DEPARTMENT OF ECONOMICS

THEORY AND EVIDENCE ON TALENT MISALLOCATION IN EUROPE AND THE UNITED STATES

DOCTOR OF PHILOSOPHY DISSERTATION

ALMARINA A. GRAMOZI

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The present doctoral dissertation was submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy of the University of Cyprus. It is a product of original work of my own, unless otherwise mentioned through references, notes, or any other statements.

Almarina A. Gramozi

Περίληψη

Η παρούσα διατριβή αποτελείται από τρία αλληλένδετα κεφάλαια, τα οποία μελετούν τόσο θεωρητικά όσο και εμπειρικά την κακή κατανομή των ταλέντων" και τις επιπτώσεις τους στην οικονομική ανάπτυξη.

Στο πρώτο κεφάλαιο, "θεωρητικό Μοντέλο για την Κακή Κατανομή των Ταλέντων", αναπτύσσουμε ένα μοντέλο αναζήτησης και αντιστοίχισης της αγοράς εργασίας, το οποίο συνδέει τις μισθολογικές διαφορές, την κακή κατανομή των ταλέντων και τις απώλειες εισοδήματος. Στο μοντέλο αυτό, αυτές οι μισθολογικές διαφορές και η κακή κατανομή δημιουργούνται από τις άνισες ευκαιρίες απασχόλησης που έχουν διάφοροι τύποι εργαζομένων στην αγορά εργασίας: όσο υψηλότερος είναι ο βαθμός άνισης μεταχείρισης των μειονεκτούντων εργαζομένων, τόσο υψηλότερο είναι το μισθολογικό χάσμα και η εσφαλμένη κατανομή . Επιπλέον, με τη βαθμονόμηση του μοντέλου που βασίζεται σε πέντε μεγάλες ευρωπαϊκές χώρες και στην αμερικανική οικονομία, αποδεικνύουμε ότι η κακή κατανομή των ταλέντων μπορεί να έχει σημαντικά οικονομικά συνολικά αποτελέσματα.

Στο κεφάλαιο 2, "Η Κακή Κατανομή των Ταλέντων στην Ευρώπη", χρησιμοποιούμε μικροοικονομικά δεδομένα σχετικά με τους μισθούς και τα ατομικά χαρακτηριστικά σε δεκαοκτώ ευρωπαϊκές οικονομίες για την περίοδο 2005 έως 2015, προκειμένου να εντοπιστούν τυχόν λανθασμένες κατανομές που προκύπτουν στις οικονομίες αυτές με βάση το φύλο, την μεταναστευτική κατάσταση ή τον ιδιωτικό έναντι τον δημόσιο τομέα. Οι μικρο-οικονομετρικές εκτιμήσεις μας δείχνουν ότι οι γυναίκες ή οι μετανάστες και οι εργαζόμενοι στον ιδιωτικό τομέα έχουν αρνητικό αντίκτυπο στους μισθούς πέραν εκείνων που εξηγούνται από τα ατομικά χαρακτηριστικά, υποδηλώνοντας την επίμονη κακή κατανομή των ταλέντων στην Ευρώπη κατά την περίοδο που εξετάζουμε. Συγκεκριμένα, οι χώρες που βρίσκονται στο επίκεντρο της ευρωπαϊκής κρίσης εντοπίζονται συστηματικά στο υψηλότερο σημείο του συνολικού μέτρου εσφαλμένης κατανομής ταλέντων που εκτιμούμε. Η μελέτη μας παρέχει νέα αποδεικτικά στοιχεία σχετικά με τη δυνητική σημασία των διαφόρων μορφών κακής κατανομής ταλέντων για τις συνολικές οικονομικές μεταβλητές.

Τέλος, στο τρίτο κεφάλαιο, "Βαθμονόμηση και οι Συνέπειες της Κακής Κατανομής των Ταλέντων για τις Ηνωμένες Πολιτείες", διερευνάμε τις επιπτώσεις κακής κατανομής που προκύπτουν στις Ηνωμένες Πολιτείες κατά την περίοδο 1960-2017 λόγω των τριβών που σχετίζονται με τη φυλή και το φύλο και εξετάζουμε τον αντίκτυπό τους στους οικονομικούς δείκτες σε όλη την επικράτεια. Συστηματικά διαπιστώνουμε ότι οι γυναίκες και οι μη-λευκοί λαμβάνουν χαμηλότερους μισθούς σε σύγκριση με τους ομολόγους τους. Επιπλέον, αναλύουμε τη σχέση μεταξύ της εσφαλμένης κατανομής που βασίζεται σε μικροοικονομικά στοιχεία, συγκεντρωμένο για κάθε κράτος και κρατική τεχνική απόδο-

ση, συνολική παραγωγικότητα παραγόντων και ΑΕΠ ανά εργαζόμενο με την πάροδο του χρόνου. Βρίσκουμε μια αρνητική σχέση μεταξύ του μέτρου της κακής κατανομής που βασίζεται σε μικροστοιχεία και αυτών των συνολικών μέτρων, σύμφωνα με έναν σημαντικό ρόλο για την κακή κατανομή των ταλέντων για μακροοικονομικά αποτελέσματα.

Abstract

The present dissertation consists of three interrelated chapters, which study both theoretical and empirical talent misallocation and its effects on economic growth.

In the first chapter, "Theoretical Model on Talent Misallocation", we develop a search and matching model of the labor market that links wage differences, talent misallocation and income losses. In this model, these wage gaps and misallocation are both generated by the unequal opportunities for employment that different types of workers have in the labor market: the higher the degree of unequal treatment for underprivileged workers, the higher the wage gap and the higher the misallocation. Additionally, calibrating the model based on five major European countries and the US economy, we show that talent misallocation can have significant economic aggregate effects.

In chapter 2, "Talent Misallocation in Europe", we use microeconomic data on wages and individual characteristics across eighteen European economies for the period 2005 to 2015 in order to detect patterns of misallocation arising in these economies based on individuals' gender, immigrant status, or private versus public sector affiliation. Our micro-econometric estimates suggest that being a female or immigrant, and working in the private sector, exert a negative impact on one's wages beyond that explained by individual characteristics, suggestive of persistent talent misallocation in Europe during the period under study. Notably, countries which have been at the heart of the European Crisis are systematically found at the high end of the overall talent misallocation measure we estimate. Our work provides new cross-country evidence about the potential importance of various forms of talent misallocation for aggregate economic outcomes.

In the final chapter, "On the Degree and Consequences of Talent Misallocation for the United States", we explore the misallocation effects arising across the United States over the period from 1960 to 2017 due to frictions related to race and gender and quantify their impact on state-wide economic outcomes. We systematically find that women and non-whites receive lower wages compared to their counterparts. Moreover, we analyze the relation of our micro-based estimated misallocation measure aggregated for each state and state-level Technical Efficiency, Total Factor Productivity, and GDP per worker over time. We find a negative relation between our micro-based misallocation measure and these aggregate measures, consistent with an important role for talent misallocation for macroeconomic outcomes.

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To Ardit

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Introduction

The allocation of talent across economic activities is an important determinant of economic growth, as argued early on by Baumol (1990) and Murphy et al. (1991). Talent misallocation can lead to inefficiencies that suppress economic growth and harm the welfare of societies. The broad aim of the thesis is to investigate talent misallocation and its effects on economic growth and to provide both theoretical and empirical contributions in the existing literature.

Specifically, in the first chapter we develop a specific theoretical model that links unequal access to employment with wage differences, talent misallocation and income losses. In the second chapter, we utilize microeconomic data on wages and individual characteristics to detect patterns of misallocation arising in European countries based on public-private affiliation, individuals' gender, and immigration status. Chapter 3 explores the degree of labor misallocation across US states over time at the micro-level, and then proceed to assess its aggregate implications for economic outcomes. The thesis has generated a number of joint papers with Marios Zachariadis and Theodore Palivos.

In chapter 1, "Theoretical Model on Talent Misallocation", we propose a search and matching model of the labor market (e.g., Mortensen and Pissarides, 1994), where the presence of underprivileged workers relating to, e.g., female gender, race or country of origin, as well as political or other affiliation, leads to lower wages and talent misallocation, resulting in significant income losses. More specifically, we consider an economic environment with two types of jobs/sectors, one of which is more productive than the other, and a labor market where workers are equally talented but differ with respect to their opportunities for employment. These differences can arise from the presence of diverse social phenomena such as prejudice, social norms, discrimination, nepotism, political favouritism, immigrant status and so on. Thus, workers can be "privileged" or "underprivileged". While all unemployed workers search for employment in both markets, the underprivileged workers have a lower probability of getting hired in the high-productivity sector compared to the privileged ones, as the former face a lower job matching rate. In such an environment, workers of both types will be matched with both low- and high-productivity jobs. However, privileged workers will be in a better bargaining position and hence receive a higher wage, despite the fact that all workers have the same ability/talent. Additionally, as the degree of unequal treatment for underprivileged workers decreases, the economy may even move to an equilibrium where the low-productivity sector shuts down. In this case, wages of privileged and underprivileged workers in each sector would converge and any talent mismatch would disappear.

Next, we calibrate our model to match the data to each of five major European countries we have data for, France, Spain, the Netherlands, Italy and Greece. Our simulation exercise suggests that a 50 percent decrease in the gender wage gap, for instance, increases net income by more than three percent per quarter relative to the benchmark case for France, by more than four percent for Spain, by more than one percent for the Netherlands, by more than two percent for Italy, and by more than three percent for Greece. In addition, calibrating our theoretical model to match the US economy over the most recent period 2010-2017, we find that a 50 percent reduction in the wage gap between African-Americans and whites increases net income by more than 0.4 percent per month, and that eliminating race discrimination results in a substantially larger increase in net income of around 4 percent per month. This implies economically significant aggregate effects arising from talent misallocation.

The second chapter, entitled "Talent Misallocation in Europe', we utilize microeconomic data on wages and individual characteristics across eighteen European economies for the period 2005-2015 to investigate the overall misallocation effects implied by the combined gender, public-private and foreign-native wage gaps. According to our theoretical model, wage gaps and misallocation are both generated by the unequal opportunities for employment that different types of workers have in the labor market. However, in the absence of data on the degree of unequal access to employment or direct numbers for misallocation, these wage differentials serve as an implicit measure of talent misallocation. Our micro-econometric estimates suggest that being a female or immigrant, and working in the private sector, exert a negative impact on one's wages beyond that explained by individual characteristics, suggestive of persistent talent misallocation in Europe during the period under study.

Moreover, we consider the aggregate country-level implications of our micro-based estimates. Estimating misallocation measures for the private-public, migrant-native, and gender wage gaps in each country, we find that countries at the heart of the European Crisis had the highest totals. Specifically, countries such as Cyprus, Ireland, Italy and Spain are systematically found at the high end of the overall talent misallocation measure we estimate, and so does Greece in the pre-crisis period prior to its fiscal adjustment. Our research provides new cross-country micro-econometric evidence in support of a surging new literature, including Hsieh et al. (2019), Jaimovich and Rud (2014), Cavalcanti and Tavares (2016), Santos and Cavalcanti (2020), and Cuberes and Teignier (2016), regarding the importance of various forms of talent misallocation for aggregate economic outcomes and economic growth.

In the final chapter, "On the Degree and Consequences of Talent Misallocation for the United

States", we use microeconomic data for individuals across the United States over the period from 1960 to 2017, we explore the misallocation effects arising due to frictions related to race and gender and quantify their impact on state-wide economic outcomes. Overall, the results show that being a female and of a race other then white exert a negative impact on earnings beyond that explained by their economic characteristics. In relation to wage differentials associated with gender, it seems that the gender wage gap is a persistent phenomenon in the US throughout the decades, even if declining from 1960 up until around 2010. Looking at the impact of race on the wage gap relative to whites, it stands out that being non-white affects hourly wages negatively. We also find wage differentials between private and public sector employees, especially in the early periods of our study. Nevertheless, these wage gaps are much lower compared to those associated with gender or race. Moreover, by the end of our sample period in 2017, these wage differentials are reversed. Unlike most European countries, the US does not appear to have a misallocation problem associated with the public sector.

In addition, we investigate the macro-implications of our state-level misallocation measure. Specifically, we create a misallocation measure for each state that indicates the overall misallocation effects arising from wage differentials associated with race, and gender wage gap. In line with our theoretical model analysed in Chapter 1, we view the above-constructed aggregate wage gap as a measure of talent misallocation within each state. To assess this hypothesis, we look at the relation of our micro-based estimated misallocation measure aggregated for each state with state-level Technical Efficiency, Total Factor Productivity, and GDP per worker over time. Overall, we find a significant negative relation between our misallocation measure with these aggregate measures. These results are in line with Hsieh et al. (2019) who show the important role that labor misallocation plays for the US economy. Rather than focusing at the US economy as a whole, we look at the relation of our micro-based estimated misallocation measure aggregated for each state with state-level aggregate measures. Noting that our goal is not to identify a causal link, we argue that the negative relation found here between aggregate economic outcomes and our estimated misallocation measure based on microeconomic data, is suggestive of a potentially important role played by talent missalocation in determining aggregate outcomes across states and over time.

Chapter 1

Theoretical Model on Talent Misallocation

1.1 Introduction

In this chapter, we propose a specific theoretical model on talent misallocation. In particular, we develop a search and matching model of the labor market that links unequal access to employment with wage differences, talent misallocation and income losses. The novel model environment that we propose is different from to the existing standard literature, which is based on Roy model of occupational choice[1]. This theoretical model generates wage gaps for workers based on unequal access to employment, which in turn might depend on individual characteristics such as gender, race or country of origin, as well as on political or other affiliation.

More specifically, we consider an economic environment where equally talented workers search for employment in high- and low-productivity jobs/sectors. Despite workers having the same abilities, they differ with respect to their opportunities for employment. These differences can arise from the presence of diverse social phenomena such as prejudice, social norms, discrimination[2], nepotism, political favouritism, immigrant status and so on. Thus, workers can be "privileged" or "underprivileged". The latter workers have a lower job matching rate in the high-productivity sector compared to the privileged ones. The lower probability of getting hired in one of the two markets put the underprivileged workers in worst bargain position compared to the privileged one and hence receive a lower wage, despite the fact that all types of workers are equally skilled. This framework generate labor

[1] See for instance Hsieh et al. (2019), Santos and Cavalcanti (2020)

[2] Becker (1957) was the first to explore the economic effects of discrimination in the market place because of race, religion, sex, color, social class and so on.

misallocation as some workers are allocated to the low-productivity sector despite having the same ability.

Additionally, as the degree of unequal treatment for underprivileged workers decreases, the economy move to an equilibrium where only the underprivileged workers find it beneficial to work in the low-productivity sector. However, as all barriers for the underprivileged workers are eliminated, the economy may even move to an equilibrium where the low-productivity sector shuts down. In this case, wages of privileged and underprivileged workers would converge and any talent mismatch would disappear.

The novel model environment that we propose is different from the existing standard literature, which is based mostly on the Roy (1951) model of occupational choice. In this classic model of selection in the labor market, workers can choose among a variety of discrete' occupational' opportunities, but they can pursue only one 'occupation' at a time. Workers face a simple choice; they choose the occupation with the highest utility. The key feature of the Roy model is a comparative advantage in which some workers earn more than others as a result of different skill levels at labor market entry. Models based on the Roy model, also do not allow for the distinction between low- and high-skill jobs. We propose a search and matching model, which gives more flexibility in the occupational choice as it allows workers to search for employment in both sectors (or more sectors) at the same time, and also, we allow for a clear distinction between sectors according to their productivity. Both models lead to wage heterogeneity. However, in the search and matching model, wages are determined endogenously through the Nash Bargaining rule between the worker and the firm. The bargaining power of the worker depends on their outside option so two equally skilled workers in the same sector/firm may earn different wages.

Our work relates to the work who investigate misallocation in the economy and its effect on aggregate outcomes. Bentolila et al. (2010) investigate labor misallocation through the prism of a standard search model. According to the model, misallocation in the economy is generated because agents based their occupational choice on factors such as social contacts other than their comparative advantages. This in turn may lead to a reduction of aggregate net income. Similarly, Bello and Morchio (2020) develop an occupational choice model and search frictions to study the link between labor misallocation and intergenerational occupational persistence. In this model, labor misallocation in the economy arises because parents help their offspring find a job faster in their current occupation, which is not necessarily where their offspring's comparative advantage lies.

In addition, this study relate to the literature that explore the wage gap between workers through the prism of a search and matching model. Chassamboulli and Palivos (2014) explain the equilibrium wage gap between otherwise identical native and immigrant workers by allowing for differential search cost between them. Liu et al. (2017) consider imperfect transferability of human capital across borders that puts skilled immigrants at a disadvantage on the bargaining table relative to skilled natives, so that they become willing to accept low-skill jobs at a much greater rate compared to their native counterparts.

In our quantitative analysis, we explore the impact of gender discrimination on the flow of total surplus in the European economies. We choose to focus on gender as our preliminary empirical investigation shows that gender inequality is an important factor across European countries. In addition, we also investigate the impact of wage differentials between African-Americans and whites on the US economy. Race seems to be quite important for the U.S. as it is harder for non-whites to be integrated into the labor market, putting them at a disadvantage as compared to white workers.

Specifically, we calibrate our model to match to each of five major European countries we have data for, France, Spain, the Netherlands, Greece, and Italy for the period 2005-2015. Our simulation exercise implies that a 50 percent decrease in the gender wage gap, for instance, increases net income by more than three percent per quarter relative to the benchmark case for France, by more than four percent for Spain, by more than one percent for the Netherlands, by more than two percent for Italy, and by more than three percent for Greece. Additionally, we also calibrate our theoretical model to match the US economy over the most recent period 2010-2017 focusing on race as it is a more important factor across the US. We find that a 50 percent reduction in the wage gap between African-Americans and whites increases net income by more than 0.4 percent per month, and that eliminating race discrimination results in a substantially larger increase in net income of around 4 percent per month. This implies that talent misallocation has important aggregate effects for the economy.

The rest of the chapter is organized as follows. Section 2 presents a search and matching model that links differences in employment opportunity between two groups of workers and macroeconomic outcomes. Section 3 presents some quantitative analysis based on calibrations of our theoretical model. Section 4 briefly concludes.

1.2 The Model

We develop a search and matching model of the labor market (e.g, Mortensen and Pissarides 1994) in which there are two groups of workers facing different opportunities for employment. These differences can arise from the presence of diverse social phenomena such as prejudice, social norms, discrimination, nepotism, social and political favoritism, immigration, etc. No matter what the underlying cause of the unequal access to employment, we show that it can lead to differences in wages and talent misallocation.

1.2.1 Main Assumptions

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

There are also two types of jobs/sectors: low-productivity (L) and high-productivity (H) jobs. They are indexed by $i \in \{L, H\}$. We assume that each firm has at most one position and use the terms firms, jobs, and positions interchangeably. A firm must decide the type of job that it will create before entering the labor market. We assume that creating either type of job is costless and entry is free. There is, however, a flow hiring cost c, which is paid until the vacancy is filled. In principle, each vacancy can be filled by a worker of either type. A match between a low- (high-) productivity job and a worker results in output y_L (y_H), where $y_H > y_L$. We assume that the output produced is fixed and exogenous.[3] Thus, the productivity of a job does not depend on the type of worker that occupies it. Furthermore, since each firm can create at most one position and the cost of it is zero, profit maximization and free entry amount to an expected-zero-profit condition for firm entry and exit. Such a condition will determine endogenously the number of firms.

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

1.2.2 Matching

Unemployed workers and vacant positions are brought together in each sector via a stochastic matching technology. A model of undirected or random search occurs when the individual has no ability to seek or direct his search towards different types of jobs, as in Albrecht and Vroman (2002) among others, in contrast to models of directed search. In our model, the type of search lies between random and directed search. Specifically, workers do not target one particular job. Instead, they devote equal search effort for both types of jobs, irrespective

[3] Alternatively, we could assume a CES production function as in the work of Acemoglu (2001) to aggregate the output of the two sectors, such that the technology of production for the final good, Y, would be described by the equation $Y = (\gamma Y_L^{\frac{\sigma-1}{\sigma}} + (1-\gamma) Y_H^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$ where $\gamma \in (0, 1)$ and $\sigma = 1$. In this case, the two inputs Y_L and Y_H are perfect substitutes which imply that the productivity of the two inputs are fixed and exogenous.

of their value of searching for each job as they choose to apply to both types of jobs. In particular, the matching function in the low-productivity sector

$$M_L = M(v_L, u_P + u_U), \tag{1.1}$$

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

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

$$M_H = M(v_H, u_P + u_U). \tag{1.2}$$

Nevertheless, workers in the high-productivity sector may differ in terms of the probability of forming a match. Thus, even if the probability of meeting a vacancy among workers is the same, a contact between a high-productivity job and a worker may not be consummated because of the existence of prejudice and social norms against the presence of underprivileged workers, e.g., women, immigrants and other minority groups, in high-productivity jobs. Such norms result in collective discrimination. In that case, the probability of getting hired (the matching rate) for underprivileged workers in the high-productivity sector is $\eta m(\theta_H)$, which is lower compared to the matching rate for the privileged workers, $\eta m(\theta_H) < m(\theta_H)$, where $\eta < 1$.[4]. Thus, the main difference between privileged and underprivileged workers lies in the probability of getting hired in high-productive jobs. More specifically, privileged workers face no restrictions in their employment opportunities besides the regular search frictions, while the underprivileged ones have a lower probability of being hired in the high-productivity jobs. The unequal access to employment could arise not just from collective discrimination against underprivileged workers, but also due to the lack of information that employers have regarding worker's quality. This lack of information comes from the possibility that underprivileged workers are more isolated and lack the social or political connection compared to certain privileged workers.

The same formulation may hold if, even though there is no discrimination, an immigrant is

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

less likely to get hired because of imperfect transferability of human capital across borders as in Liu et al. 2017. This additional obstacle may exist because of the lack of information regarding the education system in the immigrant's home country, licensing requirements, etc.[5]

A similar situation arises in the case where certain privileged workers are "connected", that is, they have strong social network connections and can get hired more easily than other (underprivileged) workers, who are "isolated".[6] More broadly, "isolation" might also apply to workers in the private sector who lack the "connectedness" characterizing workers in the public sector. It is well known that in certain countries, whenever there is a change in government, there is a substantial turnover of jobs. Such a turnover occurs even in Western democracies (e.g., Greece and Spain) at the middle and senior management levels. This is so because a certain portion of the jobs in the public sector are reserved for workers that have personal or social connection to the political party that is in government.[7] Moreover, often civil and public servants or employees in big corporations, banks, etc., use their personal connections and influence to get their friends or relatives hired by their own employer.

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

1.2.3 Asset Values and Bargaining

We let Π and V denote asset values associated with a filled and an unfilled vacancy and E and U asset values associated with an employed and an unemployed worker, respectively. For example, U_j denotes the expected present discounted income of an unemployed worker who is of type j and E_{ij} denotes the expected present discounted income of an employed worker who is of type j and is matched with a job of type i. Then in steady state:

$$rU_P = b + m(\theta_L)max[(E_{LP} - U_P), 0] + m(\theta_H)(E_{HP} - U_P), \tag{1.3}$$

[5]Here, we refer to the ex ante transferability of human capital, that is, before a worker is hired, and not to the case where an immigrant is less productive because of differences in the quality of education, technology or the organization of production across countries.

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

[7]See Chassamboulli and Gomes (2018), who examine the effects of non-meritocratic hiring in the public sector using a search and matching framework.

$$rU_U = b + m(\theta_L)max[(E_{LU} - U_U), 0] + \eta m(\theta_H)(E_{HU} - U_U), \tag{1.4}$$

$$rE_{ij} = w_{ij} - \delta(E_{ij} - U_j), \;\; i = L, H, \;\; j = U, P, \tag{1.5}$$

where w_{ij} is the wage earned by a worker of type j who is matched with a vacancy of type i. The terms $max[(E_{Lj} - U_j), 0]$, $j = P, U$, appear in equations (1.3) and (1.4) in order to capture the case where workers do not consider it worthwhile to be employed on low-productivity jobs; such a case, as we will see below, does not arise with regard to high-productivity jobs, as long as $y_H > y_L > b$.

Similarly, the asset values associated with the firms are:

$$rV_L = -c + q(\theta_L)\{\phi_{LU} max[(\Pi_{LU} - V_L), 0] + (1 - \phi_{LU})max[(\Pi_{LP} - V_L), 0]\}, \tag{1.6}$$

$$rV_H = -c + q(\theta_H)\{\eta\phi_{HU}(\Pi_{HU} - V_H) + (1 - \phi_{HU})(\Pi_{HP} - V_H)\}, \tag{1.7}$$

$$r\Pi_{ij} = y_i - w_{ij} - \delta(\Pi_{ij} - V_i), \;\; i = L, H, \;\; j = U, P, \tag{1.8}$$

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

$$V_i = 0, \;\; i = L, H. \tag{1.9}$$

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

$$S_{ij} = \Pi_{ij} + E_{ij} - V_i - U_j, \;\; i = L, H, \;\; j = U, P. \tag{1.10}$$

Hence,

$$\Pi_{ij} - V_i = (1 - \beta)S_{ij}, \tag{1.11}$$

$$E_{ij} - U_j = \beta S_{ij}. \tag{1.12}$$

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

1.2.4 Equilibrium

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

1.2.4.1 Integrated Equilibrium

Using (1.5), (1.8), and (1.9), equation (1.10) becomes

$$(r + \delta)S_{ij} = y_i - rU_j. \tag{1.13}$$

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

$$y_i \geq rU_j. \tag{1.14}$$

Moreover, (1.5), together with (1.12) and (1.13), yields

$$w_{ij} = \beta y_i + (1 - \beta)rU_j. \tag{1.15}$$

According to (1.15), the wage is a weighted average of the output of the match and the worker's flow value of unemployment, which is common in this framework.

Substituting (1.12) and (1.13) in (1.3) and (1.4), we obtain the reservation values of the two types of workers:

$$rU_P = \frac{(r + \delta)b + \beta[m(\theta_L)y_L + m(\theta_H)y_H]}{r + \delta + \beta[m(\theta_L) + m(\theta_H)]}, \tag{1.16}$$

$$rU_U = \frac{(r+\delta)b + \beta[m(\theta_L)y_L + \eta m(\theta_H)y_H]}{r+\delta+\beta[m(\theta_L)+\eta m(\theta_H)]}. \tag{1.17}$$

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

$$[m(\theta_L) + m(\theta_H)]u_P = \delta(1-\mu-u_P), \tag{1.18}$$

$$[m(\theta_L) + \eta m(\theta_H)]u_U = \delta(\mu-u_U). \tag{1.19}$$

Also, the probabilities that each type of vacancy meets an underprivileged worker are equal:

$$\phi_{LU} = \phi_{HU} = \phi = \frac{u_U}{u_P+u_U}. \tag{1.20}$$

Using (1.11), (1.13), (1.16), and (1.17), we can rewrite the free entry conditions (1.9), $V_i = 0$ $i = L, H$, as

$$\frac{(r+\delta)c}{q(\theta_H)(1-\beta)} = [1-\phi(1-\eta)]y_H - \eta\phi rU_U - (1-\phi)rU_P, \tag{1.21}$$

$$\frac{(r+\delta)c}{q(\theta_L)(1-\beta)} = y_L - \phi rU_U - (1-\phi)rU_P, \tag{1.22}$$

where rU_P and rU_U are given by equations (1.16) and (1.17), respectively. Equations (1.21) and (1.22) are the free and costless entry conditions in the high- and low-productivity sector, respectively.

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

Definition. An *integrated* steady-state equilibrium consists of a set of value functions U_j, E_{ij}, V_i, Π_{ij}, and S_{ij} that satisfy (1.3)-(1.13) and a vector $\{\theta_L, \theta_H, \phi, v_P, v_U\}$, such that all matches produce a non-negative surplus, i.e., inequality (1.14) holds, and the vector $\{\theta_L, \theta_H, \phi, v_P, v_U\}$ satisfies $a)$ the free-entry conditions (1.21) and (1.22); $b)$ the steady-state conditions (1.18) and (1.19) regarding the stocks of unemployed workers of each type and $c)$ equation (1.20), which defines the probability that a firm finds an underprivileged worker.

Solving (1.18) and (1.19), we find

$$u_P = \frac{\delta(1-\mu)}{\delta + m(\theta_L) + m(\theta_H)}, \tag{1.23}$$

$$u_U = \frac{\delta\mu}{\delta + m(\theta_L) + \eta m(\theta_H)}. \tag{1.24}$$

Substituting (1.23) and (1.24) in equation (1.20) we find

$$\phi = \frac{\mu[\delta + m(\theta_L) + m(\theta_H)}{\delta + m(\theta_L) + (\mu + \eta - \mu\eta)m(\theta_H)}. \tag{1.25}$$

Equations (1.21) and (1.22), where rU_P and rU_U are given by equations (1.16) and (1.17) and ϕ by equation (1.25), determine a unique pair of (θ_H, θ_L). Once this pair has been determined, we can obtain unique values for all other variables. First, consider the following proposition:

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

Proof. All proofs are presented in the Appendix.

The existence of an integrated steady-state equilibrium requires that the surplus generated by each match is non-negative. From equations (1.14), (1.16) and (1.17), we see that if $y_H > y_L > b$, then $S_{Hj} \geq 0$ for every $j = U, P$, i.e., the two surpluses in the high-productivity sector are always non-negative. Both types of workers find it always beneficial to work in the high-productivity sector. On the other hand, the condition specified in Proposition 1 regarding the size of y_L is necessary and sufficient for privileged workers to accept jobs in the low-productivity sector. Finally, it follows that if privileged workers accept jobs in the low-productivity sector, so do the underprivileged ones, since the latter face worse prospects in the high-productivity sector and, as shown below, have a lower reservation value.[8]

Notice from (1.23) and (1.24) that the unemployment rate among privileged workers ($= v_P/(1-\mu)$) is lower than the one among underprivileged, since the former have a higher probability of getting matched in one of the two sectors, namely, the high-productivity sector. For the same reason, the probability that a vacancy of either type meets an underprivileged worker is greater than the share of underprivileged workers in the general population, that is, $\phi > \mu$.

Proposition 2. Privileged workers have a higher reservation wage: $rU_P > rU_U$. Moreover, in each sector, privileged workers receive a higher wage than the underprivileged: $w_{HP} >$

[8]Using (1.13), (1.16) and (1.17), we find that the partially *segregated* equilibrium, in which only underprivileged workers find it beneficial to match with low-productivity jobs, that is, $S_{LU} \geq 0$ and $S_{LP} < 0$, occurs when $\frac{(r+\delta)b+\beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)} > y_L \geq \frac{(r+\delta)b+\beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)}$. Similarly, the *restricted* equilibrium in which only high-technology firms exist, i.e., $S_{Li} < 0$ for $i = P, U$, occurs when $\frac{(r+\delta)b+\beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)} > y_L$.

w_{HU} and $w_{LP} > w_{LU}$. Also, workers of each type in the high-productivity sector receive a higher wage than their counterparts in the low-productivity sector: $w_{HP} > w_{LP}$ and $w_{HU} > w_{LU}$.

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

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

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

Finally, we note that as η increases, it becomes more likely that the condition regarding the size of y_L for the existence of an integrated equilibrium, stated in Proposition 1, ceases to hold; namely, the term $\frac{(r+\delta)b+\beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)}$ increases with η and may become higher than y_L, in which case the economy jumps to a partially segregated equilibrium where only the underprivileged work in the low-productivity sector. As η increases further, then even the term $\frac{(r+\delta)b+\beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)}$ may become higher than y_L. In that case, the economy moves to a restricted equilibrium where any talent mismatch disappears; the low-productivity sector shuts down since no worker finds it worthwhile to work there (see footnote 8). The equations that describe each of these two types of equilibria are given below.

