as measured in Caunedo *et al.* (2021). We find that CETC mitigated the incidence of labor market barriers on output per worker by 9.1%, between 1984 and 2014.

To unpack the interplay between technical change and labor market barriers we first highlight that labor market barriers are linked to workers' observable characteristics whereas technical change is linked to productive activities. We consider productive activities at the occupation level and define labor market barriers as those institutional arrangements and societal norms that make workers of similar schooling attainment but different gender or race allocate differently across occupations. For example, traditional gender roles suggest that talented females face barriers to enter precision production occupations, e.g. tool sharpeners, relative to their male counterparts. Technical change over the last half-century has automated many of the activities performed in precision production, effectively lowering the demand for these activities and weakening the incidence of such barriers on aggregate output. At the same time, advances in logistics and retail trade technology have increased the demand for sales occupations, effectively increasing the incidence of barriers facing black workers in these occupations.

Our focus is on a specific form of technical change: CETC, as measured by the decline in the user cost of capital relative to the price of consumption. CETC has been singled-out as a major contributor to economic growth (Greenwood *et al.*, 1997) and wage inequality (Katz and Murphy, 1992; Krusell *et al.*, 2000). Importantly, Caunedo *et al.* (2021) show that trends in CETC across occupations are a strong predictor of shifts in occupational demand in the US. Because the allocation of workers to occupations is mediated by institutional and societal norms, it is natural to study the link between CETC and the incidence of occupation-specific barriers facing workers of different gender and race. To speak to this link, we construct the bundle of capital goods used for occupational production by workers of different race and gender, at different schooling levels. Based on it, we document disparities across demographic groups in occupational capital intensity and CETC.

College educated females are 30% less capital intensive than their male counterparts, on average across occupations; while females with less-than-college are only 5% less capital intensive than males. White females are about 5% more capital intensive than black females, on average, while white males are 15% more capital intensive than black males. These average disparities in capital intensity mask heterogeneity across occupations. The highest dispersion in capital intensity across occupations is reported for black females (log-variance of 0.6) and the lowest for black males (log-variance of 0.46). The dispersion across gender is always higher than that across race, irrespective of schooling attainment. The highest dispersion in capital intensity across groups within an occupation is recorded for technicians, mechanics, and transportation occupations. Turning to CETC, we find that, on average, workers with less-than-college experienced lower CETC between 1984 and 2014 relative to the college-educated (6.1% vs. 6.7% per year). Disparities in CETC across demographic groups are more salient among workers with less-than-college, i.e. the average standard deviation in the rate of technical change across occupations is 2.5% vs. 2% for college educated workers. The bulk of the disparities in CETC are observed for technicians, low-skill services, mechanics, and transportation occupations.

We quantify the interplay between labor market barriers and our novel patterns of CECT by demographics in a sorting model with heterogeneous workers in the tradition of Roy (1951). Our model extends the framework in Hsieh *et al.* (2019) to allow for CETC and occupational differences in the production technology as in Caunedo *et al.* (2021). The technology for production in each occupation differs by the elasticity of substitution between capital and labor, by the capital bundle required for production, and by the productivity of the workers that get assigned to them. Workers of different gender, race, and schooling sort themselves across occupations based on their schooling-specific comparative advantage and the race- and gender-specific barriers they face. These barriers capture, among other forces, taste-based discrimination by the employer as in Becker (1957), attitudes toward working females as in Fernández (2013) and gender differences in raw labor (brawn) endowment as in Galor and Weil (1996). Last, we feed changes in the relative supply of workers to match, among other things, the rise in female labor force participation (see, among others Greenwood *et al.*, 2005) the rise in schooling attainment (Goldin and Katz, 2007), and reversal in the the gender gap in schooling (Goldin *et al.*, 2006).[1] Labor reallocation and between group wage inequality are driven by changes in the relative supply of workers, labor productivity,

[1]Studies that analyze the reversal of the gender gap in schooling include, among others, Olivetti and Petrongolo (2016) and Guvenen and Rendall (2015).

and heterogeneous CETC across capital goods.

Consistently with Hsieh *et al.* (2019), barriers are identified off of the differences in the propensities of workers of different gender and race to choose a given set of occupations and to work with a given set of capital goods, relative to a base group (i.e. white males). We find that the overall dispersion in barriers decreases by 33% between 1984 and 2014. Across demographic groups, the highest dispersion corresponds to barriers facing females, while the strongest decrease over time corresponds to barriers facing black males. The within-occupation dispersion in barriers reflects the dispersion in the capital bundle used by different demographic groups and is therefore unique to this paper. This component accounts for, on average, 38% of the dispersion in barriers, it is most relevant for barriers facing females and black males, and, overall, its importance decreases over time (from 45% to 32%). Females face the highest average barriers in mechanics, transportation, and precision production occupations and the highest within-occupation dispersion in precision production (white females) and low-skill services (black females). Black males face the highest average barriers in managers, professionals, and sales occupations and the highest within-occupation dispersion in precision production. While the average labor market barriers faced by black males tends to increase with the skill requirement of the occupation, that is not so for females.

We quantify the role of CETC for the incidence of labor market barriers via a counterfactual exercise on our calibrated model. Our calibration targets labor market outcomes and capital bundles by occupation across demographic groups, for given elasticities of substitution between capital and labor in each occupation (as estimated in Caunedo *et al.*, 2021) and CETC. Our counterfactual exercise computes output losses attributable to labor market barriers in 2000, the mid-year in our sample, taking the path of CETC between 1984 to 2014 as given. We find output losses of the order of 4.0% in 1984, associated to the 2000 labor market barriers. Fixing the barriers, we find that these output losses decrease to 3.6% in 2014. We conclude that CETC of the magnitude measured between 1984 and 2014 decreased the incidence of labor market barriers by 9.1%. This lowered incidence is mostly accounted for by barriers facing females: CETC lowers this incidence by 8.4% for white females and by 11% for black females. Differently, CECT increases the incidence of barriers facing black males, by 3%. Given the profile of barriers workers face, females move toward managers and professionals occupations in response to CETC, while black males move toward mechanics and transportation occupations.

Importantly, while CETC lowers the incidence of barriers on output per worker, it fuels wage inequality. The model predicts that a rate of CETC commensurate with the one observed between 1984 and 2014 would widen the gender wage gap by 6.67p.p., the race wage gap by 3.74p.p., and the skill premium by 10.99p.p.. For comparison, the gender and race gap closed by 19.36 p.p. and 9.23p.p. between 1984 and 2014, respectively, while the skill premium rose by 15.03p.p.. The observability of CETC allows us to predict the future incidence of barriers on wage inequality and therefore provide a diagnostic tool that can help direct mitigation policies.

So absent mitigation policies, what would be the impact of CETC on the gender and the race wage gap, as well as on the skill-premium? Via an in-sample prediction exercise, we first establish that CETC is a strong predictor of the wage gaps to white males for groups of different gender, race, and schooling.[2] Importantly, it can account for the observed slow-down in the pace of the skill-premium in recent years. Then, we use CETC to predict the evolution of wage inequality over the coming 10 years. That is, we take the calibrated economy in 2014 and input the path of the user-cost of capital relative to the price of consumption predicted from the average yearly CETC observed during the 2004-2014 period, to forecast wage inequality between 2015 and 2024.

We find that, if the path of CETC follows the one observed between 2004 and 2014, the skill premium should rise by 0.24p.p. yearly during the forecast period. This increase is twice as high as the observed change in the previous 10 years, when the skill premium declined by 0.14p.p. per year. At the same time, the gender wage gap is predicted to widen by 0.14p.p. per year, and the race wage gap to widen by 0.07p.p. per year. The reason is that female and black workers face higher barriers in occupations where CETC rises the demand for labor. Among those with less-than-college, females face high labor market barriers in occupations where this schooling group is particularly productive (mechanics and transportation). It is instead the labor market barriers in managerial occupations the source of wage divergence for college-educated females and black males relative to white males.

Literature review. This paper contributes to the growing literature studying the effects of discrimination in the market place, see Altonji and Blank (1999) for a summary of the tradition started by Becker (1957). We extend the Roy (1951) framework in Hsieh *et al.* (2019) and their measurement to incorporate capital in occupational production and formally model CETC. We depart from Caunedo *et al.* (2021) by modelling different capital bundles for different demographic groups within the same occupation. This dimension

[2]White females with less-than-college are an exception to the quality of the prediction: contrary to the data, CETC generates an increase in the gender wage gap for this group. This is a consequence of CETC increasing the price of labor in mechanics and transportation occupations, which is where this demographic group faces high labor market barriers.

of heterogeneity is fundamental for assessing the interplay between technical change and barriers.

Understanding differences in occupational choice by gender and race is important due to the tight link of these differences with skill misallocation and aggregate productivity. Various papers link between the labor market prospects for females and structural change, (Lee and Wolpin, 2006; Rendall, 2010; Goldin and Katz, 2012; Goldin, 2014; Ngai and Petrongolo, 2017). We contribute to this literature by studying the role of CECT in determining labor market prospects for females. While the literature studying the origins of the racial gaps in wages, as well as the drastic changes in black workers' labor market prospects in the second half of the twentieth century is extensive (Smith and Welch, 1989; Altonji and Blank, 1999; Chetty *et al.*, 2019), the link between labor market barriers for workers of different race and aggregate outcomes has received less attention. A key contribution of our analysis is to show the disparate effects that CETC has had on workers of different race and the barriers that black males faced in reaping the benefits associated to CETC.

The rest of the paper is organized as follows. Section 2 presents motivating facts characterizing systematic differences in occupational capital intensity and CETC by gender and race. Section 3 presents an accounting framework to identify barriers to worker reallocation from their observed occupational choices. Section 4 quantifies the incidence of those barriers on output per worker and inequality. Section 4.1 presents in and out of sample predictions on wage inequality from the structural model. Section 4.2 discusses additional margins that could be incorporated in future work, including labor force participation and human capital accumulation, while Section 5 concludes.

2 Facts on capital and CETC by demographics

To motivate our study of the link between occupation-specific labor market barriers facing workers of different demographics and CETC, we document systematic disparities by gender and race in their experienced capital intensity and speed of CETC across occupations as well as in their occupational labor market outcomes.

We exploit two data sources, between 1984 and 2014: the March Current Population Survey (CPS) and the Dataset in Caunedo *et al.* (2021).[3] We consider 326 3-digit occupations for which we consistently observe labor and equipmen over time and aggregate them in

[3]We also have comparable measures to the CPS form the Census, with the caveat that these are available at 10-year frequency prior to year 2000.

9 occupational groups, which correspond to the 1-digit occupational grouping of the US census – that is, managers, professionals, technicians, sales, administrative services, low-skilled services, mechanics and transportation, precision workers and machine operators (we exclude agriculture and extractive occupations).

Labor market outcomes. We compute full-time equivalent workers by occupation and hourly wages to document patterns of occupational employment and wage inequality.[4]

Table I displays the change in occupational employment of white males, between 1984 and 2014. Consistent with the vast evidence on employment polarization (Acemoglu and Autor, 2011; Autor and Dorn, 2013), we find that white males became more likely to work in high-skill occupations (managers and professionals) and low-skill services. These employment shifts were compensated with a lower propensity to work in middle-skill occupations, including sales, precision, and machine operators occupations. For white females the change in the propensity to work in high-skill occupations was more pronounced than for white males (between 2.9% and 6.2% higher), while the employment gains in low-skill occupations were comparable to those of white males. Interestingly, the bulk of the employment losses for white females between 1984 and 2014 was concentrated in administrative services occupations, with a total decline of 12.1%. The changes in the occupational allocation of black females are comparable to those of white females, both in direction and size. The largest differences are for sales occupations, where black females gained three times more employment than white females (from no changes for white females to an increase of 3% for their black counterparts), administrative services where the fall in employment was of 8.4% compared to the 12.1% for white females, and professionals, where gains in employment for black females were 2.2% lower than for black females. These disparities are more prominent among females with less-than-college than among females with college.[5] Finally, black males also gained employment in high-skill occupations relative to white males, but these gains were lower than those observed for females (between 0.3% and 1.2% relative to black females). Black males lost employment in low-skill services relative to white males, while gaining employment in sales occupations, similarly to their female counterparts.

