Racial Inequality and Discrimination in European Labor Markets: A Comparative Study of France, Germany and the UK, 2005-2021

Shirin Mohammadi*
Paris School of Economics - École des Hautes Études en Sciences Sociales

August 28, 2024

Abstract

This study provides a comparative overview of racial/ethnic inequalities in the French, British and German labor markets using a combination of national labor force surveys and annual population surveys, complemented by harmonized Eurostat data. The racial/ethnic dimension in this research is examined separately by gender given the well-established literature on differentials in labor market outcomes between men and women. Specifically, the study examines: (i) differentials in labor force participation and employment outcomes using a probit model; (ii) differentials in average earnings using an OLS model; and (iii) distributional differences in earnings (i.e., whether there is a racial/ethnic 'glass ceiling' at the top of the income distribution) using a quantile regression model. Decomposition methods are also deployed in the quantile regression analysis. Several key findings stand out: (i) in all three countries, second-generation African/Black men (followed closely by men from the Maghreb and Middle East in France) face the worst labor market outcomes, even after controlling for education and other factors that typically influence labor market outcomes; (ii) the employment gaps for second-generation African/Black men (vis-à-vis native/white men) are largest in Germany, followed by France and the UK. These gaps persist and remain large even after controlling for education, age and experience – although they have narrowed over time; (iii) second-generation African/Black men (alongside men from the Maghreb in France and from South Asia in the UK) earn less than their native/white counterparts on average, even after controlling for education, age, experience, sector, occupation and industry; (iv) in the British labor market, Black men appear to face a racial 'glass ceiling' effect, limiting their upward mobility prospects; and (v) women do not appear to face a racial/ethnic penalty on top of any gender penalties in earnings, although they do face lower employment probabilities than their white/native female counterparts in all three countries, even after controlling for education and experience.

JEL Classifications: D63, J70, J71, P52

*The author gratefully acknowledges her thesis supervisor, Thomas Piketty, for his invaluable guidance, insights and support throughout the research process. She is also grateful for feedback received along the way from Thomas Breda, Philipp Ketz and David Margolis.

1 Introduction

Most studies on racial labor market inequalities deploy experimental methods (such as audit studies, which measure job offers, or correspondence studies, which measure callbacks) to determine potential discrimination in the hiring process. Yet such methods do not capture wage differentials between different racial/ethnic groups, nor do they track potential discrimination along an individual's career trajectory once employed. (Moreover, most of the experimental studies done to date are not exactly comparable across countries because the field experiments often target different types of firms and ranges of occupations.) This study takes an observational approach, compiling a comparable cross-country dataset using a combination of national labor force surveys and annual population surveys, complemented by harmonized Eurostat data, to determine the extent of racial/ethnic inequalities in the French, German and British labor markets.

More specifically, the study examines labor force participation differentials (controlling for marital/cohabitation status and number of children), employment probability differentials (controlling for education, age and experience), average earnings/wage differentials among those in employment (controlling for education, age, experience, occupation, sector, industry, reference year and full-time status), and whether racial/ethnic minorities face discrimination that negatively affects their prospects for upward mobility (e.g., promotions and pay raises). Quantile regression methods are deployed to determine whether and to what extent racial/ethnic minorities in these countries face a ceiling akin to the 'glass ceiling' women typically face at the top end of the income distribution. The earnings analysis of this study only covers France and the UK due to data constraints for Germany. For France and Germany, race/ethnicity are proxied using parents' country of origin, while for the UK, self-identified racial classifications are available.

Several findings stand out: (i) in all three countries, second-generation African/Black men (followed closely by men from the Maghreb and Middle East in France) face the worst labor market outcomes, even after controlling for education and other factors that typically influence labor market outcomes; (ii) the employment gaps for second-generation African/Black men (vis-à-vis native/white men) are largest in Germany, followed by France and the UK. These gaps persist and remain large even after controlling for education, age and experience – although they have narrowed over time; (iii) second-generation African/Black men (alongside men from the Maghreb in France and from South Asia in the UK) earn less than their native/white counterparts on average, even after controlling for education, age, experience, sector, occupation and industry; (iv) in the British labor market, Black men appear to face a racial 'glass ceiling' effect, limiting their upward mobility prospects; and (v) women do not appear to face a racial/ethnic penalty on top of any gender penalties in earnings, although they do face lower employment probabilities than their white/native female counterparts in all three countries, even after controlling for education and experience.

2 Literature Review

2.1 Theory

According to economic theory, discrimination in the labor market is a source of inefficiency and market failure. It challenges a central tenet of neoclassical economics: that equal productivity should yield equal pay. Understanding why this principle often falls short requires a closer examination of the economic forces that sustain such biases. Labor economists generally characterize these forces into two broad categories: "statistical" discrimination and "taste-based" discrimination.

In their seminal study on statistical theories of discrimination, Aigner and Cain (1977) dissect the roots of statistical discrimination, where employers, grappling with imperfect proxies (i.e., inadequate test instruments), such as education and test scores, underestimate the abilities of racial minorities. This systemic undervaluation forces minorities to incur higher signaling costs to prove their worth. Employers, deterred by the expense and complexity of finding more accurate measures, perpetuate wage disparities. The authors show how entrenched assumptions and economic inertia combine to maintain a status quo that shortchanges the discriminated group.

Taste-based discrimination, on the other hand, is essentially a more overt form of discrimination where individuals have an intrinsic aversion to out-group members. In sociology, the tendency of individuals to associate and surround themselves with others who are similar to them is referred to as ‘homophily’ (Lin 2000) and will be the basis of much of the hypotheses of this research – particularly in terms of the ‘glass ceiling’ effect.

Guryan and Kofi Charles (2013) bring the theories of statistical and taste-based discrimination together, arguing that taste-based discrimination compounds the problem of incomplete information. The authors are critical of regression model approaches to measuring discrimination given their vulnerability to omitted variable bias, where unobservable factors could skew the results. Their preferred approach – correspondence (experimental) studies – allow for the random assignment of racial signals, which can surgically isolate the true impact of perceived race on employment decisions, thereby allowing for a causal interpretation of the effects of race. Yet they also acknowledge a key limitation: these types of studies only measure intermediate outcomes (such as callbacks and job offers), and not the final outcome (wages). Notably, some have argued that the study of wage differentials between individuals with the same level of qualifications is only appropriate when there is a balanced labor market (i.e., when there is low unemployment) – which has typically not been the case in France[1]; when the labor supply is larger than demand, examining differentials in unemployment is arguably a better way to measure discrimination (Richard 2013).

Lang, Manove and Dickens (2005) explore yet another facet of the economics of discrimination, focusing on the persistence of discrimination even in competitive markets with wage postings. In such markets, firms set binding wage offers that cannot be tailored based on race. This rigidity, they argue, leads to systemic segregation and deep wage disparities, with firms capitalizing on the dynamics to boost profits. “In equilibrium, blacks and whites will be employed by different firms (segregation), blacks will receive lower wages with the wage differential far exceeding the taste or productivity differential (wage discrimination), and firms will retain higher profits” (Lang et al. 2005). Their work underscores a counterintuitive reality: even absent explicit biases, the structural features of the market can entrench discriminatory practices, creating a fertile ground for inequality to flourish.

[1] France has typically had a higher unemployment rate than the UK and Germany, so by this theory, the employment outcomes results of this study would be the most appropriate measure of discrimination in France.

2.2 Empirics

A wide range of empirical studies on labor market discrimination have examined employment outcomes among different racial/ethnic groups in France and in other advanced economies. They generally find significant racial/ethnic penalties in employment outcomes for racial/ethnic minorities, particularly for men of African and Middle Eastern descent (Adida et al. 2016, Aeberhardt et al. 2010a, Aeberhardt et al. 2010b, Brinbaum 2018, Combes et al. 2016 and Langevin et al. 2017, to name a few). Langevin et al. (2017), for instance, find that in France, second-generation migrants with parents from the Maghreb, Africa and Turkey are less likely to be in employment than natives, and once employed, receive lower wages on average. Aeberhardt et al. (2010a) also find significant unexplained differences in employment probabilities and wages in the French labor market between individuals with two French parents and those with at least one parent from Africa. Using data from Insee's 2003 *Formation Qualification Professionnelle* survey, they find that discrimination is more pronounced at the hiring stage, although it also persists once employed. These findings are consistent with prior audit studies, which suggest a discernable disadvantage for second-generation Africans during the job application process in France.

In the UK, Heath and Di Stasio (2019) perform a meta-analysis of studies on racial discrimination and find that racial discrimination in the British labor market has persisted over the last fifty years with little sign of decline. Their analysis underscores the enduring disadvantages faced by Black and Asian minorities there. As with others, they advocate for field experiments as the most reliable method to measure discrimination, warning that observational studies may misattribute unemployment disparities to discrimination without accounting for factors such as social capital or job search strategies.

In the German labor market, Koopmans et al. (2019) find significant discrimination against ethnic, racial and religious minorities for jobseekers whose racial/ethnic/religious groups are culturally more distant from that of Germans. Another study based on a field experiment conducted in 2014-2015 finds that applicants with a Turkish accent face significant discrimination in the early hiring process, receiving fewer positive responses from employers compared to those with a standard German accent (Schmaus and Kristen 2022).

In cross-country studies on advanced economies, France often emerges among those with higher levels of racial/ethnic disparities. Quillian et al. (2019), for instance, identify France as having the highest levels of hiring discrimination among Belgium, Canada, France, Germany, the Netherlands, Norway, Sweden, the UK and the US, followed by Sweden. In France and Sweden, white natives receive 75%-102% more callbacks than nonwhite candidates with similar job-relevant characteristics, compared to a 22%-41% advantage in Germany, the US and Norway. They also find that European-origin immigrants face significantly less discrimination than Black or Sub-Saharan African origin applicants.

Algan et al. (2010) also find France to have the highest levels of racial disparities when considering employment probability outcomes, but the picture is more mixed when examining wage outcomes. Here, they find Black African men from the UK fare worse than second-generation African men in France.

Heath, Liebig and Simon (2013) survey various studies that examine discrimination in OECD labor markets and note one of the more robust findings in the literature to be that men tend to experience racial/ethnic discrimination more than women, and that individuals from Africa and the Middle East tend to face the highest rates of discrimination. Their review introduces the concept of "ethnic penalty," suggesting that observed labor market disparities may also arise from limited social networks, lack of knowledge about job openings, or different job preferences. The authors highlight potential methodological issues, such as the exclusion of language proficiency and soft skills in measuring discrimination, which could affect the robustness of findings.

Together, these studies highlight the persistent and multifaceted nature of racial inequalities in various labor markets, particularly at the hiring stage, and emphasize the importance of robust methodological approaches for understanding and addressing these disparities.

This paper's contribution to the rich, existing literature is threefold. First, it provides an updated cross-country comparison between France, Germany and the UK – Europe's three largest economies – at a time when racial and migration issues are fueling political cleavages. Second, it looks at trends over time to determine whether racial/ethnic inequalities have improved or deteriorated since 2005. Third, it is the first – to the best of my knowledge – to examine and provide a comparative view of the 'glass ceiling' effect from a racial/ethnic perspective in the French and

British labor markets.

3 Data

For France, I use 16 years of data from the French Statistical Institute's Labor Force Surveys (hereafter LFS), from 2005-2020. The surveys include information on education (level and field of study), employment status, occupation, sector of employment, industry, earnings, gender, respondents' birthplace and parents' country of origin, which I use as a proxy to classify individuals into different racial/ethnic groups. (If at least one parent is from Sub-Saharan Africa, I classify the individual as a second-generation African.) To measure potential discrimination along racial/ethnic lines, I focus on second-generation immigrants only given that first-generation immigrants may face additional linguistic and cultural hurdles that natives do not face (which may be a bigger contributor to their labor market outcomes). One potential shortcoming to my method is that third-generation and older immigrants will be captured in the native (control) group, potentially biasing my results downward (i.e., underestimating the gap): for instance, if third-generation and older migrants also face discrimination, it would weigh down the native group's average earnings, narrowing the potential earnings gap that this study finds between the second-generation (racial) and control (native) groups. Interpretation of the results will also be complicated by statistical noise linked to the children of repatriated settlers from Algeria, which will be captured in the second-generation Maghbrebin sample – this also risks underestimating the gap between the second-generation Maghbrebin group and the native group.

For the UK, I use 16 years of Annual Population Survey (APS) data from the Office of National Statistics, also covering the 2005-2020 period. The UK surveys include a self-identified racial category, which I combine with country of birth to extract comparable second-generation and older racial groupings. Here, the self-identified nature of the classifications can complicate interpretation of the results, as will be examined further in the descriptive statistics section that follows. For the UK, I use age left education as the education variable given inadequate observations on education level and field of study in the dataset.

For Germany, I have only one year of LFS data from Eurostat (for 2021) that includes parents' country of origin information. Nevertheless, the dataset allows for the creation of comparable racial categories to those created for France, as well as comparable education level and field of study variables. (See Appendix for a full list of controls and racial classifications by country.)

Although I include first-generation immigrant groups in the results, the focus of this study is on second-generation immigrants, as noted earlier, to allow for *ceteris paribus* comparisons across groups, given that first-generation immigrants typically would not have gone through the French/German/British education systems. Moreover, first-generation immigrants typically face greater language and/or cultural barriers than do their children, as well as challenges from potentially lower social capital in their new host societies. The decisive role of social networks in securing employment is well known in the economics literature: labor economists have documented that between one-third and two-thirds of individuals hear about or obtain jobs through friends and relatives (Fontaine 2008).

3.1 Descriptive Statistics

The tables that follow include summary statistics for the samples used in this study, with the age range restricted to 16-64 as a broad definition of working age. Key demographic highlights include: (i) the native population accounts for around 82% of the active population in all three countries; (ii) the first-generation immigrant population is smallest in France (7.5%), followed by Germany (12%) and the UK (15%); (iii) the second-generation immigrant population is largest in France (9%), followed by Germany (5.5%) – the numbers for the UK are not exactly comparable given that they include third generation and older immigrants and because second-generation white immigrants are captured in the total native/white population. Nevertheless, non-white/non-immigrants make up approximately 3% of the active workforce in the UK. These proportions are roughly the same among the inactive population in France and the UK, but notably different in Germany, where the inactive population comprises 75% natives, 20% second-generation immigrants and 5% first-generation immigrants. In France, the inactive population comprises 81% natives, 11% second-generation immigrants and 8% first-generation immigrants, while in the UK, the inactive sample population comprises 81% white, 2.5% second-generation or older racial/ethnic groups and 16% first-generation immigrants (75% of which are women).