1.2.4.2 Partially Segregated Equilibrium

In a partially segregated equilibrium $S_{LP} < 0$ and hence privileged workers do not occupy high-productivity jobs. Following the same steps as before, equation (1.16) becomes

$$rU_P = \frac{(r+\delta)b + \beta m(\theta_H)y_H}{r+\delta+\beta m(\theta_H)}. \tag{1.26}$$

Also, the equation that sets the flow of newly hired privileged workers with the flow of layoffs (equation 1.18) becomes:

$$m(\theta_H)u_P = \delta(1-\mu-u_P). \tag{1.27}$$

Solving for u_P yields

$$u_P = \frac{\delta(1-\mu)}{\delta+m(\theta_H)}, \tag{1.28}$$

which replaces equation (1.23) in the main text. Furthermore, since privileged workers do not work at low-productivity jobs, $\phi_{LU} = 1$ and, using equation (1.28) for u_P given above in (1.20), we have

$$\phi_{HU} = \frac{\mu[\delta+m(\theta_H)]}{\delta+(1-\mu)m(\theta_L)+(\mu+\eta-\mu\eta)m(\theta_H)}. \tag{1.29}$$

Finally, the free-entry condition in the low-productivity sector (equation 1.22) becomes

$$\frac{(r+\delta)c}{q(\theta_L)(1-\beta)} = y_L - rU_U. \tag{1.30}$$

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

1.2.4.3 Restricted Equilibrium

In a restricted equilibrium $S_{LP} < 0$ and $S_{LU} < 0$. Hence, no worker, no matter whether privileged or underprivileged, is employed at a low-productivity job. The reservation value of privileged workers is still given by (1.26), whereas that of underprivileged workers simplifies to

$$rU_U = \frac{(r+\delta)b + \beta\eta m(\theta_H)y_H}{r+\delta+\beta\eta m(\theta_H)}. \tag{1.31}$$

Also, the measure of privileged unemployed workers is still given by (1.28), whereas that of underprivileged is

$$u_U = \frac{\delta\mu}{\delta+\eta m(\theta_H)}. \tag{1.32}$$

Moreover, equation (1.29) becomes

$$\phi_{HU} = \frac{\mu[\delta+m(\theta_H)]}{\delta+(\mu+\eta-\mu\eta)m(\theta_H)}. \tag{1.33}$$

Finally, there is only one free-entry equilibrium condition, that for the high-productivity sector, which is still given by equation (1.21).

1.3 Quantitative Analysis

1.3.1 European Countries

Here, we calibrate the model to match data from the economies of France, Spain, the Netherlands, Italy, and Greece over period 2005-2015. We are primarily interested in obtaining rough estimates regarding the impact of discrimination on the flow of total surplus in the economy, i.e., total income net of the flow cost of vacancies. More specifically, this is given by

$$\text{Total Surplus 1} \equiv (e_{LP}+e_{LU})y_L + (e_{HP}+e_{HU})y_H - c(v_L+v_H), \tag{1.34}$$

where, it may recalled that, e_{LP} and e_{LU} are employment in the low-productivity sector for privileged and underprivileged workers respectively, e_{HP} and e_{HU} are employment in the high-productivity sector for privileged and underprivileged workers respectively, y_L and y_H stand for productivity of a worker in the low- and high-productivity sectors respectively, c is a flow hiring cost, and v_L and v_H are respectively the stock of low- and high-productivity vacancies searching for workers.

We also consider an alternative measure of the total surplus, labeled Total Surplus 2, which includes the value of leisure, that is,

$$\text{Total Surplus 2} \equiv (e_{LP} + e_{LU})y_L + (e_{HP} + e_{HU})y_H + b(u_P + u_U) - c(v_L + v_H), \quad (1.35)$$

where the additional term b is a flow of income received during unemployment that captures the opportunity cost of employment, and u_P and u_U stand for the mass of the privileged and the underprivileged unemployed, respectively.

One period in the model represents one quarter; thus, all relevant parameters are interpreted quarterly. We identify as "privileged" and "underprivileged" the male and female workers, respectively. Following the literature, see for example the seminal work of Blanchard and Diamond (1990), we use Cobb-Douglas functional forms for both matching functions.

The following parameters have to be determined: The productivity parameters y_L and y_H, the interest rate r, the unemployment elasticity of the matching function, the separation rate δ, the workers' bargaining power β, the share of women in the labor force μ, the value of leisure b, the vacancy cost c, and the discrimination parameter η.

First, following the literature, for example D. Mortensen, C. Pissarides, et al. (2003), we set the unemployment elasticity of the matching function and the workers' bargaining power parameter β equal to 0.5.[9] Second, we normalize the value of y_L to unity. Third, following Shimer (2005) we use $b = 0.4$ for the value of leisure. All the calibrated parameters are shown in the Table 1.1 and 1.2. Using data from Eurostat, we compute the interest rate, the separation rate and the share of women in the labor force. More specifically, we approximate the real interest rate as the difference between the average yield to 10-year government bond and the average growth rate of the Harmonized Index of Consumer Prices. We find the values 0.375%, 0.509%, 0.321%, 0.563%, and 1.670% for the quarterly real interest rate, r, in France, Spain, the Netherlands, Italy and Greece, respectively. Also, using the method explained in detail in Shimer (2005), we find the separation rate, δ, to be 0.0216, 0.0553,

[9] This value of 0.5 for the unemployment elasticity of the matching function is within the range of estimates cited by Petrongolo and C. A. Pissarides (2001) for a variety of countries.

0.0103, 0.0144 and 0.024. Finally, we calculate directly from the data the average values of the share of women in the labor force over the period under study in the three economies; they are 0.479, 0.441, 0.454, 0.417 and 0.425, respectively.[10]

Next, we calibrate the remaining parameters to match the following targets: a) the unemployment rate among female workers over the period 2005-2015, which is equal to 7.8%, 17.1%, 5.2%, 8.9% and 18.4% respectively in France, Spain, the Netherlands, Italy, and Greece; b) the unemployment rate among male workers which is equal to 7.2%, 14.8%, 3.9%, 6.7%, and 12.1% respectively; and c) the gender wage gap ($= \frac{w_P - w_U}{w_P}$) found in our empirical estimations (as seen in Table 2.8 this takes the values 15.7%, 16.6%, 11.8%, 12.3%, and 16.6%, respectively).

Given the parameters values and the specified targets mentioned above, when we attempt to calibrate the model as being at an integrated equilibrium we find for all economies that the condition specified in Proposition 1 is not satisfied. In other words, for all economies we find that $S_{LP} < 0$, i.e., privileged workers do not consider it worthwhile to be employed on low-productivity jobs. Hence, we calibrate the model economies as being at a partially segregated equilibrium, i.e., privileged workers are matched with high productivity jobs only, whereas underprivileged workers are matched with both types of jobs (see the Appendix for the equations that describe this type of equilibrium). The resulting values of the calibrated parameters are a) for y_H: 1.234, 1.331, 1.182, 1.240, and 1.544, in France, Spain, the Netherlands, Italy and Greece, respectively; b) for c: 6.192, 5.069, 8.557, 14.331 and 20.768; and c) for η: 0.153, 0.291, 0.205, 0.309 and 0.381. Also, the resulting values for the matching rates are: for m_H: 0.278, 0.318, 0.254, 0.201 and 0.174; and for m_L: 0.213, 0.175, 0.136, 0.085 and 0.040. We call this the benchmark case.

Tables 1.3, 1.4, 1.5, 1.6 and 1.7 present the effects of a decrease in discrimination, i.e., an increase in parameter η for the respective cases of France, Spain, the Netherlands, Italy, and Greece. The numbers indicate percentage changes relative to the benchmark case, i.e., the case where, among others, $\eta = 0.153$ and the gender wage gap is 15.7% (France), $\eta = 0.291$ and the gender wage gap is 16.6% (Spain), $\eta = 0.205$ and the gender wage gap 11.8% (the Netherlands), $\eta = 0.309$ and the gender wage gap 12.3% (Italy), and $\eta = 0.381$ and the gender wage gap 16.6% (Greece).

A decrease in discrimination raises the matching rate between an underprivileged worker and a high-productivity job. This increases the expected profitability in the high-productivity sector and spurs job entry, i.e., V_H and θ_H increase. Workers, both privileged and underprivileged, find themselves in a better bargaining position (their reservation values, rU_P and rU_U, increase), which leads to higher wages (w_{HP} and w_{HU}). The higher labor market tightness

[10]To be consistent with our empirical estimations, the result of which are also used in the calibration, all computations involving employment and unemployment use data for workers aged 25-64.

(θ_H) in the high-productivity sector leads also to higher employment (e_{HP} and e_{HU}), higher output ($Y_H = (e_{HP} + e_{HU})y_H$) and higher surplus ($= Y_H - cV_H$) in that sector. Moreover, the unemployment rate among privileged workers ($\frac{u_P}{1-\mu}$) decreases (recall that they are employed only in the high-productivity sector, where the number of vacancies per unemployed worker has gone up).

On the other hand, the higher reservation value of the underprivileged workers (rU_U), mentioned above, raises the wage in the low-productivity sector (w_{LU}) and induces job exit and lower labor market tightness (V_L and θ_L decrease). The latter lowers employment (e_{LU}), output ($Y_L = e_{LU}y_L$) and the surplus ($= Y_L - cV_L$). Eventually, as the sector shuts down, all these variables become zero. Interestingly, as one sector gradually expands and the other vanishes, the unemployment rate among underprivileged workers first increases and then declines. Finally, both measures of net income, i.e., Total Surplus 1 and Total Surplus 2, go up.

Calibrating our model using values that pertain to each of five major European countries we have data for, France, Spain, the Netherlands, Italy and Greece, our simulation exercise suggests that a 50 percent decrease in the gender wage gap, for instance, increases both measures of net income by more than three percent per quarter relative to the benchmark case for France, by more than four percent for Spain, by more than one percent for the Netherlands, by more than two percent for Italy, and by more than three percent for Greece. More specifically, the percentage change is 3.2, 4.3, 1.4, 2.1 and 3.5 per quarter for Total Surplus 1, and 3.7, 4.1, 2.1, 2.4 and 3.6 for Total Surplus 2 as shown in Tables 1.3, 1.4, 1.5, 1.6 and 1.7 for the case of France, Spain, the Netherlands, Italy and Greece, respectively.

1.3.2 The US

Having provided some quantitative evidence regarding the impact of talent misallocation on total surplus based on our theoretical model for five major European countries, we now proceed to provide some quantitative evidence regarding the impact of talent misallocation on total surplus based on our theoretical model also for the US economy. Specifically, we calibrate our model to match the US economy over the most recent period 2010-2017. The flow of total surplus in the economy is given by equation (1.34). The alternative measure regarding the flow of total surplus in the economy and it takes into account the value of leisure is given by equation (1.35).

One period in the model represents one month; thus, all relevant parameters are interpreted monthly. We apply the model in relation to race focusing on African Americans as compared to whites. That is, based on the jargon of our theoretical model, we identify as potentially "privileged" and "underprivileged" the white and black workers, respectively. We use Cobb-

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

According to the literature[11], we set the unemployment elasticity of the matching function and the workers' bargaining power parameter β equal to 0.5, while for the value of leisure we follow Shimer (2005) and set it to $b = 0.4$. The productivity parameter in the low-productivity sector is normalized to one. Using the Federal Reserve Economic Data (FRED), we compute the real interest rate as the difference between the 10-year government bond and the growth rate of the Consumer Price Index. We compute a value 0.763% for the monthly real interest rate. As for the separation rate δ, we follow the method explained by Shimer (2005) and find it to be equal to 0.0199. Using data from the Current Population Survey (CPS) of the Bureau of Labor Statistics, we calculate the average share of African-Americans in the labor force to be 12.04% over the period from 2010 to 2017. In addition, we calibrate the remaining parameters to match targets such as the unemployment rate among the African-Americans which equals 11.93%, the unemployment rate among whites which equals 6.04%, and wage differentials between African-Americans relative to whites which is equal to 22.3% from our estimation shown in Table 3.11.

We calibrate the equilibrium as a partially segregated one since the integrate equilibrium is not satisfied. The resulting values of the calibrated parameters are $y_H = 1.446$, $c = 8.374$, $\eta = 0.177$, and the matching rates in the high- and low-productivity sector are $m_H = 0.31$ and $m_L = 0.092$, respectively. This is our benchmark case[12]. Table 1.8 presents the effect of a decrease in discrimination, i.e., an increase in parameter η in the US. The numbers indicate percentage changes relative to the benchmark.

A decrease in discrimination corresponding to a 50% decrease in the wage gap related to race, reduces first the matching rates in both sectors. The reduction in the matching rate in the low-productivity sector is larger as compared to the high-productivity one. As a result, the profitability in the low-productivity sector decreases and this induces job exit. Regarding employment, more underprivileged workers are employed in the high-productivity sector (e_{HU}), which results in higher output (Y_H) and higher surplus ($= Y_H - cV_H$). Moreover, the unemployment rate among privileged workers increases, and the same goes for the underprivileged. However, the unemployment rate for the underprivileged is larger as a result of the job exit in the low-productivity sector. As the discrimination is reduced further, the matching rate in the high-productivity sector increases. This increases expected profitability in the high-productivity sector and spurs job entry, i.e., V_H and θ_H increase. Both types

[11] For example, D. Mortensen, C. Pissarides, et al. (2003), Petrongolo and C. A. Pissarides (2001)

[12] All the calibrated parameters are shown in Table 1.1 and 1.2

of workers are now in a better bargaining position (their reservation values, rU_P and rU_U, increase), which leads to higher wages (w_{HP} and w_{HU}). In addition, employment in the high-productivity sector (e_{HP} and e_{HU}), output ($Y_H = (e_{HP}+e_{HU})y_H$) and surplus ($= Y_H - cV_H$) increase in that sector. The low-productivity sector shuts down. Interestingly, as one sector gradually expands and the other vanishes, the unemployment rate among underprivileged workers first increases and then declines. Finally, both measures of net income, i.e., Total Surplus 1 and Total Surplus 2, go up.

Calibrating our model using values that mimic the US economy over the period 2010-2017, our simulation exercise suggests that a 50 percent decrease in the wage gap between African-Americans and whites, for instance, increases both measures of net income relative to the benchmark case. Specifically, the percentage change is 0.4 per month for Total Surplus 1, and 0.7 for Total Surplus 2 as shown in Table 1.8. In addition, if we eliminate race discrimination completely the increase in net income is much larger, with the percentage change equal to 3.9 and 3.5 respectively for Total Surplus 1 and Total Surplus 2.

1.4 Conclusion

In our theoretical setting, wage differentials and talent misallocation are generated by unequal access to employment that arises because of the existence of prejudice, social norms, discrimination, etc against the underprivileged workers (women, immigrants, private sector employees). No matter what the causes of unequal access to employment, we show that the higher the unequal access to employment, the higher the wage differential and the higher the misallocation, resulting in income losses.

Indeed, calibrating our theoretical model, we show that the type of misallocation effects we uncover here can have substantial aggregate effects for economies such us that of Spain. Importantly, calibrating our theory model for the US economy for the period 2010 to 2017, we find that a reduction of 50 percent in the wage gap between African-Americans and whites, is associated with an increase of net income of about 0.4 percent per month, or 0.7 percent per month taking into account the value of leisure. If the wages of African-Americans and whites converged completely, this would increase net income by around 4 percent per month.

1.5 Future Work

In future work, we plan to improve the calibration of the model by estimating the replacement rate for each European country. In the existing calibration of the model, we follow the work of Shimer (2005) to set the value of leisure $b = 0.4$. However, ideally, we would need to match the replacement rate in each country. That's why we plan to estimate the replacement rate in each country to adjust the parameter b in such a way that Proposition 1 is satisfied and then we can calibrate the model for an integrated equilibrium.

In our quantitative analysis, we explored the impact of gender discrimination on the flow of total surplus in the European economies. However, women have a lower labor force participation rate compared to men, and this is not captured in the model. For this reason, the model is more suitable to investigate the misallocation effects arising from the race for the US economy and country of origin for European economies. A possible extension of the model is to incorporate as endogenous the decision of labor force participation for workers.

Finally, in terms of future work, a natural extension to the model would be to assume the existence of some creation cost needed to produce the intermediate goods. The extension will relate to Acemoglu (2001) work who develops a search and matching model in which high-wage (good) and low-wage (bad) jobs coexist. We will build on the existing model by considering good and bad entrepreneurs who can thus open one of two types of vacancies: good-jobs and bad-jobs. On the other hand, workers will have the same abilities but they will differ regarding their access to employment. It would be interesting to use this model to explore the coexistence of good and bad jobs due to the differential job creation costs in addition to the labor market frictions for certain population groups.

1.6 Tables

Table 1.1: Calibration Results

Parameter	Description	Value
β	Workers' bargaining power	0.5
y_L	Output in the low-productivity sector	1
b	Value of leisure	0.4
r	Real interest rate in:	
	France	0.375%
	Spain	0.509%
	Netherlands	0.321%
	Italy	0.563%
	Greece	1.670%
	US	0.763%
δ	Separation rate in:	
	France	0.022
	Spain	0.055
	Netherlands	0.010
	Italy	0.014
	Greece	0.024
	US	0.0199
μ	Share of the underprivileged in the labor force:	
	France	0.479
	Spain	0.441
	Netherlands	0.454
	Italy	0.417
	Greece	0.425
	US	0.124
u_U	Unemployment rate among underprivileged workers:	
	France	7.8%
	Spain	17.1%
	Netherlands	5.2%
	Italy	8.9%
	Greece	18.4%
	US	11.93%
u_P	Unemployment rate among privileged workers:	
	France	7.2%
	Spain	14.8%
	Netherlands	3.9%
	Italy	6.7%
	Greece	12.1%
	US	6.04%
$\frac{w_P - w_U}{w_P}$	Wage gap:	
	France	15.7%
	Spain	16.6%
	Netherlands	11.8%
	Italy	12.3%
	Greece	16.6%
	US	22.3%

Table 1.2: Calibration Results for the Segregated Equilibrium

Parameter	Description	Value
y_H	Output in the high-productivity sector	
	France	1.234
	Spain	1.331
	Netherlands	1.182
	Italy	1.240
	Greece	1.544
	US	1.446
c	Vacancy cost	
	France	6.192
	Spain	5.069
	Netherlands	8.557
	Italy	14.331
	Greece	20.768
	US	8.374
η	Discrimination parameter	
	France	0.153
	Spain	0.291
	Netherlands	0.205
	Italy	0.309
	Greece	0.381
	US	0.177
m_H	Matching rate high-productivity sector	
	France	0.278
	Spain	0.318
	Netherlands	0.254
	Italy	0.201
	Greece	0.174
	US	0.310
m_L	Matching rate in low-productivity sector	
	France	0.213
	Spain	0.175
	Netherlands	0.136
	Italy	0.085
	Greece	0.040
	US	0.092

Table 1.3: The effects of a decrease in discrimination in the case of France

Decrease in Gender Wage Gap	50%	100%
High-Productivity Sector		
$m(\theta_H)$	14.7	23.4
w_{HP}	0.6	0.9
w_{HU}	2.5	8.9
e_{HP}	1.0	1.4
e_{HU}	337.8	509.5
Y_H	45.9	68.8
Surplus	44.9	71,5
V_H	50.0	16.0
Low-Productivity Sector		
$m(\theta_L)$	-83.1	—
w_{LP}	—	—
w_{LU}	2.8	—
e_{LP}	—	—
e_{LU}	-73.9	—
Y_L	-73.9	—
Surplus	-73.2	—
V_L	-96.3	—
Aggregate Variables		
$\frac{u_P}{1-\mu}$	-12.0	-18.1
$\frac{u_U}{\mu}$	56.0	-24.4
Total Surplus 1	3.2	10.8
Total Surplus 2	3.7	9.8

Notes:

1. The numbers indicate percentage changes from the benchmark case: Wage gap $=$ 15.7% (discrimination parameter $\eta = 0.153$).

2. The economy is calibrated as if it is at a *partially segregated* equilibrium for reasons explained in the main text. When the Wage gap decreases by 50%, relative to the benchmark case, to 7.85% ($\eta = 0.376$), the economy continues to be at a partially segregated equilibrium.

Table 1.4: The effects of a decrease in discrimination in the case of Spain

Decrease in Gender Wage Gap	50%	100%
High-Productivity Sector		
$m(\theta_H)$	9.4	17.1
w_{HP}	0.7	1.2
w_{HU}	3.1	9.5
e_{HP}	1.3	2.3
e_{HU}	111.9	204.7
Y_H	24.3	44.5
Surplus	24.7	48.1
V_H	18.8	9.8
Low-Productivity Sector		
$m(\theta_L)$	-65.2	—
w_{LP}	—	—
w_{LU}	3.7	—
e_{LP}	—	—
e_{LU}	-61.9	—
Y_L	-61.9	—
Surplus	-60.4	—
V_L	-84.9	—
Aggregate Variables		
$\frac{u_P}{1-\mu}$	-7.4	-12.8
$\frac{u_U}{\mu}$	9.9	-24.6
Total Surplus 1	4.3	12.7
Total Surplus 2	4.1	10.8

Notes:

1. The numbers indicate percentage changes from the benchmark case: Wage gap $=$ 16.6% (discrimination parameter $\eta = 0.291$).

2. The economy is calibrated as if it is at a *partially segregated* equilibrium for reasons explained in the main text. When the Wage gap decreases by 50%, relative to the benchmark case, to 8.8% ($\eta = 0.512$), the economy continues to be at a partially segregated equilibrium.

Table 1.5: The effects of a decrease in discrimination in the case of the Netherlands

Decrease in Gender Wage Gap	50%	100%
High-Productivity Sector		
$m(\theta_H)$	7.1	13.8
w_{HP}	0.3	0.4
w_{HU}	1.4	6.9
e_{HP}	0.2	0.4
e_{HU}	205.9	268.1
Y_H	38.2	49.9
Surplus	37.6	51.8
V_H	60.8	-0.6
Low-Productivity Sector		
$m(\theta_L)$	-91.7	—
w_{LP}	—	—
w_{LU}	1.5	—
e_{LP}	—	—
e_{LU}	-84.9	—
Y_L	-84.9	—
Surplus	-84.7	—
V_L	-98.8	—
Aggregate Variables		
$\frac{u_P}{1-\mu}$	-6.4	-12.8
$\frac{u_U}{\mu}$	82.1	-34.6
Total Surplus 1	1.4	7.0
Total Surplus 2	2.1	6.4

Notes:

1. The numbers indicate percentage changes from the benchmark case: Wage gap $=$ 11.8% (discrimination parameter $\eta = 0.205$).

2. The economy is calibrated as if it is at a *partially segregated* equilibrium for reasons explained in the main text. When the Wage gap decreases by 50%, relative to the benchmark case, to 5.9% ($\eta = 0.321$), the economy continues to be at a partially segregated equilibrium.

Table 1.6: The effects of a decrease in discrimination in the case of Italy

Decrease in wage gap related to race	50%	100%
High-Productivity Sector		
$m(\theta_H)$	5.3	10.5
w_{HP}	0.3	0.5
w_{HU}	1.8	7.4
e_{HP}	0.4	0.7
e_{HU}	100.6	145.0
Y_H	23.0	33.6
Surplus	23.1	35.5
V_H	30.7	0.3
Low-Productivity Sector		
$m(\theta_L)$	-83.3	—
w_{LP}	—	—
w_{LU}	2.0	—
e_{LP}	—	—
e_{LU}	-78.2	—
Y_L	-78.2	—
Surplus	-78.8	—
V_L	-96.7	—
Aggregate Variables		
$\frac{u_P}{1-\mu}$	-4.7	-9.0
$\frac{u_U}{\mu}$	30.7	-31.5
Total Surplus 1	2.1	7.4
Total Surplus 2	2.4	6.6

Notes:

1. The numbers indicate percentage changes from the benchmark case: Wage gap $=$ 12.3% (discrimination parameter $\eta =?$).

2. The economy is calibrated as if it is at a *partially segregated* equilibrium for reasons explained in the main text. When the Wage gap decreases by 50%, relative to the benchmark case, to 6.12% ($\eta = 0.451$), the economy continues to be at a partially segregated equilibrium.

Table 1.7: The effects of a decrease in discrimination in the case of Greece

Decrease in wage gap related to race	50%	100%
High-Productivity Sector		
$m(\theta_H)$	3.5	13.8
w_{HP}	0.3	1.1
w_{HU}	2.4	11.2
e_{HP}	0.6	1.6
e_{HU}	47.7	75.5
Y_H	14.4	23.5
Surplus	14.7	26.2
V_H	24.0	5.8
Low-Productivity Sector		
$m(\theta_L)$	-87.3	—
w_{LP}	—	—
w_{LU}	3.1	—
e_{LP}	—	—
e_{LU}	-86.2	—
Y_L	-86.2	—
Surplus	-85.9	—
V_L	-97.8	—
Aggregate Variables		
$\frac{u_P}{1-\mu}$	-3.0	-10.7
$\frac{u_U}{\mu}$	12.3	-41.3
Total Surplus 1	3.5	12.2
Total Surplus 2	3.6	10.3

Notes:

1. The numbers indicate percentage changes from the benchmark case: Wage gap $=$ 16.6% (discrimination parameter $\eta = 0.381$).

2. The economy is calibrated as if it is at a *partially segregated* equilibrium for reasons explained in the main text. When the Wage gap decreases by 50%, relative to the benchmark case, to 8.3% ($\eta = 0.482$), the economy continues to be at a partially segregated equilibrium.

Table 1.8: The effects of a decrease in discrimination in the US

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

Notes:

1. The numbers indicate percentage changes from the benchmark case: Wage gap $=$ 22.3% (discrimination parameter $\eta = 0.177$).

2. The economy is calibrated as if it is at a *partially segregated* equilibrium for reasons explained in the main text. When the Wage gap decreases by 50%, relative to the benchmark case, to 11.15% ($\eta = 0.512$), the economy continues to be at a partially segregated equilibrium.

Chapter 2

Talent Misallocation in Europe

2.1 Introduction

The allocation of talent across economic activities is an important determinant of economic growth, as argued early on by Baumol (1990) and Murphy et al. (1991). Talent misallocation can lead to inefficiencies that suppress economic growth and harm the welfare of societies. We utilize microeconomic data on wages and individual characteristics across eighteen European economies for the period 2005-2015 to investigate the overall misallocation effects implied by the combined gender, public-private and foreign-native wage gaps. In our theoretical model, these wage gaps and misallocation are generated by the unequal opportunities for employment that different types of workers face in the labor market: the higher the degree of unequal treatment for underprivileged workers, the higher the wage gap and the higher the misallocation.

We assess the extent to which wages differ across public versus private, female versus male, and foreign versus native born workers that otherwise share similar characteristics. In the absence of data on the degree of unequal access to employment or direct numbers for misallocation, these conditional wage gaps serve as an implicit measure of talent misallocation. As illustrated in our theoretical model and our calibration exercise, such unwarranted differences in earnings may imply misallocation with significant adverse effects for aggregate economic outcomes. Consistent with this, our micro-based wage-gap estimates place countries that have been at the epicenter of the European Crisis at the very high end of our talent misallocation ranking.

The theoretical model we construct guides our empirical analysis, as it links unequal access to employment with wage gaps, talent misallocation and income losses. This theoretical model generates wage differences for workers based on unequal access to employment, which in turn might depend on individual characteristics such as gender, race or country of origin, as well as on political or other affiliation. More specifically, we consider an economic environment with two types of jobs/sectors, one of which is more productive than the other, and a labor market where workers are equally talented but differ with respect to their opportunities for employment. These differences can arise from the presence of diverse social phenomena such as prejudice, social norms, discrimination, nepotism, political favouritism, immigrant status and so on. Thus, workers can be "privileged" or "underprivileged". Here, "underprivileged" relates to foreign workers who lack the privileges of domestic ones or to women who do not enjoy male privileges. More broadly, "underprivileged" might also encompass workers in the private sector who lack the political or social "connectedness" characterizing those that manage to land a job in the public sector.

While all unemployed workers search for employment in both markets, underprivileged workers have a lower probability of getting hired in the high-productivity sector compared to the privileged ones as the former face a lower job matching rate. In such an environment, workers of both types can be matched with both low- and high-productivity jobs. However, privileged workers will be in a better bargaining position and hence receive a higher wage, despite the fact that all workers have the same ability/talent. Additionally, as the degree of unequal treatment for underprivileged workers decreases, the economy may even move to an equilibrium where the low-productivity sector shuts down. In this case, wages of privileged and underprivileged workers in each sector would converge and any talent mismatch would disappear.

The study closer to ours is Hsieh et al. (2019) who investigate the aggregate productivity gains in the US between 1960 and 2010 following the decrease in labor market discrimination based on gender and race. Using a model of occupational choice, they find that one quarter of aggregate growth in GDP per person for the US during the last 50 years can be explained by declines in talent misallocation. In this chapter, we focus instead on talent misallocation across European Union countries, and explore misallocation based on gender, private sector affiliation, and country of origin. As migrants comprise a much smaller part of the total workforce in the European Union compared to the US,[1] the talent misallocation problem attributed to this factor can be much greater for the European Union than for the US.

More broadly, our work relates to the literature investigating the causes of economic development and productivity differences across countries. The literature, as surveyed by Caselli (2005) and Jones (2016), suggests that Total Factor Productivity (TFP) plays an important role in explaining cross-country income differences. The main reason TFP varies across countries is because inputs are not allocated efficiently. Indeed, Hsieh and Klenow (2009) show that reallocation of factors across plants could substantially increase efficiency in the

[1] For the period under study, intra-EU migrants comprised 5 percent of the total workforce and non-EU migrants around 6 percent of it, whereas in the US for 2015, around 28 percent of the total workforce was comprised of intra-state immigrants and about 13 percent of it from foreign migrants.

likes of China and India.

Our work is also related to the literature examining the aggregate costs of gender inequality. Cavalcanti and Tavares (2016) develop a growth model with endogenous fertility and barriers to female labor market participation in the form of wage discrimination. They calibrate the model for the US economy and find that a 50 percent increase in the gender wage gap leads to a 35 percent decrease in *per capita* income.[2] They also find that a very large share of the difference in *per capita* output between several countries and the US can be explained by gender discrimination differences. Cuberes and Teignier (2016) present an occupational choice model that quantifies the effects of gender wage gaps on aggregate productivity and income *per capita*.[3] Calibrating the model for 33 OECD countries for 2010, they find that gender gaps cause an average loss of 15 percent in income *per capita*.

Moreover, our work relates to the literature studying the wage gap between immigrants and native-born workers. Chassamboulli and Palivos (2014) develop a search model with skill heterogeneity to analyze the impact of immigration on labor market outcomes in the host country. They allow for differential search costs between natives and immigrants as a key factor in explaining the equilibrium wage gap between otherwise identical native and immigrant workers. Within the same framework, Liu et al. (2017) consider imperfect transferability of human capital across borders that puts skilled immigrants at a disadvantage on the bargaining table relative to skilled natives, so that they become willing to accept low-skill jobs at a much greater rate compared to their native counterparts. Similarly, Chassambouli and Peri (2015) consider a two-country model with labor market search, where immigrants, especially illegal ones, have a worse outside option than natives so that the wages of the former are lower.[4]

Finally, our study is related to the literature that investigates the macroeconomic costs of an overpaid public sector. For example, Santos and Cavalcanti (2020) assess the implications of earning differentials between the public and private sectors by developing a model with endogenous occupational choice among the public and private sectors, where an inefficiency arises due to a public sector wage premium. They calibrate the model to Brazil and show that the presence of such a premium can generate important allocation effects for the economy. A reform reducing the public sector wage premium by 12 percent could increase aggregate output by up to 16 percent in the long-run.[5] Jaimovich and Rud (2014) also study the effect

[2]Here, gender discrimination discourages labor-force participation of women and increases fertility; both of these effects lead to a decline in *per capita* output.

[3]Here, women face several restrictions on their occupational decision and on their participation in the labor market, leading to an inefficient allocation of talent across occupations that reduces entrepreneurs' average talent and as a result aggregate productivity and *per capita* income.

[4]Thus, their presence reduces labor costs for employers who then create more jobs per unemployed when there are more immigrants.

[5]The intuition behind these results is that earning differences between public and private workers affect their occupational choice and generate misallocation. The public sector attracts highly productive agents looking for higher-paying jobs, crowding out potentially more productive private sector employment, which leads to lower

of an over-sized inefficient public sector on economic performance through an occupational choice model, and show that public sector bureaucrats with low degree of public service motivation extract rents by hiring an excessive number of unskilled workers. This leads to an equilibrium with relatively high unskilled wages, which reduces profits and makes the private sector relatively unattractive for potential entrepreneurs.

Based on microeconomic data on wages and individual characteristics across Europe over the decade ending in 2015, we find that females, migrants, and private sector employees receive lower conditional wages than what their other observable characteristics would imply. Notably, our country-specific estimates based on these microeconomic data imply that economies such as Cyprus, Ireland, Italy and Spain, all of which have been at the heart of the European Crisis, are systematically found at the high end of the overall talent misallocation measure we estimate, and so does Greece in the pre-crisis period prior to its fiscal adjustment.[6] Thus, our paper provides new cross-country micro-econometric evidence supporting the findings of the surging literature described in the previous paragraphs regarding the importance of various forms of talent misallocation for aggregate economic outcomes.