Figure I presents the time series for the gender gap, i.e. the log of the ratio of average hourly wages for males and females; the race gap, i.e. the log of the ratio of average hourly

[4]We compute hourly wages in the CPS sample by dividing labor income by total hours worked in the subsequent CPS. We deflate wages by the price of personal consumption expenditures provided by the BEA.

[5]Once we disaggregate by schooling attainment we find little difference in occupational choices for college educated females in high-skill occupations, although black females are more likely to work in low-skill services. Females with less-than-college are 3 times more likely to work in sales occupations if black, and half less likely to work in low-skill services.

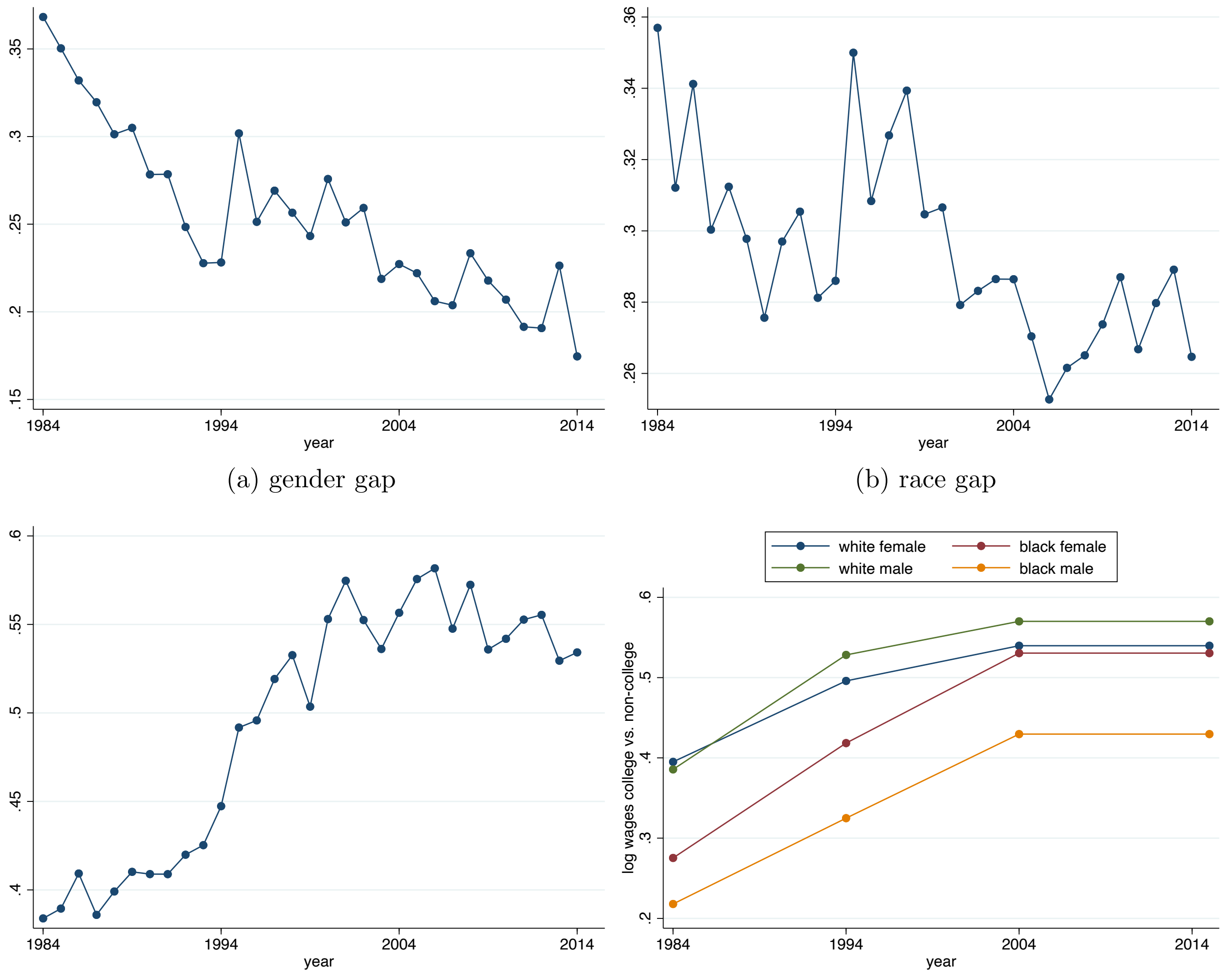
Table I: Occupational employment.

	white male			change relative to white male		
	1984	2014	change	white female	black female	black male
Managers	17.5%	19.8%	2.3%	2.9%	3.1%	2.8%
Professionals	13.8%	16.6%	2.7%	6.2%	4.0%	2.8%
Technicians	3.4%	2.9%	-0.6%	1.1%	1.5%	0.4%
Sales	11.9%	10.4%	-1.4%	1.4%	4.4%	4.1%
Administrative Serv.	6.1%	6.1%	0.0%	-12.1%	-8.5%	0.0%
Low-skilled serv.	7.6%	10.4%	2.8%	0.8%	-2.1%	-3.3%
Mechanics & Transport	24.9%	24.8%	-0.1%	0.0%	-0.6%	-4.4%
Precision workers	6.4%	3.4%	-3.0%	2.6%	2.6%	0.4%
Machine operators	8.4%	5.6%	-2.8%	-2.9%	-4.4%	-2.8%

This table displays the distribution of employment in each 1-digit occupation for white males in 1984 and in 2014. The right panel shows the difference in employment changes over time for each demographic group relative to white males. All entries are in percent. Source: BEA, CPS, and own computations.

wages for blacks and whites; and the skill premium, i.e. the log of the ratio of average wages of college educated and les-than-college educated workers. It also presents the evolution of the skill premium for different demographic groups. The observed trend in the gender wage gap is in line with the extensive literature documenting convergence (Blau and Kahn, 2017). In our sample, the gender wage gap closed by 20p.p. between 1984 and 2014, with average hourly wages for males being 18p.p. higher than their female counterparts by 2014. An important contributor to the decline in wage gaps is that the likelihood of observing females in high-skill occupations has increased over time, see Keller (2019) and our previous evidence.

The race gap closed by 10p.p. over the same period: the average wages of white workers are 30p.p. higher than those of black workers by 2014. At the same time, the skill premium has increased by more than 16p.p. although the increased plateaued since 2000, consistent with Goldin and Katz (2007), while the average wages of workers with college have remained 55p.p. higher than those with less-than-college. This aggregate trend of the skill premium hides heterogeneous paths across demographic groups. For example, the increase in the skill premium was larger for black workers than than for white workers, and slightly higher for black females. In terms of levels, the skill premium is comparable for females of different race towards the end of the period of study, indicating that the reminder of the race gap for females is likely related to systematic differences in schooling attainment between white and black females. This result is consistent with patterns of intergenerational wage gaps reported in Chetty *et al.* (2019), where black females earn more than their male counterparts conditional on parental income, and the fact that the race gap in college attendance rates



(a) gender gap (b) race gap

(c) skill-premium (d) premium by group

Figure I: Hourly wages by gender, race, and schooling.

The top panel plots the gender wage gap computed as the log of the ratio of average hourly wages of males and females (left) and the race wage gap computed as the log of the ratio of average hourly wages of black and white workers (right). The bottom panel plots the skill premium computed as the log of the ratio of average hourly wages of college and less-than-college educated workers (left), and the skill premium by demographic groups (right).

is substantially lower for females than males (2.8% versus 6.5%). Last, the skill premium is highest for white males and lowest for black males, with a difference of 16 p.p. towards the end of the period.

Occupational capital. We use the dataset and methodology in Caunedo *et al.* (2021) to construct a measure of capital per worker by demographic group (gender, race, and schooling), equipment category, and 1-digit occupation in the Census classification.[6] We start with the information on capital per worker for each equipment category and 3-digit occupational classification, that is available in the dataset. For each demographic group and equipment category, we aggregate to the 1-digit occupational classification by multiplying for the number of full-time equivalent workers in the 3-digit occupation and demographic group. This aggregation can be done linearly to the 1-digit occupational classification to obtain k_{o_jht}, i.e. capital of equipment good j in 1-digit occupation o at time t for demographic group h. Given that the equipment assignment at the 3-digit occupation does not vary by worker demographics, variation in the capital bundle used by a demographic group at the 1-digit occupation stems from disparities in the 3-digit allocation of workers across demographics. For example, among managerial occupations, the combination of equipment goods used by financial managers differ from those used by construction inspectors; among machine operators, the equipment goods used by assemblers of electrical equipment differ from those used by painting and decorating occupations. At the same time, females and males sort differently into these more disaggregated occupations, generating variation in the stocks used at the 1-digit occupation.

Then, we construct the apital per demographic group at the occupation level, k_{oht} or occupational capital. We work under the assumption of a constant returns aggregator for capital services of different equipment within each occupation-demographic bin. Such an assumption, implies that the growth rate of occupational capital for a demographic group is a weighted average of the growth rates in capital per equipment type, demographics, and occupation, $\gamma_{k_{o_j}ht}$, with weights equal to the expenditure shares,

$$\gamma^k_{oht} = \sum_j \omega_{o_jht}\gamma^k_{o_jht}, \quad \text{for: } \omega_{o_jht} = \frac{\lambda^k_{jt}k_{o_jht}}{\sum_j \lambda^k_{jt}k_{o_jht}},$$

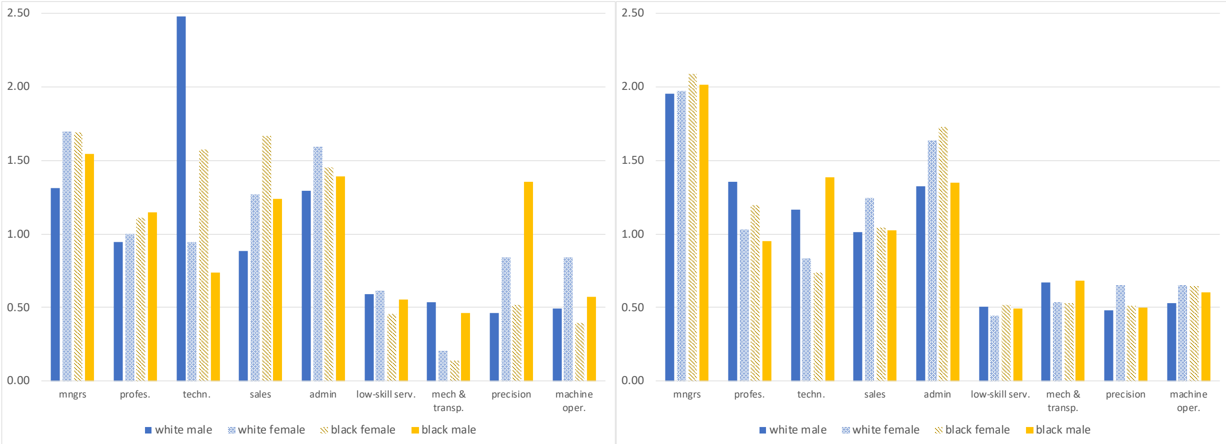
The construction of these weights requires a measure of the user cost of capital per equipment type, which we build from quality-adjusted measures of the price of capital relative to consumption and the standard no-arbitrage condition, Jorgenson (1963).[7]

In each occupation and demographic group, we initialize the series in 1984 to equalize the

[6] The dataset, for aggregated stocks at 3-digit and 1-digit occupational classification, is available for download at https://capitalbyoccupation.weebly.com.