FRANCE (2005-20)	Active population	Men (% of active population)	Median age (active population)		Median age left full-time education		Employed (employment rate)		Average log earnings		Working full time (of those employed)	
			Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Native	2,065,800	1,053,138	42	42	19	20	976,166	932,912	7.5	7.2	907,168	658,111
	83.5%	51%					93%	92%			93%	71%
SecGen African	11,664	5,644	29	29	20	21	4,467	4,942	7.3	7.2	3,824	3,640
	0.5%	48%					79%	82%			86%	74%
SecGen Maghrebin	60,401	30,094	34	35	20	20	24,111	24,947	7.4	7.2	21,733	17,787
	2.4%	50%					80%	82%			90%	71%
SecGen Middle Eastern	6,529	3,320	28	28	19	20	2,683	2,609	7.4	7.1	2,356	1,769
	0.3%	51%					81%	81%			88%	68%
SecGen Asian	5,160	2,673	30	31	21	21	2,310	2,260	7.5	7.4	2,049	1,741
	0.2%	52%					86%	91%			89%	77%
SecGen Other	138,541	70,535	42	42	19	20	64,721	62,043	7.5	7.2	59,958	43,796
	5.6%	51%					92%	91%			93%	71%
African Immigrant	31,532	16,006	40	39	22	22	13,071	12,431	7.3	7.1	11,441	8,335
	1.3%	51%					82%	80%			88%	67%
Maghrebin Immigrant	51,281	31,401	42	41	21	21	25,641	15,572	7.4	7.1	22,951	10,355
	2.1%	61%					82%	78%			90%	66%
Middle Eastern Immigrant	11,452	7,492	40	41	20	22	6,266	3,094	7.4	7.0	5,570	1,957
	0.5%	65%					84%	78%			89%	63%
Asian Immigrant	5,855	3,044	46	44	22	22	2,790	2,540	7.6	7.3	2,607	1,969
	0.2%	52%					92%	90%			93%	78%
Other Immigrant	87,111	41,095	45	45	20	21	37,346	40,843	7.6	7.2	33,746	26,951
	3.5%	47%					91%	89%			90%	66%

UK (2005-20)	Active population	Men (% of active population)	Median age (active population)		Median age left full-time education		Employed (employment rate)		Average log wages		Working full time (of those employed)	
			Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
White	1,603,794	821,334	44	43	16	16	774,878	748,664	2.6	2.4	736,841	448,532
	82%	51%					94%	96%			95%	60%
Black	14,120	6,425	40	41	16	16	5,545	6,955	2.6	2.5	5,394	5,201
	0.7%	46%					86%	90%			97%	75%
South Asian	26,444	14,151	32	32	20	20	12,724	11,137	2.6	2.5	12,025	7,749
	1.4%	54%					90%	91%			95%	70%
Asian	3,292	1,685	33	33	20	20	1,560	1,514	2.7	2.6	1,450	1,122
	0.2%	51%					93%	94%			93%	74%
Mixed	10,643	5,129	33	33	16	16	4,515	5,033	2.6	2.5	4,225	3,426
	0.5%	48%					88%	91%			94%	68%
Other	2,911	1,493	36	36	20	20	1,367	1,302	2.7	2.5	1,258	867
	0.1%	51%					92%	92%			92%	67%
White Immigrant	176,448	87,448	39	39	16	16	83,492	84,803	2.6	2.4	80,444	57,061
	9.0%	50%					95%	95%			96%	67%
Black Immigrant	25,490	11,926	41	41	16	16	10,596	12,121	2.5	2.4	9,679	8,206
	1.3%	47%					89%	89%			91%	68%
South Asian Immigrant	46,080	29,065	41	40	20	20	27,451	15,267	2.6	2.5	24,117	13,512
	2.4%	63%					94%	90%			88%	89%
Asian Immigrant	19,660	9,507	41	41	20	20	8,992	9,443	2.5	2.4	7,782	6,282
	1.0%	48%					95%	93%			87%	67%
Mixed Immigrant	4,034	1,860	39	39	16	16	1,717	2,005	2.6	2.5	1,605	1,360
	0.2%	46%					92%	92%			93%	68%
Other Immigrant	19,804	11,106	39	39	20	20	10,145	7,847	2.5	2.4	9,017	5,349
	1.0%	56%					91%	90%			89%	68%

GERMANY (2021)	Active population	Men (% of active population)	Median age (active population)		Median age left full-time education		Employed (employment rate)		Average log wages		Working full time (of those employed)	
			Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Native	93,452	43,889	46	46	20	20	37,133	34,900			33,558	18,368
	82.2%	47%					85%	70%			90%	53%
SecGen African	164	69	25	24	20	19	40	41			25	28
	0.1%	42%					58%	43%			63%	68%
SecGen Middle Eastern	1,157	469	23	23	19	19	325	298			260	183
	1.0%	41%					69%	43%			80%	61%
SecGen Asian	444	189	27	28	20	21	127	144			96	96
	0.4%	43%					67%	56%			76%	67%
SecGen Latin American	154	72	27	30	21	21	49	43			42	18
	0.1%	47%					68%	52%			86%	42%
SecGen Other	4,292	1,945	31	31	20	19	1,446	1,284			1,256	727
	3.8%	45%					74%	55%			87%	57%
African Immigrant	541	216	38	37	21	21	160	93			129	49
	0.5%	40%					74%	29%			81%	53%
Middle Eastern Immigrant	4,249	1,730	38	39	20	20	1,282	942			1,120	419
	3.7%	41%					74%	37%			87%	44%
Asian Immigrant	1,626	549	34	39	21	21	408	377			355	217
	1.4%	34%					74%	35%			87%	58%
Latin American Immigrant	433	151	35	41	23	22	124	165			94	93
	0.4%	35%					82%	59%			76%	56%
Other Immigrant	6,639	2,708	45	44	19	19	2,196	1,844			2,023	848
	5.8%	41%					81%	47%			92%	46%
Undisclosed Origin Immigrant	592	208	40	41	20	19	162	147			150	73
	0.5%	35%					78%	38%			93%	50%

Other key highlights include: (i) on average, among the active workforce, French and German natives are more educated than British natives (as measured by the age they left full-time education); and (ii) employment rates are highest for natives/whites in all three countries. In the employment models that come later in this report, I will control for other factors that influence employment outcomes (such as education and experience) to determine the potential roots of these raw differentials.

Finally, to gain a better understanding of the self-identified racial categorizations for the UK, I combined quarterly LFS data (from the Office of National Statistics) from 2012-2017, which includes a more detailed breakdown of country of birth than the annual data. This allows for the creation of detailed first-generation immigrant classifications in order to examine each group's self-identified races. The results are included in the Appendix (alongside more detail on the racial categorizations used for France and Germany).

Notably, 15% of African immigrants (excluding South Africans) in the UK classify themselves as ethnically South Asian while 11% classify themselves as ethnically white – this is likely due to the presence of a large Indian (and Parsi) diaspora in Southeast Africa (think: Freddie Mercury), some of whom arrived in the 19th century as indentured laborers from British India while others arrived by sea as traders.

Another notable observation relates to how Middle Easterners classify themselves. While 62% classify themselves as 'other', another 21% classify themselves as white. This could point to an underestimation of the gaps between white and racial/ethnic groups if the Middle Easterners captured in the white category are also facing discrimination, weighing down the numbers for the white group and resulting in narrower gaps.

4 Models and Methodology

As indicated in the existing literature, there are a number of ways to determine the presence of discrimination in the labor markets of our countries of interest. In this study, I explore four outcomes: labor force participation, employment, average wages and the distribution of wages (to determine whether there exists a 'glass ceiling' type of barrier at the highest-paid positions). As a statistical exercise, I also deploy decomposition analysis to the quantile regression.

My baseline hypothesis is that racial minorities in France, Germany and the UK are rewarded at a lower rate than natives for a given set of labor market characteristics, i.e., that they have to overcompensate in terms of labor market characteristics to be given the same opportunity and/or wage schedule as a native in a given role (which would ultimately point to inefficiencies and misallocation in labor market matching – an area one could extend this study to at a later stage for a macro analysis). I am particularly interested in distributional trends as racial/ethnic minorities move up the corporate ladder, where I hypothesize that they face a ceiling at the top due to entrenched historical inequalities. My hypothesis is based on human psychology and sociology: namely, the tendency of individuals to associate with others who are similar to them (homophily) (Lin 2000), which can lead to those who have traditionally held positions of power (e.g., at the top of the income distribution) to surround themselves with individuals of similar kin, making it more difficult for racial/ethnic minorities to break that barrier.

To test my hypothesis, I start by examining raw gaps in labor force participation and employment outcomes, then add controls for factors that typically affect both labor force participation (cohabiting with a partner and presence of children) and employment (age, education and experience). I next explore average earnings outcomes, and end by examining the entire earnings distribution. For the earnings analysis, I start with the raw earnings gap, then add 'exogenous' controls (age, education, experience and year), and finally add controls for other factors that typically influence earnings, where discrimination/market segmentation could also be at play (namely, sector, industry, occupation and full-time status).

For the quantile/distributional earnings analysis, I start by imposing the restriction that all races/ethnicities are paid the same rewards for their labor characteristics and examine the conditional wage distribution using dummy variables[2] for racial/ethnic groups. I then estimate separate quantile regressions for the racial group and perform a decomposition analysis to identify the extent

[2]A dummy variable is a variable that takes on the value of 0 or 1 to indicate the absence or presence of a categorical effect that may be expected to shift the outcome. Dummy variables are used in regression models to include qualitative data, such as gender, race or the occurrence of an event.

to which the racial wage gap at various percentiles can be explained by differences in characteristics between the distributions of races/ethnicities and how much can be explained by differences in labor market rewards to those characteristics (i.e., racial discrimination). For this part of my analysis, I focus only on second-generation African and Maghrebin men for France (vis-à-vis the native men group), and Black and South Asian men for the UK (vis-à-vis the white men group).

A note on definitions

While many Europeans took it for granted a century ago that some races were superior to others, there has been a shift since World War II as geneticists have come out with ample evidence against this theory. Yet at the same time, anthropologists, historians, sociologists and behavioral economists have all come out with strong evidence over the years of significant differences between human cultures (Harari 2019). The basis of today's political discourse on 'racism' in Europe can arguably be attributed more to cultural differences (particularly vis-à-vis individuals with migrant backgrounds) than to the traditional form of 'racism' based purely on genetic differences between racial groups. My focus on second-generation immigrants in this study is in part meant to minimize the potential 'cultural' aspect of discrimination: there should theoretically be minimal cultural differences between second-generation migrants and the native population, meaning the discrimination there could still be partly attributable to the traditional forms of racism (or based on assumptions about the individual's cultural norms given their racial/ethnic/migrant background).

4.1 Labor force participation and employment outcomes using probit

I deploy probit models to determine average gaps in labor force participation and employment outcomes. I calculate the average marginal effects from the coefficients to determine the average gap in the probability of labor force participation and in the probability of employment. The employment probability models are conditional on being active in the labor force.

For the labor force participation model, I start with the raw gap then add controls for cohabitation status (whether the individual is married or living with a partner) and number of children in the household (for France only given missing data for the UK). I exclude Germany from this model given the small sample size – all individuals in the 16-64 age range in my German sample are active participants in the labor force.

For the employment probability model, I start with the raw gap then add controls for education (level and field of study for France and Germany, age left education for the UK), followed by a third model that adds further controls for age, experience and reference year (the "all controls" model).

I also run the employment gaps analysis separately for smaller pools of years (2005-2009, 2010-2014, 2015-2019) for France and the UK to examine trends over time. I do this for the raw gaps and the gaps with all controls.

4.2 Average earnings/wage outcomes using OLS

I next examine average earnings outcomes using an OLS model. I follow a standard Mincer log-linear wage model, controlling for education (level and field of study for France, age left full-time education for the UK), age and age squared, potential experience (up to a quartic to capture non-linear effects), sector of employment (public/private), industry of employment (agriculture/manufacturing/construction/tertiary), occupation (blue collar/white collar), employment hours (full-time/part-time) and racial categorizations (Mincer 1997, Lumieux 2003).

I start by examining the raw average earnings gaps (including only racial/ethnic covariates). I then run the model using 'exogenous' controls (age, education, experience and year), and finally add controls for other factors that typically influence earnings, where discrimination/market segmentation could also be at play (namely, sector, industry, occupation and full-time status).

As with the employment gaps models, I also run this model using smaller pools of years (2005-2009, 2010-2014, 2015-2019) to examine trends over time.

4.3 Pooled quantile regressions with racial/ethnic dummies

For the distributional analysis, I start with basic quantile regression methods as outlined by Basset and Koenker (1986) and Buchinsky (1998). Here too I follow the same standard Mincer log-linear wage model used in the OLS analysis. The advantage of quantile regression is that it allows us to estimate the marginal effect of a covariate on the log-wage at various points in the distribution (not just at the mean, as with OLS).

I compare the conditional distribution of wages for racial minorities to the conditional distribution of wages for natives.