The rest of the chapter is organized as follows. Section 2.2 describes the data and variables used in our study, summary statistics and outlines our empirical approach. Section 2.3 presents estimation results, while Section 2.4 briefly concludes.

2.2 Empirically investigating talent misallocation

2.2.1 Data

Given the theoretical link we established between wage gaps for underprivileged workers and talent misallocation, we now use microeconomic data to detect patterns of misallocation in European countries based on individuals' gender, immigrant status, and private versus public sector affiliation. In particular, we use cross-sectional data at the individual level from the European Union Statistics on Income and Living Conditions (EU SILC) collected by Eurostat annually from 2005 to 2015. The number of countries varies from wave to wave. Because of the lack of detailed information regarding migration status, Estonia, Germany, Latvia, Malta and Slovenia are excluded. Moreover, due to lack of data, Croatia, Norway and Serbia are excluded, while Bulgaria, Hungary, Lithuania, Poland, Romania and Slovakia are

productivity in the private sector and the economy as a whole.

[6] Portugal, another country at the epicenter of the European Crisis, is not ranked among those with the highest estimated talent misallocation measure. This is in line with Martin and Philippon (2017), who argue that Portugal's problems were mostly due to exogenous factors, such as the ECB not acting early enough. Luxembourg, a small idiosyncratic economy with a gigantic financial sector relative to its GDP, has relatively high estimated misallocation.

also excluded as they often have extremely small annual samples for immigrants[7]. Thus, the sample we consider for estimation consists of eighteen European countries. In our empirical application, we pool all the cross-sectional data to gain in terms of efficiency.

We assess the degree to which wages depend on individual characteristics and whether gender, migration status, and private sector affiliation have explanatory power for wages. Specifically, we use the natural logarithm of average hourly earnings of each employee as the dependent variable of our analysis. We define the hourly wage as annual income divided by the number of months worked, multiplied by weekly hours of work times 4.2. Annual income is given by gross employee cash or near cash income which refers to the monetary component of the compensation of employees in cash payable by an employer to an employee.

Our main empirical objective is to compare wages between the private and public sectors, between women and men, and between immigrants and non-immigrants, in order to detect whether these pay gaps constitute evidence of talent misallocation. With this in mind, we exclude from the sample students and individuals below 25 and above 64, those retired and disabled, and soldiers. We also exclude the self-employed as well as family workers, because in a number of countries incomes are not thought to be fully declared. On the other hand, we keep individuals that worked for part of the year. Noting that annual income includes earnings from the main job and from any secondary jobs, while the information regarding the number of months worked refers only to the main job, we keep only individuals working in the main job in our sample in order to be able to calculate hourly wages. The final sample includes the unemployed, the inactive, and individuals working in full-time and part-time occupations, which can be potentially important for females in certain countries.

Finally, our distinction between private and public sector employment is based on the Statistical Classification of Economic Activities (NACE) Revisions 1.1 and 2. We note that the public sector can be defined using either the restricted or the broad definition. The first defines a public sector worker as one employed in the sector "Public administration and defence, compulsory social security", while the broad definition also takes into account the sectors "Education" and "Health and social work". Here, we will define the public sector using the restricted definition because the broad one tends to overestimate the share of public sector workers in total employees as some of the employees included in NACE sectors "Education" and "Health and social work" are actually involved in private activities.

[7]For instance, Romania has less than 10 immigrants in its annual sample, and so does Bulgaria regarding the number of EU migrants.

2.2.2 Summary Statistics

Our final sample consists of eighteen European countries and thousands of observations. As shown in Table 2.1 the majority of employees work in the private (89.56 percent), are married, work full-time and have permanent contract. Regarding the country of origin, a high percentage of workers are native-born, while foreign-born workers consist only 12 percent of the total. Females comprise on average about half of the sample. As for the education levels, the largest part of our sample has completed (upper) secondary education, followed by those who have achieved higher education which equals 38 percent. With respect to age groups, a high percentage consists of ages 25 to 54, while the 55 to 64 age group comprises only 15 percent of the total. The occupational category c, that includes professionals, technicians and so on, contain the larger number of individuals.

Table 2.2 presents descriptive statistics regarding the average hourly earnings for the period 2005-2015. Overall, the average hourly income across the European countries that have been included in our sample was €14.85. Comparing instead the average hourly income between these countries, we deduce that Switzerland has the largest one, €32.26, followed by Denmark, €23.86, and Luxembourg, €22.35. From the other hand, Czech Republic, Portugal, and Greece have the lowest average hourly income for the period under study.

Table 2.3 shows the median hourly earnings by employment sector. In general, we observe that the average median hourly earning for private sector employees across these European countries was €12.79 compared with €14.92 for the public sector. The resulting private to public ratio of median hourly earnings was around 86 percent, implying a 14 percent unconditional wage gap related to the employment sector. However, there is heterogeneity regarding the private-public income ratio. Specifically, France, Denmark, and Belgium have the highest ratio, suggesting that these countries have the lowest wage gap, while Cyprus, Portugal, and Luxembourg have the lowest ratio, implying the highest wage gap related to the employment sector.

With regard to gender, overall women's median hourly earnings were €11.72 compared with €13.53 for men, with the resulting female to male ratio of median hourly earnings around 87 percent, implying a 13 percent unconditional gender gap. Moreover, looking across countries, we note that Ireland, Belgium, and Italy have the highest female to male ratio, suggesting the lowest gender wage gap. On contrast, Cyprus, Czech Republic, and Austria have the lowest ratio, implying the highest unconditional gender gap (see Table 2.4).

Finally, regarding the country of birth, for the period 2005-2015, the average median income for native-born workers was €14.18, compared with €12.25 for immigrants from EU and €10.56 for Non-EU. As a result the EU-migrant to native-born income ration was around 86 percent, indicating a 14 percent unconditional gap related to country of birth. As for the non-

EU to native ratio was about 74 percent, implying a 16 percent wage gap for foreigners born outside EU. From Table 2.5, we observe again that there is heterogeneity across countries regarding the unconditional wage related to the country of origin. For instance, Luxembourg, Italy, and Ireland have the lowest EU to native income ration, suggesting that these countries have the highest unconditional wage gap. With respect to the non-EU migrant to native ratio, we observe that Cyprus, Luxembourg, and Spain have the highest unconditional earnings gap.

2.2.3 Empirical Specification

Our objective is to estimate wage differentials by considering a Mincer-type wage regression of the logarithm of the hourly wage on a wide set of individual characteristics as follows:

$$w_{ijt} = \beta_0 + \beta_1 Private_{ijt} + \beta_2 Fem_{ijt} + \beta_3 MigrantEU_{ijt} + \beta_4 Migrant_{ijt} + \beta \mathbf{X}_{1ijt} \\ + \alpha_j + \alpha_t + \epsilon_{ijt}$$

where w_{ijt} is the logarithm of the hourly wage of the individual *i* in country *j* at time *t*, $Private_{ijt}$ is a dummy variable indicating whether the individual works in the private sector, Fem_{ijt} is a dummy variable indicating the gender, $MigrantEU_{ijt}$ is a dummy variable indicating whether the person is an immigrant from an EU country, $Migrant_{ijt}$ is a dummy variable indicating whether the person is an immigrant from a non-EU country, and X_{1ijt} is a vector of covariates that includes three controls for education (L=less than secondary, S=secondary and H=higher education), four controls for occupation[8], four controls for age proxying for experience[9], and binary variables denoting part-time work and permanent job status. Finally, α_j and α_t are country- and time-fixed effects respectively, β_0 is a constant and ϵ_{ijt} is the residual.

The variable experience is not provided for all countries. Thus, we include age as an indicator of labor market experience. A potential problem in estimating a Mincer-type wage model is the possible measurement error in the age variable that could lead to bias and inconsistent estimates. The measurement error arises when the age variable is believed to be reported with an error. For instance, when we proxy experience with the age, there is always the possibility that an older person, does not always imply that has greater experience compared to a younger one. It this case, the age variable may be correlated with the error term in the wage model. Also, when we estimate Mincerian wage model is the unobserved heterogene-

[8]The four occupation dummies are: a=craft and related trade workers, plant and machine operators and assemblers, and elementary occupations; b=clerks, and services and shop and market sales workers; c=professionals, technicians and associate professionals, skilled agricultural and fishery workers, and armed forces; d=legislators, senior officials and managers

[9]We proxy experience by using age dummies.

ity. There is always the possibility of not including in the model important factors that are not observed such as ability or effort.

Another issue that could arise is the life-cycle bias that has to do with the timing of measurement of income. Specifically, individuals in our sample are of different cohorts, and differences in income between them at a particular point in time could be a result of life-cycle changes and not from fundamental differences. The inclusion of age variable only corrects for changes in mean earnings across age. A lifecycle bias remains so long as there are changes in earnings variance over the lifecycle.

An important problem that arises here is that we observe wages only for individuals that are in the labor market but not for those outside the labor force. We therefore have a non-random sample, which can be viewed as a specific form of endogeneity bias. To correct for this selectivity bias, we use the Heckman method which consists of two steps. First, we use all observations and estimate a probit equation that takes the form:

$$T_{ijt} = 1(\delta \mathbf{X}_{2ijt} + \alpha_j + \alpha_t + e_{ijt} > 0) \tag{2.1}$$

where T_{ijt} is a binary dependent variable with zero indicating being out of the labor force and unity indicating being in the labor force either via paid employment or by being unemployed. X_{2ijt} is a vector of covariates that includes variables from vector X_{1ijt} in the Mincer-type wage regression specified in the beginnning of this section, along with dummy variables indicating employment sector, gender, and immigration status. Moreover, as it is highly recommended to impose at least one exclusion restriction, we include marital status (*Married*), family/children related allowances (*Benefits*) and bad health status (*Health*), in addition to the above common regressors appearing in the second stage.

The selection equation needs to be specified in such a way so that there is at least one variable that determines selection but which has no direct effect on wages. The reason is that with exactly the same variables in both equations, the second stage of Heckit would possibly suffer from collinearity. We include marital status (*Married*), family/children related allowances (*Benefits*) and bad health status (*Health*), in addition to the above common regressors appearing in the second stage. For instance, from our preliminary results, children allowance variable affects the probability of entering the labor force for females, but not the income. Similarly, marital status increases the likelihood for females to enter the labor force, while health status is associated to have a direct effect for a migrant in being into the labor force. Moreover, in order to investigate the plausibility of results regarding the instruments included, we also explore the case where we do not include any instruments in the selection. More on this below.

Based on the parameter estimate $\hat{\delta}$, we then compute the inverse Mills ratio (λ) for each observation.

Next, using the selected sample, we estimate the Mincer-type wage regression on a set of individual characteristics, fixed effects, and the Mills ratio, as follows:

$$
\begin{aligned}
w_{ijt} = \beta_0 + \beta_1 Private_{ijt} + \beta_2 Fem_{ijt} + \beta_3 MigrantEU_{ijt} + \beta_4 Migrant_{ijt} + \beta \mathbf{X}_{1ijt} \\
+ \gamma_1 \lambda(\hat{\delta}\mathbf{X}_{2ijt}) + \alpha_j + \alpha_t + \upsilon_{ijt}
\end{aligned}
\tag{2.2}
$$

We estimate the private-public, gender, and immigrant-native wage gaps, as the coefficients of the private sector, female, and foreign-born dummies respectively from the above-specified wage regression of the logarithm of the hourly wage on individual characteristics. That is, parameter β_1 captures the private-public earning gap, β_2 captures the female wage gap, β_3 the earning gap between EU migrants and natives, and β_4 the earning gap between non-EU migrants and natives.

Extended specifications include interactions such as migrants with education to capture potentially different wage impact for migrants based on their educational status, as well as interactions of private sector status with education, female with education, and female with part-time job status. Finally, we consider interactions of private sector status with female, migrant with female, and migrant with private sector status. While in the theoretical model workers are divided into "privileged" and "underprivileged" abstracting from possible overlap between private sector employees, females and immigrants, we find it useful to allow for this possibility empirically at this point by adding the above-mentioned interactions.

We first consider a specification that provides us with average parameter estimates for our pooled sample of European countries. This helps assess the overall empirical plausibility of our empirical model. Next, we are interested in taking into account the possibility that the probability of participating in the labor force is different in each country, and that wage gaps may also differ for each country. Thus, we allow for the effects of our parameters of interest, $Private_{ijt}$, Fem_{ijt}, $MigrantEU_{ijt}$ and $Migrant_{ijt}$, to differ for each country in both stages of the estimation. To do so, we include interactions of our main variables with country dummies. This then constitutes our preferred empirical specification. Noting that for migrant status, we sum the separate effects for EU and non-EU migrants weighting these according to their share in total migrants obtained from Eurostat country-level data. These country-specific estimates allow us to construct the overall "misallocation measure" of each country that indicates the combined misallocation effects arising from the private-public and gender wage gaps, as well as from the pay gap between foreign and native born workers. Basically, we constructed the misallocation measure by adding the coefficients of the private sector employees, females and the weighted sum of the EU and non-EU migrants' coefficients.

We also test the hypothesis that the linear combination of the coefficients (misallocation measure) is statistically equal to zero.

2.3 Empirical Results

2.3.1 Baseline Estimates

Noting that sample selection bias arises when the residual in the Mincer-type wage equation is correlated with the residual in probit equation (26), we use the Heckit procedure to estimate the parameter for the explanatory variable $\lambda(.)$, γ_1, which measures the covariance between the two residuals. The null hypothesis is no selectivity bias, γ_1=0.[10] Table 2.6 reports the results from estimating the probit equation described in section 3.2, where unity indicates paid employment or unemployment and zero out of labor force. The results show that being a female and having being born in a foreign country, both reduce the likelihood of being in the labor force. Similarly, currently working in the private sector reduces the likelihood that this worker was in the labor force during the previous year. The same goes for low education, bad health, and being a recipient of social benefits. On the other hand, having higher education, being in age groups 35-44 or 45-54, part-time work, having a permanent contract, and being married, are all associated with higher probability of being in the labor force.

Table 2.7 reports the results of the wage regression specified in equation (27) estimated over the period 2005-2015. Our estimates suggest that for these group of countries, being a female or immigrant, and working in the private sector exert a negative impact on one's wages beyond that explained by their economic characteristics. This is suggestive of persistent talent misallocation in Europe during the period under study. These results are robust to including a number of variables in the wage regression such as education, occupation, age, part-time job, and permanent job status.

In relation to the private-public wage gap, we find that private sector employees were paid 7.6 to 9.8 percent less than public sector employees, depending on the specification in Table 2.7.[11] As for the gender gap, the range of estimates for the negative effect of being female on hourly wages from our specifications reported in Table 2.7, is between 16.7 (estimated for the more complete specification reported in the last column of the table) and 19.1 percent (for the parsimonious specification in the first column). Looking at the impact of the country

[10] As we show in Table 2.7 next, γ_1 is significantly different than zero implying it is necessary to correct for sample selection.

[11] This is in line with empirical evidence from other micro-studies, e.g. Christofides and Michael (2013), that report negative pay differentials for the private sector unexplained by observed individual characteristics such as education and experience.

of origin on the wage gap relative to locals, we obtain differential impact on hourly wages for EU versus non-EU migrants. It turns out that gaps associated with the place of birth are always larger for migrants from non-European countries which were estimated to be as high as 18.9 percent in the parsimonious specification reported in the first column of Table 2.7. As compared to this, the total effect of being an EU migrant on wages was no higher than 11.3 percent for any of the six specifications we consider.

Having looked at the total effect of our variables of interest, we now take a closer look at their interactions with a number of other variables. These interaction terms suggest different wage impact of certain variables for private as compared to public sector employees, for females as compared to males, and for migrants as compared to non-migrants. The interaction of private sector status with education indicates the important role that education plays in reducing wage gaps between public and private sector employees. In addition, high education narrows the gender gap as highly educated females face smaller wage gaps compared to females with lower levels of education. Similarly, the wage gaps between EU migrants and natives are lower for individuals with higher levels of education. This also holds for the effect of high levels of education relative to medium (secondary) level of education for non-EU migrants.[12] Furthermore, the pay gap between migrants and natives is greater for private sector employees as compared to public sector ones. Moreover, gender wage gaps are larger for private sector employees as compared to public sector employees, as well as for non-EU migrants as compared to natives. However, the gender wage gap is somewhat lower for females born in another EU country, and considerably lower for females working part-time.

Finally, we note that the average impact of the included covariates on hourly wages in these European countries typically has the expected sign, implying that our microeconomic data and our empirical specification capture average relationships reasonably well across these European countries. We find that workers with low education receive lower wages as compared to workers with secondary education, and that those with high education receive higher wages as compared to those with only secondary education. In addition, age, used as a proxy for experience, has a positive impact on hourly wages for all age groups compared to younger working individuals of ages 25 to 34. Moreover, wages are higher in high-skilled occupations as compared to low-skilled ones. Furthermore, hourly wages are lower for those that do part-time work, and higher for workers with a permanent contract.

Country-specific estimates

We now estimate regression specifications similar to the ones reported in the last column of Table 2.7 including our complete set of explanatory variables and interactions,[13] and allowing

[12] However, low levels of education lower the wage gap for non EU migrants as compared to the wage gap for those with secondary education.

[13] We chose the more complete regression specification in order to alleviate omitted variables bias for our estimated effects and given that this regression specification has the better goodness of fit as shown in the last

in addition for the estimated coefficients of private sector status, gender, and migrant status to be country-specific. These country-specific estimates allow us to construct the results presented in Table 2.8 summarizing our findings regarding the overall wage gap or 'measure of misallocation' for each country over the period from 2005 to 2015. To construct this gap, we obtain country-specific coefficients and the resulting total effect of private sector status, female status and migrant status. For migrant status, we sum the separate effects for EU and non-EU migrants weighting these according to their share in total migrants obtained from Eurostat country-level data. For each country, we also present a measure indicating the separate misallocation effect arising from the private-public, female-male, and migrant-native wage gaps. The talent misallocation measures are highest for Cyprus, Spain, Luxembourg, Ireland, Italy and Greece as can be seen in Figure 2.1, while Belgium, Denmark, France, Sweden, the Netherlands and Switzerland have the lowest measures in Europe. We also note that for the pre-crisis period 2005-2010, results reported in Table 2.9 suggest that Cyprus was still the worst, followed by Greece, Spain, Luxembourg, Ireland and Italy, in that order.

A look at the components of the measure in the first four columns of Table 2.8 reveals that the gender wage gap and the pay gap for non-EU migrants are relatively large. The average gender wage gap across these European economies over the period 2005-2015, is 16.3 percent, closely followed by the gap between non-EU migrants and natives which equals 12.4 percent. The average private-public wage gap 7.4 percent, and the wage gap between EU migrants and natives averages 6.2 percent.[14] There is, however, a high degree of heterogeneity across countries regarding the main drivers of overall misallocation.

As we can see in Table 2.8, the private-public conditional wage gap component was greater in the case of Cyprus, Spain, Portugal and Ireland, where it averaged above 7.4 percent over the period 2005 to 2015. Regarding the gender gap, conditioning on a large number of individual characteristics this was larger in the Czech Republic and Cyprus where it was estimated to be around 25 percent, while the lowest estimated gender gaps (below 10 percent) were present in Luxembourg and Belgium. The negative wage impact associated with the country of birth persisted in a number of these European economies during this period. However, as expected, the impact on wages for EU versus non-EU migrants differed across countries with the latter estimated to be much more negative. Luxembourg, with an estimated gap of 25 percent, followed by Italy, Cyprus, and Ireland had the highest levels for the conditional wage gap between EU migrants and natives. The conditional gap between non-EU migrants and native workers was quite large for Cyprus and Luxembourg estimated at about 60 and 38 percent respectively, but was also relatively large (above 20 percent) in Italy and Spain.

row of Table 2.7.

[14]These country-specific estimates averaged across our country sample are comparable to the (absolute value of the) respective pooled estimates of the total effects in the complete specification reported in the last column at the end of Table 2.7.

2.3.2 Robustness Checks

Heckman model without the exclusion restriction

In the Heckman model, it is highly desirable to impose at least one exclusion restriction in order to avoid collinearity problems in the second stage of Heckit. We have therefore included instruments such as marital status, benefits, and health status. However, in this section, we examine the case where we do not include any exclusion restriction in the selection equation. Our results suggest that we do not have problems of severe collinearity because the inverse Mills ratio is non-linear over a wide rage of values.[15] Table 2.10 illustrates the country-specific results regarding the measure of misallocation that arises from the wage gaps associated with the employment sector, gender, and migration status. Overall the results remain the same as in the case where we had included the instruments. Again, Cyprus, Spain, Luxembourg, Italy, Ireland and Greece have the largest misallocation measures, while Belgium, Denmark, France, Sweden, Switzerland and the Netherlands have the lowest.

Labor Force Weighted Measure

So far, we constructed the misallocation measure by adding the coefficients of the private sector employees, females and the weighted sum of the EU and non-EU migrants coefficients.[16] We chose to be agnostic about which form of misallocation is potentially more important for an economy's long term prospects. An alternative is to use the current (static) share of private sector employees, females, and migrants in each country as a weight for the importance of the misallocation effect attributed to each of these factors. Here, we use data from Eurostat regarding the average number of active workers that are females, immigrants, or work in the private sector for each country over the period from 2005 to 2015. We weight each factor by multiplying with the corresponding number of workers and then dividing by the labor force as follows:

$$Misallocation = \beta_p \frac{n_p}{N} + \beta_f \frac{n_f}{N} + \beta_{eu} \frac{n_{eu}}{N} + \beta_{neu} \frac{n_{neu}}{N},$$

where n_p is the average number of private sector employees in each country for the period under study, n_f is the average number of females, n_{eu} is the average number of EU migrants, n_{neu} is the average number of non-EU migrants, and $N = n_p + n_f + n_{eu} + n_{neu}$. Table 2.11 presents the results. We find that Cyprus, Spain, the Czech Republic, Ireland, Luxembourg and Portugal have the highest misallocation measures, while Belgium, Denmark, Sweden, Iceland and France have the lowest misallocation measures. Looking at the pre crisis period in the second column of Table 2.11, Cyprus was still the worst followed by Greece, with

[15]Had it been exactly linear over a wide range of values there would be no way of estimating the second stage of Heckit.

[16]We note again that the weighted sum of EU and non-EU migrants coefficients was obtained using their respective shares in total migrants.

Spain fourth and Ireland sixth.

Broad definition of the public sector

Up to now, we had defined the public sector using the restricted definition. That is, we had specified a public sector worker as one employed in the sector "Public administration and defense, compulsory social security". This restricted definition excludes public sector employees that are employed in "Education" and "Health and social work", and could thus underestimate the number of public sector employees in total workers. We now investigate how sensitive the results are to the definition of the public sector. Specifically, we now define the public sector using the broad definition that takes into account the "Education" and "Health and social work" sectors.

Overall, the results are similar to before as can be seen in Tables 2.12 and 2.13. We find that working in the private sector, being a woman, and being an immigrant affects wages negatively. While the results are qualitatively similar we do find some quantitative differences in the case of the impact on wages that comes from working in the private sector as compared to this more broadly defined concept of the public sector. We now find that private sector employees are paid 5 to 7 percent less than public sector employees depending on the specification in Table 2.12, as compared to 7.6 to 9.8 percent less than public sector employees in the baseline specifications shown in Table 2.7. As for the country-specific estimates, we observe from Table 2.13 that Cyprus, Spain, Luxembourg, Ireland, Greece, and Italy are once again found to have the highest misallocation measures for the period under study.

Full-time employment

We now explore the sensitivity of our results when including in our working sample only individuals who worked full-time for the past year, excluding all individuals that worked part-time. The results are presented in Tables B1 and B2 in the Appendix. Out main results remain intact. As for the country-specific estimates, these still place Cyprus, Spain, Luxembourg, Ireland, Italy, and Greece at the top in terms of the overall measure of talent misallocation in Table B2.

Alternative occupation categories

We also test the robustness of our results by using an alternative categorization of occupations.[17] In particular, we consider the following occupation categories: a) Clerical Support Workers, Services and Sales, Skilled Agricultural, Forestry and Fishery, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, and Elementary Occupations; b) Technicians and Associate Professionals; c) Professionals, and d) Managers. These categories now replace the ones used in our baseline which were: a) craft and related trade

[17] We note that the four occupation categories we include encompass all types of jobs/occupations.

workers, plant and machine operators and assemblers, and elementary occupations; b) clerks, and services and shop and market sales workers; c) professionals, technicians and associate professionals, skilled agricultural and fishery workers, and armed forces, and d) legislators, senior officials and managers.

Our main results remain unchanged. Moreover, looking at the occupation coefficients in Table B3, we observe that Technicians and Associate Professionals are paid more compared to workers in occupation category a, and the same goes, unsurprisingly, for Professionals and Managers. Finally, our country-specific estimates still imply that Cyprus, Spain, Luxembourg, Ireland, Italy, and Greece are at the top in terms of the overall measure of talent misallocation in Table B4, while Belgium, Denmark, France, the Netherlands, and Sweden have the lowest levels of implied misallocation.

2.4 Conclusion

We have used microeconomic data on wages and individual characteristics to detect patterns of misallocation arising in European countries based on public-private affiliation, individuals' gender, and immigration status. In our theoretical setting as analysed in Chapter 1, wage differentials and talent misallocation are generated by unequal access to employment that arises because of the existence of prejudice, social norms, discrimination, etc against the underprivileged workers (women, immigrants, private sector employees). No matter what the causes of unequal access to employment, we show that the higher the unequal access to employment, the higher the wage differential and the higher the misallocation, resulting in income losses.

Our empirical findings indicate that being a female or migrant and working in the private sector, holding other characteristics the same, exert a negative impact on hourly wages. As such unwarranted differences in earnings may imply misallocation in the economy with potentially important adverse effects for aggregate economic outcomes, we consider the aggregate country-level implications of our micro-based estimates. In the absence of data on the degree of unequal access to employment or direct numbers for talent misallocation, these wage differentials serve as an implicit measure for talent misallocation.

Estimating misallocation measures for the private-public, migrant-native, and gender wage gaps in each country, we find that countries at the heart of the European Crisis had the highest totals. That our micro-based country-specific estimates using data on individuals across these European countries provides us with a reasonably accurate mapping of aggregate country outcomes, testifies to the usefulness of the approach pursued here in terms of understanding the deeper factors behind the aggregate inefficiency in these countries. Our micro-based estimated misallocation measure placing these "problem" countries at the top, is consistent with talent misallocation having played a role in creating harmful inefficiencies in the smooth functioning of these economies that contributed to the problems they faced in the recent past.

The problem of selection bias is that the sample is not random. In our empirical exercise, we consider misallocation related to gender, employment sector, and migration. By considering all three channels, there is always the possibility of self-selection issues. For instance, selection bias has been thought to be particularly problematic for women's wages since labor force participation was lower compared to the male labor force participation. In order to correct for selectivity bias, we included some exclusion restrictions. However, due to data limitation self-selection issues might not be fully corrected. Therefore, in future work, would be interesting to investigate talent misallocation focusing only on migrants versus non-migrants rather than considering all three channels.

2.5 Tables

Table 2.1: Summary statistics about the final sample

Country	Average 2005-2015
Private sector (% of total)	89.56
Female (% of total)	49.20
Native-born (% of total)	88.05
EU migrant (% of total)	5.98
Non-EU migrant (% of total)	5.97
Low Education (% of total)	21.46
Middle Education (% of total)	40.77
High Education (% of total)	37.76
Age 25-34 (% of total)	23.63
Age 35-44 (% of total)	31.18
Age 45-54 (% of total)	30.09
Age 55-64 (% of total)	15.11
Occupation category a (% of total)	28.09
Occupation category b (% of total)	27.51
Occupation category c (% of total)	38.41
Occupation category d (% of total)	6.00
Part-time (% of total)	17.32
Permanent contract (% of total)	90.44
Married (% of total)	62.70
Countries	18
All observations	804,680

The occupation categories are as follow: a=craft and related trade workers, plant and machine operators and assemblers, and elementary occupations; b=clerks, and services and shop and market sales workers; c=professionals, technicians and associate professionals, skilled agricultural and fishery workers, and armed forces; d=legislators, senior officials and managers.

Table 2.2: Average hourly income for the period 2005-2015

Country	Mean	Std.Dev	Min	Max
Austria	15.96	13.30	0.02	598.22
Belgium	16.18	11.74	0.09	659.33
Cyprus	10.48	10.25	0.21	588.29
Czech Republic	4.09	2.71	0.07	113.24
Denmark	23.86	16.54	0.03	1295.36
Finland	16.61	12.78	0.04	1078.91
France	13.21	13.59	0.00	1865.24
Greece	7.96	8.23	0.11	780.70
Iceland	14.42	12.11	0.00	439.21
Ireland	19.55	31.66	0.09	3936.51
Italy	11.80	8.83	0.03	410.47
Luxembourg	22.35	17.29	0.43	623.81
Netherlands	22.12	17.71	0.01	1104.28
Portugal	5.97	6.57	0.00	266.65
Spain	8.96	8.14	0.02	247.37
Sweden	17.76	13.97	0.00	821.54
Switzerland	32.26	24.89	0.06	1038.89
United Kingdom	15.46	23.12	0.00	2454.66
Average	14.85	15.98	0.00	3936.51

Notes: Data are from the final sample that includes all employees ages 25-64 working in full-time and part-time occupations. Earnings are converted to constant 2015 euro using the Harmonised Index of Consumer Prices (HICP), which makes them comparable across years.