[7] The user cost of capital satisfies

$$\lambda^k_{jt} = \frac{\lambda^c_{jt-1}}{\lambda^c_{t-1}}\left[R - (1-\bar{\delta}_{jt})\frac{\frac{\lambda^k_{jt}}{\lambda^c_t}}{\frac{\lambda^k_{jt-1}}{\lambda^c_{t-1}}}\right],$$



(a) college

(b) less-than college

Figure II: Capital per worker by occupation relative to the group mean.

The figure plots the ratio between the average capital per worker in an occupation and demographic group and the mean capital per worker for a demographic group. The left panel presents results for college-educated workers while the right panel presents the same statistics for workers with less-than-college. Statistics are presented by gender and sex.

amount of capital expenditures on all equipment categories in the occupation-demographic bin. Then, iterating forward,

$$k_{oht} = k_{oht-1} e^{\gamma^k_{oht}}, \quad \text{for:} \;\; k_{oh1984} = \sum_j \lambda^k_{j1984} k_{o_j h1984}. \tag{1}$$

Finally, CETC at the occupation level by demographic group is computed following Caunedo *et al.* (2021). In particular, we use the implied user cost of capital from the ratio of capital expenses by demographic group at the 1-digit occupational level, and occupational capital by demographics, k_{oht}:

$$r_{oht} = \frac{\sum_j \lambda^k_{jt} k_{o_j ht}}{k_{oht}}.$$

Figure II shows occupational capital per worker across race and gender. We differentiate workers by schooling attainment, as this dimension is particularly important when reporting measures of capital intensity and CETC in view of previous studies finding CETC to be a key driver of the skill premium in the post-war US (Krusell *et al.*, 2000). There are sizeable disparities across demographic groups in the average capital per worker as well as

where λ^c is the price of consumption, λ^k_j is the (quality-adjusted) price of equipment of type j, and $\bar{\delta}$ corresponds to the average physical depreciation in the relevant decade of analysis. The gross return on a safe asset is set at 2% per year, for $R = 1.02$.

Table II: CETC by occupation, gender and schooling.

	CETC	CETC relative to white males w/college						
		college			less-than college			
	white male (1)	white female (2)	black female (3)	black male (4)	white male (5)	white female (6)	black female (7)	black male (8)
Managers	-8.4%	0.1%	0.1%	0.2%	-0.1%	0.0%	0.0%	-0.1%
Professionals	-6.2%	0.1%	-0.1%	0.9%	-0.1%	0.5%	-0.2%	-0.6%
Technicians	-8.0%	2.8%	3.5%	2.6%	2.5%	3.2%	-0.3%	3.7%
Sales	-9.4%	0.1%	-0.1%	0.2%	0.0%	0.1%	-0.2%	0.1%
Administrative Serv.	-9.7%	0.7%	-0.3%	1.0%	0.2%	0.4%	0.5%	0.5%
Low-skilled serv.	-6.4%	0.7%	0.5%	0.8%	1.1%	1.9%	2.8%	1.7%
Mechanics & Transport	-4.3%	0.0%	0.4%	-0.2%	2.9%	-0.1%	4.4%	-0.2%
Precision workers	-6.7%	1.6%	-3.4%	1.3%	0.1%	1.6%	-0.2%	2.0%
Machine operators	-5.3%	0.3%	0.1%	0.3%	-0.1%	0.4%	2.3%	0.5%

This table displays the annualized decline in the user cost of capital relative to consumption for the base demographic group, i.e. white males with college, in each 1-digit occupation, Column (1) . Columns (2-4) present the difference in the decline in the user cost of capital relative to the base group for college-educated workers; while Columns (5-8) present the difference for non-college-educated workers. A negative number implies stronger CETC. Source: BEA, CPS, and own computations.

in its dispersion across occupations. For college-educated white males, capital per worker is highest in managers and technicians occupations, whereas for college-educated white females the highest capital per worker is recorded for managers and administrative services. The distribution of capital per worker is more similar across females of different race compared to across males of different race. The larger differences across males of different race are concentrated in technicians and sales occupations. Still, most of the disparities in capital intensity are driven by gender rather than race and are concentrated in technicians, mechanics, and transportation occupations. The log-variance of the occupational capital per worker across demographic groups for technicians is 0.4 for college-educated workers and 0.15 for those with less-than college (the highest log-variance for this educational group). The log-variance of occupational capital per worker is highest for college-educated workers in mechanics and transportation occupations (0.69).

Differences in occupational capital and its composition generate differences in the path of the cost of capital used by workers of different demographic groups for occupational production. Table II presents disparities in the decline of the user cost of occupational capital, our measure of CETC, by gender and race, between 1984 and 2014. The occupational pattern of CETC for college-educated white males is consistent with the aggregates reported in Caunedo *et al.* (2021): the strongest technical change is in sales and administrative service occupations and the weakest is in mechanics and transportation occupations (henceforth, mechanics for short). White college-educated females display similar patterns of occupational CETC. The largest difference arises for technicians and mechanics, where CETC was about 2.5p.p. slower in the jobs that these females perform relative to males, followed by low-skill services, with a 1p.p. slower CETC. For black college-educated females the occupational pattern of CETC is qualitatively similar to that of their white counterparts, albeit technical change was quantitatively slower. For black college-educated males, two features arise. First, CETC was 3.4% slower for them in technicians occupations relative to white males and second, CETC was 3.7% faster in precision occupations. Turning to workers with less-than-college, we find that these workers faced slower CETC in technicians and precision occupations relative to their college-educated counterparts. These two occupations display the greatest heterogeneity in CETC across gender and race, followed by low-skill services, albeit, consistently with the evidence above, the disparities in this latter occupation are concentrated on the gender dimension.

The differential patterns of occupational capital intensity and CETC across gender and race already hints to the disparate effects that CETC may have had on the incidence of labor market barriers facing different demographic groups. However, while these patterns are interesting in their own right, their impact on output and inequality ultimately depends on how complementary or substitutable to capital the tasks workers perform in the occupation are as well as on the linkages across occupations. We evaluate such impact in a general equilibrium accounting framework, quantified to match the labor market outcomes described in this section and the pattern of capital-labor complementary across occupations documented in Caunedo *et al.* (2021).

3 Accounting framework

In this section, we describe the accounting framework that allows us to identify barriers to occupational mobility and study the role of CETC in determining the incidence of these barriers on aggregate output and wage inequality. Our modeling of CETC follows Caunedo *et al.* (2021) while our identification of the barriers follows the strategy in Hsieh *et al.* (2019) and exploits differential worker's assignment to occupations in the tradition of Roy (1951). The main challenge to the identification is that workers allocate across occupations following their comparative advantage, as well as the barriers they face in the labor market.

We associate observed disparities in the occupational choice between workers of different gender and race to barriers in the labor market and disparities across schooling groups to comparative advantage.

Our framework abstracts from human capital investment and labor force participation. In Section 4.2 we discuss the implications for our findings of incorporating these margins.

3.1 Environment

Time is discrete and indexed by t. The economy is populated by a continuum of heterogeneous workers indexed by i. Workers are divided into a finite number of demographic groups, indexed by h. These groups are defined on the basis of the gender g, schooling e, and race r of the worker – that is, $h \equiv (g, e, r)$. The total supply of workers of type h at a point in time is exogenously given by π_{ht}. Workers value consumption and are endowed with one unit of time, which they inelastically supply to the market.

There are three types of goods: a final good, J-types of equipment goods indexed by j, and O-types of occupational goods indexed by o.[8] Occupational goods are combined through a CES aggregator to produce final goods. Final goods can be used for consumption or to produce equipment. Equipment goods are produced using a technology that determines the amount of new equipment of type j that can be purchased for one unit of the final good. Changes in this rate of transformation formalize the notion of CETC and map one-to-one to the decline in the relative price of investment to consumption, as in Greenwood *et al.* (1997). Equipment fully depreciates after usage within the period.

An occupation is a technology that combines equipment of different types and labor of different groups to produce occupational output. Occupations differ in two dimensions: the elasticity of substitution between capital and labor and the equipment bundle used by workers. An important feature of the motivating facts in Section 2, is that equipment bundles are different for workers of different demographic groups within the same occupation. To model this heterogeneity we consider an occupation as a technology that combines the output from different production units, where a production unit is defined by the equipment good and the occupation o_j.

Workers are allocated to occupations and to production units within an occupation. Because efficiency units of labor are fungible, the total efficiency units of labor used in production in an occupation is equivalent to the one obtained with assuming that a worker

[8] For example, in line with the discussion in Section 2, one can think of equipment types to map to the equipment categories considered by NIPA.

splits its own efficiency units across different capital types within an occupation. For white males, the allocation across production units is assumed to follow comparative advantage. For other demographic groups, the allocation differs from that of white males only through labor market barriers. The differences in the equipment bundles used by demographic groups within an occupation constructed in Section 2 is a byproduct of worker selection into 3-digit occupations within the 1-digit categories. Through the lens of our model, these differences in equipment bundles within a 1-digit occupation map into labor market barriers that are production-unit specific.

Workers. Worker i supplies $\eta_{o_jt}(i)$ efficiency units of labor when employed in production unit o_j at time t. Each worker draws a profile of $\eta \equiv \left\{\{\eta_{o_j}\}_{j=1}^{J}\right\}_{o=1}^{O}$ across production units and occupations at each point in time from a multivariate Fréchet distribution with cumulative density function $F_{o_jht}(\eta) \approx \exp(-\sum_{o_j} T_{o_jht}\eta_{o_j}^{-\theta})$. The parameters θ and T_{o_jht} govern the dispersion of efficiency units of labor across workers.

The group-h common shifter in productivity T_{o_jht} determines the absolute advantage of the demographic group. For example, the average efficiency units supplied by a college educated working for an hour of time might be higher than those supplied by a less-than-college educated. The dispersion of T_{o_jht} across production units and demographic groups determines the structure of comparative advantage associated to labor. The comparative advantage of a worker of type h relative to one from group h' when working in occupation o relative to occupation $o^{'}$ with capital of type j is:

$$\frac{T_{o_jht}}{T_{o_j^{'}ht}} / \frac{T_{o_jh't}}{T_{o_j^{'}h't}}, \tag{2}$$

with a comparative advantage in favor of group h if the ratio is greater than 1.

Workers face labor market barriers, which generate wedges between the marginal product of labor and the wages they receive. These barriers capture, among other forces, taste-based discrimination by the employer as in Becker (1957), attitudes toward working females as in Fernández (2013) and gender differences in raw labor (brawn) endowment as in Galor and Weil (1996). The barrier that a worker of demographic group h, in production unit o_j faces at time t is τ_{o_jht}. In the quantitative exercise, we normalize the barriers faced by white males (wm) of all schooling groups to $\tau_{o_jh^{wm}t} = 0$. Therefore, barriers faced by females and black individuals are measured relative to their white-male counterparts of the same schooling group.