Let θ represent the quantile of a random variable y (log net monthly earnings in the case of France), conditional on $\mathbf{x}$ (a set of covariates consisting of human capital and social characteristics, e.g., the aforementioned variables such as education level, field of study, age, experience, etc.). The conditional quantile function (which is the quantile version of the conditional expectation function) can be defined as:

$$Q_\theta(y_i|\mathbf{x_i}) = \mathrm{F}^{-1}_{y|x}(\theta|\mathbf{x_i}) \tag{1}$$

where $F_y(y|\mathbf{x}_i)$ is the distribution function for y_i at y, conditional on $\mathbf{x}_i$. Following Koenker and Basset (1978), we can note the θth quantile of y conditional on x_i as:

$$\mathrm{F}^{-1}_{y|x}(\theta|\mathbf{x_i}) = \mathbf{x_i}\beta(\theta), \forall\theta \in (\mathbf{0}, \mathbf{1}) \tag{2}$$

The quantile regression assumes that the conditional quantile of y, Q_θ, is linear in x: $Q_\theta = x * \beta_\theta$, with the coefficient vector β_θ (the quantile estimator) estimated by minimizing:

$$\sum_{i:y_i \geq x_i'\beta_\theta}^{n} \theta|y_i - x_i'\beta_\theta| + \sum_{i:y_i < x_i'\beta_\theta}^{n} (1-\theta)|y_i - x_i'\beta_\theta| \tag{3}$$

In other words:

$$F_n(\beta_\theta|y,\boldsymbol{x}) = \sum_{i=1}^{n} g(y_i - \boldsymbol{x_i'\beta_\theta}|\theta) \tag{4}$$

where:

$$g(e_{i,\theta}|\theta) = \begin{bmatrix} \theta e_{i,\theta} & \text{if } e_{i,\theta} \geq 0 \\ (1-\theta)e_{i,\theta} & \text{if } e_{i,\theta} < 0 \end{bmatrix}, e_{i,\theta} = y_i - \boldsymbol{x_i'\beta_\theta} \tag{5}$$

This means that we give more weight to positive deviations than to negative deviations when we are interested in a higher quantile, e.g., at the higher end of the income distribution. In other words, the check function weights positive and negative terms asymmetrically (Angrist and Pischke 2009). Unlike traditional OLS where we minimize the sum of squared residuals, quantile regression aims to minimize a weighted sum of absolute residuals, with the check function assigning different weights to positive and negative residuals depending on the desired quantile, θ.

By minimizing absolute errors weighted by their quantile, quantile regression is much less sensitive to outliers and more robust in the absence of homoskedasticity and normality. The low sensitivity to outliers is particularly useful when using LFS data, which may be prone to outliers as individuals or the interviewer could misreport employees' earnings.

The coefficients in the log-wage quantile regression can be interpreted as the estimated rates of return to individual characteristics, x, at the different points of the conditional wage distribution (i.e., at the θth quantile of the distribution). In our case, the estimated racial coefficients indicate the extent to which the racial gap remains unexplained at the various quantiles when we control for differences at the individual level in various combinations of characteristics.

4.3.1 Bootstrapped standard errors

Bootstrapping offers an alternative to inference based on asymptotic formulas: we treat our sample as if it were the population and repeatedly draw from it with replacement. This gives us a bootstrap sampling distribution. Although it is computer-intensive, it is a useful way to calculate asymptotic standard errors. In practical terms, asymptotic standard errors provide a way to approximate the variability of an estimator when working with large samples (and are often used to construct confidence intervals and conduct hypothesis tests in large samples). This is especially useful because, for many estimators, the exact distribution may be complex or unknown, but their behavior can be approximated by simpler distributions (usually normal) as the sample size increases. Because bootstrapped standard errors are typically larger (more conservative estimates) than the normal standard errors, we are less likely to reject the null hypothesis incorrectly. The bootstrapped standard errors for the quantile regression coefficients are reported underneath the coefficients in the results section of the distributional analysis.

4.4 Decompositions

As a final statistical exercise, I carry out an Oaxaca-Blinder type of decomposition using quantile methods, as outlined by Melly (2005) and Chernozhukov et al. (2013), which builds on the methods laid out by Machado and Mata (2005) (but differs in algorithmic detail), to decompose the differences between racial groups' log-wage distributions into a component that is due to differences in labor market characteristics between the racial subsets and the native group, and a component that is due to differences in the rewards that the different groups receive for their labor market characteristics. For simplicity, I only conduct the decomposition analysis for the second-generation African and Maghrebin men (France) and Black and South Asian men (UK) groups (vis-à-vis the respective native/control groups).

The general idea of decompositions under the Oaxaca-Blinder methodology is to decompose differences between two groups (the wage gap in our case) into a component that can be explained by different characteristics/attributes between the samples of those two groups, and differences that are unexplained, due to being rewarded at a different rate for the same attributes (i.e., a

Black man with a master's degree in economics being rewarded less for that degree than a white man with the same degree, all else equal). Although the unexplained part is sometimes referred to as 'discrimination', because we can never be entirely certain that we have captured all observable and unobservable factors that could be explaining the wage differentials in our models, it is more often referred to as the 'unexplained' or 'wage structure' effect.

Specifically, the overall wage gap can be decomposed into four components: (i) returns to observable characteristics; (ii) returns to unobservable characteristics; (iii) distribution of observable characteristics; and (iv) distribution of unobservable characteristics (Fortin et al. 2010). Because decomposition analysis involves unobservable components, we have to impose several assumptions on the joint distribution of observable and unobservable characteristics, and on separability (to separate out the contribution of returns to observables from unobservables).

The basic idea is to generate two counterfactual densities: (i) the Black/second-generation African log-wage density that would arise if Black/second-generation African men were given white/native men's labor market characteristics but continued to be "paid like Black/African men," and (ii) the density that would arise if Black/African men retained their own labor market characteristics but were "paid like white/native men."

To illustrate the general framework for quantile decompositions in application, we can start with the Machado and Mata approach, which relies on bootstrapping algorithmic methods:

1) Draw a random sample of size n from a θ[0,1]: θ_1, θ_2, ..., θ_n

2) Using the Black/African dataset, estimate the quantile regression coefficient vectors $\beta^{black}(\theta_i)$ for i = 1, ..., n.

3) Make n draws at random with replacement from the white/native dataset, denoted by x_i^{white}, for i = 1, ..., n.

4) The counterfactual density is then generated as $y_i \equiv x_i^{white}\beta^{black}(\theta_i)_{i=1}^{n}$

To calculate the second counterfactual density where Blacks/second-generation Africans retain their characteristics but are "paid like whites/natives," we simply reverse the roles in steps 2 and 3 (i.e., use the white sample dataset to estimate the quantile regression coefficients and make the bootstrap draws from the Black dataset).

The linearity assumption of quantile regression implies that the decomposition of the difference between the racial group and the native group log-wage densities is exact. In other words:

$$x^{white}\beta^{white}(\theta) - x^{black}\beta^{black}(\theta) = \underbrace{[x^{white} - x^{black}]\beta^{black}(\theta)}_{\text{covariates (composition effect)}} + \underbrace{x^{white}[\beta^{white} - \beta^{black}]}_{coefficients(unexplained)} \qquad (6)$$

If the unexplained part of the decomposition is greater at the higher end of the income distribution (at the higher deciles), it would be evidence of a ceiling effect for the racial groups.

I generate pairwise sets of counterfactual densities for the second-generation African and Maghrebin (Black and South Asian) subsets of my sample for France (UK), using the Chernozhukov/Melly method: (i) the racial group log-wage density that would arise if the racial subsets were given the labor market characteristics of the native population but continued to be paid like their racial group, and (ii) the density that would arise if racial groups retained their own labor market characteristics but were paid like the native population. I then generate the results for the total gap, the part that is explained by differences in the composition of covariates, and the part that is unexplained.

5 Results

Overall, in all three labor markets, racial/ethnic minorities (second-generation Africans/Blacks in particular, but also those from the Maghreb and Middle East in France and Germany) face lower likelihoods of gaining employment relative to the white or native groups. Once employed, the British labor market tends to exhibit the largest wage differentials by race/ethnicity, even after controlling for education and other factors that typically influence wage outcomes. Black men in particular appear to face a racial 'glass ceiling' in the British labor market. In the French labor market, the raw earnings gaps are much larger than in the UK but much of the gaps disappear once we add controls. Nevertheless, there are still small gaps in earnings throughout the income distribution for second-generation African men and second-generation Maghrebin men and women, even after controlling for age, education (level and field of study), experience, sector, occupation, industry, full-time status and reference year.

5.1 Labor force participation and employment probability results

5.1.1 Labor force participation

The labor force participation gaps are generally wider in France than in the UK (with the exception of South Asian women in the UK, who appear to be 10.5 percentage points less likely to participate in the labor force compared to white women after controlling for age, education and marital status).

Looking specifically at men, the largest labor force participation gaps after controlling for age, education, marital/cohabitation status and number of children (France only) are among second-generation Africans and Maghrebins in France (both around 4 percentage points less likely to participate than their native counterparts) and among South Asians and 'Others' (which includes Arabs) in the UK (3.7 and 4.7 percentage points less likely, respectively).

For women, the largest gaps after controls are among second-generation Maghrebins and Middle Easterners in France (both around 7 percentage points less likely to participate than natives), and among South Asian and 'Others' in the UK (6.5 percentage points less likely for the latter and 10.5 percentage points for the former, as noted earlier).

The tables that follow show the average marginal effects of labor force participation with the standard errors in parentheses (e.g., on the surface, without controls, a second-generation African man in France is on average 17.8 percentage points less likely to participate in the labor force than the average native man, and this effect is statistically significant at the 1% level). Again, while the tables with results include first-generation immigrants, the focus of this research is on the second-generation only.

Labor force participation outcomes (average marginal effects)				
FRANCE 2005-20	**Men (raw gap)**	**Women (raw gap)**	**Men (w/ controls)**	**Women (w/ controls)**
SecGen African	-0.178***	-0.167***	-0.043***	-0.038***
	(0.005)	(0.005)	(0.003)	(0.004)
SecGen Maghreb	-0.039***	-0.079***	-0.040***	-0.070*
	(0.002)	(0.002)	(0.002)	(0.002)
SecGen MidEast	-0.150***	-0.203***	-0.028***	-0.069***
	(0.007)	(0.006)	(0.004)	(0.005)
SecGen Asian	-0.105***	-0.074***	-0.0489***	-0.021***
	(0.007)	(0.008)	(0.005)	(0.006)
SecGen Other	-0.022***	-0.025***	-0.007***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)
FirstGen African	0.044***	-0.012***	-0.038***	-0.068***
	(0.003)	(0.003)	(0.003)	(0.003)
FirstGen Maghreb	0.047***	-0.144***	-0.040***	-0.171***
	(0.002)	(0.003)	(0.002)	(0.002)
FirstGen MidEast	0.055***	-0.197***	-0.045***	-0.217***
	(0.004)	(0.006)	(0.004)	(0.005)
FirstGen Asian	0.054***	0.008	0.009*	-0.043***
	(0.006)	(0.007)	(0.005)	(0.006)
FirstGen Other	0.007***	-0.034***	-0.018***	-0.084***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,645,814	1,733,573	1,626,825	1,714,963

Labor force participation outcomes (average marginal effects)				
UK 2005-20	**Men (raw gap)**	**Women (raw gap)**	**Men (w/ controls)**	**Women (w/ controls)**
Black	0.022***	0.054***	-0.014***	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
South Asian	0.051***	-0.029***	-0.037***	-0.105***
	(0.002)	(0.003)	(0.003)	(0.004)
Asian	0.061***	0.086***	-0.007	0.007
	(0.006)	(0.009)	(0.009)	(0.010)
Mixed	0.019***	0.011**	-0.032***	-0.038***
	(0.004)	(0.005)	(0.005)	(0.005)
Other (incl. Arabs)	0.006	0.000	-0.047***	-0.065***
	(0.008)	(0.010)	(0.009)	(0.011)
White Immigrant	0.042***	0.027***	0.012***	-0.025***
	(0.001)	(0.001)	(0.001)	(0.001)
Black Immigrant	0.016***	-0.026***	-0.034***	-0.083***
	(0.003)	(0.003)	(0.003)	(0.003)
South Asian Immigrant	0.028***	-0.245***	-0.042***	-0.295***
	(0.002)	(0.003)	(0.002)	(0.003)
Asian Immigrant	0.019***	-0.077***	-0.057***	-0.151***
	(0.003)	(0.004)	(0.004)	(0.004)
Mixed Immigrant	0.021***	-0.001	-0.030***	-0.062***
	(0.007)	(0.008)	(0.008)	(0.009)
Other Immigrant	-0.021***	-0.161***	-0.107***	-0.238***
	(0.003)	(0.004)	(0.004)	(0.004)
Observations	1,167,881	1,280,163	1,167,881	1,280,163

Stars denote statistical significance at the 1% level (***), 5% level (**) and 10% level (*). Ages 16-64. Controls include age, age squared, education (level and field for France, age left education for the UK), marital (UK) or cohabitation (France) status, number of children (France), and reference year.

5.1.2 Employment

Overall, second-generation African or Black men (and Maghrebin men in France) tend to have the worst employment outcomes in all three countries (relative to native/white men), meaning the marginal effect of being Black or of African descent on gaining employment as a man is consistently among the most negative – and these marginal effects are all statistically significant at the 1% level. For instance, in France and the UK, even after controlling for age, education, experience and reference year, second-generation African or Black men are 7-8 percentage points less likely to be employed relative to their native or white counterparts, and in Germany they are 16 percentage points less likely to be employed than their native counterparts.

Interestingly, in the models that include controls only for education (level and field of study for France and Germany, age left education for the UK), the gaps do not narrow significantly – meaning education does not explain away the majority of the employment gaps. In the UK, the employment gaps for all racial groups widen when education controls are added.