Table 2.3: Median hourly income and private-to-public income ratio

Country	Median Private (€)	Median Public (€)	Private-Public ratio (%)
Austria	14.34	16.47	87.07
Belgium	16.16	16.59	97.41
Cyprus	8.61	13.17	65.38
Czech Republic	3.76	4.64	81.03
Denmark	22.63	23.07	98.09
Finland	16.35	18.35	89.10
France	12.57	12.74	98.67
Greece	7.86	10.17	77.29
Iceland	12.07	13.19	91.51
Ireland	17.24	22.76	75.75
Italy	11.81	15.16	77.90
Luxembourg	18.49	27.34	67.63
Netherlands	19.14	23.40	81.79
Portugal	5.02	7.60	66.05
Spain	8.95	13.03	68.69
Sweden	16.29	17.22	94.60
Switzerland	28.80	33.98	84.76
United Kingdom	12.34	14.99	82.32
Average	12.79	14.92	85.72

Table 2.4: Median hourly income and female-to-male income ratio

Country	Median Female (€)	Median Male (€)	Female-to-Male ratio (%)
Austria	12.24	15.38	79.58
Belgium	14.62	15.90	91.95
Cyprus	6.97	9.62	72.45
Czech Republic	3.14	4.15	75.66
Denmark	21.35	23.77	89.82
Finland	13.68	16.53	82.76
France	11.32	12.88	87.89
Greece	6.16	7.38	83.47
Ireland	15.86	16.19	97.96
Iceland	11.43	13.95	81.94
Italy	10.43	11.57	90.15
Luxembourg	16.67	19.73	84.50
Netherlands	17.93	20.98	85.46
Portugal	4.07	4.87	83.57
Spain	6.77	8.27	81.86
Sweden	14.99	17.27	86.80
Switzerland	25.74	31.36	82.08
United Kingdom	10.99	13.62	80.69
Average	11.72	13.53	86.62

Table 2.5: Median hourly income and income ratio related to the country of origin

Country	Native	EU	NonEU	EU-to-native ratio	NonEU-to-native ratio
Austria	14.60	12.30	9.50	84.25	65.07
Belgium	15.60	14.69	11.81	94.17	75.71
Cyprus	9.04	7.02	2.53	77.65	27.99
Czech Republic	3.65	3.45	3.30	94.52	90.41
Denmark	22.56	22.25	19.40	98.63	85.99
Finland	14.93	14.29	10.52	95.71	70.46
France	12.17	11.82	10.42	97.12	85.62
Greece	7.11	5.68	4.64	79.89	65.26
Ireland	16.68	12.79	14.54	76.68	87.17
Iceland	12.75	10.84	9.61	85.02	75.37
Italy	11.42	8.34	7.81	73.03	68.39
Luxembourg	24.79	14.47	11.69	58.37	47.16
Netherlands	19.47	18.10	17.38	92.96	89.27
Portugal	4.42	4.68	4.64	105.88	104.98
Spain	7.87	6.09	4.75	77.38	60.36
Sweden	16.33	15.59	13.37	95.47	81.87
Switzerland	29.54	28.02	22.44	94.85	75.96
United Kingdom	12.31	12.25	11.72	93.34	95.21
Average	14.18	12.25	10.56	86.39	74.47

Table 2.6: Probit selection equation results

Variables	(2005-2015)
Private	-0.158***
	(0.012)
Fem	-0.126***
	(0.007)
MigrantEU	-0.110***
	(0.015)
Migrant	-0.117***
	(0.012)
Educ L	-0.141***
	(0.009)
Educ H	0.038***
	(0.009)
Age 35-44	0.129***
	(0.009)
Age 45-54	0.152***
	(0.009)
Age 55-64	0.010
	(0.011)
Occup-b	-0.035***
	(0.009)
Occup-c	0.026***
	(0.010)
Occup-d	0.025
	(0.017)
Part-time	0.390***
	(0.011)
Permanent	0.762***
	(0.008)
Health	-0.337***
	(0.016)
Benefits	-0.013***
	(0.001)
Married	0.070***
	(0.007)
Constant	1.329***
	(0.024)
Country-fixed effects	Yes
Year-fixed effects	Yes
Observations	804,680

Table 2.7: Selection-corrected hourly wage regression for the period 2005-2015 EU SILC wave

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Private	-0.096***	-0.076***	-0.085***	-0.103***	-0.079***	-0.078***
	(0.006)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
Fem	-0.191***	-0.190***	-0.173***	-0.185***	-0.146***	-0.154***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)	(0.004)
MigrantEU	-0.113***	-0.092***	-0.100***	-0.130***	-0.058***	-0.057***
	(0.008)	(0.007)	(0.003)	(0.004)	(0.012)	(0.012)
Migrant	-0.189***	-0.152***	-0.160***	-0.196***	-0.063***	-0.061***
	(0.007)	(0.007)	(0.002)	(0.004)	(0.011)	(0.011)
Educ L	-0.196***	-0.138***	-0.148***	-0.105***	-0.106***	-0.106***
	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)	(0.005)
Educ H	0.322***	0.187***	0.188***	0.110***	0.107***	0.108***
	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)	(0.004)
Age 35-44	0.151***	0.141***	0.152***	0.154***	0.154***	0.153***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.231***	0.215***	0.227***	0.228***	0.228***	0.228***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.275***	0.254***	0.259***	0.260***	0.260***	0.261***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occup-b		0.068***	0.065***	0.067***	0.067***	0.068***
		(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occup-c		0.303***	0.300***	0.298***	0.299***	0.300***
		(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occup-d		0.449***	0.436***	0.439***	0.439***	0.439***
		(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
Part-time			-0.074***	-0.071***	-0.071***	-0.155***
			(0.002)	(0.002)	(0.002)	(0.004)
Permanent			0.193***	0.196***	0.197***	0.194***
			(0.004)	(0.004)	(0.004)	(0.004)
Private *Educ L				-0.036***	-0.037***	-0.036***
				(0.005)	(0.005)	(0.005)
Private *Educ H				0.055***	0.058***	0.059***
				(0.004)	(0.004)	(0.004)
Fem *Educ L				-0.027***	-0.025***	-0.026***
				(0.003)	(0.003)	(0.003)
Fem *Educ H				0.045***	0.045***	0.045***
				(0.002)	(0.002)	(0.002)
MigrantEU *Educ L				-0.020***	-0.018***	-0.019***
				(0.006)	(0.006)	(0.006)
MigrantEU *Educ H				0.082***	0.081***	0.081***
				(0.005)	(0.005)	(0.005)
Migrant *Educ L				0.068***	0.068***	0.068***
				(0.006)	(0.006)	(0.006)
Migrant *Educ H				0.048***	0.048***	0.048***
				(0.005)	(0.005)	(0.005)

Private *Fem					-0.043***	-0.046***
					(0.004)	(0.004)
Private *MigrantEU					-0.085***	-0.084***
					(0.011)	(0.011)
Private *Migrant					-0.116***	-0.115***
					(0.010)	(0.010)
Fem *MigrantEU					0.016***	0.015***
					(0.005)	(0.005)
Fem *Migrant					-0.048***	-0.050***
					(0.004)	(0.004)
Fem *Part-time						0.106***
						(0.004)
lambda	-1.534***	-1.400***	-0.456***	-0.432***	-0.420***	-0.421***
	(0.041)	(0.037)	(0.027)	(0.027)	(0.027)	(0.027)
Constant	2.781***	2.652***	2.428***	2.445***	2.421***	2.425***
	(0.012)	(0.011)	(0.006)	(0.007)	(0.007)	(0.007)
Total effect Private	-0.096***	-0.076***	-0.085***	-0.090***	-0.098***	-0.098***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Fem	-0.191***	-0.190***	-0.173***	-0.174***	-0.174***	-0.167***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect MigrantEU	-0.113***	-0.092***	-0.100***	-0.103***	-0.099***	-0.099***
	(0.008)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect Migrant	-0.189***	-0.152***	-0.160***	-0.164***	-0.158***	-0.157***
	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	804,680	804,680	804,680	804,680	804,680	804,680
Adj.R^2	0.553	0.582	0.586	0.587	0.587	0.588

Note: Pooled estimates for 18 European countries. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8: Talent Misallocation Measure and its decomposition for the period 2005-2015

Country	Private	Female	MigrantEU	Migrant	Misallocation Measure
Cyprus	0.201***	0.246***	0.170***	0.598***	0.856***
Spain	0.173***	0.166***	0.129***	0.206***	0.525***
Luxembourg	0.120***	0.078***	0.249***	0.376***	0.465***
Ireland	0.164***	0.142***	0.165***	0.083***	0.448***
Italy	0.117***	0.123***	0.186***	0.216***	0.448***
Greece	0.065***	0.166***	0.117***	0.174***	0.395***
Austria	0.018**	0.183***	0.088***	0.176***	0.346***
Czech Republic	0.113***	0.256***	-0.029**	-0.055**	0.327***
Portugal	0.164***	0.159***	-0.013	-0.022*	0.302***
Iceland	-0.037**	0.217***	0.099***	0.154***	0.301***
United Kingdom	0.117***	0.175***	0.045***	-0.032***	0.286***
Finland	0.009	0.218***	0.008	0.081***	0.276***
Switzerland	0.090***	0.124***	-0.003	0.069***	0.241***
Netherlands	0.089***	0.118***	-0.048**	0.037***	0.224***
Sweden	-0.050***	0.190***	0.001	0.100***	0.209***
France	0.011**	0.157***	-0.037***	0.003	0.160***
Denmark	-0.029**	0.131***	0.033	0.020	0.127***
Belgium	-0.004	0.084***	-0.046***	0.040***	0.080***
Average	0.074	0.163	0.062	0.124	0.334

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.9: Talent Misallocation Measure and its decomposition for the period 2005-2010

Country	Private	Female	MigrantEU	Migrant	Misallocation Measure
Cyprus	0.186***	0.269***	0.113***	0.609***	0.875***
Greece	0.117***	0.197***	0.218***	0.274***	0.579***
Spain	0.158***	0.158***	0.110***	0.185***	0.483***
Luxembourg	0.113***	0.102***	0.231***	0.354***	0.463***
Ireland	0.173***	0.147***	0.135***	0.075**	0.438***
Italy	0.114***	0.108***	0.123***	0.181***	0.389***
Czech Republic	0.123***	0.265***	-0.008	0.002	0.385***
Austria	0.018	0.179***	0.081***	0.162***	0.334***
Iceland	-0.020	0.203***	0.143***	0.142**	0.325***
Finland	0.007	0.225***	-0.009	0.141***	0.307***
Portugal	0.160***	0.161***	-0.073	-0.031	0.280***
United Kingdom	0.111***	0.181***	0.001	-0.037**	0.266***
Switzerland	0.080***	0.128***	0.004	0.072***	0.241***
Netherlands	0.097***	0.121***	-0.086**	0.029	0.222***
Sweden	-0.064***	0.187***	0.008	0.101***	0.192***
Denmark	-0.019	0.138***	0.049	0.034	0.157***
France	0.008	0.150***	-0.028	-0.002	0.149***
Belgium	-0.015	0.078***	-0.067***	0.024	0.045**
Average	0.075	0.166	0.053	0.129	0.341

Table 2.10: Talent Misallocation Measure derived from Heckman method without the exclusion restrictions

Countries	Private	Female	MigrantEU	Migrant	Misallocation Measure
Cyprus	0.216***	0.245***	0.174***	0.602***	0.875***
Spain	0.181***	0.161***	0.143***	0.217***	0.540***
Luxembourg	0.124***	0.089***	0.246***	0.378***	0.480***
Italy	0.123***	0.131***	0.184***	0.222***	0.465***
Ireland	0.164***	0.143***	0.165***	0.083***	0.448***
Greece	0.067***	0.166***	0.118***	0.168***	0.392***
Austria	0.022***	0.199***	0.117***	0.176***	0.377***
Czech Republic	0.114***	0.263***	-0.029**	-0.058**	0.335***
Iceland	-0.030*	0.226***	0.113***	0.157***	0.326***
United Kingdom	0.126***	0.191***	0.043***	-0.028***	0.312***
Portugal	0.173***	0.142***	0.006	-0.022*	0.300***
Finland	0.015	0.216***	0.009	0.093***	0.287***
Netherlands	0.100***	0.137***	-0.034*	0.043***	0.263***
Switzerland	0.094***	0.137***	-0.003	0.070***	0.259***
Sweden	-0.041***	0.204***	0.009	0.116***	0.245***
France	0.016***	0.161***	-0.037***	0.015**	0.178***
Denmark	-0.019*	0.137***	0.032	0.041**	0.156***
Belgium	0.003	0.094***	-0.039***	0.058***	0.110***
Average	0.080	0.169	0.066	0.130	0.353

Table 2.11: Labor Force Weighted Measure

Countries	Misallocation 2005-2015	Misallocation 2005-2010	Ranking 2005-2010
Cyprus	0.250***	0.238***	1
Spain	0.172***	0.159***	4
Czech Republic	0.160***	0.162***	3
Ireland	0.154***	0.143***	6
Luxembourg	0.152***	0.157***	5
Portugal	0.148***	0.086***	13
Italy	0.128***	0.113***	9
United Kingdom	0.123***	0.132***	7
Greece	0.114***	0.189***	2
Netherlands	0.092***	0.098***	10
Switzerland	0.088***	0.095***	11
Austria	0.087***	0.081***	14
Finland	0.086***	0.087***	12
France	0.061***	0.061***	15
Iceland	0.060***	0.122***	8
Sweden	0.042***	0.026**	17
Denmark	0.029***	0.037**	16
Belgium	0.026***	0.018**	18
Average	0.110	0.111	

Table 2.12: Selection-corrected hourly wage regression for the period 2005-2015, alternative measure of the public sector, EU SILC wave

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Private	-0.070***	-0.034***	-0.049***	-0.035***	-0.010***	-0.011***
	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)
Fem	-0.208***	-0.199***	-0.183***	-0.193***	-0.168***	-0.181***
	(0.004)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
MigrantEU	-0.111***	-0.093***	-0.100***	-0.134***	-0.091***	-0.090***
	(0.008)	(0.007)	(0.003)	(0.004)	(0.007)	(0.007)
Migrant	-0.188***	-0.152***	-0.159***	-0.199***	-0.058***	-0.055***
	(0.007)	(0.007)	(0.003)	(0.004)	(0.007)	(0.007)
Educ L	-0.195***	-0.137***	-0.147***	-0.107***	-0.112***	-0.111***
	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)	(0.004)
Educ H	0.310***	0.183***	0.182***	0.165***	0.168***	0.169***
	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.149***	0.141***	0.151***	0.152***	0.152***	0.151***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.226***	0.214***	0.223***	0.225***	0.225***	0.224***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.268***	0.252***	0.254***	0.256***	0.256***	0.257***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occup b		0.072***	0.067***	0.070***	0.071***	0.071***
		(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occup c		0.301***	0.294***	0.295***	0.294***	0.295***
		(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occup d		0.452***	0.439***	0.443***	0.443***	0.443***
		(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
Part-time			-0.080***	-0.077***	-0.077***	-0.161***
			(0.002)	(0.002)	(0.002)	(0.004)
Permanent			0.189***	0.191***	0.192***	0.189***
			(0.004)	(0.004)	(0.004)	(0.004)
Private *Educ L				-0.036***	-0.033***	-0.034***
				(0.004)	(0.004)	(0.004)
Private *Educ H				-0.017***	-0.015***	-0.016***
				(0.003)	(0.003)	(0.003)
Fem *Educ L				-0.032***	-0.029***	-0.030***
				(0.003)	(0.003)	(0.003)
Fem *Educ H				0.040***	0.035***	0.036***
				(0.003)	(0.003)	(0.003)
MigrantEU *Educ L				-0.018***	-0.015**	-0.016***
				(0.006)	(0.006)	(0.006)
MigrantEU *Educ H				0.093***	0.086***	0.086***
				(0.005)	(0.005)	(0.005)
Migrant *Educ L				0.071***	0.076***	0.075***
				(0.006)	(0.006)	(0.006)
Migrant *Educ H				0.055***	0.035***	0.034***
				(0.005)	(0.005)	(0.005)

Private *Fem					-0.029***	-0.026***
					(0.002)	(0.002)
Private *MigrantEU					-0.062***	-0.061***
					(0.006)	(0.006)
Private *Migrant					-0.135***	-0.135***
					(0.006)	(0.006)
Fem *MigrantEU					0.011**	0.009**
					(0.005)	(0.005)
Fem *Migrant					-0.066***	-0.069***
					(0.005)	(0.005)
Fem *Part-time						0.104***
						(0.004)
lambda	-1.534***	-1.423***	-0.511***	-0.492***	-0.474***	-0.474***
	(0.040)	(0.038)	(0.027)	(0.026)	(0.026)	(0.026)
Constant	2.756***	2.615***	2.403***	2.395***	2.371***	2.378***
	(0.012)	(0.011)	(0.007)	(0.007)	(0.007)	(0.007)
Total effect Private	-0.070***	-0.034***	-0.049***	-0.049***	-0.049***	-0.049***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Fem	-0.208***	-0.199***	-0.183***	-0.184***	-0.184***	-0.177***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect MigrantEU	-0.111***	-0.093***	-0.100***	-0.103***	-0.098***	-0.098***
	(0.008)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect Migrant	-0.188***	-0.152***	-0.159***	-0.163***	-0.152***	-0.150***
	(0.007)	(0.007)	(0.003)	(0.002)	(0.003)	(0.003)
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	806,190	806,190	806,190	806,190	806,190	806,190

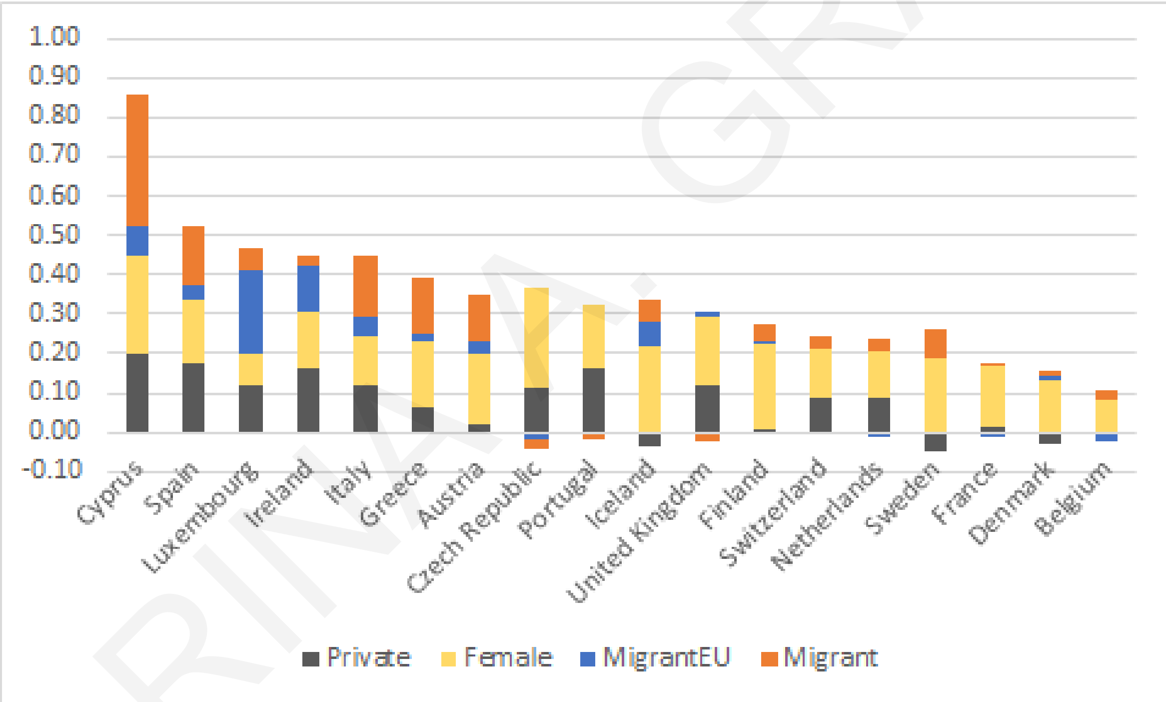
Note: Pooled estimates for 18 European countries. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 2.13: Talent Misallocation Measure derived from using the broad definition of the public sector

Country	Private	Female	MigrantEU	Migrant	Misallocation Measure
Cyprus	0.292***	0.284***	0.156***	0.534***	0.944***
Spain	0.163***	0.197***	0.116***	0.183***	0.525***
Luxembourg	0.165***	0.115***	0.215***	0.339***	0.514***
Ireland	0.149***	0.176***	0.163***	0.114***	0.474***
Greece	0.106***	0.180***	0.104***	0.144***	0.423***
Italy	0.075***	0.142***	0.188***	0.208***	0.418***
Portugal	0.208***	0.216***	-0.021	-0.022*	0.402***
Austria	0.019***	0.189***	0.090***	0.172***	0.351***
Finland	-0.036***	0.205***	0.011	0.087***	0.223***
Czech Republic	0.002	0.254***	-0.029***	-0.059**	0.214***
Switzerland	0.022***	0.134***	0.004	0.074***	0.188***
United Kingdom	-0.014***	0.172***	0.055***	-0.027***	0.158***
Netherlands	-0.001	0.123***	-0.044***	0.036***	0.139***
Iceland	-0.172***	0.158***	0.110***	0.160***	0.115***
France	-0.060***	0.143***	-0.030***	0.005	0.079***
Sweden	-0.154***	0.133***	0.003	0.102***	0.050***
Belgium	-0.069***	0.065***	-0.037***	0.047***	0.004
Denmark	-0.121***	0.091***	0.033	0.024	-0.003
Average	0.032	0.165	0.060	0.118	0.290

2.6 Figure

Figure 2.1: Talent Misallocation Measure



Chapter 3

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

3.1 Introduction

Input misallocation can have long-term negative effects on economic growth. In particular, labor market frictions in the form of barriers for some or privileged treatment for others, can result in significant output losses. In this chapter, we investigate the degree of labor misallocation across US states over time at the micro-level, and then proceed to assess its aggregate implications for economic outcomes. More specifically, we use individual data across the United States over the period from 1960 to 2017 to explore the misallocation effects arising due to frictions related to race and gender, and to quantify their impact on aggregate economic outcomes.

According to our theoretical model, wage gaps and misallocation are both generated by the unequal opportunities for employment that different types of workers have in the labor market. Specifically, in an economy where equally talented workers search for employment in both low- and high-productivity jobs/sectors, they face different opportunities for employment. They can be "privileged" or "underprivileged". These differences can arise for different reasons such as discrimination, nepotism, political favouritism, and so on. Here, "underprivileged" refers to workers that due to barriers related to, e.g., race and sex find it more difficult to be employed in the market as compared to other individuals that otherwise share their economic characteristics.

In this environment, we show that underprivileged workers are paid less compared to the privileged ones, despite being equally talented. The model generates wage differentials between equally talented workers because "underprivileged" workers have a lower matching rate with high-productivity jobs. This results in labor misallocation in the economy as some workers are allocated to the low-productivity sector despite having the same ability. Providing equal treatment in the labor market, then the low-productivity sector shuts down, wages of privileged and underprivileged workers converge, and any talent mismatch disappears.[1]

Our study stems from the branch of the growth literature which assigns a central role to total factor productivity (TFP) as an explanation for economic growth and cross-country income differences.[2] Hsieh and Klenow (2009) provide quantitative evidence on the potential impact of resource misallocation on aggregate output. Using plant-level data from China and India, they measure marginal products and find that if capital and labor were reallocated towards US levels this would increase TFP by 30 to 50 percent in China and 40 to 60 percent in India.

Our work is closely related to the literature on talent misallocation going back to Murphy et al. (1991).[3] According to Hsieh et al. (2019) who investigate the allocation of talent in the US, women and African-Americans have historically been poorly represented in high-skilled occupations, with 94 percent of doctors and lawyers in 1960 being white men. According to them, the significant convergence in the occupational distribution during the last few decades resulted in large productivity gains, explaining 20 to 40 percent of growth in output per worker. As innate talent among members of a group is unlikely to have changed over time, the occupational distribution in 1960 likely reflected misallocation of talent due to labor market discrimination, barriers to forming human capital, and preferences or social norms.[4] Other work showing race or gender gaps can have large macroeconomic consequences includes Cavalcanti and Tavares (2016) who develop a growth model with endogenous fertility and calibrating it to the US economy find large increases in *per capita* income related to reduced barriers to female labor market participation in the form of a wage gap: a 50 percent fall in the wage gap leads to a 35 percent rise in *per capita* income. Similarly, Cuberes and Teignier (2016) calibrate an occupational choice model for 33 OECD countries for 2010 and find that gender wage gaps cause an average income *per capita* loss of 15 percent. Finally, Gradstein (2019) also shows that barriers to skill acquisition and other barriers that make it more difficult for certain population groups to enter skilled occupations can have large economic costs.

[1]Our theoretical model is related to work by Chassamboulli and Palivos (2014), Liu et al. (2017) and Chassamboulli and Peri (2018) among others, that develop search and matching models to explain wage gaps between workers.

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

[3]Restuccia and Rogerson (2013, 2017) provide reviews of the literature on misallocation as a potential source of aggregate productivity differences across countries.

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

Our work draws inspiration from the large body of work documenting the relation between individual economic outcomes and race or gender.[5] That body of work shows that despite reductions in the level of gender and racial discrimination in, e.g., the US relative to the 1960s, gender and race continue to matter for economic outcomes to this date. Blau and Kahn (2017) provide empirical evidence on the extent of and trends in the gender wage gap using microdata from 1980 to 2010. Lang and Lehmann (2012) report that labor market outcomes of black Americans, particularly males,[6] continue to be significantly worse than those of white Americans. Bertrand and Mullainathan (2004) perform a field experiment and find significant racial inequality in the US labor market: African American-sounding names are 50 percent less likely to receive callbacks for interviews compared to white-sounding names.[7] Bayer and Charles (2018) explore black-white earning differences among men in the US for the past seven decades and report that between 1940 and the mid-1970s these were reduced but only to rise again.[8]

Using microeconomic data on wages and individual characteristics across the United States over the period from 1960 to 2017, we systematically find that women and non-whites receive lower wages as compared to their counterparts. We investigate the macroeconomic implications of our state-level misallocation measure. Looking at the relation of our estimated misallocation measure for each state with state-level Technical Efficiency, TFP, or GDP per worker over time, we find a negative relation between our micro-based measure and these aggregate outcome measures, consistent with an important role for talent misallocation for macroeconomic outcomes. This suggests important aggregate effects arising from talent misallocation in the United States over this period.

The rest of the chapter is organized as follows. Section 2 presents the data, summary statistics, and our empirical methodology. Section 3 presents the results of our estimation. The last section briefly concludes.

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

[6] This shows up as a positive female-African American interaction term in our Table 3.11.

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

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

3.2 Empirically investigating talent misallocation

3.2.1 Data

We use cross-sectional data at the individual level by the U.S. Decennial Censuses covering the period from 1960 to 2000 and the 2010 and 2017 waves of the annual American Community Survey (ACS). We construct a total of seven samples, one for each of the census decades plus the two annual ACS samples, as shown in Table 3.1. The 1960, 1980, 1990, and 2000 decennial census samples each have more than eight million observations, while for the 1970 sample we have about four million. The annual samples for 2000 and 2017 have around three million observations each. Information is provided for all fifty states and the District of Columbia.[9]

Our main objective is to investigate talent misallocation across the United States focusing on individuals' gender and race. In particular, we investigate whether being a female or non-white has explanatory power for wages beyond that explained by individual characteristics. The dependent variable in our analysis is the log of hourly income. This is defined as annual income divided by the number of months worked, multiplied by weekly hours of work times 4.2. Annual income is given by income earned from wages or a person's own business or farm for the previous year.[10]

We use a broad definition of race taking into account all races and identifying them as white and non-white. Specifically, we consider as non-white African-Americans, Hispanics, American Indians, Alaska Natives, Asians or mixed race (combinations of different races). The non-white to white ratio for the median hourly earnings ranged between 65.86 to 82.44 for the period under study as shown in Table 3.1 and Figure 3.2. These earning differentials might reflect disadvantages that non-white individuals have in the labor market compared to whites ones. We note that our preliminary investigation shows large (positive) wage differentials between whites and any of the races included as non-whites, suggesting we should consider all types of non-whites rather than just African Americans as having a potential disadvantage in the labor market.

The distinction between private and public sector employment is based on information pro-

[9] We could have extended the database by including the decennial 1950 sample. However, we choose not to use it in our analysis because the sample is not as comparable to other decades. The number of observations is much lower compared to the rest of the waves, 506,318 as compared to several million, and the number of states included in this case is also limited.

[10] Annual income is available from 1990 onward. Similar amounts can also be derived for previous years by adding the components provided separately in the database as in Ruggles et al. 2019. Moreover, there are cases where the weeks that someone worked during the previous year are provided in intervals. If so, we transform this into a continuous variable by taking the average for each interval. The usual hours worked per week are not provided for the 1960 and 1970 waves. In these cases, we use hours worked during the previous week in intervals and calculate the average of each interval.

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

We also utilize data regarding GDP per worker, Technical Efficiency and TFP, to investigate the impact that our estimated micro-based misallocation measure has on the economy at the aggregate level. The data regarding real GDP and total employment by state are from the Bureau of Economic Analysis (BEA). Real GDP data start from 1977. Until 1997 these are based on the Standard Industrial Classification (SIC) and from 1997 onward are based on the North American Industry Classification System (NAICS). Data regarding technical efficiency are from Sharma et al. (2007). As for the state-level TFP data, these are available from 1980 to 2000 (available from Sharma et al. (2007)) and we extend these for the 2000 and 2010 waves using data provided by Cardarelli and Lusinyan (2015).

As our objective is to estimate wage differentials between women and men and non-whites compared to whites, holding all the other characteristics constant, we exclude individuals below 25 and above 64, soldiers, and family workers. Our final sample for each wave includes employees, the unemployed, individuals working in full-time and part-time occupations, and the self-employed. The latter are included because there is no reason to believe that there is a severe non-declaration of income problem in the case of the US.

3.2.2 Summary Statistics

Our final sample consists of millions of observations. As shown in Table 3.1, the number of observations is approximately 1.4 to 6.4 millions, depending on the year. Overall, females comprise 41 to 49 percent of the total based on the sample year, while non-whites comprise 13 percent in 1960 and 32 percent in the most recent available year. Historically, the majority of individuals work in the private sector (more than 80 percent) and are married (59.1 to 79.6 percent). Moreover, around 33.5 percent in 1960 worked part-time, while by 2017 only 12.9 percent were working in part-time occupations. Regarding education levels, we observe a reduction in the percentage of individuals with low educational levels and a significant rise in the share of high-educated individuals over time. In 1960, only 20 percent of our sample had completed at least a year of college, while by 2017 this reached around 61 percent. As for the age groups, from Table 3.1 it can be observed that a high percentage consists of ages 25 to 54, with an increase in the percentage of the age group 55-64 after year 2000.

Table 3.1 shows median hourly earnings by gender, race, and employment sector. We observe that in 1960, women's median hourly earnings were \$8.77 compared with \$14.05 for men, with the resulting female to male ratio of median hourly earnings around 62 percent, implying a 38 percent unconditional gender gap. While this ratio has increased over the years, the unconditional gender gap persisted even to 2017. An alternative measure of the unconditional wage gap is derived from the female to male ratio of median annual earnings for full-time workers provided by the U.S. Census Bureau. From Figure 3.1, we see that both types of measures follow a similar pattern and clearly indicate that the unconditional gender wage gap is a persistent phenomenon across the United States for the period under study.

With regard to race, in 1960 the median hourly earnings for non-white individuals were \$8.43 compared with \$12.80 for whites one, with the resulting ratio of 65.9 climbing to a high of 82.4 by 2000 and then falling to 78.6 percent by 2017. Both of these earnings differentials clearly reflect that these groups are rather disadvantaged in the labor market.

Finally, comparing the median hourly earnings related to the employment sector we observe that private-sector employees were typically paid a little less than public sector employees in previous decades. In the 1960s, the median hourly earnings for private-sector employees were \$12.08 compared with \$13.48 for public sector employees. However, from Table 3.1 we can observe that the unconditional hourly wage gap related to employment sector is historically relatively lower to the wage gaps related to gender or race. In the 1980s, the unconditional wage gap related to the employment sector was only 7.7 percent as compared with a gender gap of around 40 percent and a race gap of 26.4 percent.[11]

3.2.3 Empirical Specification

Having examined the unconditional wage gaps, our next step is to investigate the conditional wage differentials. Specifically, our main empirical objective is to estimate wage gaps related to race and gender, conditioning on a broad set of individual characteristics. To achieve this, we consider a Mincer-type wage regression. To correct for selectivity bias, we first use the Heckman method by estimate the following probit equation:

$$T_{ij} = 1(\delta \mathbf{X}_{1ij} + \alpha_j + e_{ij} > 0) \tag{3.1}$$

where T_{ij} is a binary dependent variable with zero indicating being out of the labor force and unity indicating being in the labor force via paid employment or by being unemployed. X_{1ij} is a vector of covariates that includes dummy variables such as $Female_{ij}$ indicating the gender of individual i in state j, and $Nonwhite_{ij}$ denoting whether the individual is of a race other than white. The non-white race includes African-Americans, Hispanics, Amer-

[11]This gap has nevertheless risen to 16.6 percent at the end of our sample in 2017.

ican Indians, Alaska Natives, Asian, and "mixed race" individuals. The vector X_{1ij} also includes a binary variable $Private_{ij}$ that indicates employment sector, along with three controls for education (L= till 8^{th} grade, S=between 9^{th} to 12^{th} grade, and H=higher education), four controls for age, a continuous measure of occupation $Occupscor$ and a binary variable indicating part-time work.[12] Since it is recommended to impose at least one exclusion restriction to avoid collinearity problems in the second stage of Heckit, we include in the probit equation instruments such as marital status ($Married$), number of own children under age 5 in the household ($nchild5$), public assistance programs commonly referred to as "welfare" ($welf - inc$), and exogenous income ($exg - inc$).[13] The instruments included affect the labor force participation, but they do not have a direct effect on wages. For instance, the variable indicating the presence of children under age 5 in the household affect negatively the probability of women in entering the labor force. Indeed, our preliminary results show that the variable $nchild5$ is associated with a reduced likelihood of being in the labor force. Similarly, other income received from public assistance programs or interest, dividends, and so on, have an effect on the probability of entering the labor force, they do not affect directly the income received from employment. Finally, α_j and e_{ij} are state-fixed effects and the error term, respectively. We derive the inverse Mills ratio λ for each observation based on the parameter estimate $\hat{\delta}$.

We estimate the Mincer-type wage regression as follows:

$$w_{ij} = \beta_0 + \beta_1 Female_{ij} + \beta_2 Nonwhite_{ij} + \beta \mathbf{X}_{2ij} + \gamma_1 \lambda(\hat{\delta}\mathbf{X}_{1ij}) + \alpha_j + \epsilon_{ij} \tag{3.2}$$

where w_{ij} is the logarithm of the hourly earnings of individual *i* in state *j*, Female is a binary variable that takes a value of unity if the individual is a female and zero otherwise, Nonwhite is a binary variable that takes a value of unity if the individual is non-white and zero otherwise,[14] and X_{2ij} is a vector of covariates that includes variables from vector X_{1ij} such as education, age, occupation and part-time work. We also consider interactions for the employment sector with education, female with education, non-white with education, female with part-time job,female with non-white, female with private sector, and private sector with non-white. ϵ_{ij} is the error term of the wage regression. We estimate wage differentials between female and male and non-white versus white from the above wage regression, where parameter β_1 captures the gender wage gap, and β_2 the earning differential associated with race.