A worker i in group h who provides $\eta_{o_jt}(i)$ efficiency units to production unit o_j receives compensation:

$$w_{o_jht}(i) \equiv (1 - \tau_{o_jht})\eta_{o_jt}(i)\lambda^n_{o_jt}.$$

Workers maximize their consumption, $c_{o_jht}(i) = w_{o_jht}(i)$ (and therefore instantaneous utility), by choosing the production unit that yields the highest compensation. Hence, given a set of wages per efficiency units $\{\{\lambda^n_{o_jt}\}_{o=1}^{O}\}_{j=1}^{J}$, the problem of worker i in demographic group h reads:

$$o^{\star}_{jht}(i) \equiv \arg\max_{o_j}\{w_{o_jht}(i)\}. \tag{3}$$

Occupational good producer. Occupational output is the sum of the output produced by occupational production units, y_{o_j}:

$$y_{ot} = \sum_j y_{o_jt}. \tag{4}$$

Each occupational production unit uses a CES technology in equipment of a given type and labor, with an elasticity of substitution that depends on the occupation:

$$y_{o_jt} = \left[\alpha k_{o_jt}^{\frac{\sigma_o - 1}{\sigma_o}} + (1-\alpha)(n_{o_jt})^{\frac{\sigma_o - 1}{\sigma_o}}\right]^{\frac{\sigma_o}{\sigma_o - 1}}, \tag{5}$$

where n_{o_jt} are the efficiency units of labor of different demographic groups, $n_{o_jt} = \sum_h n_{o_jht}$, and k_{o_jt} are the efficiency units of capital in production.

There is a continuum of households who operate the production technologies for occupational output. We assume that these households have identical preferences and, following Becker (1971), discriminate workers of certain groups. As in Hsieh *et al.* (2019), we model taste discrimination as lower utility of the owner when hiring a worker of a group he dislikes, d_{o_jh}, and we assume that the disutility of hiring a certain group might differ by the equipment being allocated them. For example, females may be particularly discriminated in managerial occupations that intensively use hardware, e.g. a manager at a garage, relative to the discrimination they face in managerial occupations that less intensively use hardware, i.e. a manager in a coffee shop.[9]

The utility of the household operating the production technology for occupational output

[9]This equipment-specific discrimination allows us to rationalize systematic disparities in the bundle of capital used by different demographic groups within a 1-digit occupation. These differences stem from differences in the allocation of workers to the 3-digit occupations and the equipment of different types allocated to them.

is separable across production units:

$$U_{ot} \equiv \underbrace{\sum_j (\lambda_{o_jt} y_{o_jt} - \lambda_{jt} k_{o_jt} - \lambda^n_{o_jt} \sum_h (1-\tau_{o_jht}) n_{o_jht})}_{\text{profits}} - \underbrace{\sum_j \sum_h d_{o_jht} n_{o_jht}}_{\text{utility loss via discrimination}},$$

where λ_{ot} is the occupational price, and λ_{jt} is the price per efficiency unit equipment. The optimal demand of efficiency units of equipment and labor in the occupation solves:

$$\max_{\{k_{o_jt}\}_j, \{n_{o_jht}\}_{jh}} U_{ot}. \tag{6}$$

Final good producer. The final consumption good is produced combining occupational goods using a CES technology:

$$y_t = \left(\sum_o \omega_{ot}^{1/\rho} y_{ot}^{(\rho-1)/\rho} \right)^{\frac{\rho}{\rho-1}}, \tag{7}$$

where ρ is the elasticity of substitution across occupational goods. Changes in ω_o over time are isomorphic to demand shifters. They capture, for example, the increase in demand for low-skill services discussed by Autor and Dorn (2013); and the increase in demand for skill-intensive output discussed by Buera *et al.* (2015).

A producer facing a final good price λ^y_t and prices of occupational goods λ^y_{ot} maximizes profits:

$$\max_{\{y_{ot}\}_{o=1}^O} \lambda^y_t y_t - \sum_o \lambda^y_{ot} y_{ot}. \tag{8}$$

Capital producer. Each equipment good j is produced with a linear technology in the final good. Let q_{jt} be the rate of transformation for capital-j.

A producer facing a price of equipment λ^k_{jt} and a price of the final good λ^y_t demands x_{jt} units of final output to maximize profits:

$$\max_{\{x_{jt}\}} \lambda^k_{jt} q_{jt} x_{jt} - \lambda^y_t x_{jt}. \tag{9}$$

3.2 Equilibrium

We characterize the equilibrium prices and allocations of labor and capital. We start by defining equilibrium, given a set of technological parameters $\{\omega_o\}_{o=1}^O$, $\{q_j\}_{j=1}^J$, a set of utility loss parameters, average efficiency units, barriers, and scale parameters $\{\{\{d_{o_jh}, T_{o_jh}, \tau_{o_jh}\}_{j=1}^{J}\}_{o=1}^{O}\}_{h=1}^{H}$, and the measure of workers by demographic group, $\{\pi_h\}_{h=1}^{H}$.[10]

Definition. A competitive equilibrium consists of (1) consumption and labor decisions for workers of each type i and demographic group h, $\{o^\star_{jh}(i), c_{o^\star_j h}(i)\}_{h=1}^{H}$, (2) labor, capital and output allocations across production units, $\{\{\{\{n_{o_jh}\}_{h=1}^{H}, k_{o_j}, x_j\}_{j=1}^{J}, y_o\}_{o=1}^{O}, y\}$; such that given prices $\{\{\{\{\lambda^n_{o_jh}\}_{h=1}^{H}, \lambda^k_j\}_{j=1}^{J}, \lambda^y_o\}_{o=1}^{O}\lambda^y\}$:

1. Workers maximize wages, equation 3;
2. The utility in all production units is maximized, equation 6;
3. Profits in final output, and capital production units are maximized, equations 8, 9;
4. Perfect competition in the production unit sector implies that $\tau_{o_jh} = d_{o_jh}/\lambda^n_{o_j}$;
5. The labor market for each production unit clears, i.e., $n_{o_jh} = \int_{i\in\Omega^h_{o_j}} \eta_{o_j}(i)\pi_h dF_h(i)$, where $\Omega^h_{o_j}$ identifies the set of workers with $(o_j)^\star_h(i) = o_j$;
6. The market for each equipment-j clears, $\sum_{j=1}^{J}\sum_o k_{o_j} = k_j = q_j x_j$;
7. The market for final output clears, i.e. $\sum_h \int_i c_{o^\star_j h}(i) + \sum_j x_j + \sum_{o_jh} d_{o_jh}n_{o_jh} = y$.

Input and output prices across production units. From the zero-profit condition for each occupational production unit, we express the wage per efficiency unit of labor as a function of the price of occupational output and the price of equipment:

$$\lambda^n_{o_jt} = \left(\left(\frac{1}{1-\alpha_o}\right)^{\sigma_o}(\lambda^y_{ot})^{1-\sigma_o} - \left(\frac{\alpha_o}{1-\alpha_o}\right)^{\sigma_o}(\lambda^k_{jt})^{1-\sigma_o}\right)^{\frac{1}{1-\sigma_o}}. \tag{10}$$

The wage per efficiency unit does not equalize across production units because workers are not equally productive across them, i.e. they draw different efficiency units depending on the production unit $\{\eta_{o_jht}(i)\}$, as in Roy (1951). Note that the wage per efficiency unit is identical across demographic groups in the same occupations and for the same equipment good. Importantly, the equilibrium wage per efficiency unit in each production unit adjusts so that disparate trends in price of equipment are consistent with a common output price for all production units within the occupation.[11]

[10] This version abstract from labor force participation but this is a dimension that should be incorporated in future versions.

[11] Wages adjust so that equilibrium allocations are interior despite a linear output aggregator at the occupation level, equation 4.

From the zero-profit condition of the capital producer, the price of equipment-j equals the inverse of the exogenous rate of transformation from consumption, $\lambda^k_j = 1/q_j$.

The optimal demand from the final good producer characterizes occupation output prices,

$$\lambda^y_{ot} = \lambda^y_t \left(\omega_{ot}\frac{y_t}{y_{ot}}\right)^{\frac{1}{\rho}}, \tag{11}$$

where λ^y_t is the price index for the final good and which we normalize to 1 at each point in time, $\lambda^y_t = (\sum_o \omega_{ot}(\lambda^y_{ot})^{1-\rho})^{\frac{1}{1-\rho}} = 1$.

Workers' labor supply. The probability that worker i of group h chooses occupation o and works with equipment j is:

$$\pi_{o_jht} \equiv \text{Prob}\left(w_{o_jht}(i) > w_{o'_{j'}ht}(i)\right) \ \ \forall o' \neq o \text{ and } \forall j' \neq j.$$

Workers choose the occupation that yield the highest compensation for them. In addition, they are also endogenously allocated to the equipment good they are most productive with.

Replacing equilibrium wages and using the properties of the Fréchet distribution, we solve for the allocation of workers of group h:

$$\pi_{o_jht} = \frac{T_{o_jht}((1-\tau_{o_jht})\lambda^n_{o_jt})^\theta}{\sum_{o',j'} T_{o'_{j'}ht}((1-\tau_{o'_{j'}ht})\lambda^n_{o'_{j'}t})^\theta}. \tag{12}$$

Workers' expected wages. The average hourly wages of workers of type h in production unit o_j are the product of the wage per efficiency unit, the labor market barrier, and the average efficiency units supplied, $w_{o_jht} = (1-\tau_{o_jht})\lambda^n_{o_jt}E(\eta|o_jht)$. Using equation 12 these wages are:

$$w_{ht} = w_{o_jht} = \left(\sum_{o,j} T_{o_jht}((1-\tau_{o_jht})\lambda^n_{o_jt})^\theta\right)^{\frac{1}{\theta}} \Gamma(1-\frac{1}{\theta}). \tag{13}$$

The equilibrium of the model predicts no differences in the average wages of a group h across production units. The assumption of i.i.d. Fréchet draws implies that selection effects perfectly offset differences in productivity and barriers across production units (or mean efficiency of the workers). For example, an increase in the mean worker productivity associated to occupation o increases the returns to working in that occupation. This increases the number of workers that choose such an occupation and therefore decreases the efficiency units of the inframarginal worker, pushing average wages down.

Table III: Parameters chosen without solving the model.

Parameter	Symbol	Value	Source
Fréchet distribution, shape	θ	1.30	Caunedo *et al.* (2021)
Final output prod., demand elasticity	ρ	1.33	Caunedo *et al.* (2021)
Production units prod., elasticity of substitution, k-l	$\{\sigma_1, \sigma_2, \sigma_3\}$	{0.93, 0.86, 0.65}	Caunedo *et al.* (2021)
	$\{\sigma_4, \sigma_5, \sigma_6\}$	{1.38, 2.18, 1.32}	
	$\{\sigma_7, \sigma_8, \sigma_9\}$	{0.73, 2.06, 1.41}	
Production units prod., capital share	α	0.24	Burstein *et al.* (2013)

This table lists the parameters that are set outside of the model. The occupational index, o, refers to the following occupations: 1 managers, 2 professionals, 3 technicians, 4 sales, 5 administrative services, 6 low-skill services, 7 mechanics and transportation, 8 precision production, 9 machine operators.

3.3 Parameterization

We calibrate the model economy to replicate labor market outcomes and capital bundles by occupation across demographic groups. We consider 8 demographic groups defined by gender (females and males), race (black and white), and two schooling groups (less-than 4-year of college and 4-year of college or more). We consider 17 equipment goods, which correspond to the 24 equipment categories considered in NIPA, for: *Furniture and fixtures* merged with *Office and accounting equipment*; *Ships and boats*, *Railroad equipment*, *Cars and trucks* and *Other equipment* merged in one group; *Medical instruments* merged with *Non-medical instruments*; *Agricultural* merged with *Mining*; and *Electrical equipment* merged with *Electrical transmissions and industrial apparatus*.[12]

Our parameterization strategy borrows from Hsieh *et al.* (2019) and Caunedo *et al.* (2021). First, we list the parameters that are chosen without solving the model, either set a-priori or taken from the data. Then, we describe calibration targets of the remaining parameters and model performance.

Parameters set without solving the model. Table III lists the parameters of our accounting framework that we take from previous literature. We borrow estimates of the elasticity of substitution between capital and labor in occupational output production, σ_o, of the elasticity of substitution across occupational output, ρ, and of the shape parameter of the Fréchet distribution, θ, from Caunedo *et al.* (2021). We set the equipment share in the technology of the occupational production units, α, in line with Burstein *et al.* (2013).