Employment outcomes (average marginal effects)						
FRANCE 2005-20	**Men (raw gap)**	**Women (raw gap)**	**Men (educ controls)**	**Women (educ controls)**	**Men (all controls)**	**Women (all controls)**
SecGen African	-0.137***	-0.103***	-0.126***	-0.105***	-0.067***	-0.045***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
SecGen Maghreb	-0.129***	-0.101***	-0.116***	-0.098***	-0.096***	-0.071***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SecGen MidEast	-0.120***	-0.111***	-0.107***	-0.111***	-0.051***	-0.047***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
SecGen Asian	-0.065***	-0.012*	-0.067***	-0.021***	-0.032***	0.009*
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)
SecGen Other	-0.009***	-0.008***	-0.006***	-0.006***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FirstGen African	-0.114***	-0.124***	-0.117***	-0.118***	-0.114***	-0.103***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FirstGen Maghreb	-0.114***	-0.142***	-0.101***	-0.138***	-0.121***	-0.137***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
FirstGen MidEast	-0.094***	-0.142***	-0.094***	-0.144***	-0.101***	-0.145***
	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
FirstGen Asian	-0.010*	-0.017***	-0.011**	-0.016***	-0.028***	-0.029***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
FirstGen Other	-0.017***	-0.033***	-0.020***	-0.039***	-0.031***	-0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,262,521	1,209,064	1,248,351	1,198,493	1,248,351	1,198,493

Employment outcomes (average marginal effects)						
UK 2005-20	**Men (raw gap)**	**Women (raw gap)**	**Men (educ controls)**	**Women (educ controls)**	**Men (all controls)**	**Women (all controls)**
Black	-0.081***	-0.056***	-0.087***	-0.061***	-0.081***	-0.055***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
South Asian	-0.045***	-0.054***	-0.058***	-0.065***	-0.030***	-0.037***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Asian	-0.018***	-0.016**	-0.034***	-0.028***	-0.014**	-0.013**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Mixed	-0.064***	-0.047***	-0.069***	-0.050***	-0.041***	-0.029***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
Other (incl. Arabs)	-0.028***	-0.041***	-0.040***	-0.052***	-0.027***	-0.036***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
White Immigrant	0.012***	-0.004***	0.007***	-0.010***	0.006***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Black Immigrant	-0.055***	-0.066***	-0.076***	-0.077***	-0.082***	-0.079***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
South Asian Immigrant	0.001	-0.062***	-0.009***	-0.076***	-0.016***	-0.077***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Asian Immigrant	0.002	-0.028***	-0.009***	-0.041***	-0.013***	-0.044***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mixed Immigrant	-0.021***	-0.037***	-0.032***	-0.048***	-0.032***	-0.047***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
Other Immigrant	-0.030***	-0.058***	-0.046***	-0.074***	-0.046***	-0.072***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Observations	1,001,129	951,591	1,001,129	951,591	1,001,129	951,591

Employment outcomes (average marginal effects)						
GERMANY 2021	**Men (raw gap)**	**Women (raw gap)**	**Men (educ controls)**	**Women (educ controls)**	**Men (all controls)**	**Women (all controls)**
SecGen African	-0.260***	-0.157***	-0.202***	-0.101*	-0.157***	-0.072
	(0.059)	(0.060)	(0.056)	(0.055)	(0.051)	(0.052)
SecGen MidEast	-0.133***	-0.142***	-0.085***	-0.076***	-0.024	-0.030*
	(0.021)	(0.022)	(0.019)	(0.020)	(0.016)	(0.018)
SecGen Asian	-0.175***	-0.047	-0.137***	-0.028	-0.105***	-0.021
	(0.035)	(0.032)	(0.032)	(0.031)	(0.030)	(0.029)
SecGen LatAm	-0.147***	-0.056	-0.119**	-0.038	-0.099**	-0.019
	(0.055)	(0.059)	(0.052)	(0.056)	(0.048)	(0.052)
SecGenOther	-0.097***	-0.103***	-0.065***	-0.066***	-0.053***	-0.066***
	(0.010)	(0.011)	(0.009)	(0.010)	(0.009)	(0.010)
FirstGen African	-0.107***	-0.177***	-0.070**	-0.130***	-0.117***	-0.188***
	(0.030)	(0.040)	(0.028)	(0.037)	(0.029)	(0.038)
FirstGen MidEast	-0.103***	-0.166***	-0.079***	-0.138***	-0.123***	-0.183***
	(0.011)	(0.013)	(0.010)	(0.012)	(0.011)	(0.013)
FirstGen Asian	-0.105***	-0.238***	-0.096***	-0.216***	-0.120***	-0.252***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
FirstGen LatAm	-0.024	-0.081***	-0.037	-0.091***	-0.057*	-0.131***
	(0.032)	(0.030)	(0.033)	(0.030)	(0.033)	(0.030)
FirstGen Other	-0.027***	-0.095***	-0.012	-0.060***	-0.051***	-0.100***
	(0.008)	(0.009)	(0.007)	(0.009)	(0.008)	(0.009)
Observations	51,671	51,980	51,438	51,662	51,438	51,662

Stars denote statistical significance at the 1% level (***), 5% level (**) and 10% level (*)

Ages 16-64. Controls include age (for France and Germany), education (level and field for France and Germany, age left education for the UK), experience (derived using age and age left education), and reference year.

Focusing on the models with all controls, Middle Eastern and North African (Maghrebin) men also exhibit some of the worst employment outcomes relative to the native populations in these countries. In France, controlling for education, age, experience and year, second-generation men from the Maghreb are 10 percentage points less likely to gain employment than their native counterparts, while men of Middle Eastern descent are 5 percentage points less likely. In the UK, Arab men are captured alongside other racial groups and together are around 3 percentage points less likely to be in employment than their white counterparts. In both of these countries, the marginal effects are statistically significant at the 1% level. In Germany, that gap is much smaller at around 2.5 percentage points after controlling for age, education and experience, and is not statistically significant.

While the relative rankings of the three countries differ by racial group, the UK tends to have consistently narrower racial employment gaps compared to Germany and France (with the exception of Black men and women, which tend to fare worse than in France when we add controls for education, age, experience and year).

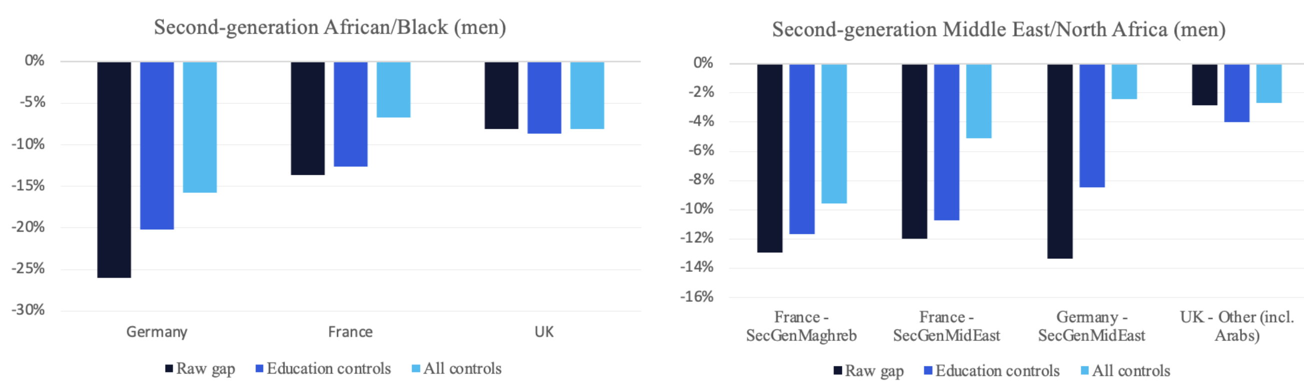

Figure 1: Raw racial employment gaps are largest in Germany and France

5.1.3 Historical trends

Trends over time have generally been improving, with the exception of second-generation Middle Eastern men and second-generation African women in France, who have seen their percentage point gaps in employment probabilities relative to natives widen over time. In France, the percentage point gaps in employment probabilities remain largest for second-generation men (and women) from Africa, the Maghreb and Middle East, while in the UK the gaps remain largest for Black men and women, and for women of South Asian descent.

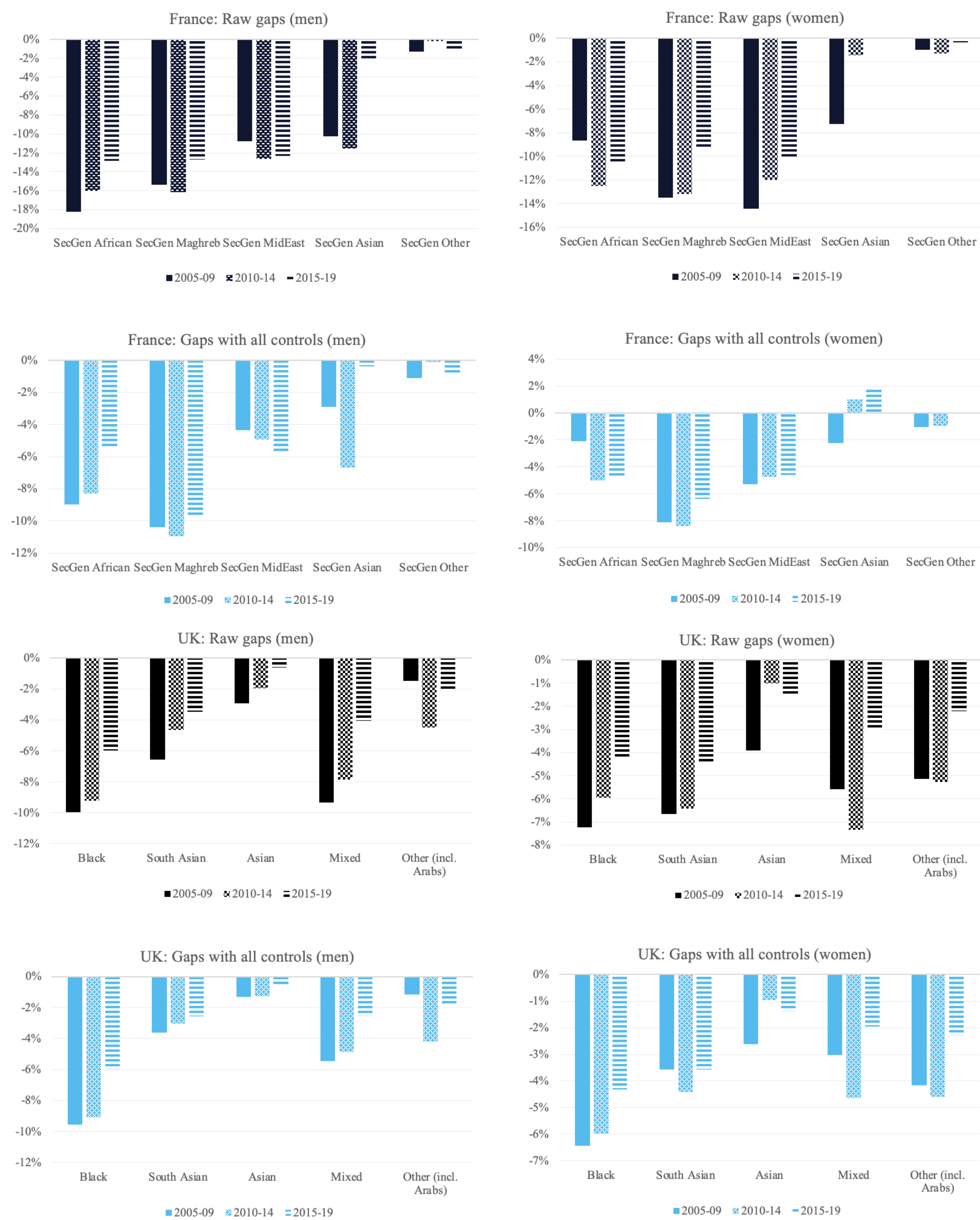

Figure 2: Most racial employment gaps have narrowed in France and the UK, with some exceptions

France employment outcomes (average marginal effects)						
	Men (raw gap)			Men (all controls)		
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
SecGen African	-0.182***	-0.160***	-0.129***	-0.090***	-0.083***	-0.055***
	(0.018)	(0.010)	(0.008)	(0.013)	(0.008)	(0.006)
SecGen Maghreb	-0.154***	-0.161***	-0.127***	-0.104***	-0.110***	-0.097***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
SecGen MidEast	-0.107***	-0.126***	-0.123***	-0.044***	-0.049***	-0.057***
	(0.019)	(0.011)	(0.011)	(0.013)	(0.008)	(0.008)
SecGen Asian	-0.103***	-0.115***	-0.023**	-0.029*	-0.067***	-0.004
	(0.023)	(0.013)	(0.010)	(0.015)	(0.010)	(0.008)
SecGen Other	-0.013***	-0.002	-0.012***	-0.011***	-0.001	-0.008***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FirstGen African	-0.133***	-0.136***	-0.093***	-0.125***	-0.143***	-0.090***
	(0.010)	(0.005)	(0.005)	(0.009)	(0.005)	(0.005)
FirstGen Maghreb	-0.115***	-0.136***	-0.103***	-0.120***	-0.141***	-0.112***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
FirstGen MidEast	-0.065***	-0.108***	-0.089***	-0.065***	-0.114***	-0.101***
	(0.012)	(0.007)	(0.007)	(0.011)	(0.007)	(0.007)
FirstGen Asian	-0.033**	-0.012	0.001	-0.043***	-0.031***	-0.018*
	(0.014)	(0.008)	(0.009)	(0.014)	(0.009)	(0.010)
FirstGen Other	-0.014***	-0.014***	-0.022***	-0.027***	-0.031***	-0.033***
	(0.004)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Observations	226,136	493,068	473,505	226,049	479,027	473,466

France employment outcomes (average marginal effects)						
	Women (raw gap)			Women (all controls)		
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
SecGen African	-0.087***	-0.125***	-0.106***	-0.021*	-0.050***	-0.047***
	(0.016)	(0.009)	(0.008)	(0.012)	(0.007)	(0.006)
SecGen Maghreb	-0.135***	-0.132***	-0.093***	-0.081***	-0.084***	-0.064***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
SecGen MidEast	-0.144***	-0.120***	-0.101***	-0.053***	-0.047***	-0.046***
	(0.022)	(0.012)	(0.010)	(0.016)	(0.009)	(0.008)
SecGen Asian	-0.073***	-0.014	-0.002	-0.022	0.010	0.018**
	(0.024)	(0.010)	(0.009)	(0.018)	(0.008)	(0.007)
SecGen Other	-0.010***	-0.013***	-0.003*	-0.011***	-0.010***	0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
FirstGen African	-0.124***	-0.138***	-0.120***	-0.110***	-0.112***	-0.098***
	(0.011)	(0.005)	(0.005)	(0.010)	(0.005)	(0.005)
FirstGen Maghreb	-0.130***	-0.154***	-0.145***	-0.123***	-0.140***	-0.142***
	(0.009)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)
FirstGen MidEast	-0.115***	-0.174***	-0.127***	-0.107***	-0.168***	-0.140***
	(0.021)	(0.011)	(0.010)	(0.020)	(0.011)	(0.010)
FirstGen Asian	-0.031*	-0.028***	-0.003	-0.046**	-0.038***	-0.014
	(0.017)	(0.010)	(0.009)	(0.018)	(0.010)	(0.009)
FirstGen Other	-0.019***	-0.028***	-0.042***	-0.036***	-0.043***	-0.057***
	(0.005)	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)
Observations	187,684	478,463	472,320	187,622	467,993	472,285