[12]The binary variable $Part - time$ is constructed following Hsieh et al. (2019). They define a part-time worker as those who usually work up to thirty hours per week, while those who work more are considered full-time.

[13]This includes income from an estate or trust, interest, dividends, royalties, and rents received.

[14]Although country of birth is also available, race appears more important than country origin in determining wages in this US sample, thus we follow the example of Hsieh et al. (2019) who focus on race and gender. We also consider wage gaps for each non-white race by including dummy variables that identify each race.

First, we estimate the parameters for the U.S as a whole each decade to assess the overall empirical plausibility of our empirical model. Next, we allow the coefficients of $Female_{ij}$ and $Nonwhite_{ij}$ to differ for each state in both stages of the estimation. This provides the means for us to create a measure for each state that indicates the overall misallocation effects arising from these wage differentials. The state-level measure that we create focuses only on misallocation related to race and gender. Despite controlling for the employment sector, we will show in the next section that in the US there is no misallocation problem related to the employment sector, unlike European countries.

Finally, we also investigate the relationship of our estimated misallocation measure with Technical Efficiency, TFP and GDP per worker at the state-level.[15]

3.3 Results

Table 3.2 reports the results from estimating equation (3.1), where unity indicates paid employment or unemployment and zero indicates being out of the labor force. This table summarises the results for the probit estimation for each decennial census starting from 1960 to 2000, and the annual surveys 2010 and 2017. The results indicate that for 1960 and 1970 being a female reduces the likelihood of being in the labor force. However, there have been significant changes throughout the decades regarding the probability of being into the labor force. For instance, from the 1980s onward we observe that women are more likely to enter the labor force. A similar pattern is also observed for those currently working in the private sector. By contrast, being of a race other than white is associated with a lower likelihood of being in the labor force starting in the 1990s. Higher education consistently increases the probability of being in the labor force. On the other hand, currently working part-time, being married, having children of age under 5, receiving welfare, and other income are usually associated with reduced likelihood of being in the labor force, and particularly so in recent decades.

Tables 3.3 to 3.9 present estimates from the wage regression specified in equation (3.2) for the decennial samples form 1960 to 2000, along with years 2010 and 2017. We observe that the estimated parameter for the explanatory variable *lambda*, γ_1, is significantly different from zero, indicating that our sample selection correction is indeed necessary. Overall, our estimates suggest that being a female and of a race other than white exert a negative impact on earnings beyond that explained by individual economic characteristics. Our basic findings apply consistently over time and results are robust to adding a number of covariates to the baseline wage regression.

[15]Technical Efficiency is a component of TFP, since the latter can be decomposed into the contribution of technological progress, technical efficiency and changes in economies of scale.

As shown in Figure 3.3 and Tables 3.3 to 3.9, the gender wage gap appears to be a persistent phenomenon in the US throughout the decades even if declining from 1960 up until around 2010. Between 1960 and 1980, women were paid around 50 percent less than men, depending on the specification in Tables 3.3, 3.4 and 3.5. Wage differentials related to gender were reduced considerably to 18 percent by 2010 in Table 3.8, but were up to 24 percent in 2017 in Table 3.9.

Looking at the impact of race on the wage gap relative to whites, it stands out that being non-white affects hourly wages negatively. For instance, in the 1960s, non-white workers were paid 27.2 to 28.7 percent less compared to white ones, as shown in Table 3.3. Wage differentials were about half this size but still present by 2017, with non-white workers being paid around 13 percent less than their white counterparts.

We also consider wage gaps between each of the different types of non-whites relative to whites in Tables 3.10 and 3.11 for 1960 and 2017. We find that black, Hispanic, American Indian, Alaska Native, Asian and mixed race individuals are systematically paid less then whites. While wage gaps vary across these races, they remain consistently negative suggesting it is reasonable to distinguish non-whites from white workers in estimating wage gaps in our baseline analysis.

Race appears to be a more important factor as compared to the country of birth. Tables 3.12 and 3.13 show estimates from a wage regression that accounts for the country of birth, *Migrant*, in addition to race for 1960 and 2017. The results clearly show that migrants are not paid less than native-born workers in the US conditional on their individual characteristics. This is consistent with the US being a dynamic country that historically welcomed new immigrants, unlike the case of European countries as shown, e.g., in Chapter 2. On the other hand, race seems to be quite important for the U.S. as it is harder for non-whites to be integrated into the labor market, putting them at a disadvantage as compared to white workers.

We also find wage differentials between private and public sector employees, but these are much lower compared to those associated with gender or race and are reversed by the end of our sample period. More specifically, by 2017, private sector employees were paid around 3.4 to 4.9 percent more compared to public sector ones controlling for their characteristics, depending on the specification in Table 3.9. This contrasts with European countries where on average, private-sector employees were paid systematically less compared to public sector employees as shown in Chapter 2. Thus, unlike most European countries, the US does not appear to have a misallocation problem associated with the public sector.

In all Tables of results, we consider interactions of our main variables with a number of covariates. More specifically, we consider the interaction of gender, non-whites and private sector with education, and the interaction of gender with part-time job status. These interaction terms suggest different wage impact of certain variables for females as compared to males, and for non-whites as compared to whites. In particular, the interaction of female with education indicates the crucial role that high education plays in reducing gender wage gaps. Similarly, wage differentials associated with race are lower for females and for individuals with higher levels of education. The former is consistent with Lang and Lehmann (2012)'s finding that wage gaps between black and white women have been historically lower than for males, and the latter is in line with Borowczyk-Martins et al. (2018) who show that wage gaps associated with race are reduced as the level of skill increases. Moreover, gender wage gaps are higher for private-sector employees as compared to public sector employees. Finally, since the 1990s, part-time work appears to reduce wage differentials between men and women.

We note that the impact of the included covariates on hourly wages in the United States generally has the expected sign: workers with low education receive lower hourly wages as compared to workers with secondary education, those with high education receive higher hourly wages as compared to those with only secondary education, age as a proxy for experience has a positive impact on hourly wages for all age groups, individuals with higher occupational education scores have higher wages, and those that do part-time work have lower wages since the 1990s.

Estimation without exclusion restrictions

So far, we have included instruments such as marital status, number of own children under age 5 in the household, exogenous income, and public assistance programs. To examine, whether our results are sensitive to imposing exclusion restrictions we consider here the case where we do not include any instruments in the probit equation in the first stage. For the sake of brevity, we provide results of the Mincer-type wage regression for 1960 and 2017. Figure 3.4 summarises the results of the average conditional wage gaps derived without the exclusion restrictions for all the years in our sample. Overall, results are similar as before. From Tables 3.14 and 3.15 we can observe that being a female or non-white exert negative impact on hourly wages beyond that explained by their economic characteristics, and that this impact is typically quite similar irrespective of whether we impose the above exclusion restrictions or not.

3.4 State-level talent misallocation and aggregate economic outcomes

We now estimate regression specifications that allow the estimated coefficients related to gender and race to be state-specific. We include our complete set of explanatory variables and interactions, as in the specifications reported in the last column of Tables 3.3 to 3.9 for 1960 to 2017.[16] This allows us to compute state-specific wage gaps based on individual-level data, and to consider a ranking of all states for each period based on the wage gaps characterizing each state. Tables 3.16 to 3.22 present state-specific results for each period.

Looking at the estimated misallocation measure across the United States, we note that the average measure was relatively large, particularly in the early decades. Specifically, in the 1960s, the average misallocation measure was 78.3 percent. Over the years, we observe a gradual reduction of the estimated misallocation measure. By 2017, the average misallocation measure was reduced by half, reaching 36.2 percent. If we look at the state-level, we can observe from Table 3.16 that in the 1960s, Alabama, South Carolina, Louisiana, Mississippi and Georgia have the highest overall misallocation measure, while Vermont, Nebraska, Iowa, Wisconsin, and Minnesota have the lowest. By 2017, we again find Louisiana, Mississippi, and Alabama to have the largest overall misallocation measure along with South Dakota and West Virginia. Given the large number of states and years that we cover in our study, Figures 3.5 to 3.13 provide a better understanding of the overall misallocation measure and its decomposition for each state over the period under study[17].

We systematically find that the gender wage gap is systematically the main contributor to the overall misallocation measure. In the 1960s, the average gender wage gap was about 56 percent while wage differentials related to race were around 23 percent. Despite the significant reduction for both wage gaps, by 2017 we still find an average gender wage gap of around 24 percent that is twice the wage gap of 12 percent related to race.

In line with our theoretical model, we view the above-constructed aggregate wage gap as a measure of talent misallocation within each state. To assess this hypothesis, we investigate the link that our micro-based talent misallocation measure has on state-level economic outcomes. We use Pearson correlations of our estimated misallocation measures with aggregate outcome measures such as real GDP per worker, TFP and Technical Efficiency, as shown in Table 3.23. Overall, we find a significant negative relation between our misallocation measure with these aggregate measures. These results are in line with Hsieh et al. (2019) who show the important role that labor misallocation plays for US economic outcomes. Rather than focusing at the US economy as a whole, we look at the relation of our micro-based estimated misallocation measure aggregated for each state with state-level aggregates of economic outcomes.

As shown in Figure 3.14 and Table 3.23 for 1980 to 2017, the correlation between real GDP per worker and our estimated misallocation measure is equal to -0.680, significant at the 1% level. A negative correlation is also found for our micro-based estimated talent misallocation

[16]This specification has the better goodness of fit as shown at the bottom of Table 3.3 to 3.9.
[17]Note that we group the states according to the region and division they are part of.

measure and TFP. As illustrated in Figure 3.16 and Table 3.23 for 1980 to 2000, the correlation coefficient is equal to -0.316, significant at the 1% level. Extending this period by using another database provided from Cardarelli and Lusinyan (2015) covering 2000 to 2010, we find again a negative correlation coefficient of -0.356, significant at the 1% level, as shown in Figure 3.15. Thus, using data from two different databases we confirm a robust negative relationship between productivity and our micro-based estimated talent misallocation measure. Finally, Figure 3.17 and Table 3.23 show a negative relation between Technical Efficiency and our misallocation measure for 1980 to 2000. The correlation coefficient is equal to -0.182, significant at the 5% level.

The above findings are in line with the literature arguing that input misallocation can have long-term negative effects for aggregate economic outcomes. Noting that our goal is not to identify a causal link, we argue that the negative relation found here between aggregate economic outcomes and our estimated misallocation measure based on microeconomic data, is suggestive of a potentially important role played by talent misallocation in determining aggregate outcomes across states and over time.

Labor Force Weighted Measure

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

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

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

Having constructed the talent misallocation measure weighted with the labor force for each state and period, we compute Pearson correlations with state-level economic outcomes. The second row of Table 3.23 presents the results of the correlation between our talent misallocation measure and aggregate measures such as GDP, TFP, and Technical Efficiency. Once again, we find a negative relationship between our micro-based estimated misallocation measure and these aggregate outcomes. In particular, the correlation coefficient between the misallocation measure thus constructed and GDP per worker equal -0.791, significant at the 1% level. The respective correlations with TFP and Technical Efficiency over the period 1980-2000 are -0.364 and -0.431, also strongly significant at the 1% level. All three correlations are higher than the ones using the equally weighted measure as can be seen by comparing the first and second rows of Table 3.23.

3.5 Conclusion

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

We find that our state-level talent misallocation measure based on these micro-level data has aggregate economic effects. A negative relation exists between our micro-based misallocation measure and state-level Technical Efficiency, Total Factor Productivity, and GDP per worker over time.

Overall, having linked wage gaps to talent misallocation within a search model of the labor market, we have shown that talent misallocation matters for aggregate economic outcomes. Our work thus has clear implications about the aggregate economic importance of policies that address any remaining existing labor market barriers applying to specific population groups.

In terms of future work, one could focus on exploring the misallocation effects by focusing on a restricted sample. Specifically, by restricting the sample only to white versus black men. As explained already in chapter 2, by considering both channels, gender and race, we increase the possibility of having sample selection issues.

3.6 Tables

Table 3.1: Summary statistics from the final sample

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

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

Table 3.2: Probit selection equation results for the waves from 1960 to 2017

Variables	(1960)	(1970)	(1980)	(1990)	(2000)	(2010)	(2017)
Female	-0.750***	-0.556***	0.140***	0.209***	0.239***	0.088***	0.177***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Non-white	0.215***	0.110***	0.002	-0.088***	-0.129***	-0.016***	0.006
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.006)
Private	-0.063***	0.025***	0.019***	0.020***	0.004	0.164***	0.236***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
Educ L	0.015***	-0.080***	-0.105***	-0.057***	-0.106***	0.042***	0.034***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.011)	(0.013)
Educ H	0.013***	0.023***	0.131***	0.153***	0.156***	0.146***	0.181***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
Age 35-44	0.190***	0.190***	0.058***	0.009***	-0.000	0.001	-0.013*
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.007)	(0.007)
Age 45-54	0.192***	0.161***	-0.108***	-0.134***	-0.087***	-0.060***	-0.063***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.008)
Age 55-64	-0.053***	-0.112***	-0.498***	-0.548***	-0.454***	-0.516***	-0.517***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Occupscor	0.001***	0.002***	0.002***	0.002***	0.002***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part_time	-2.111***	-2.312***	-2.829***	-3.000***	-3.683***	-3.791***	-4.074***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.015)	(0.065)	(0.083)
Married	-0.124***	-0.085***	-0.041***	-0.003	0.012***	0.021***	-0.021***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
nchild5	-0.176***	-0.207***	-0.316***	-0.261***	-0.228***	-0.234***	-0.257***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
welf_inc		-0.087***	-0.077***	-0.067***	-0.034***	-0.027***	-0.032***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
exg_inc			0.018***	0.012***	0.017***	-0.003***	-0.009***
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	2.512***	2.666***	3.177***	3.396***	3.985***	4.428***	4.551***
	(0.011)	(0.015)	(0.013)	(0.013)	(0.019)	(0.069)	(0.087)
Observations	3,105,144	1,461,597	4,397,316	5,492,116	6,353,277	1,391,357	1,390,390
Number of states	51	51	51	51	51	51	51
State-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.3: Selection-corrected hourly wage regression for the period 1960, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.596***	-0.531***	-0.550***	-0.376***	-0.378***
	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
Non-white	-0.284***	-0.287***	-0.269***	-0.131***	-0.131***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Private	-0.046***	-0.043***	-0.038***	0.054***	0.054***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.198***	-0.191***	-0.177***	-0.165***	-0.165***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.145***	0.145***	0.113***	0.128***	0.128***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.129***	0.114***	0.114***	0.115***	0.117***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.129***	0.111***	0.111***	0.111***	0.113***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.062***	0.061***	0.060***	0.060***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.124***	-0.125***	-0.141***	-0.160***
		(0.004)	(0.004)	(0.004)	(0.005)
Private *Educ L			-0.016***	-0.031***	-0.032***
			(0.003)	(0.003)	(0.004)
Private *Educ H			0.013***	0.010***	0.010***
			(0.003)	(0.003)	(0.003)
Female *Educ L			0.029***	0.037***	0.038***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.058***	0.013***	0.013***
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			-0.050***	-0.036***	-0.036***
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.066***	0.021***	0.020***
			(0.004)	(0.005)	(0.005)
Private *Female				-0.203***	-0.203***
				(0.003)	(0.003)
Private *Non-white				-0.167***	-0.167***
				(0.004)	(0.004)
Female *Non-white				0.014***	0.016***
				(0.003)	(0.003)
Female *Part-time					-0.021***
					(0.004)
lambda	0.283***	0.313***	0.314***	0.336***	0.371***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.008)
Constant	0.812***	0.844***	0.844***	0.764***	0.762***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Total effect Female	-0.596***	-0.531***	-0.530***	-0.537***	-0.545***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Total effect Non-white	-0.284***	-0.287***	-0.272***	-0.278***	-0.277***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.046***	-0.043***	-0.041***	-0.058***	-0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.235	0.240	0.240	0.242	0.242
Observations	3,105,144	3,105,144	3,105,144	3,105,144	3,105,144

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

Table 3.4: Selection-corrected hourly wage regression for the period 1970, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.463***	-0.507***	-0.530***	-0.404***	-0.405***
	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Non-white	-0.206***	-0.206***	-0.199***	-0.162***	-0.162***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Private	-0.038***	-0.040***	-0.042***	0.040***	0.040***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Educ L	-0.166***	-0.175***	-0.195***	-0.182***	-0.181***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Educ H	0.150***	0.149***	0.113***	0.132***	0.133***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Age 35-44	0.097***	0.106***	0.108***	0.108***	0.103***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.104***	0.116***	0.117***	0.118***	0.114***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.076***	0.077***	0.077***	0.078***	0.078***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part_time		0.039***	0.033***	0.030***	0.077***
		(0.007)	(0.007)	(0.007)	(0.008)
Private *Educ L			0.026***	0.009*	0.010*
			(0.005)	(0.005)	(0.005)
Private *Educ H			0.009**	-0.004	-0.005
			(0.004)	(0.004)	(0.004)
Female *Educ L			0.026***	0.024***	0.024***
			(0.004)	(0.004)	(0.004)
Female *Educ H			0.071***	0.041***	0.040***
			(0.003)	(0.003)	(0.003)
Non-white *Educ L			-0.053***	-0.037***	-0.038***
			(0.004)	(0.004)	(0.004)
Non-white *Educ H			0.056***	0.041***	0.040***
			(0.005)	(0.005)	(0.005)
Private *Female				-0.159***	-0.160***
				(0.004)	(0.004)
Private *Non-white				-0.085***	-0.086***
				(0.005)	(0.005)
Female *Non-white				0.071***	0.071***
				(0.004)	(0.004)
Female *Part_time					0.061***
					(0.005)
lambda	-0.051***	0.060***	0.068***	0.074***	-0.021**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)
Constant	1.289***	1.266***	1.274***	1.209***	1.212***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)

Total effect Female	-0.463***	-0.507***	-0.507***	-0.512***	-0.493***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.206***	-0.206***	-0.196***	-0.199***	-0.200***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.038***	-0.040***	-0.034***	-0.042***	-0.042***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.238	0.240	0.241	0.243	0.243
Observations	1,461,597	1,461,597	1,461,597	1,461,597	1,461,597

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

Table 3.5: Selection-corrected hourly wage regression for the period 1980, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.358***	-0.466***	-0.496***	-0.430***	-0.415***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Non-white	-0.101***	-0.107***	-0.117***	-0.179***	-0.182***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Private	-0.029***	-0.027***	-0.029***	0.040***	0.038***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.154***	-0.197***	-0.244***	-0.225***	-0.227***
	(0.002)	(0.001)	(0.004)	(0.004)	(0.004)
Educ H	0.119***	0.130***	0.094***	0.105***	0.102***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age 35-44	0.150***	0.170***	0.170***	0.169***	0.170***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.205***	0.215***	0.215***	0.214***	0.215***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.299***	0.216***	0.216***	0.215***	0.217***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.006***	0.007***	0.007***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		0.038***	0.033***	0.052***	0.210***
		(0.004)	(0.004)	(0.004)	(0.005)
Private *Educ L			0.029***	0.015***	0.014***
			(0.004)	(0.004)	(0.004)
Private *Educ H			0.005**	-0.005**	-0.003
			(0.002)	(0.002)	(0.002)
Female *Educ L			0.086***	0.052***	0.057***
			(0.003)	(0.003)	(0.003)
Female *Educ H			0.058***	0.048***	0.047***
			(0.002)	(0.002)	(0.002)
Non-white *Educ L			-0.027***	0.000	0.002
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.039***	0.041***	0.041***
			(0.002)	(0.002)	(0.002)
Private *Female				-0.115***	-0.114***
				(0.002)	(0.002)
Private *Non-white				-0.035***	-0.035***
				(0.003)	(0.003)
Female *Non-white				0.182***	0.184***
				(0.002)	(0.002)
Female *Part-time					-0.157***
					(0.003)
Constant	1.693***	1.615***	1.633***	1.589***	1.586***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.358***	-0.466***	-0.465***	-0.468***	-0.485***

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.101***	-0.107***	-0.104***	-0.109***	-0.111***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Private	-0.029***	-0.027***	-0.024***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.174	0.171	0.171	0.174	0.175
Observations	4,397,316	4,397,316	4,397,316	4,397,316	4,397,316

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

Table 3.6: Selection-corrected hourly wage regression for the period 1990, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.317***	-0.381***	-0.411***	-0.356***	-0.363***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Non-white	-0.118***	-0.132***	-0.151***	-0.185***	-0.184***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Private	-0.043***	-0.044***	-0.073***	-0.006***	-0.005**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.128***	-0.168***	-0.165***	-0.151***	-0.150***
	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
Educ H	0.147***	0.169***	0.097***	0.103***	0.103***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age 35-44	0.147***	0.163***	0.164***	0.163***	0.163***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.224***	0.231***	0.232***	0.232***	0.231***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.364***	0.249***	0.248***	0.248***	0.246***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.008***	0.009***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.065***	-0.070***	-0.050***	-0.137***
		(0.003)	(0.003)	(0.003)	(0.004)
Private *Educ L			-0.027***	-0.029***	-0.028***
			(0.006)	(0.006)	(0.006)
Private *Educ H			0.048***	0.043***	0.042***
			(0.002)	(0.002)	(0.002)
Female *Educ L			0.106***	0.055***	0.052***
			(0.003)	(0.004)	(0.004)
Female *Educ H			0.047***	0.044***	0.046***
			(0.001)	(0.001)	(0.001)
Non-white *Educ L			-0.024***	-0.000	-0.002
			(0.003)	(0.003)	(0.003)
Non-white *Educ H			0.044***	0.034***	0.034***
			(0.002)	(0.002)	(0.002)
Private *Female				-0.101***	-0.102***
				(0.002)	(0.002)
Private *Non-white				-0.052***	-0.052***
				(0.002)	(0.002)
Female *Non-white				0.163***	0.162***
				(0.002)	(0.002)
Female *Part-time					0.075***
					(0.002)
Constant	2.093***	1.997***	2.037***	1.993***	1.995***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.317***	-0.381***	-0.381***	-0.382***	-0.375***

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.118***	-0.132***	-0.130***	-0.133***	-0.133***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Private	-0.043***	-0.044***	-0.050***	-0.044***	-0.044**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.202	0.203	0.203	0.205	0.205
Observations	5,492,116	5,492,116	5,492,116	5,492,116	5,492,116

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

Table 3.7: Selection-corrected hourly wage regression for the period 2000, US Decennial Census

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.247***	-0.315***	-0.340***	-0.316***	-0.331***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Non-white	-0.100***	-0.121***	-0.142***	-0.142***	-0.141***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Private	-0.006***	-0.011***	-0.075***	-0.022***	-0.020***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.121***	-0.180***	-0.201***	-0.205***	-0.203***
	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)
Educ H	0.152***	0.176***	0.055***	0.061***	0.062***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age 35-44	0.148***	0.164***	0.164***	0.163***	0.163***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.200***	0.212***	0.213***	0.212***	0.212***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.366***	0.244***	0.244***	0.244***	0.240***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.008***	0.009***	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.107***	-0.115***	-0.100***	-0.309***
		(0.004)	(0.004)	(0.004)	(0.005)
Private *Educ L			-0.015**	0.002	0.004
			(0.007)	(0.007)	(0.007)
Private *Educ H			0.104***	0.098***	0.097***
			(0.002)	(0.002)	(0.002)
Female *Educ L			0.041***	-0.008**	-0.015***
			(0.004)	(0.004)	(0.004)
Female *Educ H			0.045***	0.046***	0.050***
			(0.001)	(0.001)	(0.001)
Non-white *Educ L			0.042***	0.060***	0.056***
			(0.004)	(0.004)	(0.004)
Non-white *Educ H			0.040***	0.029***	0.029***
			(0.002)	(0.002)	(0.002)
Private *Female				-0.062***	-0.064***
				(0.002)	(0.002)
Private *Non-white				-0.061***	-0.061***
				(0.002)	(0.002)
Female *Non-white				0.113***	0.112***
				(0.002)	(0.002)
Female *Part-time					0.155***
					(0.002)
Constant	2.384***	2.251***	2.323***	2.289***	2.293***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
Total effect Female	-0.247***	-0.315***	-0.316***	-0.317***	-0.300***

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Non-white	-0.100***	-0.121***	-0.120***	-0.121***	-0.121***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect Private	-0.006***	-0.011***	-0.024***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.182	0.185	0.186	0.187	0.187
Observations	6,353,277	6,353,277	6,353,277	6,353,277	6,353,277

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

Table 3.8: Selection-corrected hourly wage regression for the period 2010, ACS

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.220***	-0.215***	-0.222***	-0.274***	-0.348***
	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)
Non-white	-0.141***	-0.148***	-0.155***	-0.115***	-0.108***
	(0.003)	(0.002)	(0.003)	(0.006)	(0.006)
Private	-0.083***	-0.052***	-0.174***	-0.171***	-0.149***
	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.069***	-0.064***	-0.201***	-0.222***	-0.211***
	(0.007)	(0.005)	(0.024)	(0.025)	(0.024)
Educ H	0.176***	0.215***	0.060***	0.064***	0.062***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.201***	0.218***	0.217***	0.216***	0.211***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.248***	0.263***	0.261***	0.261***	0.258***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.407***	0.273***	0.272***	0.271***	0.259***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Occupscor	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.700***	-0.700***	-0.701***	-1.133***
		(0.008)	(0.008)	(0.008)	(0.009)
Private *Educ L			0.066***	0.097***	0.100***
			(0.023)	(0.023)	(0.023)
Private *Educ H			0.172***	0.166***	0.156***
			(0.005)	(0.005)	(0.005)
Female *Educ L			0.039***	0.008	-0.009
			(0.010)	(0.010)	(0.010)
Female *Educ H			0.009**	0.016***	0.041***
			(0.004)	(0.004)	(0.004)
Non-white *Educ L			0.089***	0.099***	0.086***
			(0.012)	(0.012)	(0.012)
Non-white *Educ H			0.009**	-0.003	-0.002
			(0.004)	(0.004)	(0.004)
Private *Female				0.039***	0.012***
				(0.005)	(0.005)
Private *Non-white				-0.075***	-0.072***
				(0.005)	(0.005)
Female *Non-white				0.055***	0.049***
				(0.004)	(0.004)
Female *Part-time					0.482***
					(0.005)
Constant	2.276***	2.205***	2.316***	2.320***	2.350***
	(0.013)	(0.009)	(0.009)	(0.010)	(0.010)
Total effect Female	-0.220***	-0.215***	-0.216***	-0.216***	-0.179***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)

Total effect Non-white	-0.141***	-0.148***	-0.147***	-0.148***	-0.142***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.083***	-0.052***	-0.072***	-0.074***	-0.070***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.201	0.226	0.227	0.227	0.227
Observations	1,391,357	1,391,357	1,391,357	1,391,357	1,391,357

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

Table 3.9: Selection-corrected hourly wage regression for the period 2017, ACS

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.305***	-0.267***	-0.288***	-0.307***	-0.355***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Non-white	-0.128***	-0.131***	-0.142***	-0.121***	-0.117***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Private	0.034***	0.058***	-0.034***	-0.003	0.008
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.068***	-0.066***	-0.159***	-0.172***	-0.168***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.188***	0.203***	0.073***	0.078***	0.076***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.240***	0.237***	0.237***	0.236***	0.232***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.310***	0.307***	0.306***	0.306***	0.303***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.365***	0.326***	0.326***	0.325***	0.312***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.502***	-0.502***	-0.501***	-0.875***
		(0.007)	(0.007)	(0.007)	(0.008)
Private *Educ L			0.044**	0.067***	0.069***
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.126***	0.122***	0.118***
			(0.005)	(0.005)	(0.005)
Female *Educ L			0.055***	0.016*	0.011
			(0.010)	(0.010)	(0.010)
Female *Educ H			0.030***	0.036***	0.052***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ L			0.052***	0.063***	0.055***
			(0.011)	(0.011)	(0.011)
Nonwhite *Educ H			0.016***	0.002	0.003
			(0.003)	(0.003)	(0.003)
Private *Female				-0.013***	-0.026***
				(0.004)	(0.004)
Private *Non-white				-0.066***	-0.065***
				(0.005)	(0.005)
Female *Non-white				0.086***	0.085***
				(0.003)	(0.003)
Female *Part-time					0.354***
					(0.004)
lambda	0.355***	0.130***	0.131***	0.133***	0.418***
	(0.023)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	2.174***	2.199***	2.293***	2.277***	2.299***
	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)

Total effect Female	-0.305***	-0.267***	-0.268***	-0.268***	-0.238***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.128***	-0.131***	-0.130***	-0.131***	-0.127***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	0.034***	0.058***	0.045***	0.047***	0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.201	0.226	0.227	0.227	0.231
Observations	1,390,390	1,390,390	1,390,390	1,390,390	1,390,390

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

Table 3.10: Selection-corrected hourly wage regression for the period 1960, US Decennial Census. Race decomposition

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.593***	-0.528***	-0.547***	-0.376***	-0.376***
	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
African-Americans	-0.318***	-0.321***	-0.317***	-0.155***	-0.155***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Hispanic	-0.175***	-0.178***	-0.116***	-0.047***	-0.047***
	(0.003)	(0.003)	(0.005)	(0.009)	(0.009)
American Indian/Alaska Native	-0.348***	-0.328***	-0.269***	-0.082***	-0.082***
	(0.011)	(0.011)	(0.018)	(0.030)	(0.030)
Asian	-0.217***	-0.224***	-0.172***	-0.111***	-0.111***
	(0.007)	(0.007)	(0.010)	(0.017)	(0.017)
Mixed races	-0.239***	-0.226***	-0.171***	-0.071*	-0.071*
	(0.017)	(0.017)	(0.025)	(0.036)	(0.036)
Private	-0.047***	-0.044***	-0.039***	0.053***	0.053***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.199***	-0.193***	-0.178***	-0.168***	-0.168***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.146***	0.146***	0.115***	0.131***	0.131***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.130***	0.114***	0.115***	0.116***	0.116***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.131***	0.112***	0.112***	0.113***	0.113***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.064***	0.063***	0.061***	0.062***	0.062***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.115***	-0.115***	-0.130***	-0.133***
		(0.004)	(0.004)	(0.004)	(0.005)
Private *Educ L			-0.015***	-0.030***	-0.030***
			(0.003)	(0.003)	(0.003)
Private *Educ H			0.014***	0.009***	0.009***
			(0.003)	(0.003)	(0.003)
Female *Educ L			0.030***	0.036***	0.036***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.056***	0.011***	0.011***
			(0.003)	(0.003)	(0.003)
African-Americans *Educ L			-0.029***	-0.011***	-0.011***
			(0.003)	(0.003)	(0.003)
African-Americans *Educ H			0.103***	0.032***	0.032***
			(0.005)	(0.006)	(0.006)
Hispanic *Educ L			-0.112***	-0.100***	-0.100***
			(0.006)	(0.006)	(0.006)
Hispanic *Educ H			-0.032***	-0.037***	-0.037***
			(0.009)	(0.009)	(0.009)

American Indian/Alaska Native *Educ L			-0.132***	-0.095***	-0.095***
			(0.023)	(0.024)	(0.024)
American Indian/Alaska Native *Educ H			0.074*	0.034	0.034
			(0.041)	(0.041)	(0.041)
Asian *Educ L			-0.095***	-0.062***	-0.062***
			(0.013)	(0.013)	(0.013)
Asian *Educ H			-0.075***	-0.078***	-0.078***
			(0.015)	(0.015)	(0.015)
Mixed races *Educ L			-0.052	-0.040	-0.041
			(0.036)	(0.036)	(0.036)
Mixed races *Educ H			-0.160***	-0.174***	-0.174***
			(0.041)	(0.041)	(0.041)
Private *Female				-0.202***	-0.202***
				(0.003)	(0.003)
Private *African-Americans				-0.196***	-0.195***
				(0.005)	(0.005)
Private *Hispanic				-0.109***	-0.109***
				(0.009)	(0.009)
Private *American Indian/Alaska Native				-0.268***	-0.268***
				(0.029)	(0.029)
Private *Asian				-0.130***	-0.130***
				(0.016)	(0.016)
Private *Mixed races				-0.148***	-0.148***
				(0.035)	(0.035)
Female *African-Americans				0.011***	0.011***
				(0.003)	(0.003)
Female *Hispanic				0.092***	0.092***
				(0.006)	(0.006)
Female *American Indian/Alaska Native				0.052**	0.052**
				(0.026)	(0.026)
Female *Asian				0.153***	0.152***
				(0.013)	(0.013)
Female *Mixed races				0.048	0.047
				(0.033)	(0.033)
Female *Part-time					-0.004
					(0.004)
lambda	0.279***	0.303***	0.304***	0.325***	0.331***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.008)
Constant	0.812***	0.844***	0.844***	0.764***	0.764***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.593***	-0.528***	-0.527***	-0.533***	-0.535***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Total effect African-American	-0.318***	-0.321***	-0.306***	-0.318***	-0.317***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Hispanic	-0.175***	-0.178***	-0.158***	-0.143***	-0.143***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect American Indian/Alaska Native	-0.348***	-0.328***	-0.296***	-0.317***	-0.317***
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)