We measure the growth rate of the price of each equipment good relative to consumption,

[12]The merging across some of the NIPA equipment categories is needed for the measurement of the labor market barriers, which requires positive capital of a given category assigned to white males whenever there is a positive assignment for any other demographic group.

λ_{jt}, from the average growth rate of the quality-adjusted relative price of investment to consumption between 1984 and 2014, following the methodology in Caunedo *et al.* (2021). Table VIII shows the growth of λ_j across the 24 equipment categories in NIPA.

Parameters calibrated by solving the model. The list of the remaining parameters to be calibrated is:

$$\Lambda = (\{\{\{\{T_{o_jht}, \omega_{ot}, \tau_{o_jht}, d_{o_jht}\}_{o=1}^{O}\}_{j=1}^{J}\}_{h=1}^{H}\}_{t=\{1984\}}^{2014}).$$

We infer those parameters from the labor market outcomes of each group of workers, the allocation of equipment across occupations by demographic group, and the equipment to labor expenditure shares across occupations.

We measure the profile of labor market barriers, τ_{o_jht}, and that of average efficiency units of labor, T_{o_jht}, using the model predicted allocation of workers and average wages of workers in each group along with two identification restrictions. First, we assume that the labor market outcomes of white males are un-distorted – that is, $\tau_{o_jh^{wm}t} = 0$. Second, we assume that the profiles of comparative and absolute advantage are shaped by schooling only – that is, $T_{o_jht} = T_{et}T_{o_jet}$ where e indexes schooling, T_e determines the absolute advantage of a group, and the ratio $\frac{T_{o_jet}}{T_{o_{j'}et}}$ determines the comparative advantage across schooling groups e and production units o_j. In other words, we take the comparative advantage of workers of different schooling groups in using capital across occupations to be identical for groups of different race and gender. Instead, we rationalize differences in occupational choice and in the capital bundles used by workers of different gender and race via labor market barriers.

To measure the labor market barriers, we follow Hsieh *et al.* (2019) and exploit group differences in labor market outcomes to white males. Combining equations 12 and 13 and the two identifying assumptions, we obtain:

$$\frac{\pi_{o_jh^e}}{\pi_{o_jh^{wm,e}}} = (1 - \tau_{o_jh^e})^{\theta} \left(\frac{w_{h^{wm,e}}}{w_{h^e}}\right)^{\theta},$$

for each schooling group e. For observable worker allocations, π_{o_jh}, and average wages by demographic group, w_h, we infer $\tau_{o_jh^e}$ as a residual. Given that average wages for a demographic group do not vary across occupations in our model, the dispersion of the barriers is identified via the allocation of workers of each group.

To observe the allocation of workers we require information on the allocation across equipment goods within an occupation. We extract this information from our newly constructed statistics in Section 2. We exploit the fungibility of efficiency units of labor in occupation o, to allocate a unit of time provided by a worker (and its efficiency units) across production units o_j, proportionally to the capital equipment of a given type used by a demographic group in an occupation. That is, for a given demographic group and occupation we map:

$$\frac{\pi_{o_j h}}{\pi_{o_{j'} h}} = \frac{k_{o_j h}}{k_{o_{j'} h}},$$

where $k_{o_j h}$ is the observed quantity of equipment good j used by demographic group h in occupation o. Differences in $\pi_{o_j h}$ across demographic groups in an occupation reflect differences in the capital bundles used by workers within the occupation.[13]

We measure the profiles of absolute and comparative advantage of workers of different schooling groups across production units for given values of the labor input prices. To infer $T_{o_j e}$ we exploit data on the occupational choice of white males as well as on their allocation to capital of different types across occupations, while to infer T_e we exploit data on average wages of white males across schooling groups. Equation 12 and the two identifying assumptions imply,

$$\frac{\pi_{o_j h^{wm,e}}}{\pi_{o'_{j'} h^{wm,e}}} = \frac{T_{o_j e}}{T_{o'_{j'} e}} \left(\frac{\lambda^n_{oj}}{\lambda^n_{o'j'}} \right)^{\theta}.$$

Normalizing the average efficiency units for a baseline production unit and a demographic group to 1 in each year allows us to identify $T_{o_j et}$. That is, occupational heterogeneity in the profile of $T_{o_j et}$ intuitively reflects the structure of complementarity between white males of different characteristics and equipment of different types across occupations. For example, a comparative advantage of college-educated white males using communication equipment versus less-than-college educated white males using communication equipment in managerial occupations results in a higher relative labor productivity of college-educated white males when using communication equipment in comparison to less-than-college educated white male in that occupation. Then, for a measure of the labor input price, average wages for white males by schooling group pin down the average efficiency units of a schooling group, T_{et}:

$$w_{h^{wm,e}} = \Gamma(1 - \frac{1}{\theta}) \left(T_e \sum_{oj} T_{o_j e} \lambda^{n\ \theta}_{o_j} \right)^{\frac{1}{\theta}}.$$

Next, we measure the labor input price. For a value of the elasticity of substitution

[13]In our accounting framework, equipment per efficiency unit of labor is equalized across workers of different groups within a production unit. However, equipment per worker is not.

Table IV: Dispersion in labor market barriers.

	1984	2000	2014	2014/1984-1, %
All				
All	0.92	0.61	0.62	-33.1
White females	1.47	0.92	0.96	-35.0
Black females	1.16	1.06	0.98	-15.6
Black males	0.62	0.27	0.24	-61.8
Less-than college				
All	0.78	0.63	0.65	-16.7
White females	1.43	1.07	1.07	-24.7
Black females	1.02	1.11	1.13	11.0
Black males	0.32	0.16	0.15	-52.8
College				
All	1.07	0.59	0.58	-45.6
White females	1.53	0.76	0.84	-45.2
Black females	1.31	1.02	0.83	-36.9
Black males	0.91	0.39	0.29	-67.6

This table shows the log-variance of $(1-\tau_{o_jh})$ for all the population (*All*), by schooling group (*Less-than college* and (*College*) and by gender and race.

between equipment and labor, this price is a function of the relative user cost of equipment to consumption, which we input directly from the data; of the labor market barriers, which we infer from occupational choice differences to white males; and of the price of occupational output, which we measure from the ratio of equipment to labor expenditures in each occupation. For an occupation o:

$$\frac{\sum_j \lambda_j k_{o_j}}{\sum_{j,h}(1-\tau_{o_jh})\lambda^n_{o_jh} n_{o_jh}} = \frac{\sum_j \left(\left(\lambda_o^{\frac{\sigma_o}{\sigma_o-1}} - \lambda_j^{\frac{\sigma_o}{\sigma_o-1}}\right)^{\frac{1}{\sigma_o}} \lambda_j^{\sigma_o}\right)^{-1} \sum_h n_{o_jh}}{\sum_{j,h}(1-\tau_{o_jh})\lambda^n_{o_jh} n_{o_jh}},$$

where the denominator is the total wage bill for the occupation. Figure VIII in the Appendix shows the performance of the model on the ratio of equipment to labor expenditures, across occupations.

Last, we are left with parameterizing the profile of the demand shifters, ω_o, and the utility loss parameter, d_{o_jh}. Given the above-inferred parameters, we compute the former from the first-order conditions of the final good producer, equation 11, and the production function, equation 7; and the latter from the equilibrium relationship between τ_{o_jh}, $\lambda^n_{o_jh}$, and d_{o_jh}.

Labor market barriers. Table IV shows the dispersion in the labor market barriers across occupations, equipment types, and demographic groups, as measured by the log-

Table V: Variance decomposition in labor market barriers.

	Across occupations	Within occupations
All	62.4	37.9
Less-than college		
White females	64.0	36.0
Black females	63.7	36.3
Black males	67.6	46.8
College		
White females	63.4	36.6
Black females	53.2	46.8
Black males	42.0	58.0
Years		
1984	54.5	45.5
1990	62.2	37.8
2000	57.5	42.5
2010	69.9	30.1
2014	68.3	31.7

This table shows the variance decomposition of $\log(1-\tau_{ojh})$. We estimate an ANOVA with year, group and occupation as factors. The column *Across occupations* reports the fraction of the variance attributable to the occupation factor. The column *With occupations* reports the fraction of the variance that is unexplained by the three factors considered and so attributable to capital types.

variance of $(1-\tau_{ojh})$. We focus on the dispersion in barriers since the heterogeneity in the barriers across occupations and equipment goods for a given demographic group influences the occupational choice, and through it, other economic outcomes.[14] The dispersion in barriers decreases by 33% between 1984 and 2014. This is consistent with the findings of Hsieh *et al.* (2019) and the documented convergence in the occupational choice across demographic groups toward white males. Females record a higher dispersion in the barriers they face, compared to black males. Black males experience the strongest decrease in their barriers over time (in relative terms), by 62%, while the dispersion in the barriers faced by black females decreases the least, by 16%. Looking across schooling groups, individuals with a college degree record a higher dispersion in their barriers compared to those with less-than-college in 1984, 1.07 compared to 0.78. However, the former group also records a stronger decline in the barriers over time, so that by 2014 the picture is reversed, with a higher dispersion in the barriers faced by individuals with less-than-college. An exception to this trend are the barriers faced by black males. A combination of a more sizeable difference in the dispersion of the barriers by schooling in 1984 and a smaller differences in the trends between 1984 and 2014 result in a higher dispersion in the barriers faced by college graduates

[14]Differently, the level of the average barrier faced by workers of a demographic group has no bearing on their occupational choice. Such level only influences average wages trivially, by shifting them proportionally.

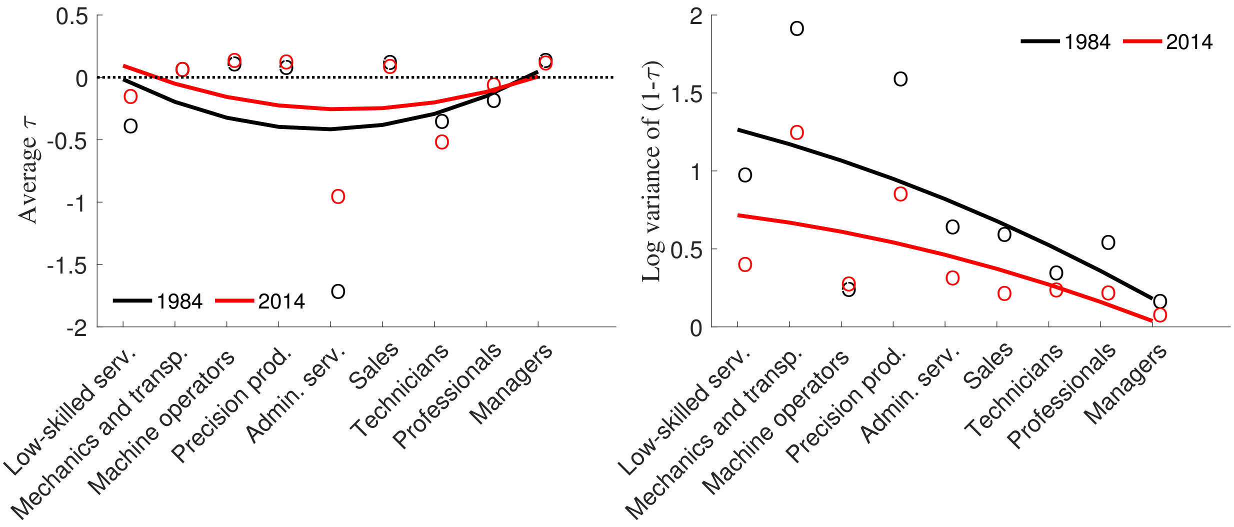


Figure III: Dispersion in labor market barriers.