UK employment outcomes (average marginal effects)						
	Men (raw gap)			**Men (all controls)**		
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
Black	-0.100***	-0.092***	-0.060***	-0.096***	-0.091***	-0.060***
	(0.008)	(0.009)	(0.006)	(0.008)	(0.008)	(0.006)
South Asian	-0.066***	-0.047***	-0.035***	-0.036***	-0.030***	-0.026***
	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.003)
Asian	-0.029**	-0.019	-0.006	-0.013	-0.013	-0.006
	(0.014)	(0.013)	(0.009)	(0.012)	(0.012)	(0.008)
Mixed	-0.093***	-0.078***	-0.041***	-0.054***	-0.049***	-0.025***
	(0.010)	(0.009)	(0.006)	(0.008)	(0.008)	(0.005)
Other (incl. Arabs)	-0.015	-0.045***	-0.021**	-0.012	-0.042***	-0.018*
	(0.013)	(0.015)	(0.010)	(0.013)	(0.015)	(0.010)
White Immigrant	0.006***	0.019***	0.013***	0.000	0.010***	0.009***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Black Immigrant	-0.073***	-0.073***	-0.033***	-0.100***	-0.107***	-0.051***
	(0.006)	(0.006)	(0.004)	(0.007)	(0.007)	(0.005)
South Asian Immigrant	-0.012***	0.005*	0.005***	-0.028***	-0.030***	-0.007***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)
Asian Immigrant	-0.008*	0.013***	0.001	-0.027***	-0.006	-0.008**
	(0.005)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)
Mixed Immigrant	-0.025**	-0.001	-0.033***	-0.033***	-0.015	-0.041***
	(0.012)	(0.012)	(0.010)	(0.012)	(0.013)	(0.011)
Other Immigrant	-0.043***	-0.029***	-0.024***	-0.057***	-0.050***	-0.035***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)
Observations	335,267	302,420	318,098	335,267	302,420	318,098

UK employment outcomes (average marginal effects)						
	Women (raw gap)			**Women (all controls)**		
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
Black	-0.072***	-0.060***	-0.042***	-0.064***	-0.060***	-0.043***
	(0.007)	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)
South Asian	-0.067***	-0.064***	-0.045***	-0.036***	-0.044***	-0.036***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)
Asian	-0.039***	-0.010	-0.014	-0.026**	-0.009	-0.014
	(0.014)	(0.012)	(0.009)	(0.012)	(0.012)	(0.009)
Mixed	-0.056***	-0.073***	-0.030***	-0.030***	-0.046***	-0.020***
	(0.009)	(0.008)	(0.006)	(0.007)	(0.007)	(0.005)
Other (incl. Arabs)	-0.051***	-0.053***	-0.022*	-0.042***	-0.046***	-0.023**
	(0.015)	(0.015)	(0.011)	(0.014)	(0.014)	(0.011)
White Immigrant	-0.001	-0.008***	-0.008***	-0.006***	-0.016***	-0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Black Immigrant	-0.065***	-0.086***	-0.054***	-0.076***	-0.102***	-0.065***
	(0.005)	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)
South Asian Immigrant	-0.062***	-0.080***	-0.049***	-0.071***	-0.099***	-0.064***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Asian Immigrant	-0.039***	-0.024***	-0.026***	-0.051***	-0.042***	-0.039***
	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)
Mixed Immigrant	-0.039***	-0.062***	-0.024***	-0.045***	-0.074***	-0.033***
	(0.011)	(0.013)	(0.009)	(0.012)	(0.014)	(0.010)
Other Immigrant	-0.075***	-0.063***	-0.041***	-0.083***	-0.082***	-0.055***
	(0.006)	(0.007)	(0.005)	(0.007)	(0.007)	(0.006)
Observations	310,154	286,261	309,252	310,154	286,261	309,252

5.2 Average earnings (OLS) results

5.2.1 Pooled OLS

The raw earnings/wage gap is widest for second-generation African/Black men in both France and the UK (Germany is excluded from this part of the study due to data constraints). While in France, the gap narrows considerably when we control for other factors that typically influence wage outcomes (age, experience, education, occupation, sector, industry, etc.), in the UK, the average wage gap between Black men and white men widens after adding controls.[3] It increases considerably when we add exogenous controls (for education, experience and reference year) then narrows slightly when we add the sectoral, occupation, industry and full-time status controls (yet remains larger than the raw gap). According to the theories of statistical discrimination, this could be an indication that Black men face high signaling costs in the British labor market: in other words, on average, a Black man in the UK has to overcompensate on qualifications to be given an equal opportunity to a white man with less qualifications. This also appears to be the case for South Asian men in the UK, where adding controls leads to a wider gap.

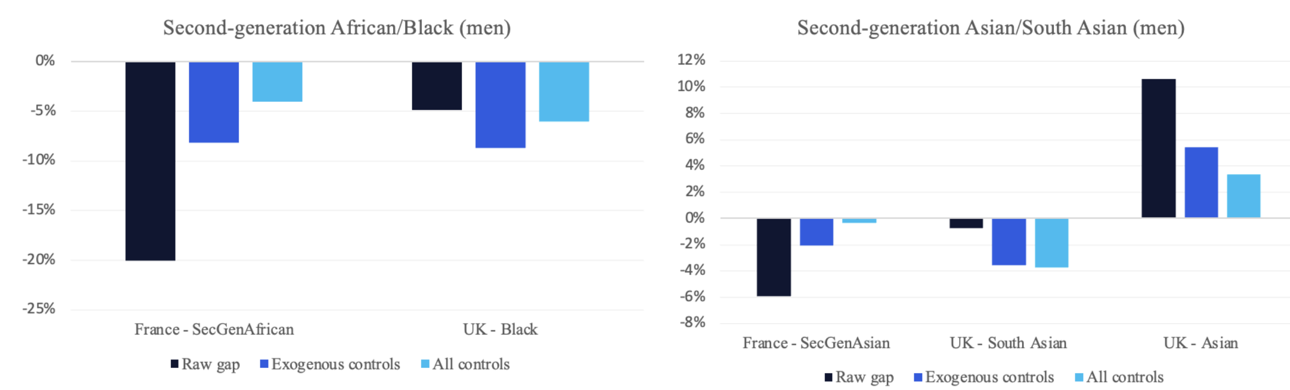

Figure 3: Racial earnings gaps in France narrow with education controls, but widen in UK for some

[3]For the UK, because I use 'age left education' as both the *education* control and to calculate *potential experience* by subtracting it from the 'age' variable, I cannot include all three covariates in my regression analyses. I therefore exclude the age controls.

Log earnings outcomes (OLS)						
FRANCE 2005-20	Men (raw gap)	Women (raw gap)	Men (exog controls)	Women (exog controls)	Men (all controls)	Women (all controls)
SecGen African	-0.224***	-0.080***	-0.086***	0.001	-0.042***	-0.012
	(0.015)	(0.015)	(0.012)	(0.013)	(0.010)	(0.011)
SecGen Maghreb	-0.108***	-0.053***	-0.061***	-0.019**	-0.034***	-0.019***
	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)
SecGen MidEast	-0.138***	-0.114***	0.030*	-0.019	0.048***	0.003
	(0.020)	(0.021)	(0.016)	(0.018)	(0.014)	(0.015)
SecGen Asian	-0.061***	0.108***	-0.023	0.111***	-0.003	0.084***
	(0.021)	(0.023)	(0.017)	(0.020)	(0.015)	(0.017)
SecGen Other	0.012***	-0.015***	0.015***	-0.006	0.013***	-0.007*
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
FirstGen African	-0.191***	-0.186***	-0.255***	-0.164***	-0.195***	-0.123***
	(0.009)	(0.010)	(0.007)	(0.008)	(0.006)	(0.007)
FirstGen Maghreb	-0.111***	-0.180***	-0.200***	-0.193***	-0.147***	-0.145***
	(0.006)	(0.009)	(0.005)	(0.008)	(0.005)	(0.006)
FirstGen MidEast	-0.097***	-0.198***	-0.143***	-0.268***	-0.085***	-0.190***
	(0.013)	(0.020)	(0.011)	(0.018)	(0.010)	(0.015)
FirstGen Asian	0.039**	0.076***	-0.078***	0.011	-0.084***	-0.007
	(0.019)	(0.022)	(0.016)	(0.020)	(0.014)	(0.017)
FirstGen Other	0.071***	-0.038***	-0.011**	-0.102***	0.013***	-0.053***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Observations	325,056	334,592	321,673	331,869	319,495	330,033

Log wage outcomes (OLS)						
UK 2005-20	Men (raw gap)	Women (raw gap)	Men (exog controls)	Women (exog controls)	Men (all controls)	Women (all controls)
Black	-0.050***	0.118***	-0.091***	0.140***	-0.062***	0.050***
	(0.010)	(0.007)	(0.009)	(0.010)	(0.008)	(0.007)
South Asian	-0.008	0.072***	-0.036***	0.006	-0.038***	-0.011*
	(0.007)	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)
Asian	0.101***	0.197***	0.053***	0.116***	0.033**	0.036**
	(0.017)	(0.015)	(0.015)	(0.021)	(0.014)	(0.015)
Mixed	-0.022**	0.051***	0.003	0.064***	0.003	0.033***
	(0.010)	(0.008)	(0.009)	(0.011)	(0.008)	(0.008)
Other (incl. Arabs)	0.076***	0.098***	0.022	0.017	0.001	-0.014
	(0.020)	(0.017)	(0.017)	(0.023)	(0.015)	(0.016)
White Immigrant	-0.049***	-0.016***	-0.085***	-0.024***	-0.031***	-0.004*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Black Immigrant	-0.154***	-0.031***	-0.327***	-0.119***	-0.189***	-0.017***
	(0.007)	(0.005)	(0.006)	(0.008)	(0.005)	(0.005)
South Asian Immigrant	-0.055***	0.021***	-0.218***	-0.155***	-0.116***	-0.074***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)	(0.005)
Asian Immigrant	-0.105***	-0.007	-0.267***	-0.171***	-0.149***	-0.070***
	(0.007)	(0.006)	(0.007)	(0.009)	(0.006)	(0.006)
Mixed Immigrant	0.028*	0.076***	-0.067***	0.008	-0.022*	0.014
	(0.016)	(0.013)	(0.014)	(0.018)	(0.013)	(0.013)
Other Immigrant	-0.117***	-0.012*	-0.249***	-0.147***	-0.124***	-0.059***
	(0.007)	(0.007)	(0.006)	(0.010)	(0.006)	(0.007)
Observations	578,965	645,081	578,965	645,081	575,140	641,205

Stars denote statistical significance at the 1% level (***), 5% level (**) and 10% level (*)

Active population, ages 16-64. "Exogenous" controls include age (for France), education (level and field for France, age left education for the UK), experience (derived using age and age left education) and reference year. "All" controls adds industry, sector, occupation and full-time status to the list of "exogenous" controls.

Figure 4: Average log earnings and wage outcomes for France and the UK

In France, the raw gap in average earnings is 20% (equivalent to 22.4 log points) for second-generation African men, which narrows to 8% when controls are added for age, education, experience and reference year. In the UK, the raw wage gap is 5% for Black men, which widens to 9% when controls for education, experience and reference year are added. Although the gap narrows to 6% (6.2 log points) when additional controls are added for industry, sector, occupation and full-time status, it remains wider than the raw wage gap. In France, when all controls are added second-generation African men on average earn 4% less than their native counterparts.

5.2.2 Historical trends

While employment gaps have generally narrowed over time, the average earnings/wage gaps widened in the post-global financial crisis (GFC) period (2010-14) for second-generation African men in France and for Blacks and South Asian men in the UK. And although in most cases the gaps narrowed in the 2015-19 period, they remain wider than the pre-GFC period in some cases (for second-generation African men in France, for instance). The exhibit below shows the gaps with all controls for the racial/ethnic groups with the largest gaps in each country, while the tables that follow include the full results.

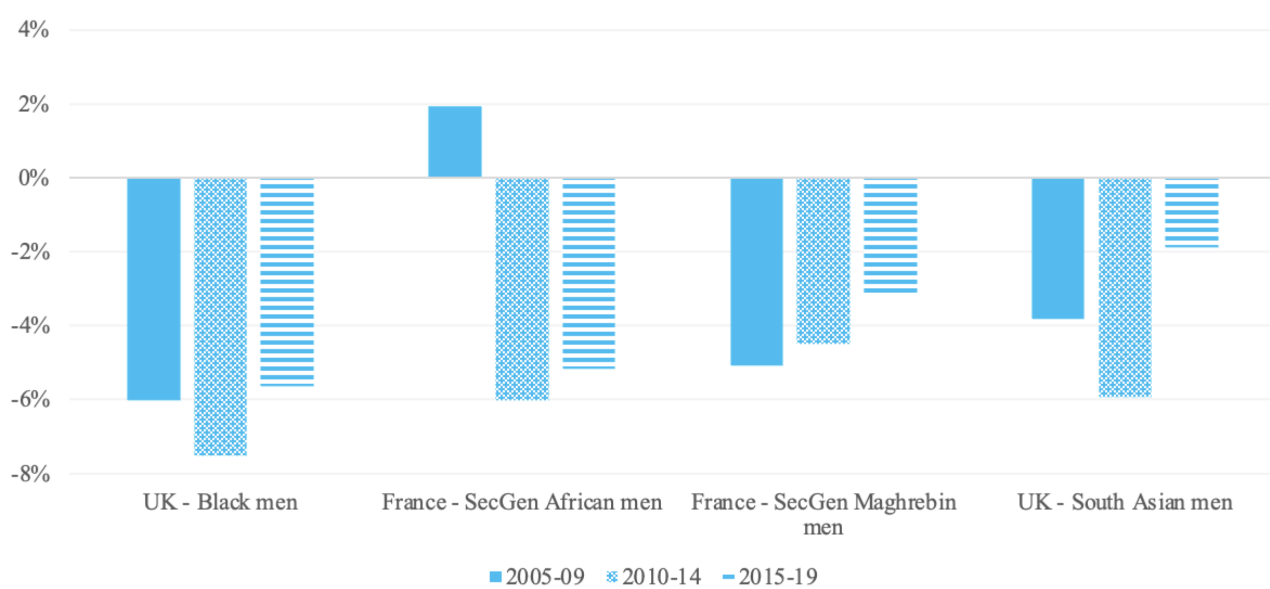

Figure 5: Average earnings/wage gaps widened for some in the post-GFC period, then narrowed