Total effect Asian	-0.217***	-0.224***	-0.217***	-0.197***	-0.197***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Total effect Mixed races	-0.239***	-0.226***	-0.219***	-0.227***	-0.227***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
Total effect Private	-0.047***	-0.044***	-0.042***	-0.059***	-0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,105,144	3,105,144	3,105,144	3,105,144	3,105,144

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

Table 3.11: Selection-corrected hourly wage regression for the period 2017, ACS. Race decomposition

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.305***	-0.265***	-0.285***	-0.309***	-0.356***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
African-Americans	-0.217***	-0.220***	-0.221***	-0.161***	-0.150***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.008)
Hispanic	-0.119***	-0.122***	-0.093***	-0.042***	-0.045***
	(0.003)	(0.002)	(0.004)	(0.008)	(0.008)
American Indian/Alaska Native	-0.219***	-0.223***	-0.213***	-0.226***	-0.214***
	(0.009)	(0.009)	(0.012)	(0.020)	(0.020)
Asian	0.004	-0.000	-0.092***	-0.108***	-0.108***
	(0.003)	(0.003)	(0.007)	(0.012)	(0.012)
Mixed races	-0.112***	-0.111***	-0.126***	-0.124***	-0.119***
	(0.006)	(0.006)	(0.010)	(0.017)	(0.017)
Private	0.026***	0.050***	-0.043***	-0.003	0.009*
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.082***	-0.080***	-0.162***	-0.181***	-0.177***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.186***	0.199***	0.077***	0.089***	0.087***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.240***	0.236***	0.236***	0.236***	0.232***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.312***	0.307***	0.307***	0.307***	0.304***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.361***	0.328***	0.329***	0.328***	0.316***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.496***	-0.497***	-0.495***	-0.859***
		(0.007)	(0.007)	(0.007)	(0.008)
Private *Educ L			0.044**	0.068***	0.070***
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.126***	0.116***	0.112***
			(0.005)	(0.005)	(0.005)
Female *Educ L			0.056***	0.033***	0.024**
			(0.010)	(0.010)	(0.010)
Female *Educ H			0.031***	0.036***	0.052***
			(0.003)	(0.003)	(0.003)
African-Americans *Educ L			0.026	0.039*	0.039*
			(0.022)	(0.022)	(0.022)
African-Americans *Educ H			0.000	-0.031***	-0.031***
			(0.005)	(0.006)	(0.006)
Hispanic *Educ L			0.020*	0.028**	0.023*
			(0.012)	(0.012)	(0.012)
Hispanic *Educ H			-0.064***	-0.078***	-0.075***
			(0.005)	(0.005)	(0.005)

American Indian/Alaska Native *Educ L			0.151**	0.165**	0.162**
			(0.068)	(0.068)	(0.067)
American Indian/Alaska Native *Educ H			-0.036**	-0.052***	-0.050***
			(0.017)	(0.017)	(0.017)
Asian *Educ L			0.002	0.009	0.008
			(0.019)	(0.019)	(0.019)
Asian *Educ H			0.120***	0.115***	0.114***
			(0.008)	(0.008)	(0.008)
Mixed races *Educ L			0.063	0.073*	0.078*
			(0.044)	(0.044)	(0.044)
Mixed races *Educ H			0.020	0.004	0.004
			(0.012)	(0.012)	(0.012)
Private *Female				-0.010**	-0.023***
				(0.004)	(0.004)
Private *African-Americans				-0.144***	-0.142***
				(0.007)	(0.007)
Private *Hispanic				-0.082***	-0.081***
				(0.007)	(0.007)
Private *American Indian/Alaska Native				-0.031*	-0.033*
				(0.018)	(0.018)
Private *Asian				-0.036***	-0.035***
				(0.010)	(0.010)
Private *Mixed races				-0.052***	-0.048***
				(0.015)	(0.015)
Female *African-Americans				0.140***	0.133***
				(0.005)	(0.005)
Female *Hispanic				0.058***	0.062***
				(0.005)	(0.005)
Female *American Indian/Alaska Native				0.097***	0.083***
				(0.017)	(0.017)
Female *Asian				0.105***	0.106***
				(0.006)	(0.006)
Female *Mixed races				0.106***	0.097***
				(0.011)	(0.011)
Female *Part-time					0.345***
					(0.004)
lambda	-0.309***	0.122***	0.122***	0.125***	0.401***
	(0.023)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	2.183***	2.217***	2.306***	2.282***	2.303***
	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Total effect Female	-0.305***	-0.265***	-0.264***	-0.264***	-0.355***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect African-American	-0.217***	-0.220***	-0.220***	-0.231***	-0.223***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect Hispanic	-0.119***	-0.122***	-0.131***	-0.130***	-0.128***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Total effect American Indian/Alaska Native	-0.219***	-0.223***	-0.231***	-0.232***	-0.226***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)

Total effect Asian	0.004	0.000	-0.018***	-0.017***	-0.015***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Total effect Mixed races	-0.112***	-0.111***	-0.112***	-0.111***	-0.108***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Total effect Private	0.026***	0.050***	0.035***	0.038***	0.041***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,390,390	1,390,390	1,390,390	1,390,390	1,390,390

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

Table 3.12: Selection-corrected hourly wage regression for the period 1960. Race and country of origin.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.510***	-0.531***	-0.550***	-0.377***	-0.379***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Nonwhite	-0.294***	-0.287***	-0.269***	-0.133***	-0.132***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Migrant	0.013***	0.012***	-0.013***	-0.020***	-0.020***
	(0.002)	(0.002)	(0.003)	(0.007)	(0.007)
Private	-0.041***	-0.043***	-0.038***	0.054***	0.053***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.194***	-0.192***	-0.181***	-0.170***	-0.170***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.145***	0.145***	0.115***	0.130***	0.130***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.107***	0.114***	0.115***	0.116***	0.117***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.102***	0.110***	0.111***	0.112***	0.114***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.057***	0.060***	0.058***	0.058***	0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part-time		-0.124***	-0.123***	-0.139***	-0.159***
		(0.004)	(0.004)	(0.004)	(0.005)
Private *Educ L			-0.019***	-0.035***	-0.035***
			(0.003)	(0.004)	(0.004)
Private *Educ H			0.017***	0.013***	0.014***
			(0.003)	(0.003)	(0.003)
Female *Educ L			0.028***	0.035***	0.036***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.058***	0.013***	0.013***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ L			-0.050***	-0.036***	-0.036***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ H			0.072***	0.026***	0.026***
			(0.004)	(0.005)	(0.005)
Migrant *Educ L			0.081***	0.082***	0.082***
			(0.004)	(0.004)	(0.004)
Migrant *Educ H			-0.080***	-0.071***	-0.071***
			(0.005)	(0.005)	(0.005)
Private *Female				-0.202***	-0.203***
				(0.003)	(0.003)
Private *Nonwhite				-0.166***	-0.165***
				(0.004)	(0.004)
Female *Nonwhite				0.016***	0.018***
				(0.003)	(0.003)

Private *Migrant				0.003	0.003
				(0.007)	(0.007)
Female *Migrant				0.012***	0.012***
				(0.004)	(0.004)
Female *Part-time					-0.023***
					(0.004)
lambda	0.173***	0.312***	0.312***	0.334***	0.372***
	(0.001)	(0.005)	(0.005)	(0.005)	(0.008)
Constant	0.847***	0.844***	0.842***	0.763***	0.761***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total effect Female	-0.510***	-0.531***	-0.530***	-0.537***	-0.546***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Total effect Non-white	-0.294***	-0.287***	-0.270***	-0.277***	-0.275***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Total effect Migrant	0.013***	0.012***	-0.003***	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.041***	-0.043***	-0.041***	-0.059***	-0.059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,091,603	3,091,603	3,091,603	3,091,603	3,091,603

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

Table 3.13: Selection-corrected hourly wage regression for the period 2017, ACS. Race and country of origin

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.311***	-0.266***	-0.288***	-0.308***	-0.356***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Nonwhite	-0.149***	-0.153***	-0.166***	-0.138***	-0.132***
	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)
Migrant	0.064***	0.067***	0.072***	0.070***	0.062***
	(0.002)	(0.002)	(0.004)	(0.008)	(0.008)
Private	0.031***	0.054***	-0.040***	-0.007	0.004
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.091***	-0.090***	-0.162***	-0.176***	-0.171***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.190***	0.201***	0.069***	0.075***	0.074***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.238***	0.233***	0.233***	0.233***	0.229***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.309***	0.303***	0.302***	0.301***	0.299***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.352***	0.324***	0.323***	0.322***	0.310***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part_time		-0.497***	-0.498***	-0.497***	-0.863***
		(0.007)	(0.007)	(0.007)	(0.008)
Private *Educ L			0.042*	0.065***	0.067***
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.129***	0.123***	0.118***
			(0.005)	(0.005)	(0.005)
Female *Educ L			0.055***	0.023**	0.016
			(0.010)	(0.010)	(0.010)
Female *Educ H			0.031***	0.038***	0.054***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ L			0.044***	0.056***	0.053***
			(0.015)	(0.015)	(0.014)
Nonwhite *Educ H			0.018***	0.002	0.002
			(0.004)	(0.004)	(0.004)
Migrant *Educ L			-0.023*	-0.026*	-0.028**
			(0.013)	(0.013)	(0.013)
Migrant *Educ H			-0.005	-0.001	0.002
			(0.005)	(0.005)	(0.005)
Private *Female				-0.011***	-0.024***
				(0.004)	(0.004)
Private *Nonwhite				-0.079***	-0.078***
				(0.005)	(0.005)
Female *Nonwhite				0.096***	0.093***
				(0.004)	(0.004)

Private *Migrant				0.015**	0.016**
				(0.007)	(0.007)
Female *Migrant				-0.020***	-0.014***
				(0.005)	(0.005)
Female *Part_time					0.349***
					(0.004)
lambda	-0.259***	0.123***	0.123***	0.125***	0.402***
	(0.023)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	2.157***	2.200***	2.295***	2.277***	2.299***
	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Total effect Female	-0.311***	-0.266***	-0.267***	-0.267***	-0.238***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Non-white	-0.149***	-0.153***	-0.153***	-0.154***	-0.150***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Migrant	0.064***	0.067***	0.068***	0.071***	0.069***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Private	0.031***	0.054***	0.040***	0.042***	0.045***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,390,297	1,390,297	1,390,297	1,390,297	1,390,297

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

Table 3.14: Selection-corrected hourly wage regression without exclusion restrictions for the period 1960, US Decennial Census.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.492***	-0.524***	-0.544***	-0.372***	-0.363***
	(0.006)	(0.001)	(0.002)	(0.003)	(0.003)
Nonwhite	-0.289***	-0.289***	-0.272***	-0.132***	-0.135***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Private	-0.036***	-0.042***	-0.038***	0.054***	0.055***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Educ L	-0.188***	-0.191***	-0.177***	-0.166***	-0.166***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Educ H	0.146***	0.145***	0.112***	0.127***	0.127***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Age 35-44	0.106***	0.112***	0.112***	0.114***	0.107***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age 45-54	0.101***	0.109***	0.109***	0.110***	0.102***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age 55-64	0.059***	0.061***	0.060***	0.061***	0.058***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupscor	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part_time		-0.075***	-0.075***	-0.097***	-0.027***
		(0.005)	(0.005)	(0.005)	(0.008)
Private *Educ L			-0.016***	-0.031***	-0.031***
			(0.003)	(0.003)	(0.003)
Private *Educ H			0.014***	0.011***	0.011***
			(0.003)	(0.003)	(0.003)
Female *Educ L			0.031***	0.039***	0.037***
			(0.002)	(0.002)	(0.002)
Female *Educ H			0.057***	0.012***	0.012***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ L			-0.050***	-0.035***	-0.036***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ H			0.065***	0.020***	0.020***
			(0.004)	(0.005)	(0.005)
Private *Female				-0.202***	-0.201***
				(0.003)	(0.003)
Private *Nonwhite				-0.168***	-0.169***
				(0.004)	(0.004)
Female *Nonwhite				0.013***	0.008***
				(0.003)	(0.003)
Female *Part_time					0.058***
					(0.005)
lambda	0.064***	0.249***	0.249***	0.278***	0.161***
	(0.012)	(0.005)	(0.005)	(0.005)	(0.011)
Constant	0.847***	0.845***	0.845***	0.765***	0.771***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Total effect Female	-0.492***	-0.524***	-0.523***	-0.531***	-0.503***
	(0.006)	(0.001)	(0.001)	(0.001)	(0.003)
Total effect Non-white	-0.289***	-0.289***	-0.274***	-0.281***	-0.286***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Total effect Private	-0.036***	-0.042***	-0.040***	-0.058***	-0.056***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,105,144	3,105,144	3,105,144	3,105,144	3,105,144

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

Table 3.15: Selection-corrected hourly wage regression without exclusion restrictions for the period 2017, US Decennial Census.

Variables	(1)	(2)	(3)	(4)	(5)
Female	-0.386***	-0.269***	-0.289***	-0.306***	-0.354***
	(0.004)	(0.002)	(0.003)	(0.005)	(0.005)
Nonwhite	-0.118***	-0.131***	-0.142***	-0.120***	-0.116***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)
Private	0.053***	0.057***	-0.036***	-0.004	0.007
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Educ L	-0.065***	-0.066***	-0.157***	-0.170***	-0.167***
	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Educ H	0.224***	0.201***	0.071***	0.076***	0.075***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.005)
Age 35-44	0.263***	0.237***	0.237***	0.237***	0.233***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.341***	0.307***	0.306***	0.306***	0.303***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.241***	0.331***	0.330***	0.329***	0.316***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
Occupscor	0.014***	0.012***	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Part_time		-0.441***	-0.442***	-0.441***	-0.840***
		(0.008)	(0.008)	(0.008)	(0.009)
Private *Educ L			0.041*	0.065***	0.068***
			(0.022)	(0.022)	(0.022)
Private *Educ H			0.126***	0.122***	0.118***
			(0.005)	(0.005)	(0.005)
Female *Educ L			0.054***	0.017*	0.011
			(0.010)	(0.010)	(0.010)
Female *Educ H			0.029***	0.035***	0.052***
			(0.003)	(0.003)	(0.003)
Nonwhite *Educ L			0.051***	0.062***	0.055***
			(0.011)	(0.011)	(0.011)
Nonwhite *Educ H			0.017***	0.003	0.003
			(0.003)	(0.003)	(0.003)
Private *Female				-0.015***	-0.026***
				(0.004)	(0.004)
Private *Nonwhite				-0.066***	-0.066***
				(0.005)	(0.005)
Female *Nonwhite				0.085***	0.084***
				(0.003)	(0.003)
Female *Part_time					0.347***
					(0.004)
lambda	0.816***	0.015	0.015	0.018	0.356***
	(0.050)	(0.015)	(0.015)	(0.015)	(0.015)
Constant	1.957***	2.199***	2.293***	2.276***	2.298***
	(0.013)	(0.008)	(0.008)	(0.009)	(0.009)

Total effect Female	-0.386***	-0.269***	-0.289***	-0.269***	-0.270***
	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
Total effect Non-white	-0.118***	-0.131***	-0.142***	-0.130***	-0.130***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Total effect Private	0.053***	0.057***	-0.036***	0.043***	0.045***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
State-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,400,027	1,400,027	1,400,027	1,400,027	1,400,027

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

Table 3.16: Misallocation Measure and its decomposition across the United States for the period 1960

State	Female	Nonwhite	Misallocation Measure
Alabama	0.611***	0.491***	1.102***
South Carolina	0.460***	0.638***	1.097***
Louisiana	0.626***	0.465***	1.091***
Mississippi	0.443***	0.633***	1.076***
Georgia	0.516***	0.534***	1.050***
Texas	0.620***	0.365***	0.985***
Arkansas	0.512***	0.469***	0.981***
Delaware	0.615***	0.333***	0.948***
Virginia	0.527***	0.415***	0.941***
West Virginia	0.724***	0.217***	0.940***
Arizona	0.650***	0.285***	0.935***
Alaska	0.589***	0.324***	0.912***
Oklahoma	0.600***	0.311***	0.911***
Florida	0.592***	0.319***	0.911***
Tennessee	0.506***	0.392***	0.898***
New Mexico	0.639***	0.255***	0.895***
Maryland	0.581***	0.304***	0.885***
North Carolina	0.386***	0.497***	0.883***
Kentucky	0.520***	0.327***	0.847***
Montana	0.616***	0.218***	0.833***
Utah	0.696***	0.120***	0.816***
North Dakota	0.521***	0.269***	0.790***
Ohio	0.620***	0.156***	0.776***
District of Columbia	0.424***	0.349***	0.773***
Washington	0.595***	0.168***	0.763***
New Jersey	0.538***	0.222***	0.760***
Michigan	0.591***	0.153***	0.744***
Rhode Island	0.502***	0.241***	0.743***
Pennsylvania	0.574***	0.167***	0.741***
Oregon	0.635***	0.100***	0.735***
Missouri	0.532***	0.193***	0.725***
Illinois	0.555***	0.170***	0.725***
California	0.562***	0.157***	0.718***
Nevada	0.584***	0.129***	0.713***
Idaho	0.576***	0.135***	0.711***
Colorado	0.588***	0.113***	0.701***

Wyoming	0.622***	0.078	0.700***
Hawaii	0.588***	0.093***	0.681***
New York	0.471***	0.210***	0.681***
Connecticut	0.523***	0.154***	0.677***
Massachusetts	0.508***	0.153***	0.661***
South Dakota	0.500***	0.159***	0.660***
Kansas	0.602***	0.048**	0.650***
Indiana	0.612***	0.036***	0.647***
Main	0.530***	0.083	0.613***
New Hampshire	0.501***	0.079	0.580***
Minnesota	0.495***	0.039	0.534***
Wisconsin	0.539***	-0.007	0.532***
Iowa	0.542***	-0.043	0.498***
Nebraska	0.491***	-0.069**	0.421***
Vermont	0.437***	-0.112	0.324***
Average	**0.557**	**0.226**	**0.783**

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

Table 3.17: Misallocation Measure and its decomposition across the United States for the period 1970

State	Female	Nonwhite	Misallocation Measure
Alabama	0.519***	0.395***	0.914***
Louisiana	0.550***	0.359***	0.909***
South Carolina	0.445***	0.416***	0.861***
Mississippi	0.447***	0.412***	0.859***
Georgia	0.470***	0.386***	0.856***
Delaware	0.563***	0.283***	0.846***
North Dakota	0.487***	0.330***	0.817***
Texas	0.539***	0.269***	0.808***
Virginia	0.472***	0.301***	0.773***
Wyoming	0.597***	0.174*	0.771***
West Virginia	0.586***	0.169***	0.755***
Montana	0.572***	0.170***	0.742***
Maryland	0.501***	0.238***	0.738***
Arkansas	0.452***	0.285***	0.737***
Florida	0.489***	0.225***	0.714***
Tennessee	0.440***	0.274***	0.714***
New Jersey	0.524***	0.185***	0.709***
New Mexico	0.567***	0.141***	0.708***
Oklahoma	0.494***	0.210***	0.704***
Kentucky	0.467***	0.235***	0.703***
Idaho	0.524***	0.176***	0.700***
Ohio	0.567***	0.132***	0.699***
North Carolina	0.373***	0.325***	0.698***
District of Columbia	0.397***	0.298***	0.696***
Nevada	0.494***	0.195***	0.689***
Illinois	0.513***	0.153***	0.666***
Connecticut	0.501***	0.165***	0.665***
Kansas	0.528***	0.135***	0.663***
Oregon	0.535***	0.127***	0.663***
Michigan	0.548***	0.104***	0.652***
Rhode Island	0.455***	0.191***	0.646***
Missouri	0.499***	0.147***	0.646***
Washington	0.51***	0.125***	0.644***
Indiana	0.549***	0.094***	0.643***
Iowa	0.537***	0.106**	0.642***
Arizona	0.518***	0.121***	0.639***

Alaska	0.545***	0.093*	0.638***
Utah	0.562***	0.065	0.627***
Pennsylvania	0.492***	0.127***	0.620***
Main	0.422***	0.196	0.619***
California	0.488***	0.126***	0.614***
Massachusetts	0.453***	0.147***	0.601***
New Hampshire	0.458***	0.140	0.598***
Hawaii	0.587***	0.004	0.591***
Colorado	0.489***	0.099***	0.588***
New York	0.428***	0.155***	0.583***
South Dakota	0.422***	0.161**	0.582***
Wisconsin	0.493***	0.088***	0.581***
Minnesota	0.487***	0.083**	0.570***
Nebraska	0.464***	0.086**	0.550***
Vermont	0.427***	0.055	0.482***
Average	**0.499**	**0.190**	**0.689**

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

Table 3.18: Misallocation Measure and its decomposition across the United States for the period 1980

State	Female	Nonwhite	Misallocation Measure
Louisiana	0.580***	0.197***	0.777***
Alabama	0.508***	0.202***	0.709***
Texas	0.550***	0.148***	0.698***
Mississippi	0.475***	0.215***	0.690***
New Jersey	0.532***	0.137***	0.669***
Utah	0.550***	0.078***	0.628***
New Mexico	0.535***	0.090***	0.625***
Ohio	0.530***	0.094***	0.624***
North Dakota	0.448***	0.175***	0.623***
Washington	0.523***	0.099***	0.622***
Wyoming	0.593***	0.029	0.622***
Oklahoma	0.514***	0.105***	0.619***
Georgia	0.454***	0.163***	0.616***
South Carolina	0.434***	0.181***	0.615***
Delaware	0.518***	0.089***	0.607***
West Virginia	0.541***	0.064***	0.605***
Virginia	0.479***	0.126***	0.605***
Kentucky	0.486***	0.119***	0.604***
Pennsylvania	0.497***	0.105***	0.602***
Illinois	0.516***	0.081***	0.597***
Montana	0.438***	0.153***	0.592***
South Dakota	0.412***	0.177***	0.589***
Maryland	0.485***	0.102***	0.587***
Tennessee	0.459***	0.127***	0.586***
Connecticut	0.506***	0.080***	0.586***
Michigan	0.500***	0.085***	0.585***
Oregon	0.475***	0.105***	0.580***
Arizona	0.511***	0.066***	0.577***
California	0.469***	0.104***	0.574***
Minnesota	0.458***	0.113***	0.571***
Rhode Island	0.416***	0.154***	0.570***
Arkansas	0.430***	0.139***	0.570***
Missouri	0.482***	0.085***	0.567***
North Carolina	0.409***	0.155***	0.564***
Indiana	0.548***	0.015*	0.563***
Kansas	0.515***	0.046***	0.561***

Colorado	0.506***	0.050***	0.556***
Florida	0.460***	0.096***	0.555***
Iowa	0.505***	0.037*	0.541***
Nevada	0.461***	0.065***	0.526***
Massachusetts	0.432***	0.083***	0.515***
Hawaii	0.565***	-0.051***	0.514***
New York	0.408***	0.096***	0.504***
Nebraska	0.479***	0.019	0.498***
Idaho	0.459***	0.037	0.496***
Alaska	0.433***	0.058**	0.491***
Main	0.400***	0.086*	0.486***
New Hampshire	0.440***	0.044	0.484***
Wisconsin	0.474***	0.005	0.480***
District of Columbia	0.309***	0.132***	0.441***
Vermont	0.366***	0.054	0.420***
Average	**0.480**	**0.098**	**0.578**

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

Table 3.19: Misallocation Measure and its decomposition across the United States for the period 1990

State	Female	Nonwhite	Misallocation Measure
Montana	0.361***	0.294***	0.655***
Louisiana	0.438***	0.211***	0.649***
South Dakota	0.355***	0.260***	0.615***
Wyoming	0.498***	0.115***	0.613***
Mississippi	0.420***	0.188***	0.609***
Alabama	0.427***	0.158***	0.585***
New Jersey	0.389***	0.173***	0.563***
Texas	0.389***	0.170***	0.558***
Delaware	0.386***	0.155***	0.541***
West Virginia	0.442***	0.096***	0.538***
Georgia	0.387***	0.148***	0.535***
Illinois	0.423***	0.112***	0.535***
South Carolina	0.391***	0.138***	0.528***
North Dakota	0.355***	0.173***	0.528***
New Mexico	0.396***	0.130***	0.526***
California	0.362***	0.155***	0.517***
Wisconsin	0.378***	0.138***	0.516***
Utah	0.441***	0.073***	0.514***
Virginia	0.394***	0.119***	0.512***
Ohio	0.405***	0.105***	0.510***
Alaska	0.402***	0.108***	0.509***
Oregon	0.391***	0.115***	0.506***
Washington	0.403***	0.102***	0.505***
Kentucky	0.404***	0.100***	0.504***
Indiana	0.435***	0.068***	0.503***
Oklahoma	0.380***	0.121***	0.501***
North Carolina	0.369***	0.132***	0.501***
Arizona	0.364***	0.132***	0.495***
Michigan	0.410***	0.084***	0.494***
Arkansas	0.369***	0.121***	0.490***
Nebraska	0.415***	0.075***	0.490***
Rhode Island	0.299***	0.183***	0.482***
Connecticut	0.334***	0.138***	0.473***
Maryland	0.361***	0.111***	0.471***
District of Columbia	0.192***	0.278***	0.470***
Tennessee	0.371***	0.095***	0.466***

Missouri	0.380***	0.081***	0.462***
Idaho	0.419***	0.040*	0.458***
Florida	0.341***	0.115***	0.455***
Massachusetts	0.283***	0.168***	0.451***
Pennsylvania	0.362***	0.081***	0.444***
Iowa	0.405***	0.037*	0.442***
Kansas	0.401***	0.040***	0.441***
Nevada	0.352***	0.084***	0.437***
New York	0.322***	0.108***	0.430***
Minnesota	0.319***	0.102***	0.421***
Colorado	0.345***	0.074***	0.419***
New Hampshire	0.316***	0.091***	0.406***
Hawaii	0.437***	-0.035***	0.402***
Main	0.300***	0.092**	0.392***
Vermont	0.269***	0.087	0.357***
Average	**0.376**	**0.122**	**0.499**

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

Table 3.20: Misallocation Measure and its decomposition across the United States for the period 2000

State	Female	Nonwhite	Misallocation Measure
Louisiana	0.394***	0.182***	0.577***
North Dakota	0.295***	0.273***	0.568***
Wyoming	0.408***	0.153***	0.561***
Mississippi	0.366***	0.148***	0.514***
Alabama	0.367***	0.123***	0.491***
Texas	0.349***	0.137***	0.486***
New Jersey	0.295***	0.190***	0.486***
Montana	0.288***	0.187***	0.475***
Utah	0.366***	0.103***	0.469***
Alaska	0.244***	0.220***	0.464***
South Dakota	0.268***	0.194***	0.462***
Rhode Island	0.251***	0.208***	0.459***
South Carolina	0.330***	0.127***	0.457***
Georgia	0.318***	0.128***	0.446***
Indiana	0.351***	0.087***	0.438***
Connecticut	0.266***	0.167***	0.433***
California	0.277***	0.157***	0.433***
District of Columbia	0.132***	0.300***	0.432***
Illinois	0.333***	0.099***	0.432***
Arizona	0.296***	0.130***	0.426***
New Mexico	0.333***	0.083***	0.416***
North Carolina	0.296***	0.120***	0.415***
Washington	0.288***	0.126***	0.415***
Ohio	0.311***	0.100***	0.411***
Virginia	0.307***	0.100***	0.406***
Kentucky	0.332***	0.069***	0.401***
Florida	0.283***	0.116***	0.398***
Oklahoma	0.332***	0.064***	0.396***
Michigan	0.321***	0.068***	0.389***
Tennessee	0.320***	0.068***	0.388***
Massachusetts	0.245***	0.140***	0.***
New Hampshire	0.283***	0.102***	0.385***
Delaware	0.279***	0.106***	0.385***
Pennsylvania	0.285***	0.099***	0.384***
Missouri	0.314***	0.064***	0.378***
West Virginia	0.328***	0.049**	0.377***

Idaho	0.319***	0.056***	0.375***
Wisconsin	0.282***	0.090***	0.373***
Arkansas	0.305***	0.065***	0.369***
Maryland	0.269***	0.100***	0.369***
Colorado	0.296***	0.068***	0.365***
New York	0.245***	0.114***	0.360***
Minnesota	0.255***	0.098***	0.352***
Kansas	0.329***	0.015	0.344***
Oregon	0.269***	0.072***	0.342***
Iowa	0.297***	0.035**	0.332***
Vermont	0.226***	0.101**	0.327***
Nevada	0.267***	0.032***	0.299***
Main	0.266***	0.023	0.289***
Hawaii	0.278***	-0.007	0.271***
Nebraska	0.293***	-0.023	0.270***
Average	**0.299**	**0.110**	**0.409**

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

Table 3.21: Misallocation Measure and its decomposition across the United States for the period 2010

State	Female	Nonwhite	Misallocation Measure
South Dakota	0.173***	0.377***	0.549***
Louisiana	0.315***	0.216***	0.531***
North Dakota	0.269***	0.259***	0.527***
Mississippi	0.284***	0.237***	0.520***
Alabama	0.261***	0.207***	0.469***
South Carolina	0.241***	0.185***	0.426***
Kentucky	0.228***	0.187***	0.415***
Texas	0.253***	0.145***	0.398***
District of Columbia	-0.012	0.387***	0.375***
Oklahoma	0.267***	0.100***	0.366***
Wyoming	0.330***	0.035	0.365***
Connecticut	0.173***	0.188***	0.361***
Georgia	0.199***	0.160***	0.359***
Arkansas	0.239***	0.114***	0.353***
Indiana	0.201***	0.152***	0.353***
Alaska	0.088**	0.264***	0.352***
Illinois	0.190***	0.160***	0.350***
North Carolina	0.198***	0.151***	0.349***
Montana	0.169***	0.177***	0.346***
Nebraska	0.180***	0.164***	0.344***
New Jersey	0.167***	0.175***	0.343***
West Virginia	0.250***	0.086*	0.336***
Virginia	0.209***	0.120***	0.329***
Missouri	0.189***	0.138***	0.327***
New Mexico	0.214***	0.113***	0.327***
Utah	0.215***	0.105***	0.320***
Wisconsin	0.145***	0.174***	0.319***
Ohio	0.151***	0.166***	0.317***
Arizona	0.173***	0.144***	0.316***
Rhode Island	0.119***	0.196***	0.314***
Tennessee	0.214***	0.098***	0.312***
Pennsylvania	0.171***	0.139***	0.309***
Kansas	0.224***	0.073***	0.296***
California	0.150***	0.145***	0.295***
Colorado	0.170***	0.118***	0.288***
Iowa	0.223***	0.065*	0.288***

Main	0.133***	0.143**	0.276***
Maryland	0.134***	0.141***	0.275***
Michigan	0.135***	0.140***	0.275***
Delaware	0.181***	0.087**	0.268***
Florida	0.147***	0.116***	0.263***
New York	0.118***	0.145***	0.262***
Hawaii	0.213***	0.045	0.258***
Washington	0.176***	0.076***	0.252***
Minnesota	0.152***	0.085***	0.237***
Vermont	0.150***	0.079	0.229**
Massachusetts	0.105***	0.121***	0.225***
Idaho	0.203***	0.019	0.222***
New Hampshire	0.181***	0.021	0.202***
Nevada	0.119***	0.050***	0.169***
Oregon	0.110***	0.049**	0.159***
Average	**0.186**	**0.142**	**0.328**

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

Table 3.22: Misallocation Measure and its decomposition across the United States for the period 2017

State	Female	Nonwhite	Misallocation Measure
Louisiana	0.339***	0.228***	0.566***
Mississippi	0.330***	0.171***	0.501***
South Dakota	0.313***	0.184***	0.496***
West Virginia	0.255***	0.231***	0.486***
Alabama	0.319***	0.140***	0.459***
Alaska	0.099***	0.356***	0.455***
District of Columbia	0.100***	0.353***	0.453***
Texas	0.296***	0.141***	0.438***
Wyoming	0.299***	0.134***	0.433***
South Carolina	0.261***	0.164***	0.425***
New Jersey	0.242***	0.161***	0.404***
Georgia	0.246***	0.155***	0.402***
Montana	0.201***	0.200***	0.401***
Ohio	0.230***	0.164***	0.393***
North Carolina	0.249***	0.135***	0.384***
New Mexico	0.240***	0.142***	0.381***
Oklahoma	0.312***	0.066***	0.378***
Indiana	0.283***	0.093***	0.376***
Pennsylvania	0.249***	0.119***	0.368***
Illinois	0.255***	0.110***	0.365***
Connecticut	0.188***	0.176***	0.364***
Utah	0.281***	0.080***	0.361***
Arkansas	0.273***	0.087***	0.359***
Missouri	0.257***	0.100***	0.356***
Florida	0.221***	0.129***	0.350***
Wisconsin	0.259***	0.090***	0.349***
Virginia	0.242***	0.106***	0.349***
Michigan	0.240***	0.107***	0.347***
North Dakota	0.244***	0.102**	0.347***
California	0.202***	0.143***	0.345***
Arizona	0.212***	0.133***	0.345***
Iowa	0.272***	0.071**	0.343***
Minnesota	0.209***	0.130***	0.339***
Maryland	0.198***	0.133***	0.332***
Kansas	0.275***	0.050**	0.326***
Hawaii	0.284***	0.039	0.323***

Vermont	0.153***	0.168**	0.321***
Idaho	0.281***	0.040	0.320***
Tennessee	0.238***	0.076***	0.315***
Nebraska	0.265***	0.043	0.309***
Kentucky	0.252***	0.055***	0.307***
Washington	0.246***	0.058***	0.303***
Massachusetts	0.182***	0.121***	0.303***
Colorado	0.222***	0.076***	0.298***
Delaware	0.186***	0.111***	0.297***
New York	0.184***	0.107***	0.292***
Main	0.218***	0.073	0.291***
Rhode Island	0.164***	0.124***	0.288***
Nevada	0.184***	0.079***	0.264***
Oregon	0.185***	0.059***	0.244***
New Hampshire	0.217***	-0.021	0.196***
Average	**0.238**	**0.123**	**0.362**

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

Table 3.23: Correlations between the estimated talent misallocation measure and aggregate measures

	$GDP_{perworker}$	TFP	TFP	Technical Efficiency
Talent Misallocation Measure	-0.680***	-0.316***	-0.356***	-0.182**
Talent Misallocation $Measure_{weighted}$	-0.791***	-0.364****	-0.292***	-0.431***
Period	1980-2017	1980-2000	2000-2010	1980-2000
Observations	255	141	102	144

Note: *** p<0.01, ** p<0.05, * p<0.1 In this table we report the Pearson correlations of our estimated misallocation measures with aggregate outcome measures.