The figure shows the average of $\tau_{o_j h}$ (left panel) and the variance of $\log(1 - \tau_{o_j h})$ (right panel) across occupations.

compared to those faced by those with less-than-college in 2014, 0.29 compared to 0.15. Last, black females with less-than-college is the only demographic group for which we measure an increase in the dispersion of barriers between 1984 and 2014.

The patterns highlighted above reflect both across and within occupation dispersion in barriers. Our within occupation component reflects the capital bundle dimension, and is therefore unique in its measurement. Table V shows the relative importance of the within and across component.[15] We find that both components are important determinants of the dispersion in barriers, with the former accounting, on average, for 38% of the variance in barriers and the latter for the remaining 62%. The within component is more relevant for the dispersion in the barriers facing black females as well as black females with a college degree, accounting for between 47% and 58% of the dispersion. Over time, the importance of the within occupation component decreases, going from 45% to 32%. Figure III gives a visual representation of the distribution of barriers across occupations, when occupations are ordered by increasing skill requirements (Acemoglu and Autor, 2011). Females face the highest average barriers in mechanics, transportation, and precision production occupations and the lowest in administrative occupations. The average barriers faced by black males tend to increase with the skill requirement of the occupation: it is highest for managers, profes-

[15] We run an ANOVA on $\ln(1 - \tau_{o_j h})$ where we control for year and occupation along with demographic group components in the specifications that are run merging groups together.

sionals, and sales and lowest for low-skill services. Over time, the dispersion in the barriers across occupations decreases, driven mostly by reversion to the mean in low-skill services and administrative occupations. Turning to the the dispersion in barriers within occupations, we find that dispersion is lower in occupations with higher skill requirements and that within occupation dispersion has declined over time.[16] Occupations with the most sizeable differences in within-occupation barriers across demographics are low-skill services, administrative, precision production, and technician occupations. The highest within-occupation barriers facing females are in low-skill services, precision production, and administrative occupations, while the lowest are in managers. The highest within-occupation barriers facing black males are in precision production while the lowest are in managers and machine operators occupations.

4 CETC and the incidence of barriers to worker reallocation

In this section, we use our parameterized accounting framework described in Section 3 to quantify the role of CETC in determining the incidence of labor market barriers, i.e. their contribution to output per worker and wage inequality. We close the section by using CETC to predict the impact of labor market barriers on inequality over the coming 10-years.

Output per worker, levels. To quantify the importance of CETC for the incidence of labor market barriers, we conduct a counterfactual exercise. Our exercise computes losses in output per worker that are attributable to labor market barriers in 2000, the mid year in our sample, taking as given the path of CETC between 1984 and 2014. We consider the counterfactual world in which CETC is the sole driver of differences in the economic environment over the years. We then compute the losses in output per worker that are associated to labor market barriers (fixed at their 2000 level) by shutting down the dispersion of the barriers faced by workers across production units and computing the associated variation in output per worker. Shutting down the dispersion of the barriers faced by workers entails setting $\tau_{o_j ht}$ for each group to its mean across production units in each year.[17]

Figure IV shows the incidence of barriers faced by workers measured as the losses in output per worker they generate. We measure output losses of the order of 4.0% in 1984

[16] Pictures of the mean and dispersion of the average labor market barriers across occupations by demographic group are available upon request.

[17] Note that a change in the average barrier has no effect on output in our framework. This is different from Hsieh *et al.* (2019) where instead the level of the barrier has an effect through the accumulation of human capital. See a discussion of these differences in Section 4.2.

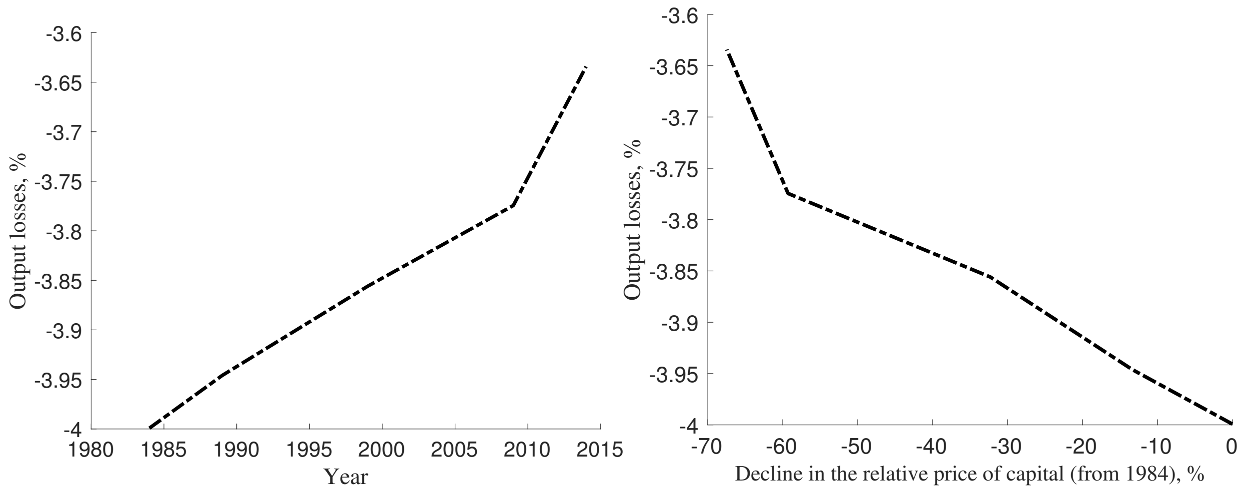


Figure IV: CECT and incidence of barriers.

The figure shows output losses generated by labor market barriers facing workers at different extents of CETC. The left panel plots output losses through time, where the only changing variable is CETC. The right panel plots output losses against the decline in the relative price of equipment to consumption from 1984. Stronger relative price declines correspond to later years.

associated to the 2000 labor market barriers faced by workers. These losses decrease to 3.6% in 2014. We conclude that CETC alone decreased the incidence of the 2000 labor market barriers faced by workers by 9.1% (=3.6%/4.0%-1).[18]

We then turn to the incidence of barriers faced by different demographic groups in the presence of CETC. Table VI reports output losses that are associated to the removal of the dispersion in barriers faced by different demographic groups. First, we find that the incidence of barriers facing white females is higher than that facing black females and black males. The output losses related to the barriers facing white females account for about 3p.p., compared to losses of less than 1p.p. associated to barriers facing the remaining two groups. Second, we find that the lower incidence of barriers generated by CETC is mostly accounted for by a lower incidence of the barriers facing females. CETC lowers this incidence by 8.4% for white females and by 11% for black females. Differently, CECT increased the incidence of barriers for black males, by 3%. Given the profile of barriers workers face, females move toward managerial and professional occupations in response to CETC, while black males move toward technicians, mechanics, and transportation occupations.

Output per worker, growth rates. Hsieh *et al.* (2019) study the contribution to

[18] Alternatively, in a similar exercise, one can compute the gains in output per worker implied by removing the labor market barriers faced by workers. We find that CETC decreases the incidence of those barriers by 9.5%, i.e. the output gains are smallest towards the end of the sample.

Table VI: CECT and the incidence of barriers by demographic groups.

	1984	1990	2000	2010	2014	2014/1984-1
All	-4.00	-3.95	-3.86	-3.77	-3.63	-9.13
White females	-3.23	-3.19	-3.13	-3.07	-2.96	-8.40
Black females	-0.68	-0.66	-0.64	-0.62	-0.60	-11.00
Black males	-0.10	-0.10	-0.10	-0.11	-0.11	3.04

The table reports output losses generated by labor market barriers facing workers at different extents of CETC. It reports output losses through time, where the only changing variable is CETC, related to barriers faced by all workers (column *All*), by white females, by black females, and by black males.

growth in output per worker of the reduced labor market barriers documented in Section 3.3 over time. We run a comparable calculation focusing on the dispersion of labor market barriers within a framework that features CECT (our baseline economy) and a framework that features only labor as input in occupational output production. We calibrate both frameworks using the approach described in Section 3.3. Importantly both calibrated frameworks measure the exact same labor market barriers faced by workers. To assess the quantitative importance of evolving dispersion in labor market barriers for output growth between 1984 and 2014, we run a counterfactual exercise in which we remove the decline in the dispersion of the barriers – that is, we set $\tau_{o_jht} = \tau_{o_jh1984}\frac{\bar{\tau}_{ht}}{\bar{\tau}_{h1984}}$, where $\bar{\tau}_h$ is the employment weighted average τ across production units and occupations for group h.

In the calibrated economy, output per worker grows by 38.5% between 1984 and 2014, i.e. an average growth rate of 1.1p.p. per year. In the framework that features CETC, declining labor market barriers contributes 5.95% of the observed output growth over 30 years. Differently, in a framework that does not consider capital, the same decline in labor market barriers contributes 6.73% of observed output growth. Hence, consistently with the conclusion drawn above, CETC decreases the incidence of labor market barriers on output per worker.

Wage inequality. The benefits of CETC in reducing the incidence of labor market barriers on output per worker are associated to widening wage inequality: CECT widens the gender wage gap, the race wage gap as well as the skill premium.

Between 1984 and 2014, the gender wage gap decreased by 19.36p.p.. The decline in labor market barriers faced by females contributed to this trend, generating a closure of 4.82p.p. over the period (4.26p.p.+0.56p.p., for white and black females respectively). Differently, CECT and labor market barriers faced by men widened the gender gap in wages by 6.67p.p. and 0.80p.p., respectively. Similarly, the race wage gap decreased over time, by 9.23p.p.

Table VII: Drivers of wage inequality

	Data	CETC	Barriers			
			all	white females	black females	black males
Skill premium	15.03	10.99	-4.07	-3.97	0.13	-0.19
Gender gap	-19.36	6.67	-4.17	-4.26	-0.56	0.80
Race gap	-9.23	3.74	-5.23	1.75	-1.92	-4.80

The table lists the change in the skill premium, gender gap, and race gap between 1984 and 2014 in percentage points (column *Data*). Along with it, it lists the changes generated by CETC (column *CETC*) and those generated by the barriers faced by workers (column *Barriers*).

between 1984 and 2014. The decline in labor market barriers faced by black workers contributed to this trend, generating a closure of 6.72p.p. over the period (1.92p.p.+4.80p.p.), while CECT and labor market barriers faced by white females widened the gap by 3.74p.p. and 1.75p.p., respectively. At the same time, the percentage difference in wages between college and non-college workers, i.e. the skill premium, increased by 15.03p.p. between 1984 and 2014. CETC contributed to this rise by 10.99p.p. while the decline the barriers faced by workers reduced the skill premium by 4.07p.p..

4.1 Predicting the future incidence of barriers

We use CETC to predict the incidence of barriers on wage inequality over the next 10 years.

We first test the predictive capacity of CETC on wage inequality via an in-sample prediction exercise. Standing in 2004, we ask how well one would had predicted the gender wage gap, the race wage gap, and the skill premium over the subsequent 10 years in the US using only information on CETC. To do so, we take the calibrated model economy in 2004 and input the path of CETC realized over the next 10 years to predict wage inequality between 2004 and 2014. The results are in Figure VI, which plots the predicted gender wage gap, race wage gap, and skill premium (dotted lines) along with the data (solid lines).