France earnings outcomes (OLS)									
	Men (raw gap)			Men (exogenous controls)			Men (all controls)		
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
SecGen African	-0.238***	-0.274***	-0.276***	-0.078**	-0.107***	-0.094***	0.019	-0.062***	-0.053***
	(0.040)	(0.026)	(0.022)	(0.034)	(0.021)	(0.018)	(0.030)	(0.018)	(0.016)
SecGen Maghreb	-0.164***	-0.166***	-0.122***	-0.076***	-0.070***	-0.065***	-0.052***	-0.046***	-0.032***
	(0.015)	(0.011)	(0.011)	(0.012)	(0.009)	(0.009)	(0.011)	(0.008)	(0.008)
SecGen MidEast	-0.060	-0.238***	-0.120***	0.031	-0.004	0.055**	0.052	0.033	0.060***
	(0.053)	(0.032)	(0.032)	(0.045)	(0.026)	(0.026)	(0.040)	(0.023)	(0.023)
SecGen Asian	-0.347***	-0.065*	-0.101***	-0.188***	0.016	-0.052**	-0.077*	0.026	-0.044*
	(0.056)	(0.035)	(0.033)	(0.047)	(0.029)	(0.026)	(0.043)	(0.025)	(0.023)
SecGen Other	0.020**	0.014**	0.001	0.016**	0.011**	0.017***	0.010*	0.008	0.017***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
FirstGen African	-0.163***	-0.230***	-0.208***	-0.244***	-0.295***	-0.240***	-0.183***	-0.219***	-0.184***
	(0.023)	(0.014)	(0.013)	(0.020)	(0.012)	(0.011)	(0.017)	(0.010)	(0.010)
FirstGen Maghreb	-0.104***	-0.145***	-0.126***	-0.178***	-0.223***	-0.203***	-0.138***	-0.162***	-0.148***
	(0.015)	(0.010)	(0.010)	(0.013)	(0.009)	(0.008)	(0.011)	(0.008)	(0.007)
FirstGen MidEast	-0.052	-0.127***	-0.105***	-0.122***	-0.147***	-0.146***	-0.080***	-0.086***	-0.086***
	(0.033)	(0.020)	(0.023)	(0.028)	(0.018)	(0.018)	(0.025)	(0.016)	(0.016)
FirstGen Asian	-0.026	0.015	0.083**	-0.116***	-0.100***	-0.049*	-0.120***	-0.111***	-0.049**
	(0.042)	(0.029)	(0.033)	(0.035)	(0.025)	(0.027)	(0.031)	(0.022)	(0.024)
FirstGen Other	0.090***	0.081***	0.033***	0.012	0.005	-0.036***	0.026***	0.026***	-0.007
	(0.013)	(0.009)	(0.009)	(0.011)	(0.007)	(0.007)	(0.010)	(0.006)	(0.006)
Observations	60,542	125,611	121,905	60,519	122,258	121,898	60,115	121,374	121,142

France earnings outcomes (OLS)									
	Women (raw gap)			Women (exogenous controls)			Women (all controls)		
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
SecGen African	-0.065	-0.129***	-0.131***	0.013	-0.006	-0.003	-0.031	-0.024	-0.006
	(0.047)	(0.027)	(0.022)	(0.043)	(0.024)	(0.019)	(0.036)	(0.020)	(0.016)
SecGen Maghreb	-0.097***	-0.092***	-0.079***	-0.013	-0.008	-0.029***	-0.021	-0.017*	-0.020**
	(0.018)	(0.012)	(0.011)	(0.017)	(0.011)	(0.010)	(0.014)	(0.009)	(0.008)
SecGen MidEast	-0.197***	-0.151***	-0.081***	-0.049	-0.027	0.006	-0.038	-0.008	0.030
	(0.062)	(0.035)	(0.031)	(0.056)	(0.031)	(0.027)	(0.047)	(0.026)	(0.023)
SecGen Asian	-0.045	0.099***	0.066*	0.064	0.123***	0.094***	0.088	0.086***	0.069***
	(0.073)	(0.038)	(0.034)	(0.066)	(0.033)	(0.030)	(0.055)	(0.028)	(0.025)
SecGen Other	-0.025**	-0.026***	-0.009	-0.024**	-0.009	0.002	-0.019**	-0.011**	0.002
	(0.011)	(0.007)	(0.007)	(0.010)	(0.006)	(0.006)	(0.008)	(0.005)	(0.005)
FirstGen African	-0.203***	-0.220***	-0.195***	-0.201***	-0.178***	-0.149***	-0.147***	-0.145***	-0.100***
	(0.029)	(0.015)	(0.014)	(0.026)	(0.014)	(0.013)	(0.022)	(0.012)	(0.011)
FirstGen Maghreb	-0.098***	-0.223***	-0.201***	-0.130***	-0.195***	-0.149***	-0.094***	-0.156***	-0.155***
	(0.024)	(0.014)	(0.013)	(0.022)	(0.013)	(0.012)	(0.018)	(0.011)	(0.010)
FirstGen MidEast	-0.091	-0.185***	-0.266***	-0.152***	-0.228***	-0.327***	-0.028	-0.191***	-0.229***
	(0.060)	(0.032)	(0.031)	(0.055)	(0.029)	(0.027)	(0.046)	(0.024)	(0.023)
FirstGen Asian	0.079	0.047	0.070**	0.023	0.006	0.014	0.023	-0.029	-0.001
	(0.062)	(0.035)	(0.035)	(0.057)	(0.032)	(0.030)	(0.047)	(0.027)	(0.026)
FirstGen Other	-0.021	-0.072***	-0.036***	-0.078***	-0.104***	-0.110***	-0.046***	-0.057***	-0.050***
	(0.016)	(0.009)	(0.009)	(0.015)	(0.008)	(0.007)	(0.012)	(0.007)	(0.006)
Observations	53,125	131,942	130,890	53,111	129,245	130,879	52,794	128,526	130,199

UK wage outcomes (OLS)									
		Men			**Men**			**Men**	
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
Black	-0.034**	-0.080***	-0.059***	-0.093***	-0.101***	-0.089***	-0.062***	-0.078***	-0.058***
	(0.017)	(0.018)	(0.016)	(0.015)	(0.016)	(0.014)	(0.013)	(0.014)	(0.013)
South Asian	-0.053***	-0.056***	0.009	-0.043***	-0.066***	-0.007	-0.039***	-0.061***	-0.019**
	(0.014)	(0.012)	(0.011)	(0.012)	(0.011)	(0.010)	(0.011)	(0.010)	(0.009)
Asian	0.005	0.048	0.168***	0.008	0.019	0.117***	-0.007	0.012	0.081***
	(0.033)	(0.031)	(0.028)	(0.029)	(0.027)	(0.025)	(0.026)	(0.024)	(0.023)
Mixed	-0.087***	0.003	-0.046***	-0.027	0.032**	0.005	-0.021	0.013	0.012
	(0.021)	(0.018)	(0.016)	(0.018)	(0.016)	(0.014)	(0.016)	(0.014)	(0.013)
Other (incl. Arabs)	0.004	0.092**	0.082***	-0.046	0.038	0.055*	-0.050*	0.018	0.021
	(0.037)	(0.037)	(0.031)	(0.032)	(0.033)	(0.028)	(0.029)	(0.029)	(0.025)
White Immigrant	-0.055***	-0.006	-0.032***	-0.060***	-0.094***	-0.115***	-0.027***	-0.030***	-0.041***
	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
Black Immigrant	-0.152***	-0.154***	-0.182***	-0.324***	-0.323***	-0.334***	-0.178***	-0.184***	-0.201***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)
South Asian Immigrant	-0.103***	-0.069***	-0.037***	-0.248***	-0.232***	-0.192***	-0.137***	-0.128***	-0.096***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Asian Immigrant	-0.122***	-0.147***	-0.085***	-0.307***	-0.300***	-0.222***	-0.186***	-0.164***	-0.117***
	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)
Mixed Immigrant	-0.021	0.048	0.035	-0.100***	-0.048*	-0.062**	-0.047**	-0.008	-0.016
	(0.028)	(0.030)	(0.027)	(0.024)	(0.026)	(0.024)	(0.022)	(0.023)	(0.022)
Other Immigrant	-0.167***	-0.100***	-0.098***	-0.298***	-0.247***	-0.223***	-0.169***	-0.111***	-0.102***
	(0.012)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Observations	192,888	174,156	185,540	192,888	174,156	185,540	191,729	173,070	184,156

UK wage outcomes (OLS)									
		Women			**Women**			**Women**	
	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19	2005-09	2010-14	2015-19
Black	0.120***	0.145***	0.078***	0.072***	0.089***	0.046***	0.035***	0.064***	0.036***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
South Asian	0.065***	0.034***	0.054***	0.035***	0.007	0.019**	0.020**	-0.004	0.009
	(0.012)	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
Asian	0.246***	0.158***	0.146***	0.133***	0.055**	0.069***	0.094***	0.041*	0.032
	(0.031)	(0.028)	(0.024)	(0.027)	(0.026)	(0.022)	(0.024)	(0.022)	(0.020)
Mixed	0.029*	0.024	0.030**	0.053***	0.051***	0.051***	0.050***	0.031***	0.041***
	(0.016)	(0.015)	(0.013)	(0.015)	(0.013)	(0.012)	(0.013)	(0.012)	(0.010)
Other (incl. Arabs)	0.091***	0.098***	0.060**	0.042	0.025	0.006	0.014	-0.008	-0.018
	(0.031)	(0.029)	(0.028)	(0.028)	(0.026)	(0.026)	(0.024)	(0.023)	(0.023)
White Immigrant	-0.018***	0.026***	0.000	-0.029***	-0.080***	-0.095***	-0.011***	-0.018***	-0.032***
	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Black Immigrant	0.006	-0.047***	-0.079***	-0.105***	-0.166***	-0.176***	-0.028***	-0.068***	-0.067***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
South Asian Immigrant	0.023**	0.009	-0.001	-0.105***	-0.128***	-0.113***	-0.051***	-0.051***	-0.048***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
Asian Immigrant	-0.033***	-0.028**	-0.020**	-0.195***	-0.187***	-0.139***	-0.099***	-0.085***	-0.052***
	(0.012)	(0.011)	(0.010)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)
Mixed Immigrant	0.087***	0.083***	0.039*	-0.012	-0.001	-0.043**	0.007	0.018	0.007
	(0.023)	(0.024)	(0.022)	(0.021)	(0.022)	(0.020)	(0.018)	(0.019)	(0.018)
Other Immigrant	-0.015	-0.019	-0.023**	-0.155***	-0.162***	-0.149***	-0.075***	-0.070***	-0.051***
	(0.012)	(0.013)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)
Observations	211,480	193,513	206,636	211,480	193,513	206,636	210,421	192,453	205,163

5.3 Distributional earnings (quantile) results

The pooled quantile regressions impose the restriction that the returns to included labor market characteristics are the same for all racial/ethnic groups. The estimated racial/ethnic coefficients thus indicate the extent to which the racial gap remains unexplained at the various quantiles when we control for individual differences in various combinations of characteristics. The objective of this part of the research is to determine whether there is a racial 'glass ceiling' in the French and British labor markets. By a racial glass ceiling, I mean a phenomenon whereby Black men do well in the labor market up to a point after which there is an effective limit on their prospects. The existence of a racial glass ceiling would imply that Black men's wages fall behind white men's more at the top of the wage distribution than at the middle or bottom. In other words, the average wage gap is mainly attributed to the gap at the top of the wage distribution.

We start by looking at the raw gaps along the income distribution. In the UK, being a Black man has a very negative effect on wages at the 90th percentile (i.e., for higher-income earners) of the income distribution of men, and has no effect at the 10th percentile of the income distribution for men (i.e., among the low-income earners). (Notably, when we start to add controls to the model there is an effect at the lower-end of the income distribution as well.) The effect on wages from being Black becomes more negative as we move up the income distribution, indicating a 'glass ceiling' effect for Black men in the British labor market.

In France, being a second-generation African man has a very negative effect on earnings at the 10th percentile of the income distribution of men. That negative effect nearly halves at the 25th percentile and narrows slightly more through the top of the income distribution. The same pattern holds for second-generation African women (when examining the income distribution of women alone), although the magnitude of the negative effect on earnings is smaller (roughly half the size of the negative effect of being a second-generation Black man relative to a native man). The raw earnings gap for second-generation African men in France is much larger than the raw wage gap for Black men in the UK; however, this is not the case once we start adding controls for education and other characteristics.

Once we start adding controls, the interpretation of our results becomes conditional on the distribution of other attributes. Conditional quantile coefficients tell us about effects on distributions and not individuals: if being Black lowers the lower decile of the wage distribution, this does not necessarily mean that someone who would have been poor (i.e., at the lower decile, without being Black) is now poorer for being Black. It means those who are poor in the regime while being Black are poorer than the poor would be in a regime without being Black (Angrist and Pischke 2009). We can only say that the poor – defined as the group in the bottom 10% of the wage distribution, whoever they may be – are worse off if they are Black (Angrist and Pischke 2009).

In the UK, the conditional quantile that controls for education, experience, sector, occupation, industry, etc. shows a similar pattern for Black men: the negative impact of being a Black man on wages increases as we move up the income distribution. In other words, the group in the top 90% of the wage distribution – whoever they may be – are worse off if they are Black. And the effect is larger there than the effect of being Black for the group that is in the 50th percentile of the wage distribution (see exhibit below). Effectively, this widening wage gap can be interpreted as a 'glass ceiling' effect of sorts.