3.7 Figures

Figure 3.1: Gender-earnings-ratio

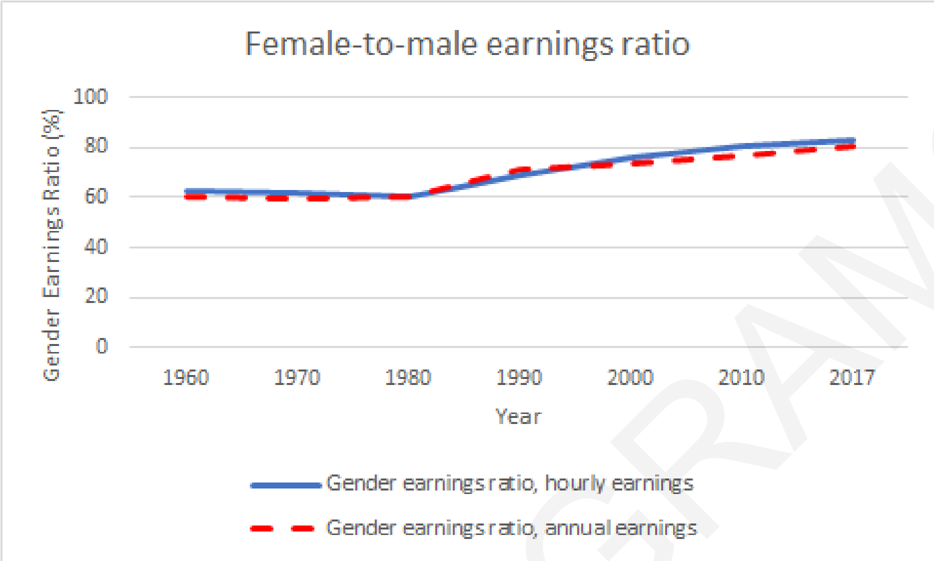


Figure 3.2: Earnings-ratio

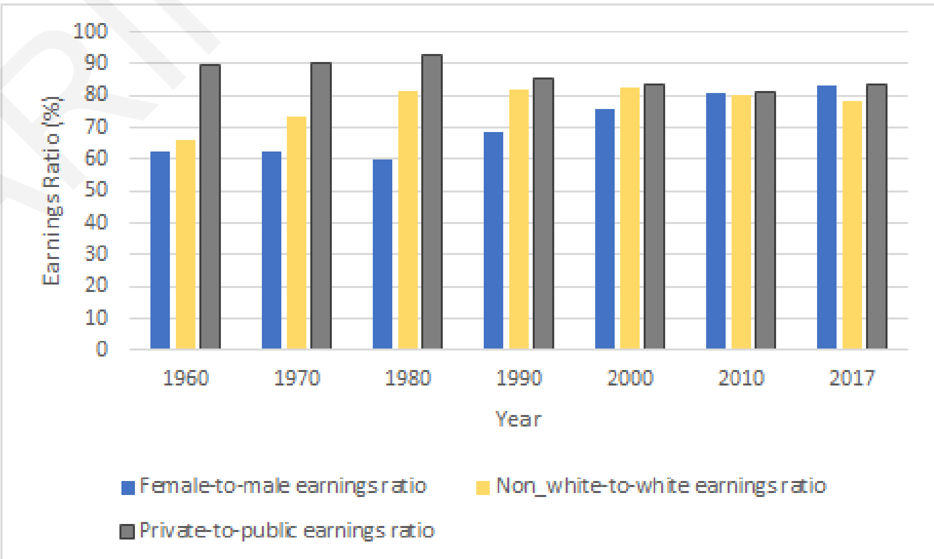


Figure 3.3: Wage gaps in the US over time

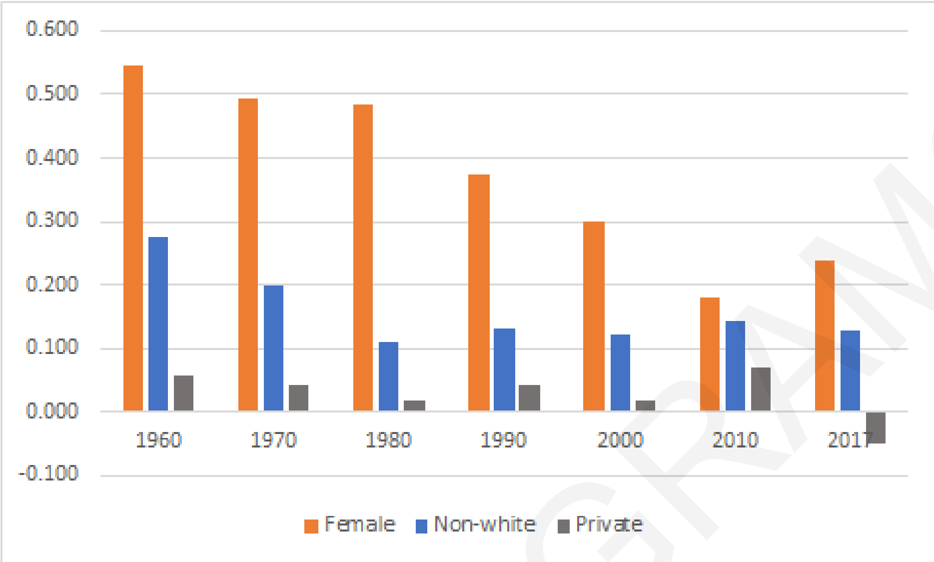


Figure 3.4: Wage gaps in the US over time without instruments

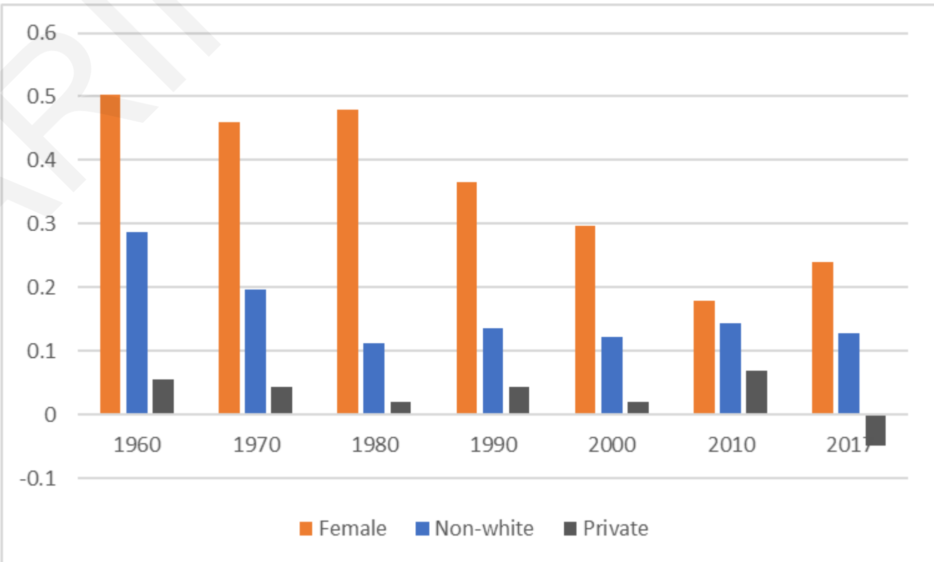


Figure 3.5: Northeast Region, New England Division

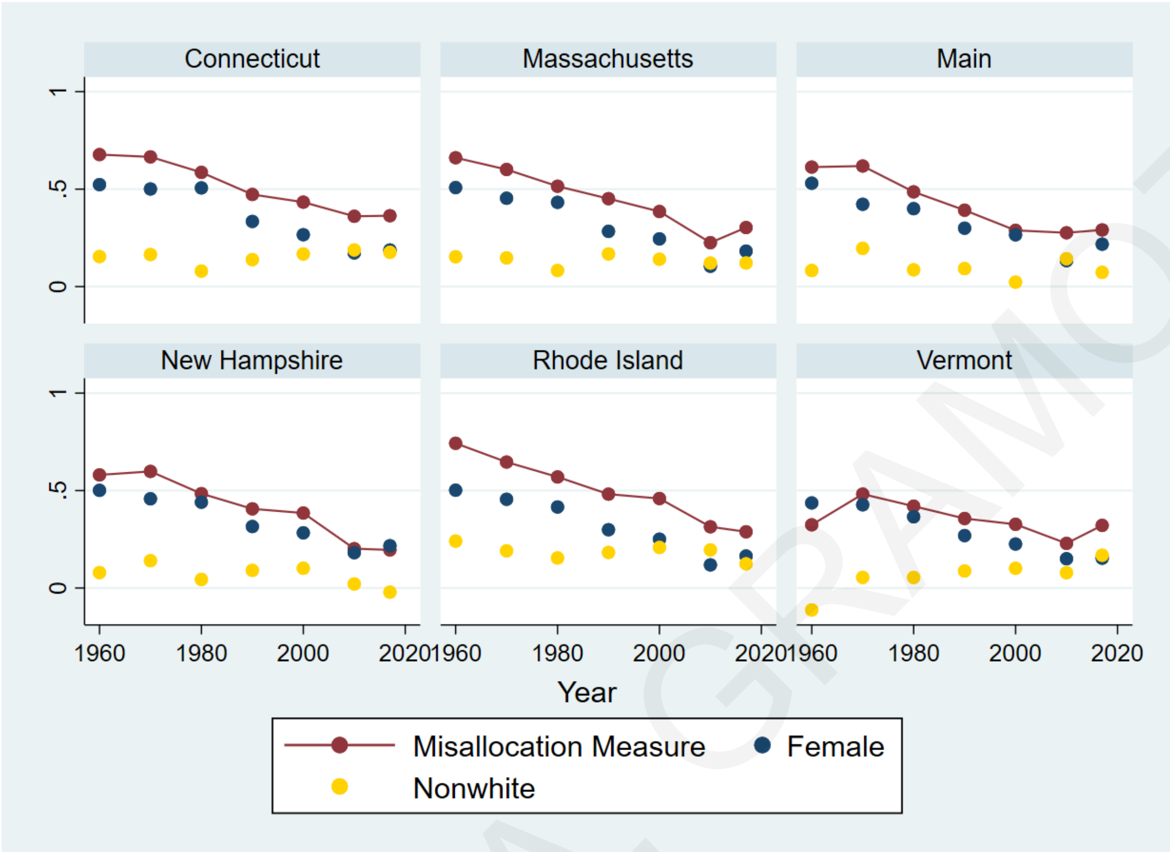


Figure 3.6: Northeast Region, Middle Atlantic Division

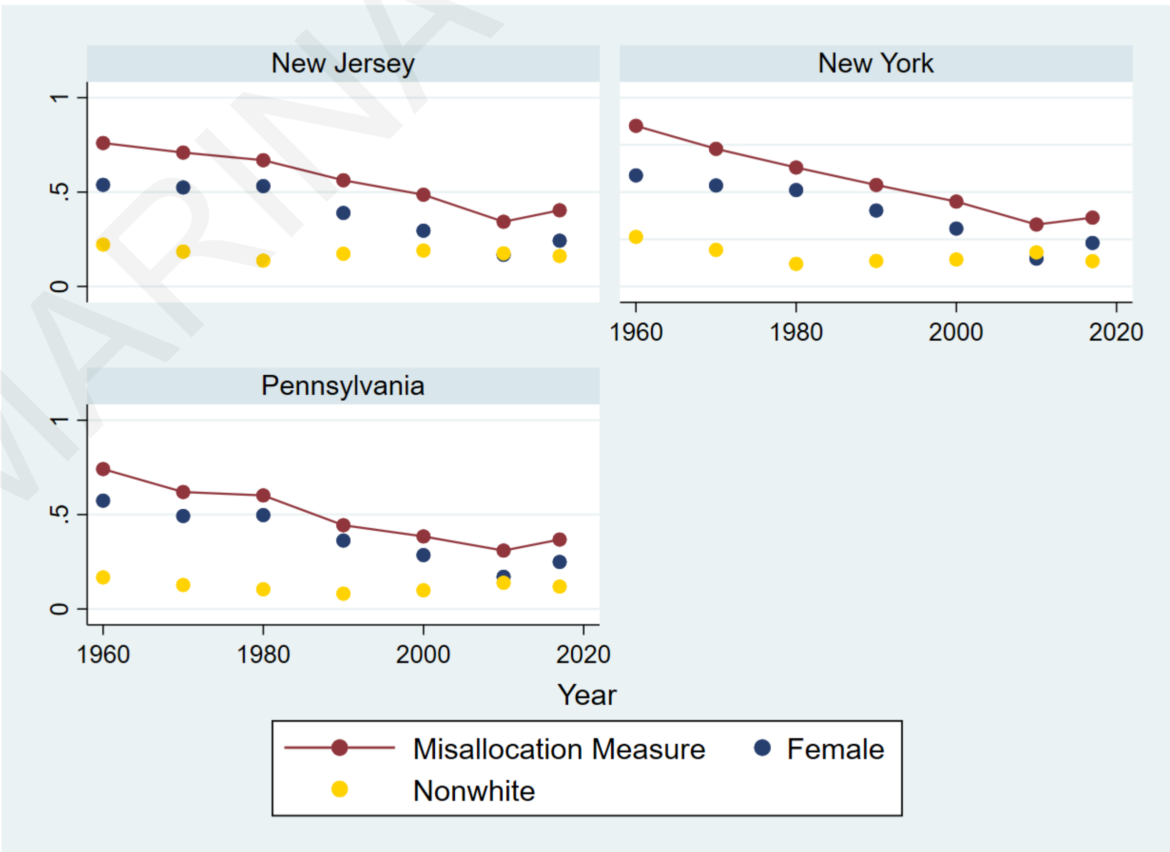


Figure 3.7: Midwest Region, East North Central Division

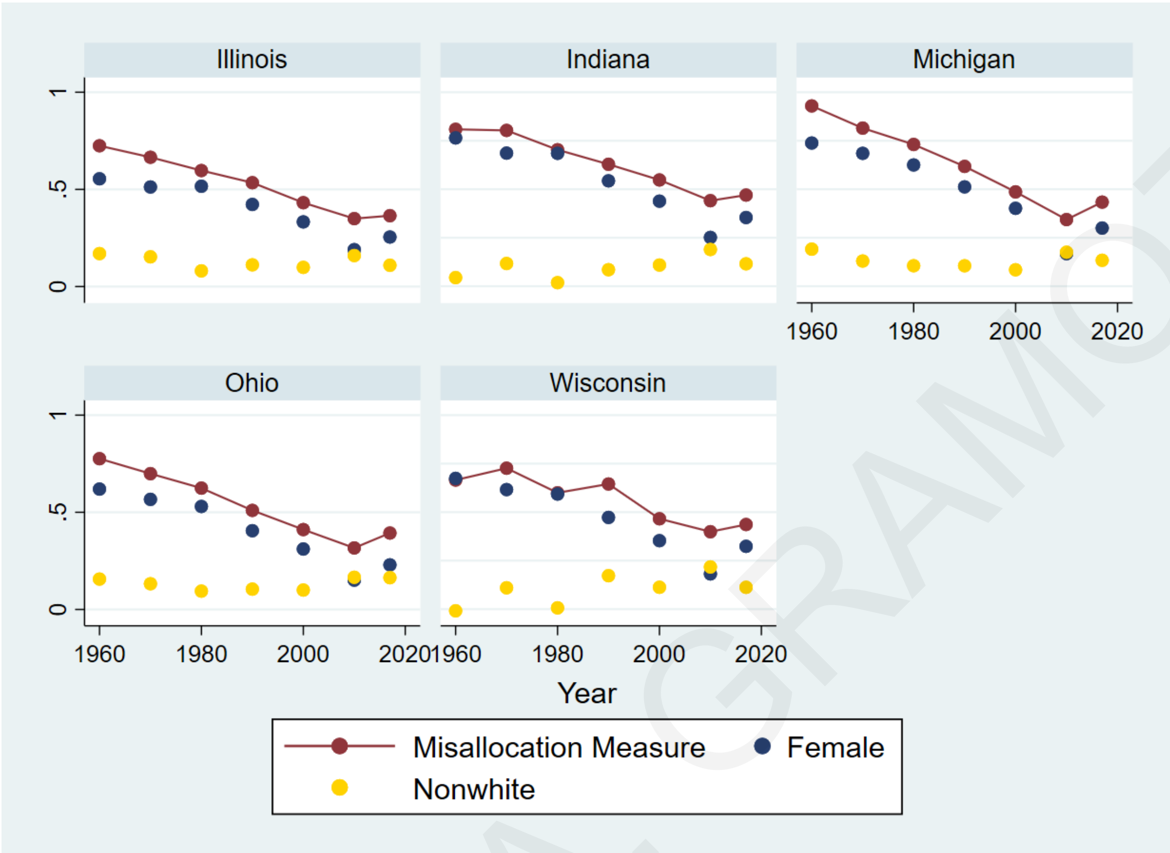


Figure 3.8: Midwest Region, West North Central Division

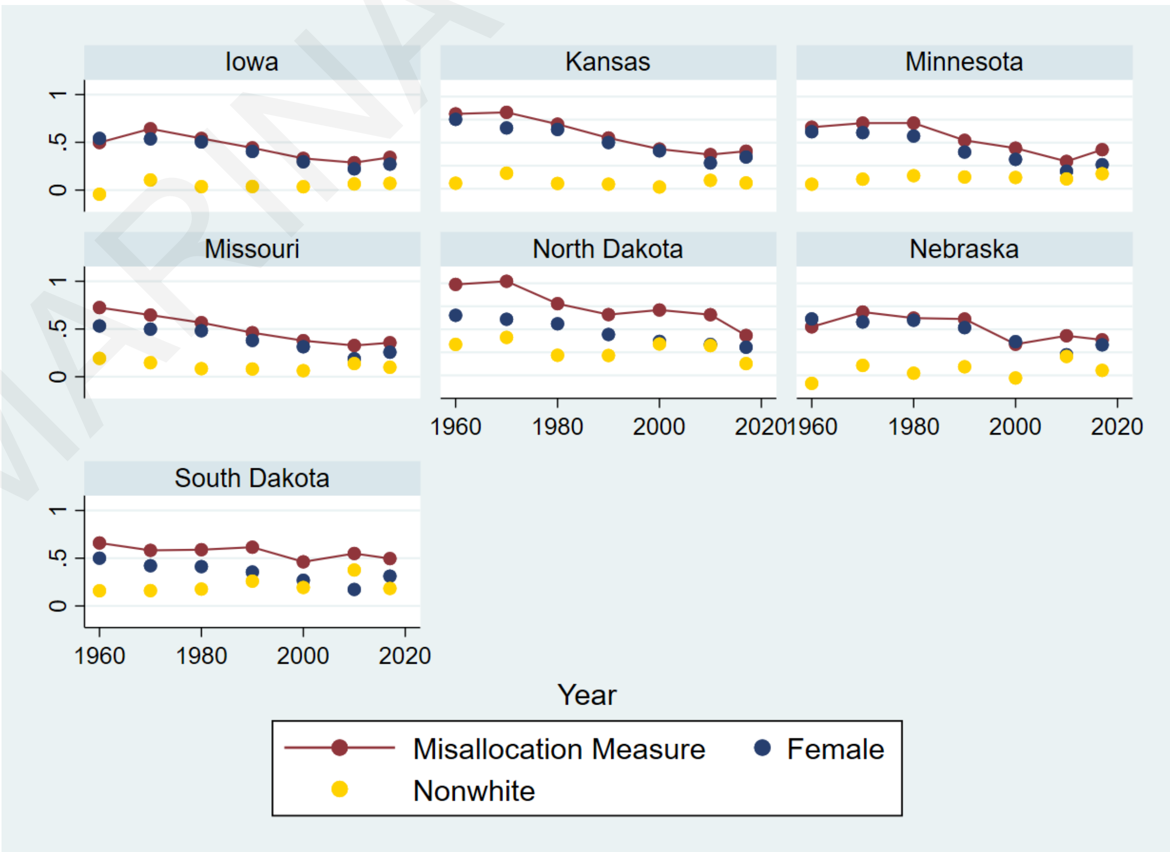


Figure 3.9: South Region, South Atlantic Division

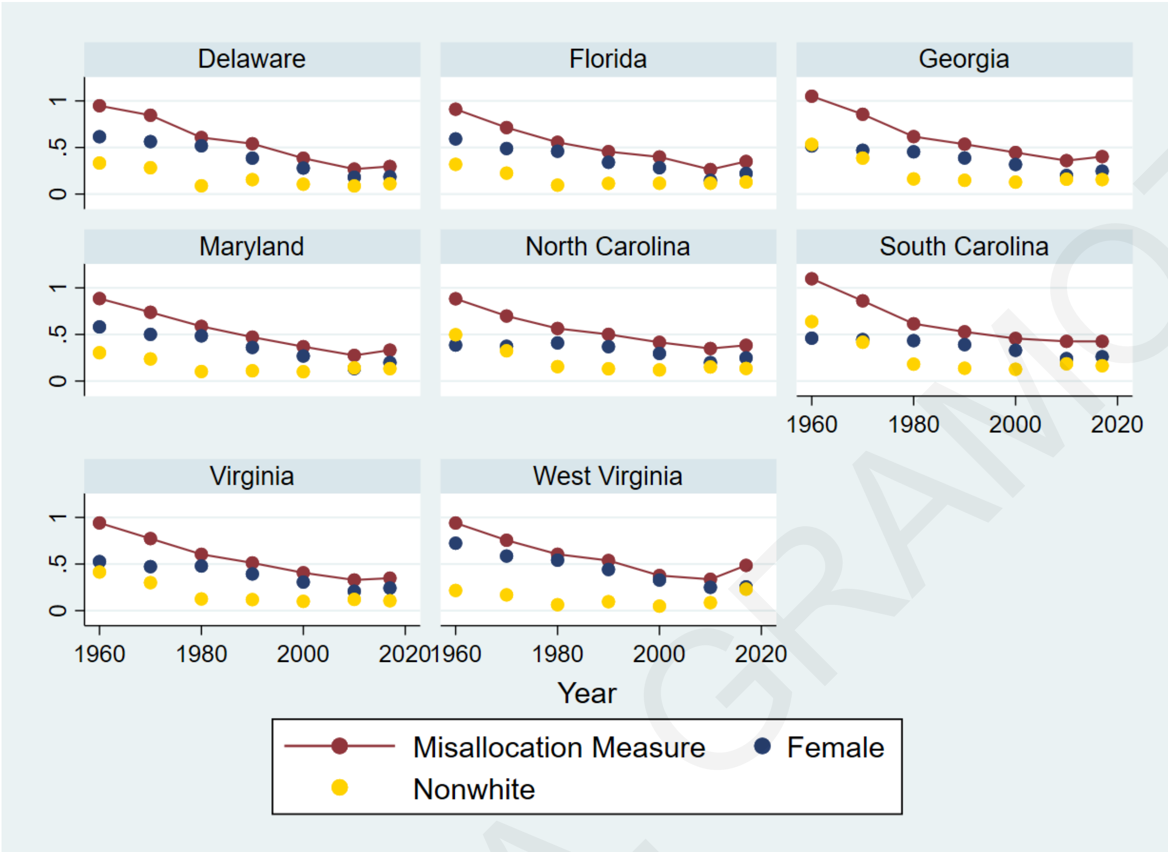


Figure 3.10: South Region, East South Central Division

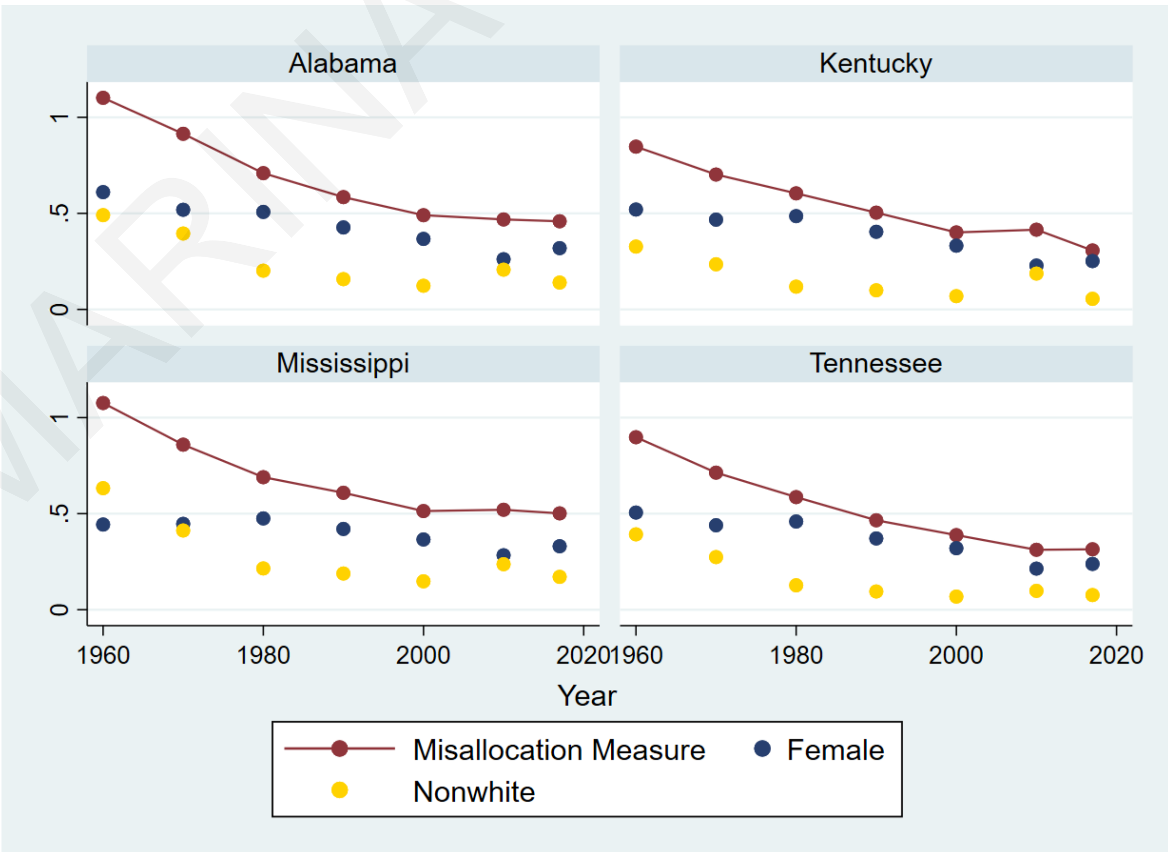


Figure 3.11: South Region, West South Central Division

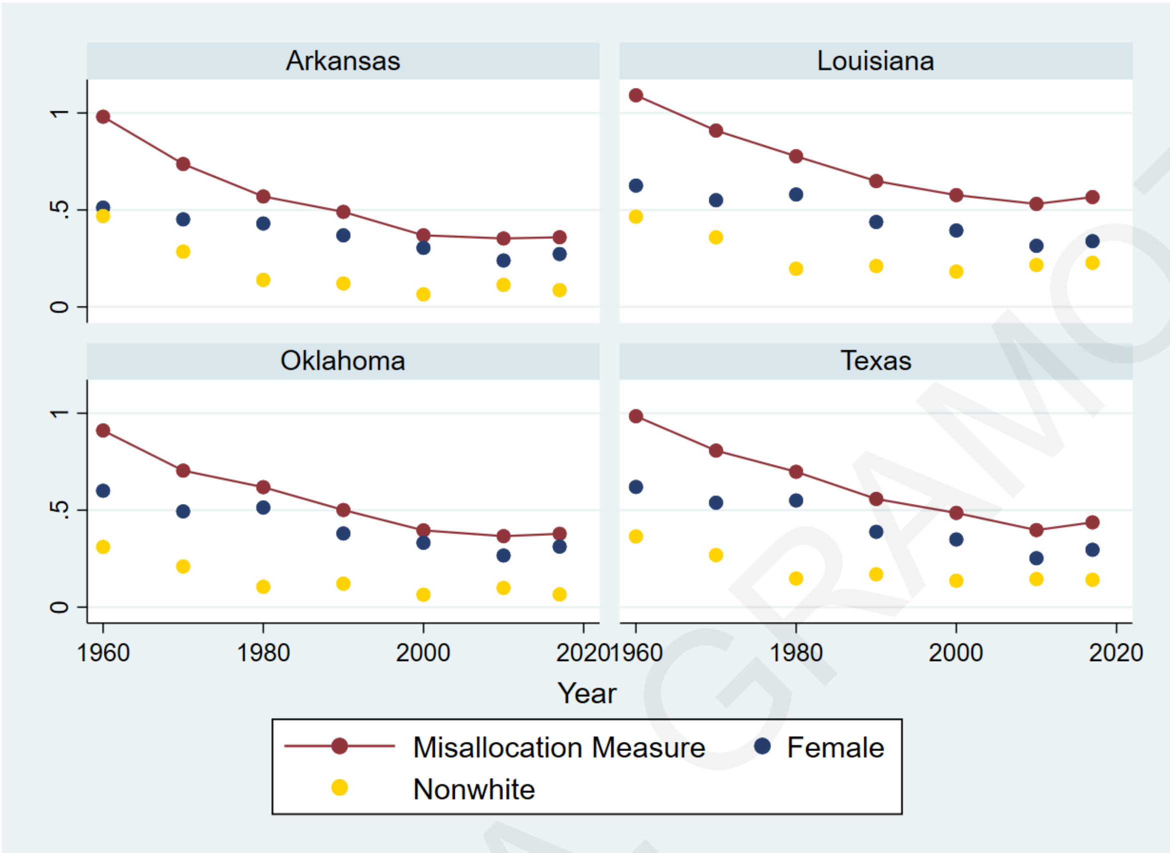


Figure 3.12: West Region, Mountain Division

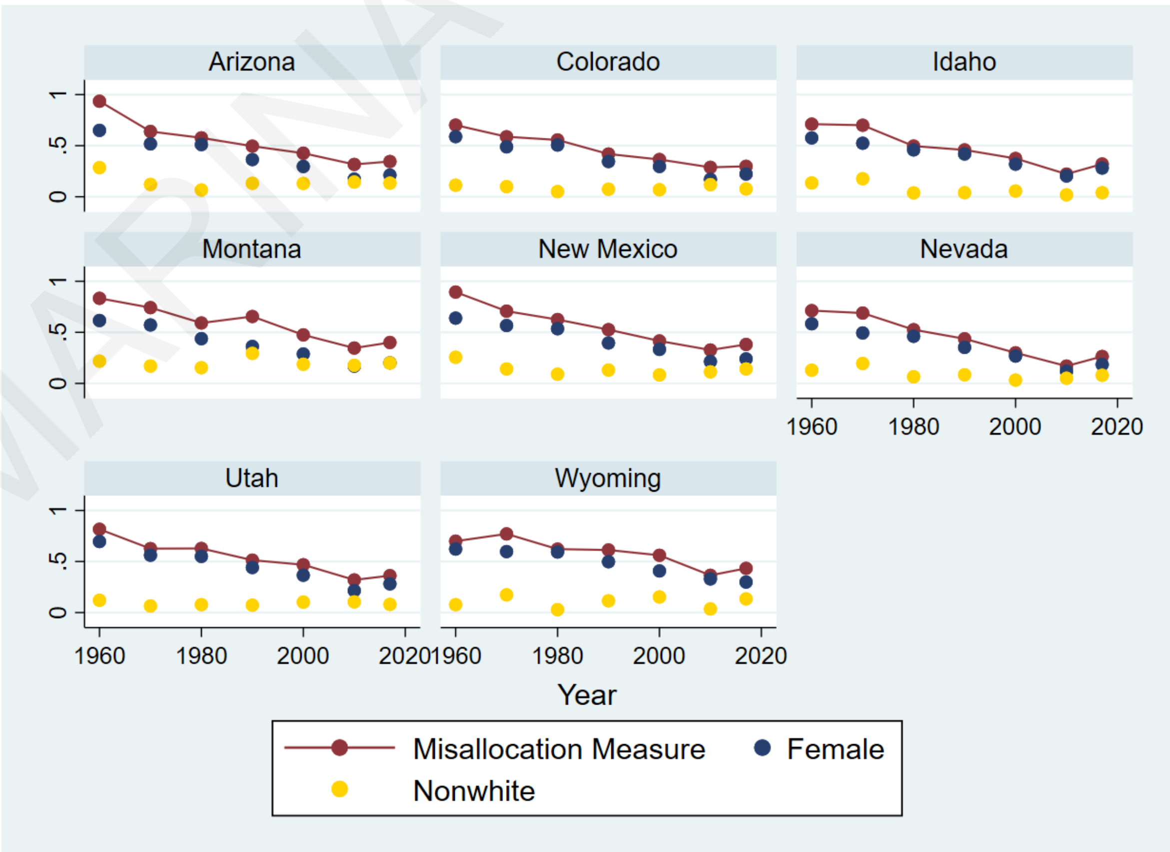


Figure 3.13: West Region, Pacific Divisio

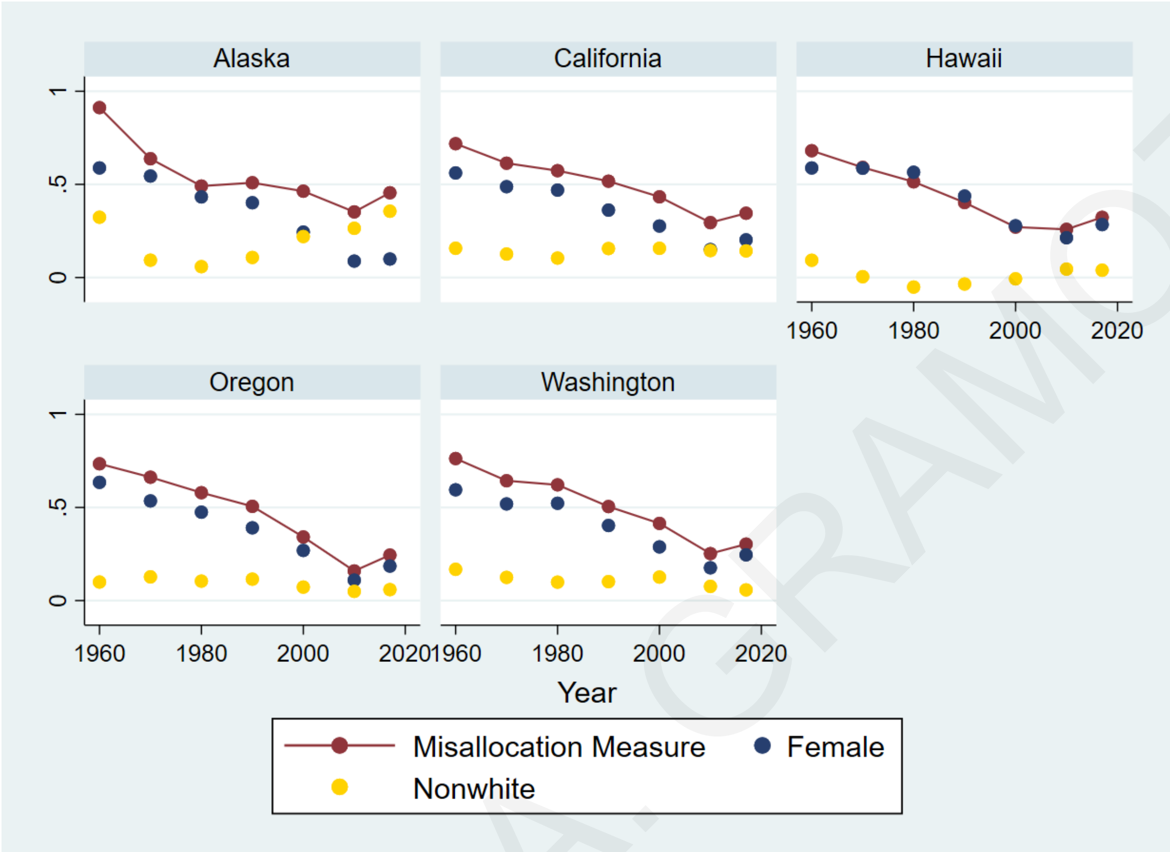


Figure 3.14: Correlation of the real GDP per worker with the talent misallocation measure for the period from 1980-2017

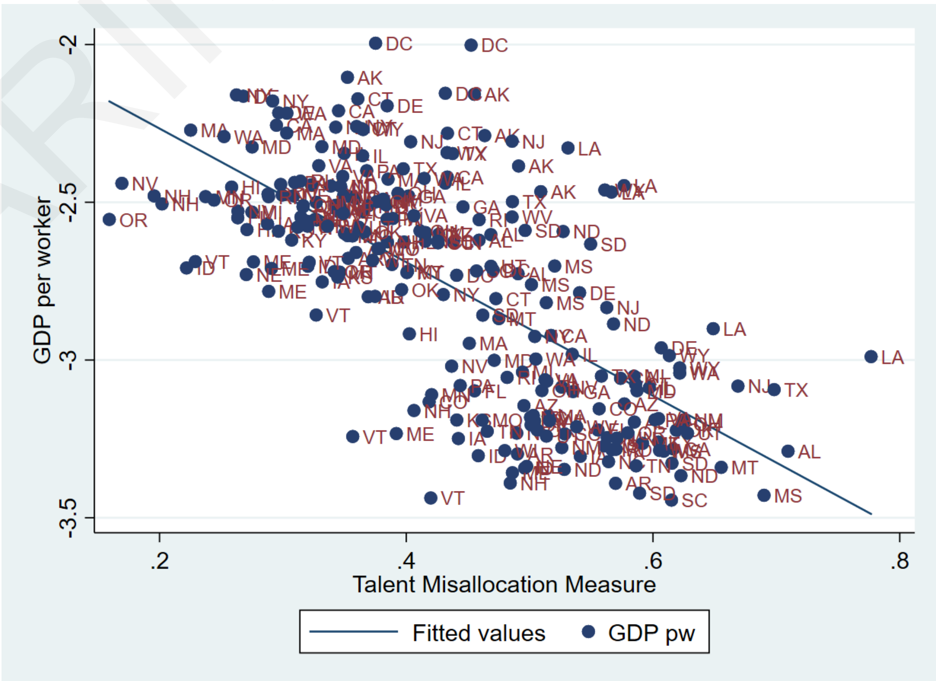


Figure 3.15: Correlation of Total Factor Productivity the with misallocation measure 2000-2010

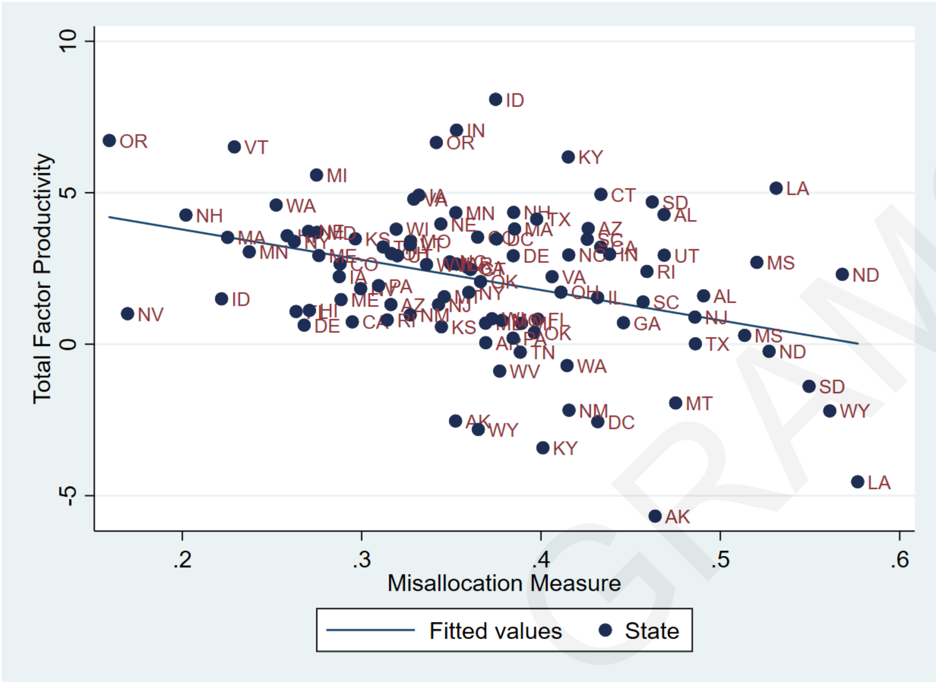


Figure 3.16: Correlation of Total Factor Productivity with the misallocation measure for the period from 1980 to 2000.

Figure 3.17: Correlation of Technical Efficiency with the talent misallocation measure for the period 1980-2000.

Note: Data cleared from outliers, thus North Dakota excluded here

Conclusions

The aim of the present dissertation is to provide both theoretical and empirical contributions in the existing literature that study talent misallocation and its effects on aggregate economic outcomes.

In the first chapter, we propose a search and matching model, where the presence of under-privileged workers relating to, e.g., female gender, immigrant status or private sector affiliation, leads to lower wages and talent misallocation, resulting in significant income losses. We proceed in calibrating the model to match the data from five different European economies (France, Spain, the Netherlands, Italy, and Greece) and the US economy with the goal of quantifying the effect of discrimination on net income. Our simulation exercise implies that reducing the gender wage gap alone by 50 percent leads to an increase of both measures of net income by more than three percent per quarter relative to the benchmark case for France, by more than four percent for Spain, by more than one percent for the Netherlands, by more than two percent for Italy, and by more than three percent for Greece, implying economically significant aggregate effects arising from talent misallocation. In addition, calibrating our theoretical model to match the US economy over the most recent period used in our estimation, 2010-2017, we find that a 50 percent reduction in the wage gap between African-Americans and whites increases net income by more than 0.4 percent per month, and that eliminating race discrimination results in a substantially larger increase in net income of around 4 percent per month. The simulation exercises suggest that talent misallocation has important aggregate effects for the economy.

In chapter 2, we use microeconomic data on wages and individual characteristics across European economies in order to detect patterns of misallocation arising in these economies based on individuals' gender, immigrant status, or private versus public sector affiliation. Our micro-econometric estimates suggest that being a female or immigrant, and working in the private sector, exert a negative impact on one's wages beyond that explained by individual characteristics, suggestive of persistent talent misallocation in Europe during the period under study. Notably, countries which have been at the heart of the European Crisis are systematically found at the high end of the overall talent misallocation measure we estimate.

Chapter 3 explores the misallocation effects arising due to frictions related to race and gender and quantify their impact on state-wide economic outcomes. We systematically find that women and non-whites receive lower wages compared to their counterparts. State-level misallocation implied by these wage gaps correlates negatively with total factor productivity, technical efficiency and output.

Our research provides new cross-country micro-econometric evidence in support of a surging new literature, including Hsieh et al. (2019), Jaimovich and Rud (2014), Cavalcanti and Tavares (2016), Santos and Cavalcanti (2020), and Cuberes and Teignier (2016), regarding the importance of various forms of talent misallocation for aggregate economic outcomes and economic growth. Furthermore, our theoretical model serves to highlight the shared nature of the different facets of talent misallocation considered in this literature and to reiterate the considerable aggregate effects of talent misallocation on economic welfare. While our work suggests that talent misallocation remains an important concern even in the case of developed economies, we would expect it to be a crucial concern for less developed economies hampering their economic growth prospects. Understanding talent misallocation should then be key to understanding cross-country income differences, with potentially important policy implications.

In terms of future work, a natural extension of the theoretical model would be to explore the effect of barriers to human capital accumulation and how it will affect the allocation of talent and economic growth. According to Gradstein (2019) who investigate barriers to skill acquisition along with other barriers that affect the occupation decision of specifics population groups can have large economic costs. The extension would rely on incorporating in the existing model the human capital accumulation decision in the period prior to entering the labor market. Barriers that would affect the incentives to invest in human capital accumulation intuitively would possibly result in larger talent misallocation and adverse economic growth.

In the third chapter, we constructed state-specific estimated misallocation measures and we provided some correlations with aggregate variables, without focusing on providing a causal relationship. In terms of future research, it would be interesting to investigate empirically through growth regression, the causal relationship between our state-specific estimated misallocation measures, and economic growth.

Bibliography

Acemoglu, Daron (2001). “Good jobs versus bad jobs”. In: *Journal of Labor Economics* 19.1, pp. 1–21.

Albrecht, James and Susan Vroman (2002). “A matching model with endogenous skill requirements”. In: *International Economic Review* 43.1, pp. 283–305.

Baumol, William J (1990). “Entrepreneurship: Productive, Unproductive, and Destructive”. In: *Journal of Political Economy* 98.5, pp. 893–921.

Bayer, Patrick and Kerwin Kofi Charles (2018). “Divergent paths: A new perspective on earnings differences between black and white men since 1940”. In: *The Quarterly Journal of Economics* 133.3, pp. 1459–1501.

Becker, Gary S (1957). *The Economics of Discrimination*. University of Chicago Press.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen (2018). “Who becomes an inventor in America? The importance of exposure to innovation”. In: *The Quarterly Journal of Economics* 134.2, pp. 647–713.

Bello, Salvatore Lo and Iacopo Morchio (2020). “Like father, like son: Occupational choice, intergenerational persistence and misallocation”. In: *Working paper*.

Bentolila, Samuel, Claudio Michelacci, and Javier Suarez (2010). “Social contacts and occupational choice”. In: *Economica* 77.305, pp. 20–45.

Bertrand, Marianne and Sendhil Mullainathan (2004). “Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination”. In: *American Economic Review* 94.4, pp. 991–1013.

Blanchard, Olivier Jean and Peter Diamond (1990). “The Aggregate Matching Function”. In: *Growth, Productivity, Unemployment: Essays to Celebrate Bob Solow’s Birthday*, pp. 159–201.

Blau, Francine D and Lawrence M Kahn (2017). “The gender wage gap: Extent, trends, and explanations”. In: *Journal of Economic Literature* 55.3, pp. 789–865.

Borowczyk-Martins, Daniel, Jake Bradley, and Linas Tarasonis (2018). “Racial discrimination in the US labor market: Employment and wage differentials by skill”. In: *Labour Economics* 50, pp. 45–66.

Cardarelli, Roberto and Lusine Lusinyan (2015). “U.S. Total factor productivity Slowdown: Evidence from the U.S. States”. In: *IMF Working Paper No.15/116*.

Caselli, Francesco (2005). “Accounting for cross-country income differences”. In: *Handbook of Economic Growth* 1, pp. 679–741.

Cavalcanti, Tiago and José Tavares (2016). “The Output Cost of Gender Discrimination: A Model-based Macroeconomics Estimate”. In: *The Economic Journal* 126.590, pp. 109–134.

Chassambouli, Andri and Giovanni Peri (2015). “The Labor Market Effects of Reducing the Number of Illegal Immigrants”. In: *Review of Economic Dynamics* 18.4, pp. 792–821.

Chassamboulli, Andri and Pedro Gomes (2018). *Meritocracy, Public-Sector Pay and Human Capital Accumulation*. Tech. rep. University of Cyprus Department of Economics.

Chassamboulli, Andri and Theodore Palivos (2014). “A Search-Equilibrium Approach to the Effects of Immigration on Labor Market Outcomes”. In: *International Economic Review* 55.1, pp. 111–129.

Chassamboulli, Andri and Giovanni Peri (2018). “The Economic Effect of Immigration Policies: Analyzing and Simulating the US Case”. In: *NBER Working Paper*.

Christofides, Louis N and Maria Michael (2013). “Exploring the public-private sector wage gap in European countries”. In: *IZA Journal of European Labor Studies* 2.1, p. 15.

Cuberes, David and Marc Teignier (2016). “Aggregate effects of gender gaps in the labor market: A quantitative estimate”. In: *Journal of Human Capital* 10.1, pp. 1–32.

Edelman, Benjamin, Michael Luca, and Dan Svirsky (2017). “Racial discrimination in the sharing economy: Evidence from a field experiment”. In: *American Economic Journal: Applied Economics* 9.2, pp. 1–22.

Gradstein, Mark (2019). “Misallocation of Talent and Human Capital: Political Economy Analysis”. In: *European Economic Review*.

Hsieh, Chang-Tai, Erik Hurst, Charles I Jones, and Peter J Klenow (2019). “The allocation of talent and US economic growth”. In: *Econometrica* 87.5, pp. 1439–1474.

Hsieh, Chang-Tai and Peter J Klenow (2009). “Misallocation and manufacturing TFP in China and India”. In: *The Quarterly Journal of Economics* 124.4, pp. 1403–1448.

Jaimovich, Esteban and Juan Pablo Rud (2014). “Excessive public employment and rent-seeking traps”. In: *Journal of Development Economics* 106, pp. 144–155.

Jones, Charles I (2016). “The Facts of Economic Growth”. In: *Handbook of Macroeconomics*. Vol. 2. Elsevier, pp. 3–69.

Lang, Kevin and Jee-Yeon K Lehmann (2012). “Racial discrimination in the labor market: Theory and empirics”. In: *Journal of Economic Literature* 50.4, pp. 959–1006.

Liu, Xiangbo, Theodore Palivos, and Xiaomeng Zhang (2017). “Immigration, Skill Heterogeneity, and Qualification Mismatch”. In: *Economic Inquiry* 55.3, pp. 1231–1264.

Martin, Philippe and Thomas Philippon (2017). “Inspecting the mechanism: Leverage and the great recession in the eurozone”. In: *American Economic Review* 107.7, pp. 1904–37.