CECT generates a yearly increase of 0.51p.p. in the skill premium compared to a 0.12p.p. decrease realized in the data over the period 2004-2014. Importantly, CETC generates the slowdown in the skill premium observed after 2000, partly explained by the slow-down in the decline of the price of computers. Starting the prediction in 2000 rather than in 2004, the skill premium goes from a 1.06p.p. yearly increase between 1984 and 2000 to a predicted 0.39p.p. increase between 2000 and 2014, in comparison to the realized 0.06p.p. decrease (see Figure IX in the Appendix). We take the ability of CETC to predict such trend break

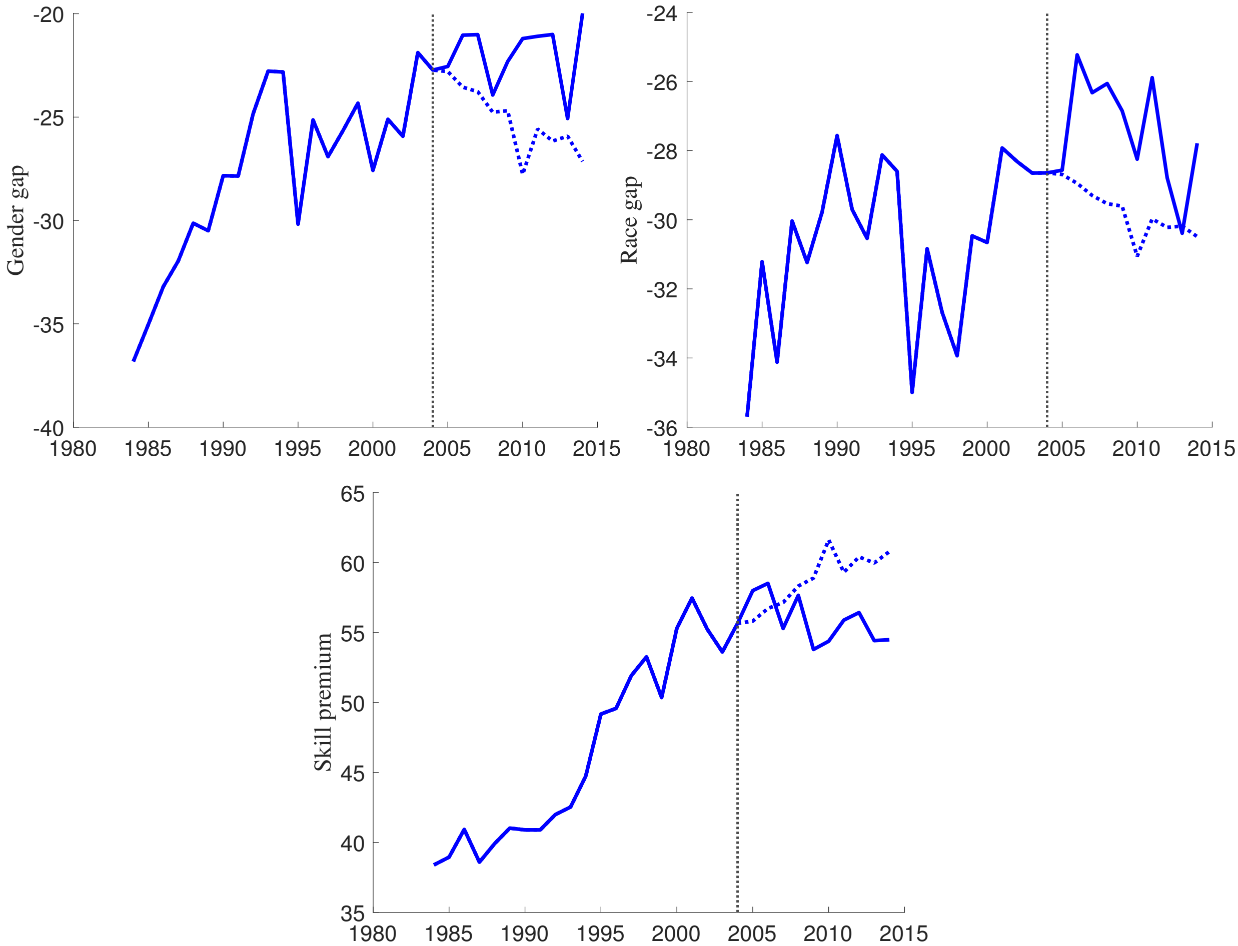


Figure V: Forecasting exercise: in sample.

Solid line is data, dotted line is predicted. The first panel plots 100 times the difference in log wages between females and men in the data (solid line) and as predicted by our in-sample forecasting exercise (dotted line), between 2004 and 2014. Forecasting starts in 2005. The remaining panels plot the same statistics, but for the race gap and for the skill premium.

as evidence of CETC being a valid predictor for the path of the skill premium. This is consistent with the role of capital-skill complementary for the skill premium (Krusell *et al.*, 2000).

Similarly, CETC also generates the slowdown in the closure of the race wage gap recorded in the data. The race gap closes at a rate of 0.31p.p. per year between 1984 and 2004 compared to the rate of 0.09p.p. per year recorder after 2004. CETC predicts an increase in the gap starting in 2004, at a rate of 0.18p.p. per year. On the other hand, the gender wage gap closes throughout the period in the data, while CETC predicts a divergence in wages between males and females after 2004. CETC predicts the gender gap enlarging by 0.44p.p.

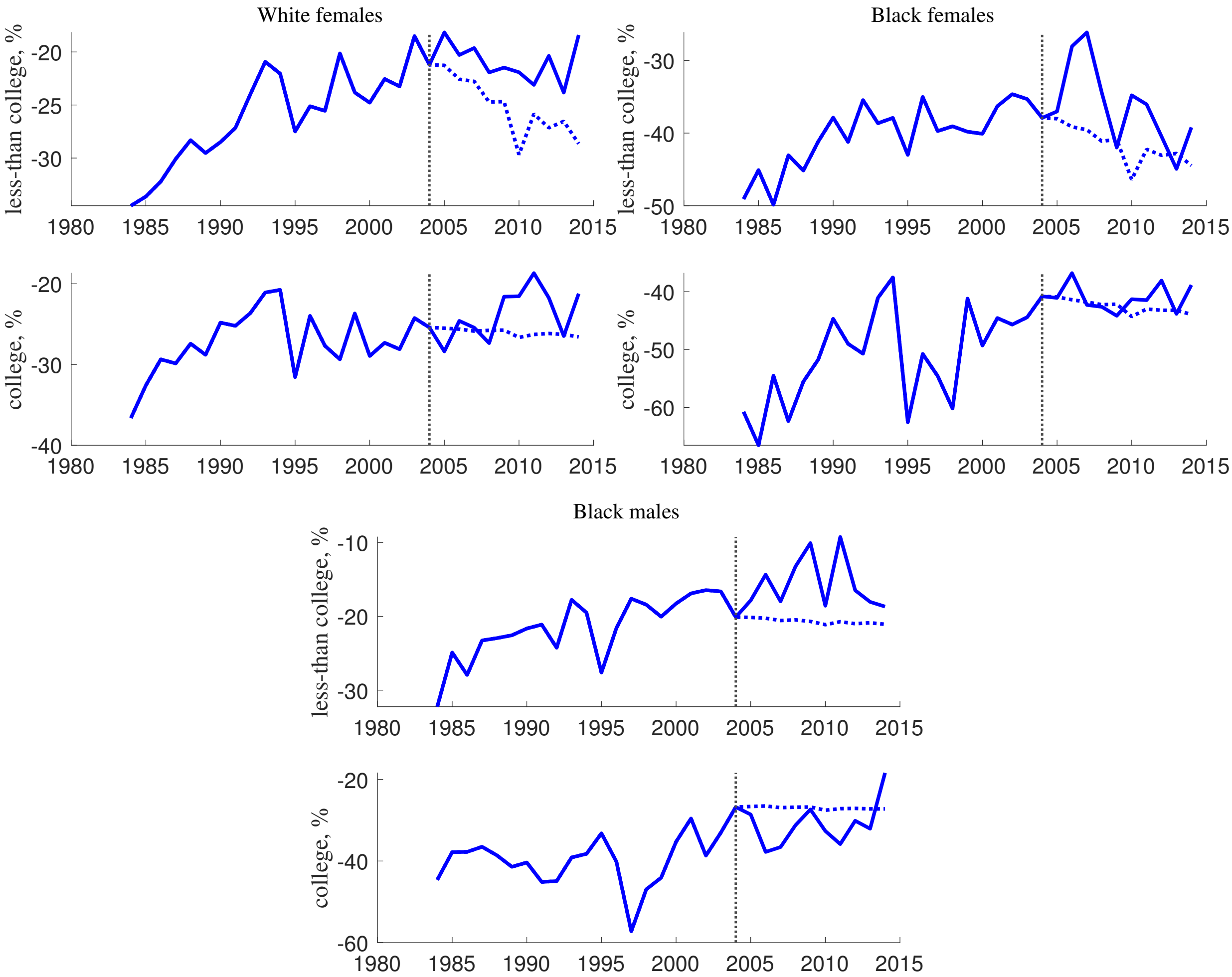


Figure VI: Forecasting exercise: in sample.

Average wages relative to white males by group. Solid line is data, dotted line is predicted. The first panel plots 100 times the difference in log wages between white females and white men in the data (solid line) and as predicted by our in-sample forecasting exercise (dotted line), between 2004 and 2014, by schooling group. Forecasting starts in 2005. The remaining panels plot the same statistics, but for the wages of black females and black males.

per year, opposite to the 0.27p.p. yearly closure in the gap observed in the data. Figure VII splits the predictions across demographic groups and shows that the low-performance of CETC in predicting the gender wage gap is entirely accounted for by the low-performance for white females with less-than-college, to which we turn next.

The increase in the gender wage gap among those with less-than-college is mostly driven by females facing high labor market barriers in mechanics and transportation occupations. These are occupations for which those with less-than-college measure a relatively higher labor productivity, $T_{o_j e}$, and for which CETC has increased the price of labor (the second highest increase across all occupations). The higher labor productivity implies a higher exposure to changes in the price of labor. Females with college also face high barriers in mechanics and transportation occupations but this group records lower exposure to changes in the price of labor, which results in a small increase in the gender wage gap. The main force that pushes the divergence in wages of females to white males for those with college education (and also for black males), is instead the high labor market barriers faced in managerial occupations while low barriers in professional occupations attenuate such effect. Lastly, labor market barriers faced in low-skill service occupations are the main source of differences in the path of the gender wage gap between white and black females with less-than-college. The latter group faces lower barriers in this occupation, which record a small increase in the price of labor as a consequence of CETC.

We then use CETC to forecast the evolution of the wage inequality over the coming 10 years. We take the calibrated model economy in 2014 and input the path of CETC that is implied by the average yearly decline in the price of capital relative to consumption we observe over the 2004-2014 period, to forecast wage inequality between 2015 and 2024. The results are in Figure VII, which plots the predicted gender wage gap, race gap, and skill premium. We forecast further increases in the skill premium, rising by 0.24p.p. yearly, on average. This magnitude is sizeable in comparison to the decrease we observed in the previews 10 years (0.12p.p. decrease per year). We also forecast a widening gender wage gap, by 0.14p.p. per year, and of the race wage gap, by 0.07p.p. per year, a weaker increase than what CETC generated in the previous 10 years. We conclude that, absent institutional changes, CETC will exacerbate wage inequality in the form of a higher skill premium and an enlarged gap in wages between males and females and blacks and whites.

4.2 Additional margins

Before concluding, we discuss two additional margins through which labor market barriers interact with technical change that we abstracted from in the main analysis: decisions on labor-force participation and human capital accumulation.