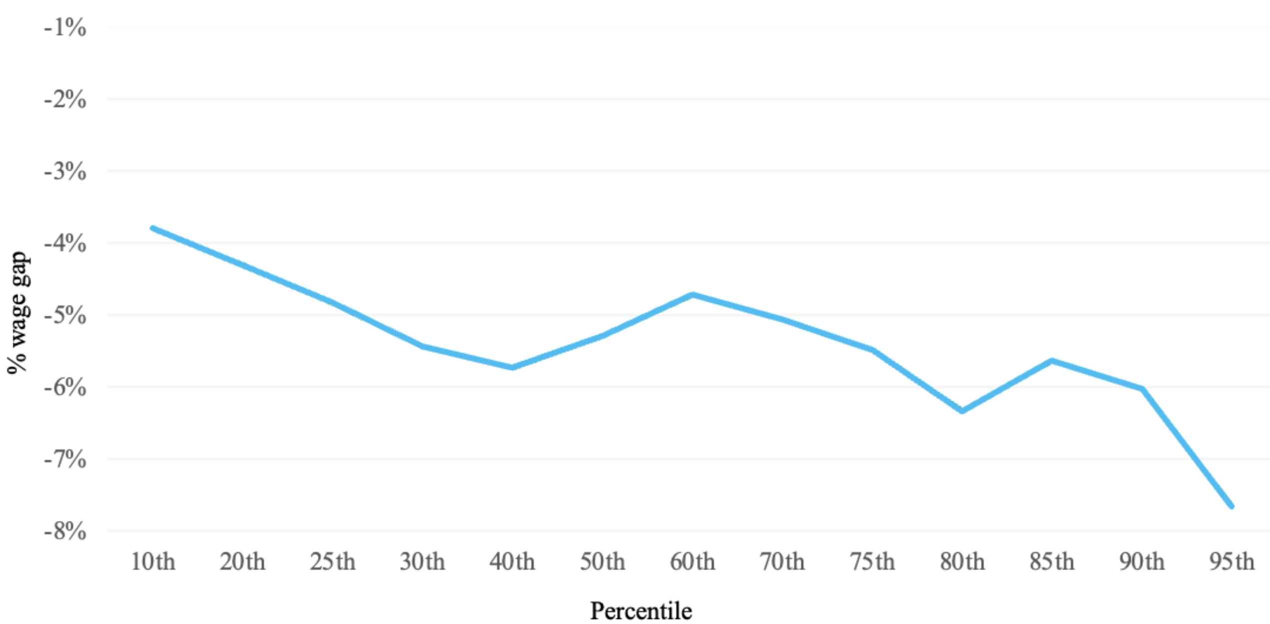

Figure 6: UK wage gap with all controls - Black men

In France, when we control for education, experience, sector, occupation, industry, etc., the effect of being a second-generation African man on earnings decreases substantially for all groups across the conditional earnings distribution. Yet there remains a negative effect throughout. We see a roughly similar effect from being a second-generation Maghrebin man. The consistency of the effect on earnings throughout the distribution means there is no 'glass ceiling' effect for racial/ethnic minorities in the French labor market – just a small, persistent earnings differential throughout the income distribution.

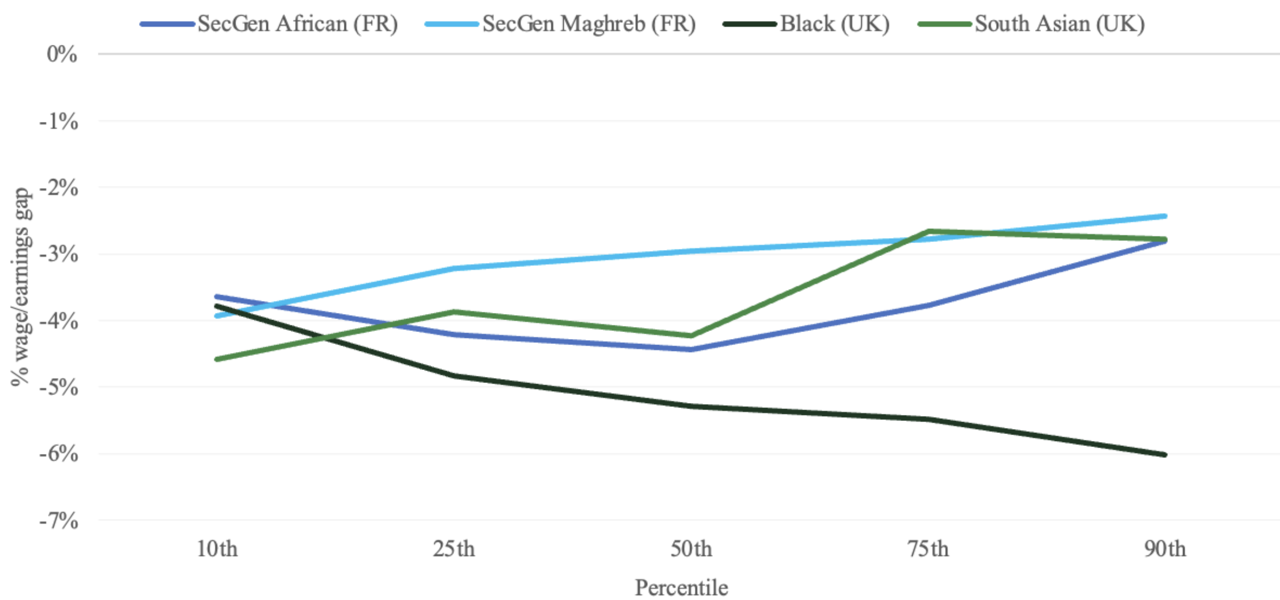

Figure 7: Earnings/wage gaps with controls - men

The advantage of a pooled quantile regression in this context is that we can attach standard errors to the estimated racial gaps at the various percentiles. The tables that follow include the full results with bootstrapped standard errors. The covariates used in the 'exogenous' and 'all' controls models are identical to those used in the OLS regressions (namely, 'exogenous' controls include age, education, experience and reference year, while 'all' also includes sector, industry, occupation and full-time status).

	Log monthly earnings outcomes (raw)					Log monthly earnings outcomes (w/ exogenous controls)					Log monthly earnings outcomes (w/ all controls)				
FRANCE (men)															
2005-20	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
SecGen African	-0.413***	-0.197***	-0.184***	-0.189***	-0.149***	-0.137***	-0.069***	-0.075***	-0.055***	-0.040**	-0.030**	-0.046***	-0.049***	-0.041***	-0.026
	(0.052)	(0.019)	(0.012)	(0.022)	(0.031)	(0.040)	(0.014)	(0.012)	(0.014)	(0.021)	(0.012)	(0.008)	(0.012)	(0.013)	(0.020)
SecGen Maghreb	-0.112***	-0.074***	-0.083***	-0.123***	-0.144***	-0.080***	-0.055***	-0.048***	-0.049***	-0.039***	-0.041***	-0.032***	-0.032***	-0.030***	-0.022***
	(0.019)	(0.001)	(0.008)	(0.007)	(0.009)	(0.011)	(0.005)	(0.004)	(0.006)	(0.008)	(0.007)	(0.005)	(0.004)	(0.005)	(0.008)
SecGen MidEast	-0.306***	-0.124***	-0.119***	-0.107***	-0.084***	0.009	0.023	0.026*	0.031	0.070**	0.049**	0.029**	0.028*	0.056***	0.101***
	(0.079)	(0.026)	(0.019)	(0.027)	(0.031)	(0.029)	(0.019)	(0.015)	(0.021)	(0.031)	(0.022)	(0.014)	(0.016)	(0.018)	(0.026)
SecGen Asian	-0.204**	-0.074***	-0.019	0.004	0.025	-0.032	-0.028*	-0.016	-0.015	0.001	0.001	0.005	-0.002	-0.023	-0.012
	(0.084)	(0.023)	(0.027)	(0.028)	(0.038)	(0.028)	(0.017)	(0.018)	(0.018)	(0.035)	(0.021)	(0.016)	(0.011)	(0.017)	(0.030)
SecGen Other	0.014	0.013**	0.030***	0.005**	-0.008	0.006	0.011***	0.017***	0.020***	0.024***	0.011***	0.015***	0.015***	0.015***	0.017***
	(0.009)	(0.005)	(0.006)	(0.002)	(0.009)	(0.005)	(0.003)	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)
FirstGen African	-0.204***	-0.138***	-0.184***	-0.218***	-0.212***	-0.340***	-0.245***	-0.212***	-0.186***	-0.176***	-0.203***	-0.182***	-0.157***	-0.163***	-0.155***
	(0.031)	(0.013)	(0.006)	(0.004)	(0.018)	(0.025)	(0.010)	(0.008)	(0.007)	(0.012)	(0.011)	(0.008)	(0.007)	(0.007)	(0.009)
FirstGen Maghreb	-0.062***	-0.074***	-0.119***	-0.146***	-0.149***	-0.242***	-0.194***	-0.168***	-0.158***	-0.167***	-0.143***	-0.142***	-0.129***	-0.127***	-0.140***
	(0.013)	(0.003)	(0.003)	(0.011)	(0.007)	(0.010)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.007)
FirstGen MidEast	-0.125**	-0.121***	-0.119***	-0.123***	0.048	-0.286***	-0.160***	-0.106***	-0.061***	-0.074***	-0.120***	-0.098***	-0.073***	-0.048***	-0.036**
	(0.049)	(0.015)	(0.014)	(0.017)	(0.049)	(0.042)	(0.014)	(0.009)	(0.010)	(0.020)	(0.013)	(0.010)	(0.009)	(0.016)	(0.015)
FirstGen Asian	0.034	0.000	0.020	0.031	0.081*	-0.096***	-0.101***	-0.084***	-0.075***	-0.036*	-0.110***	-0.097***	-0.074***	-0.088***	-0.062***
	(0.029)	(0.015)	(0.021)	(0.022)	(0.047)	(0.024)	(0.023)	(0.016)	(0.018)	(0.022)	(0.018)	(0.015)	(0.012)	(0.020)	(0.016)
FirstGen Other	0.019	0.015**	0.052***	0.086***	0.195***	-0.104***	-0.054***	-0.009**	0.033***	0.104***	-0.039***	-0.020***	0.006	0.043***	0.100***
	(0.012)	(0.007)	(0.005)	(0.010)	(0.013)	(0.010)	(0.006)	(0.005)	(0.006)	(0.010)	(0.007)	(0.004)	(0.004)	(0.006)	(0.009)

	Log monthly earnings outcomes (raw)					Log monthly earnings outcomes (w/ exogenous controls)					Log monthly earnings outcomes (w/ all controls)				
FRANCE (women)															
2005-20	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
SecGen African	-0.154***	-0.056*	-0.069***	-0.060***	-0.036*	-0.063*	-0.003	0.017*	0.041***	0.040***	0.007	-0.014	0.001	0.013	0.012
	(0.035)	(0.034)	(0.011)	(0.016)	(0.022)	(0.037)	(0.020)	(0.010)	(0.010)	(0.013)	(0.018)	(0.011)	(0.007)	(0.011)	(0.013)
SecGen Maghreb	-0.074***	-0.037***	-0.060***	-0.069***	-0.069***	-0.055***	-0.024***	-0.009*	-0.008	-0.009	-0.020***	-0.020***	-0.018***	-0.013***	-0.006
	(0.018)	(0.014)	(0.007)	(0.009)	(0.012)	(0.017)	(0.009)	(0.005)	(0.005)	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)	(0.006)
SecGen MidEast	-0.332***	-0.145***	-0.120***	-0.051	0.072**	-0.110	-0.022	0.009	0.026*	0.055**	-0.004	-0.014	0.021	0.036**	0.067***
	(0.090)	(0.036)	(0.027)	(0.033)	(0.035)	(0.085)	(0.028)	(0.017)	(0.015)	(0.021)	(0.021)	(0.018)	(0.018)	(0.016)	(0.023)
SecGen Asian	0.133***	0.064***	0.059*	0.089***	0.216***	0.108**	0.093***	0.084***	0.088***	0.101***	0.061***	0.075***	0.079***	0.075***	0.089***
	(0.047)	(0.025)	(0.031)	(0.028)	(0.039)	(0.050)	(0.024)	(0.012)	(0.016)	(0.021)	(0.020)	(0.014)	(0.014)	(0.015)	(0.018)
SecGen Other	-0.054***	-0.014***	0.000	0.000	-0.002	-0.035***	-0.009*	0.003	0.007**	0.008*	-0.010**	-0.005	-0.002	0.003	0.003
	(0.013)	(0.002)	(0.003)	(0.002)	(0.006)	(0.011)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)
FirstGen African	-0.193***	-0.215***	-0.155***	-0.223***	-0.203***	-0.251***	-0.224***	-0.134***	-0.100***	-0.112***	-0.109***	-0.105***	-0.110***	-0.106***	-0.109***
	(0.027)	(0.017)	(0.010)	(0.005)	(0.016)	(0.026)	(0.012)	(0.008)	(0.007)	(0.011)	(0.010)	(0.007)	(0.005)	(0.007)	(0.009)
FirstGen Maghreb	-0.336***	-0.238***	-0.143***	-0.153***	-0.073***	-0.411***	-0.267***	-0.140***	-0.097***	-0.088***	-0.161***	-0.137***	-0.120***	-0.091***	-0.092***
	(0.024)	(0.025)	(0.006)	(0.012)	(0.014)	(0.020)	(0.014)	(0.007)	(0.008)	(0.009)	(0.013)	(0.007)	(0.006)	(0.007)	(0.009)
FirstGen MidEast	-0.544***	-0.358***	-0.164***	-0.111***	0.054	-0.653***	-0.346***	-0.185***	-0.106***	-0.079***	-0.251***	-0.183***	-0.118***	-0.111***	-0.090***
	(0.066)	(0.053)	(0.028)	(0.023)	(0.039)	(0.060)	(0.044)	(0.020)	(0.021)	(0.024)	(0.034)	(0.025)	(0.015)	(0.016)	(0.024)
FirstGen Asian	0.133**	0.056***	0.000	0.049*	0.186***	-0.021	-0.009	-0.024	0.028	0.058	-0.052**	-0.051***	-0.030*	0.027	0.057
	(0.061)	(0.018)	(0.020)	(0.028)	(0.040)	(0.036)	(0.026)	(0.018)	(0.020)	(0.044)	(0.023)	(0.015)	(0.016)	(0.018)	(0.042)
FirstGen Other	-0.189***	-0.110***	-0.040***	0.009	0.141***	-0.309***	-0.192***	-0.086***	-0.014***	0.065***	-0.110***	-0.079***	-0.050***	-0.009*	0.060***
	(0.024)	(0.006)	(0.007)	(0.010)	(0.005)	(0.018)	(0.010)	(0.005)	(0.006)	(0.007)	(0.009)	(0.005)	(0.004)	(0.006)	(0.010)