Mortensen, D, C Pissarides, et al. (2003). *Tax, Subsidies and Labour Market Outcomes*.

Mortensen and Pissarides (1994). “Job creation and job destruction in the theory of unemployment”. In: *The Review of Economic Studies* 61.3, pp. 397–415.

Murphy, Kevin M, Andrei Shleifer, and Robert W Vishny (1991). “The allocation of talent: Implications for growth”. In: *The Quarterly Journal of Economics* 106.2, pp. 503–530.

Neumark, David (2018). “Experimental research on labor market discrimination”. In: *Journal of Economic Literature* 56.3, pp. 799–866.

Petrongolo, Barbara and Christopher A Pissarides (2001). “Looking into the black box: A survey of the matching function”. In: *Journal of Economic Literature* 39.2, pp. 390–431.

Restuccia, Diego and Richard Rogerson (2013). “Misallocation and productivity”. In: *Review of Economic Dynamics*.

– (2017). “The causes and costs of misallocation”. In: *Journal of Economic Perspectives* 31.3, pp. 151–74.

Roy, Andrew Donald (1951). “Some thoughts on the distribution of earnings”. In: *Oxford economic papers* 3.2, pp. 135–146.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek (2019). “IPUMS USA: Version 9.0 [dataset]”. In: *Minneapolis, MN: IPUMS* https://doi.org/10.18128/D010.V9.0.

Santos, Marcelo and Tiago Cavalcanti (2020). *(Mis) Allocation Effects of an Overpaid Public Sector*. Tech. rep. Working paper.

Sharma, Subhash C, Kevin Sylwester, and Heru Margono (2007). “Decomposition of total factor productivity growth in US states”. In: *The Quarterly Review of Economics and Finance* 47.2, pp. 215–241.

Shimer, Robert (2005). “The cyclical behavior of equilibrium unemployment and vacancies”. In: *American Economic Review* 95.1, pp. 25–49.

Appendix A

A.1 Appendix A

A.1.1 Proofs of Propositions

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

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

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

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

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

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

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

Proof of Proposition 3. Denote equations (21) and (22) as $F(\theta_H, \theta_L, \eta) = 0$ and $G(\theta_H, \theta_L, \eta) = 0$, respectively. At least for sufficiently high η the following hold: $F_{\theta_H} > 0, F_{\theta_L} > 0, F_\eta < 0, G_{\theta_H} > 0, G_{\theta_L} > 0, and F_\eta > 0$. Applying Cramer's rule, it follows that $(d\theta_H/d\eta) > 0$ and $(d\theta_L/d\eta) < 0$. Next, differentiate (18) and (19) to show that $(du_P/d\eta)/u_P > (du_U/d\eta)/u_U$ and hence ϕ decreases. Finally the limiting values of ϕ, w_{ij} and $u_j, i = L, H$ and $j = P, U$ as η approaches 1, follow easily by substitution in (16), (17), (15), (18), (19) and (20).

Appendix B

B.1 Appendix B

Table B1: Selection-corrected hourly wage regression for the period 2005-2015, sample with full-time workers, EU SILC wave

Variables	(1)	(2)	(3)	(4)	(5)
Private	-0.087***	-0.070***	-0.083***	-0.104***	-0.083***
	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
Fem	-0.165***	-0.172***	-0.184***	-0.202***	-0.158***
	(0.004)	(0.004)	(0.001)	(0.002)	(0.004)
MigrantEU	-0.121***	-0.102***	-0.105***	-0.145***	-0.055***
	(0.007)	(0.007)	(0.003)	(0.004)	(0.012)
Migrant	-0.207***	-0.172***	-0.173***	-0.223***	-0.064***
	(0.007)	(0.007)	(0.003)	(0.004)	(0.011)
Educ L	-0.197***	-0.142***	-0.157***	-0.109***	-0.109***
	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)
Educ H	0.325***	0.194***	0.198***	0.108***	0.104***
	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)
Age 35-44	0.160***	0.150***	0.157***	0.160***	0.161***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
Age 45-54	0.245***	0.229***	0.239***	0.242***	0.242***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Age 55-64	0.288***	0.265***	0.265***	0.268***	0.268***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)
Occup b		0.061***	0.054***	0.057***	0.057***
		(0.004)	(0.002)	(0.002)	(0.002)
Occup c		0.289***	0.290***	0.289***	0.289***
		(0.004)	(0.002)	(0.002)	(0.002)
Occup d		0.431***	0.430***	0.433***	0.433***
		(0.006)	(0.003)	(0.003)	(0.003)
Permanent			0.222***	0.233***	0.235***
			(0.005)	(0.005)	(0.005)
Private *Educ L				-0.040***	-0.043***
				(0.005)	(0.005)
Private *Educ H				0.062***	0.066***
				(0.004)	(0.004)
Fem *Educ L				-0.042***	-0.037***
				(0.003)	(0.003)
Fem *Educ H				0.061***	0.060***
				(0.003)	(0.003)
MigrantEU *Educ L				-0.013*	-0.011*
				(0.007)	(0.007)
MigrantEU *Educ H				0.098***	0.097***
				(0.006)	(0.006)
Migrant *Educ L				0.071***	0.070***
				(0.006)	(0.006)
Migrant *Educ H				0.081***	0.085***

				(0.006)	(0.006)
Private *Fem					-0.044***
					(0.004)
Private *MigrantEU					-0.093***
					(0.012)
Private *Migrant					-0.125***
					(0.011)
Fem *MigrantEU					-0.007
					(0.005)
Fem *Migrant					-0.100***
					(0.005)
lambda	-1.261***	-1.112***	-0.299***	-0.214***	-0.183***
	(0.097)	(0.086)	(0.028)	(0.028)	(0.028)
Constant	2.746***	2.623***	2.362***	2.371***	2.344***
	(0.013)	(0.012)	(0.007)	(0.007)	(0.008)
Total effect Private	-0.087***	-0.070***	-0.083***	-0.089***	-0.097***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Total effect Fem	-0.165***	-0.172***	-0.184***	-0.187***	-0.188***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Total effect MigrantEU	-0.121***	-0.102***	-0.105***	-0.110***	-0.106***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Total effect Migrant	-0.207***	-0.172***	-0.173***	-0.177***	-0.169***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Country-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	666,826	666,826	666,826	666,826	666,826

Note: Pooled estimates for 18 European countries. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Talent Misallocation Measure derived from the sample with full-time workers

Country	Private	Female	MigrantEU	Migrant	Misallocation Measure
Cyprus	0.205***	0.252***	0.177***	0.613***	0.878***
Spain	0.172***	0.167***	0.150***	0.225***	0.544***
Luxembourg	0.117***	0.114***	0.241***	0.368***	0.491***
Ireland	0.146***	0.139***	0.191***	0.098***	0.450***
Italy	0.110***	0.129***	0.192***	0.215***	0.447***
Greece	0.057***	0.175***	0.116***	0.170***	0.392***
Austria	0.007	0.186***	0.108***	0.179***	0.346***
Czech Republic	0.117***	0.273***	-0.036***	-0.069***	0.339***
Sweden	-0.020*	0.290***	0.016	0.091***	0.337***
Iceland	-0.039***	0.226***	0.123******	0.167***	0.327***
Finland	0.015	0.244***	-0.002	0.109***	0.320***
United Kingdom	0.114***	0.192***	0.066***	-0.026***	0.311***
Portugal	0.163***	0.153***	-0.002	-0.022*	0.299***
Switzerland	0.096***	0.144***	0.006	0.063***	0.270***
France	-0.006	0.178***	-0.041***	0.016**	0.173***
Denmark	-0.018	0.163***	0.033	0.023	0.171***
Netherlands	0.064***	0.086***	-0.035	0.029*	0.165***
Belgium	-0.003	0.121***	-0.067***	0.033***	0.105***
Average	0.072	0.180	0.069	0.127	0.354

Table B3: Selection-corrected hourly wage regression for the period 2005-2015, alternative occupation categories, EU SILC wave

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Private	-0.097***	-0.100***	-0.110***	-0.128***	-0.117***	-0.116***
	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
Fem	-0.192***	-0.179***	-0.164***	-0.168***	-0.153***	-0.162***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)	(0.004)
MigrantEU	-0.115***	-0.096***	-0.104***	-0.134***	-0.069***	-0.069***
	(0.007)	(0.008)	(0.003)	(0.004)	(0.012)	(0.012)
Migrant	-0.192***	-0.156***	-0.164***	-0.208***	-0.081***	-0.079***
	(0.007)	(0.007)	(0.002)	(0.004)	(0.011)	(0.011)
Educ L	-0.198***	-0.148***	-0.158***	-0.111***	-0.113***	-0.113***
	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)	(0.005)
Educ H	0.322***	0.147***	0.145***	0.073***	0.071***	0.072***
	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)	(0.004)
Age 35-44	0.153***	0.137***	0.149***	0.150***	0.150***	0.149***
	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Age 45-54	0.233***	0.208***	0.220***	0.221***	0.221***	0.221***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Age 55-64	0.277***	0.244***	0.249***	0.250***	0.250***	0.251***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occupation_b		0.213***	0.213***	0.211***	0.210***	0.211***
		(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occupation_c		0.373***	0.381***	0.379***	0.378***	0.380***
		(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Occupation_d		0.433***	0.426***	0.427***	0.427***	0.427***
		(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Part-time			-0.069***	-0.066***	-0.066***	-0.153***
			(0.002)	(0.002)	(0.002)	(0.004)
Permanent			0.198***	0.202***	0.202***	0.199***
			(0.004)	(0.004)	(0.004)	(0.004)
Private *Educ L				-0.035***	-0.034***	-0.034***
				(0.005)	(0.005)	(0.005)
Private *Educ H				0.054***	0.057***	0.057***
				(0.004)	(0.004)	(0.004)
Fem *Educ L				-0.036***	-0.035***	-0.036***
				(0.003)	(0.003)	(0.003)
Fem *Educ H				0.030***	0.030***	0.030***
				(0.002)	(0.002)	(0.002)
MigrantEU *Educ L				-0.027***	-0.025***	-0.026***
				(0.006)	(0.006)	(0.006)
MigrantEU *Educ H				0.086***	0.086***	0.085***
				(0.005)	(0.005)	(0.005)
Migrant *Educ L				0.070***	0.070***	0.070***
				(0.006)	(0.006)	(0.006)
Migrant *Educ H				0.066***	0.066***	0.066***
				(0.005)	(0.005)	(0.005)

Private *Fem					-0.015***	-0.018***
					(0.004)	(0.004)
Private *MigrantEU					-0.078***	-0.077***
					(0.011)	(0.011)
Private *Migrant					-0.108***	-0.107***
					(0.010)	(0.010)
Fem *MigrantEU					0.018***	0.017***
					(0.004)	(0.004)
Fem *Migrant					-0.051***	-0.053***
					(0.004)	(0.004)
Fem *Part-time						0.109***
						(0.004)
lambda	-1.431***	-1.444***	-0.465***	-0.438***	-0.429***	-0.428***
	(0.038)	(0.038)	(0.026)	(0.026)	(0.026)	(0.026)
Constant	2.775***	2.719***	2.486***	2.501***	2.489***	2.494***
	(0.011)	(0.011)	(0.006)	(0.007)	(0.007)	(0.007)
Total effect Private	-0.097***	-0.100***	-0.110***	-0.115***	-0.121***	-0.121***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
Total effect Fem	-0.192***	-0.179***	-0.164***	-0.165***	-0.165***	-0.157***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Total effect MigrantEU	-0.115***	-0.096***	-0.104***	-0.107***	-0.103***	-0.103***
	(0.007)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
Total effect Migrant	-0.192***	-0.156***	-0.164***	-0.168***	-0.163***	-0.161***
	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	806,190	806,190	806,190	806,190	806,190	806,190

Note: Pooled estimates for 18 European countries. Standard errors in parentheses *** p¡0.01, ** p¡0.05, * p¡0.1.

Table B4: Talent Misallocation Measure derived from using alternative occupation categories

Country	Private	Female	MigrantEU	Migrant	Misallocation Measure
Cyprus	0.236***	0.239***	0.169***	0.611***	0.891***
Spain	0.197***	0.162***	0.129***	0.206***	0.545***
Luxembourg	0.143***	0.069***	0.258***	0.384***	0.489***
Italy	0.146***	0.118***	0.189***	0.217***	0.473***
Ireland	0.170***	0.126***	0.164***	0.093***	0.440***
Greece	0.105***	0.159***	0.119***	0.176***	0.429***
Austria	0.034***	0.176***	0.092***	0.185***	0.362***
Czech Republic	0.142***	0.243***	-0.024*	-0.046*	0.352***
Iceland	-0.033**	0.225***	0.110***	0.155***	0.320***
Portugal	0.181***	0.156***	-0.011	-0.020*	0.319***
United Kingdom	0.140***	0.160***	0.046***	-0.029***	0.295***
Finland	0.032***	0.194***	0.015	0.086***	0.281***
Switzerland	0.104***	0.116***	0.001	0.076***	0.252***
Sweden	-0.029*	0.181***	0.004***	0.104	0.224***
Netherlands	0.095***	0.110***	-0.042**	0.036***	0.223***
France	0.036***	0.149***	-0.031***	0.005	0.180***
Denmark	-0.010	0.118***	0.038	0.025	0.138***
Belgium	0.018***	0.077***	-0.043***	0.045***	0.100***
Average	0.095	0.154	0.066	0.128	0.351