Female labor force participation increased by 3.7p.p. between 1984 and 2014 (from 53% to 56.7%, peaking at 60% in 2000). Our quantitative exercise accounts for this shift in the demographical composition of the labor force through the calibrated group shares, π_h. However, this composition effect is exogenous and not allowed to respond to CETC. A common extension within the class of Roy (1951) models we use is to include non-market activities

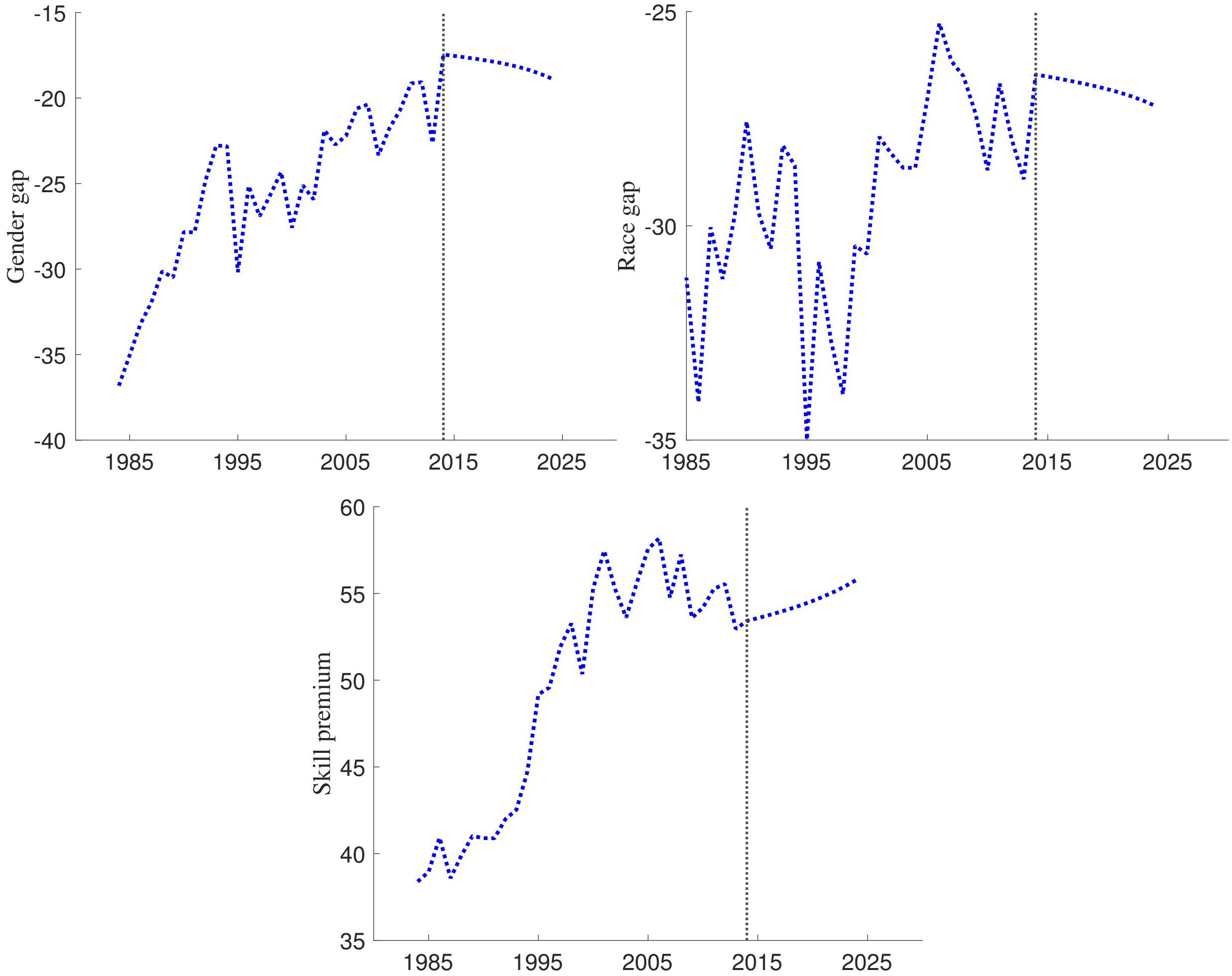


Figure VII: Forecasting exercise: out of sample.

The first panel plots 100 times the difference in log wages between females and men in the data (up to 2014) and as predicted by our out-of-sample forecasting exercise (between 2015 and 2024). The remaining panels plot the same statistics, but for the race gap and for the skill premium.

as an additional occupation and allow for endogenous sorting of workers to market and non-market activities (Hsieh *et al.*, 2019).[19] The measurement of the role of CETC in easing the incidence of the labor marker barriers facing females that is based on our accounting framework is likely a lower bound to a measurement based on an augmented framework that includes non-market acivities. The reason is that CETC drives females towards high-skill occupations and, at the same time, rises the price of labor in these occupations (due to the occupational pattern of capital-labor complementarity), therefore rising the returns to

[19]Studies of labor reallocation over long time-horizons in the US typically abstract away from unemployment, which has remained remarkably stable over the past 40 years.

labor force participation. Then, in a counterfactual world with no CETC, we would expect the demand for high-skill occupations to be lower, inducing females to remain engaged in non-market activities. Insofar the presence of CTETC catalyzes female labor force participation relative to their male counterparts, endogenizing this margin will increase the role of technical change in lowering the incidence of barriers facing females.

Labor market barriers may influence workers' investment in human capital via their effect on wages, i.e. the returns to such an investment. Consider first human capital investment to only increase the average efficiency units the worker provides to market work, T_e in our accounting framework. A decline in the average barriers faced by a worker would incentivize human capital investment. As the resulting higher T_e does not change the worker's occupational choice, we expect the role of CETC in determining the incidence of barriers not be significantly affected. Alternatively, consider human capital investment to change the distribution of efficiency units across production units, T_{oje}, in favour of high-skill occupations. Human capital investment shifts occupational choices and so we expect our measurement of the role of CETC for the incidence of barriers to be a lower-bound relative to one based on a framework that endogenizes human capital investment in such a way. The reason is that CETC drives workers towards high-skill occupations and at the same time, raises the price of labor in this occupations, inducing higher returns to human capital investment.

Lastly, over the last 30 years, schooling attainment increased and the gender gap in schooling reversed. The implied compositional changes of the evolving schooling attainment are picked up in our framework by the calibrated π_h, similarly to the demographical changes generated by the evolving labor force participation. Various studies highlight the importance of the returns to skill acquisition for schooling choices, in the aggregate and by demographics (Goldin and Katz, 2007, Olivetti and Petrongolo, 2016, Greenwood *et al.*, 2016). CETC is a driver of the observed rise in the returns to skill as capital is less substitutable to labor in high-skill occupations and output is substitutable across occupations. We expect that endogenizing the schooling composition would strengthened the interaction between CETC and labor market barriers, and in particular those barriers facing black males given their negative correlation with the skill requirement of the occupation.

5 Conclusion

Has technical change mitigated or exacerbated the impact of barriers to the transition of workers across occupations on output and wage inequality? We find that CETC mitigated the incidence of these barriers on output per worker by 9.1%, between 1984 and 2014. At the same time, CETC fuelled wage inequality.

Through forecasting exercises we predict that, absent mitigation policies, if CETC continues at the pace observed in the 2004-2014 period wage inequality in the economy should raise, and even accelerate relative to what we have observed so far. The raise in inequality is salient for the skill-premium and particularly important for the gender wage gap. This is mostly explained by barriers facing females with less-than-college in middle-skill occupations and by barriers facing college educated females in managerial occupations. Finally, we find that black males have not been able to reap the benefits of CETC because of the strong barriers they face to access high-skill occupations, where the return to labor increases the most.

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A Tables & Figures

Table VIII: Equipment assignment by CETC.

Description	**Fixed-Asset Code**	**Price of Investment**	**Usercost**	**Stock per worker**
			1984-2015 annual % change	
i) Computers and peripheral equipment	4	-13.17	-13.96	17.07
Software	99	-4.87	-4.97	11.36
ii) High—CETC				
Communication equipment	5	-13.71	-11.62	20.16
Aircraft	26	-9.42	-9.43	11.90
Engines and turbines	14	-5.05	-5.45	4.69
Special industry machinery, n.e.c.	18	-4.87	-4.97	11.36
Nonmedical instruments	9	-4.35	-3.36	6.73
Photocopy and related equipment	10	-4.35	-3.63	1.44
Medical equipment and instruments	6	-4.35	-3.36	9.37
Service industry machinery	40	-4.29	-4.31	5.86
iii) Low—CETC				
Electrical transmission and industrial apparatus	20	-3.19	-3.02	3.87
Autos & trucks	22-25	-2.95	-3.70	4.51
Fabricated metal products	13	-2.63	-3.05	-0.18
Ships and boats	27	-2.57	-2.03	1.34
Other nonresidential equipment	29	-1.82	-2.14	4.14
Office and accounting equipment	11	-1.50	-2.00	-1.21
General industrial	19	-1.29	-2.15	1.93
Electrical equipment, n.e.c.	41	-1.20	-1.08	0.74
Mining and oilfield machinery	39	-1.11	-1.40	3.06
Railroad equipment	28	-1.09	-1.32	0.35
Metalworking machinery	17	-0.83	-2.00	-0.02
Furniture and fixtures	30	-0.73	-0.45	1.56
Construction machinery	36	-0.30	-1.34	2.72
Agricultural machinery	33	-0.30	-1.33	-0.96

Notes: Column 1 presents a description of the equipment category while column 2 reports the corresponding code in the fixed-asset tables of the BEA. Column 3 presents the change in the quality-adjusted relative price of investment to consumption, column 4 presents the change in the user cost of capital and column 5 presents the change in the stock per worker.

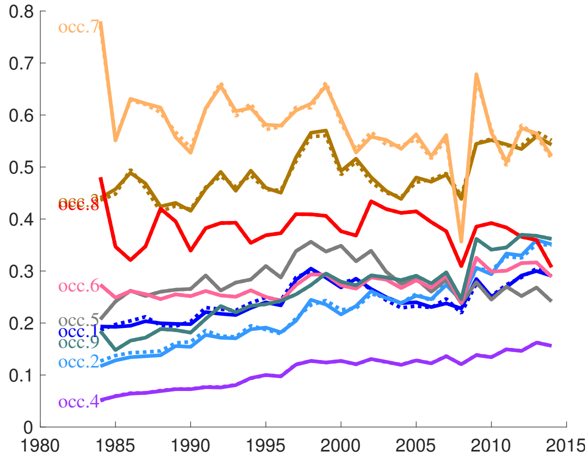
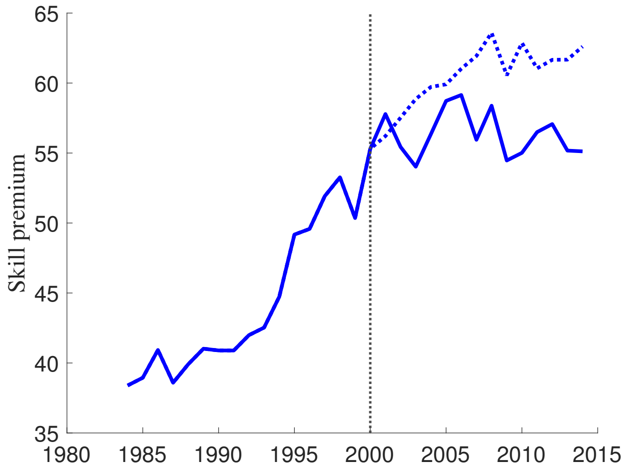


Figure VIII: Ratio of equipment to labor expenditures across occupations.

This figure displays the performance of the model (dotted line) on the ratio of equipment to labor expenditures across occupations in the data (solid line). The occupational index refers to the following occupations: 1 managers, 2 professionals, 3 technicians, 4 sales, 5 administrative services, 6 low-skill services, 7 mechanics and transportation, 8 precision production, 9 machine operators.



(a)

Figure IX: Forecasting exercise: in sample.

Solid line is data, dotted line is predicted. Panel (a) plots 100 times the difference in log wages between individuals with and with less-than-college in the data (solid line) and as predicted by our in-sample forecasting exercise (dotted line), between 2000 and 2014. Forecasting starts in 2001.