Figure 8: France quantile results

	Log hourly wage outcomes (raw)					Log hourly wage outcomes (w/ exogenous controls)					Log hourly wage outcomes (w/ all controls)				
UK (men)															
2005-20	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Black	0.004	-0.018	-0.053***	-0.075***	-0.093***	-0.051***	-0.066***	-0.086***	-0.093***	-0.097***	-0.039***	-0.050***	-0.054***	-0.056***	-0.062***
	(0.014)	(0.013)	(0.010)	(0.013)	(0.014)	(0.012)	(0.010)	(0.010)	(0.011)	(0.015)	(0.010)	(0.009)	(0.010)	(0.009)	(0.013)
South Asian	-0.031***	-0.036***	-0.008	0.012	0.049***	-0.073***	-0.065***	-0.041***	-0.028***	0.005	-0.047***	-0.039***	-0.043***	-0.027***	-0.028***
	(0.009)	(0.009)	(0.008)	(0.012)	(0.013)	(0.007)	(0.008)	(0.006)	(0.007)	(0.011)	(0.009)	(0.007)	(0.005)	(0.007)	(0.008)
Asian	-0.029	0.044	0.132***	0.143***	0.207***	-0.009	-0.006	0.051***	0.074***	0.137***	-0.007	0.024	0.017	0.045**	-0.077**
	(0.026)	(0.029)	(0.027)	(0.035)	(0.030)	(0.021)	(0.022)	(0.018)	(0.022)	(0.031)	(0.023)	(0.021)	(0.014)	(0.021)	(0.032)
Mixed	-0.031**	-0.029***	-0.013	-0.004	0.000	-0.003	-0.002	-0.003	0.012	0.024*	0.018*	0.008	0.001	0.008	0.001
	(0.014)	(0.015)	(0.010)	(0.015)	(0.020)	(0.014)	(0.010)	(0.010)	(0.011)	(0.015)	(0.010)	(0.011)	(0.009)	(0.009)	(0.017)
Other (incl. Arabs)	-0.004	0.042*	0.071***	0.117**	0.188***	-0.043*	-0.019	0.004	0.052**	0.087**	-0.059**	-0.043**	0.001	0.040*	0.037*
	(0.030)	(0.026)	(0.026)	(0.046)	(0.045)	(0.027)	(0.023)	(0.025)	(0.030)	(0.037)	(0.028)	(0.017)	(0.019)	(0.023)	(0.020)
White Immigrant	-0.064***	-0.096***	-0.094***	-0.030***	0.060***	-0.100***	-0.128***	-0.113***	-0.067***	-0.016***	-0.055***	-0.058***	-0.047***	-0.029***	-0.014***
	(0.002)	(0.001)	(0.003)	(0.004)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Black Immigrant	-0.052***	-0.119***	-0.176***	-0.194***	-0.211***	-0.244***	-0.308***	-0.333***	-0.305***	-0.273***	-0.158***	-0.175***	-0.183***	-0.173***	-0.175***
	(0.008)	(0.005)	(0.008)	(0.010)	(0.013)	(0.008)	(0.007)	(0.007)	(0.009)	(0.014)	(0.007)	(0.006)	(0.007)	(0.007)	(0.009)
South Asian Immigrant	-0.099***	-0.154***	-0.124***	0.052***	0.099***	-0.231***	-0.287***	-0.267***	-0.154***	-0.104***	-0.139***	-0.142***	-0.124***	-0.093***	-0.083***
	(0.003)	(0.004)	(0.009)	(0.003)	(0.011)	(0.005)	(0.004)	(0.006)	(0.008)	(0.009)	(0.006)	(0.004)	(0.004)	(0.005)	(0.008)
Asian Immigrant	-0.100***	-0.154***	-0.151***	-0.057***	-0.031*	-0.251***	-0.304***	-0.288***	-0.235***	-0.191***	-0.160***	-0.146***	-0.143***	-0.139***	-0.139***
	(0.007)	(0.007)	(0.013)	(0.013)	(0.019)	(0.009)	(0.007)	(0.009)	(0.010)	(0.014)	(0.010)	(0.007)	(0.006)	(0.009)	(0.011)
Mixed Immigrant	-0.052***	-0.071***	-0.003	0.100***	0.149***	-0.136***	-0.132***	-0.080***	-0.025	0.029	-0.048***	-0.042***	-0.058***	-0.012	-0.004
	(0.016)	(0.017)	(0.035)	(0.028)	(0.035)	(0.019)	(0.019)	(0.015)	(0.021)	(0.028)	(0.014)	(0.015)	(0.013)	(0.016)	(0.029)
Other Immigrant	-0.100***	-0.164***	-0.185***	-0.094***	0.003	-0.229***	-0.289***	-0.288***	-0.229***	-0.138***	-0.131***	-0.138***	-0.125***	-0.126***	-0.080***
	(0.003)	(0.007)	(0.008)	(0.013)	(0.017)	(0.009)	(0.006)	(0.008)	(0.010)	(0.015)	(0.008)	(0.006)	(0.006)	(0.007)	(0.011)

	Log hourly wage outcomes (raw)					Log hourly wage outcomes (w/ exogenous controls)					Log hourly wage outcomes (w/ all controls)				
UK (women)															
2005-20	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Black	0.077***	0.148***	0.178***	0.107***	0.053***	0.063***	0.090***	0.088***	0.069***	0.063***	0.048***	0.054***	0.055***	0.049***	0.047***
	(0.009)	(0.009)	(0.012)	(0.011)	(0.013)	(0.007)	(0.009)	(0.006)	(0.008)	(0.010)	(0.007)	(0.007)	(0.006)	(0.007)	(0.010)
South Asian	0.038***	0.065***	0.101***	0.080***	0.096***	0.017**	0.017***	0.006	0.024***	0.038***	-0.003	0.004	0.004	0.015**	0.028***
	(0.007)	(0.005)	(0.010)	(0.010)	(0.013)	(0.007)	(0.006)	(0.006)	(0.007)	(0.009)	(0.006)	(0.005)	(0.005)	(0.006)	(0.008)
Asian	0.088***	0.185***	0.243***	0.222***	0.218***	0.051*	0.083***	0.047**	0.092***	0.128***	0.023	0.027*	0.040***	0.046***	0.087***
	(0.023)	(0.018)	(0.022)	(0.025)	(0.051)	(0.029)	(0.018)	(0.019)	(0.019)	(0.024)	(0.020)	(0.014)	(0.014)	(0.018)	(0.030)
Mixed	0.006	0.043***	0.066***	0.058***	0.077***	0.013	0.028***	0.044***	0.062***	0.053***	0.010	0.028***	0.035***	0.034***	0.062***
	(0.008)	(0.009)	(0.011)	(0.011)	(0.018)	(0.008)	(0.009)	(0.008)	(0.011)	(0.012)	(0.012)	(0.008)	(0.007)	(0.008)	(0.013)
Other (incl. Arabs)	0.026	0.077***	0.158***	0.163***	0.111***	0.017	0.009	0.050***	0.025	0.051	-0.030	-0.015	0.015	0.007	0.050**
	(0.025)	(0.015)	(0.023)	(0.024)	(0.041)	(0.028)	(0.014)	(0.018)	(0.017)	(0.033)	(0.019)	(0.015)	(0.016)	(0.016)	(0.025)
White Immigrant	-0.052***	-0.044***	-0.033***	0.006	0.041***	-0.058***	-0.079***	-0.085***	-0.050***	-0.010***	-0.030***	-0.035***	-0.029***	-0.015***	0.005
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Black Immigrant	0.001	-0.007	-0.007	-0.052***	-0.091***	-0.109***	-0.118***	-0.146***	-0.128***	-0.109***	-0.042***	-0.040***	-0.042***	-0.042***	-0.038***
	(0.003)	(0.007)	(0.005)	(0.008)	(0.009)	(0.007)	(0.005)	(0.005)	(0.007)	(0.009)	(0.007)	(0.005)	(0.004)	(0.005)	(0.007)
South Asian Immigrant	-0.013*	-0.017***	0.018**	0.047***	0.073***	-0.106***	-0.119***	-0.142***	-0.111***	-0.050***	-0.052***	-0.065***	-0.064***	-0.044***	-0.010
	(0.007)	(0.004)	(0.009)	(0.007)	(0.011)	(0.006)	(0.005)	(0.005)	(0.007)	(0.009)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)
Asian Immigrant	-0.039***	-0.039***	-0.009	0.020*	0.053***	-0.140***	-0.166***	-0.194***	-0.168***	-0.081***	-0.065***	-0.074***	-0.082***	-0.073***	-0.043***
	(0.006)	(0.007)	(0.010)	(0.012)	(0.015)	(0.007)	(0.007)	(0.007)	(0.010)	(0.012)	(0.007)	(0.006)	(0.006)	(0.007)	(0.010)
Mixed Immigrant	0.006	0.053***	0.117***	0.098***	0.111***	-0.078***	-0.052***	-0.005	0.043***	0.083***	-0.042**	-0.015	0.018	0.055***	0.087***
	(0.017)	(0.013)	(0.018)	(0.019)	(0.025)	(0.015)	(0.013)	(0.019)	(0.016)	(0.019)	(0.017)	(0.011)	(0.012)	(0.012)	(0.020)
Other Immigrant	-0.033***	-0.030***	-0.028***	-0.018	0.037*	-0.121***	-0.151***	-0.177***	-0.138***	-0.083***	-0.067***	-0.079***	-0.073***	-0.047***	-0.007
	(0.008)	(0.007)	(0.011)	(0.013)	(0.020)	(0.007)	(0.007)	(0.008)	(0.009)	(0.014)	(0.007)	(0.006)	(0.005)	(0.007)	(0.012)

Figure 9: UK quantile results

5.4 Decompositions

For the decomposition analysis, I use the entire dataset and apply selection correction methods. The OLS and quantile analyses that preceded were conditional on being active participants in the labor force. The decomposition model corrects for selection into labor force participation and into employment.

For simplicity, I only apply this part of the study to second-generation African men and second-generation Maghrebin men (vis-à-vis native men) in the French case and to Black and South Asian men (vis-à-vis white men) in the British case. I apply the quantile regression model with all controls, and also add the controls from the labor force participation models (namely, marital/cohabitation status and number of children – the latter only for France).

The findings are in line with those of the quantile regression analyses. In France, much of the earnings gap between second-generation African men and native men is explained by differences in the composition of characteristics that typically influence earnings, such as education, sector of employment, etc. It is a similar story for second-generation Maghrebin men. Although for both of these groups, there is a 5%-6% unexplained gap in earnings relative to the native group throughout most of the income distribution.

This is not the case in the UK, however, where the unexplained portion of the wage gap is quite large at the 90th percentile of the income distribution (there is a roughly 10% unexplainable wage differential in the 90th percentile for Black men). Interestingly, this is not the case for South Asian men in the UK, where being in the 70th, 80th and 90th percentiles of the wage distribution has a more positive effect than being a white man in those percentiles – although much of this is explained by higher qualifications or labor market characteristics (potentially more being in sectors or industries that typically pay higher wages, or having higher education/qualifications than their white counterparts in those deciles of the income distribution).

FRANCE (2005-2020)

Native - SecGen African (men)	10th	20th	30th	40th	50th	60th	70th	80th	90th
Total gap w/ selection correction	0.417	0.228	0.223	0.178	0.184	0.176	0.189	0.205	0.176
of which explained by observable characteristics (composition effects)	0.395	0.180	0.157	0.140	0.127	0.115	0.140	0.142	0.149
of which difference in selection	0.016	0.000	0.008	0.006	0.012	0.013	0.000	0.018	0.020
of which unexplained (structural effects)	0.007	0.049	0.057	0.031	0.046	0.048	0.049	0.045	0.006

Native - SecGen Maghrebin (men)	10th	20th	30th	40th	50th	60th	70th	80th	90th
Total gap w/ selection correction	0.102	0.093	0.078	0.082	0.087	0.090	0.132	0.128	0.149
of which explained by observable characteristics (composition effects)	0.068	0.034	0.062	0.040	0.043	0.043	0.060	0.077	0.085
of which difference in selection	0.012	0.007	0.002	0.008	0.008	0.009	0.008	0.000	0.010
of which unexplained (structural effects)	0.022	0.052	0.014	0.034	0.036	0.038	0.064	0.051	0.054

UK (2005-2020)

White - Black (men)	10th	20th	30th	40th	50th	60th	70th	80th	90th
Total gap w/ selection correction	-0.005	0.009	0.012	0.021	0.053	0.070	0.087	0.072	0.094
of which explained by observable characteristics (composition effects)	0.014	0.015	0.013	0.011	0.005	(0.001)	(0.007)	(0.004)	(0.015)
of which difference in selection	0.003	0.005	0.007	0.006	0.005	0.006	0.003	0.000	0.000
of which unexplained (structural effects)	(0.022)	(0.011)	(0.008)	0.003	0.043	0.065	0.091	0.076	0.109

White - South Asian (men)	10th	20th	30th	40th	50th	60th	70th	80th	90th
Total gap w/ selection correction	0.031	0.044	0.032	0.024	0.008	0.005	-0.003	-0.004	-0.049
of which explained by observable characteristics (composition effects)	0.008	0.002	(0.011)	(0.028)	(0.043)	(0.049)	(0.055)	(0.056)	(0.066)
of which difference in selection	(0.003)	(0.012)	(0.011)	(0.015)	(0.014)	(0.011)	(0.015)	(0.011)	(0.018)
of which unexplained (structural effects)	0.026	0.054	0.053	0.067	0.064	0.065	0.067	0.063	0.035

Figure 10: Decompositions of log earnings/wage gaps

6 Econometric Issues

There are several econometric issues worth noting or reemphasizing at this stage which may impact the interpretability of results. The first is selection bias. In the context of labor economics, if a study on wages only includes employed individuals, it misses those who are unemployed, potentially skewing the analysis of wage determinants. Selection bias can also occur when individuals self-select into a sample based on the characteristics that are related to the outcome being studied. In other words, if indeed there is discrimination against certain racial groups, some members of that racial group may become discouraged and select not to participate in the labor force, potentially leading to an overestimation of wages and employment outcomes for the racial group (resulting in smaller gaps).

To be able to attribute a wage gap as resulting from wage discrimination, we must be certain that conditional on the observable characteristics (the controls), the unobservables of the two groups are on average the same. But typically, if discrimination truly is at play, it is also very likely that it has an impact on employment prospects. The barriers to employment will logically be higher for the potentially discriminated group than for the majority group, which will lead to the unobservables of the minority group being on average more favorable than those of the majority group and to an *a priori* underestimation of wage discrimination (Boutchenik et al. 2019).

While my employment and earnings/wage analyses were conditional on being active participants in the labor force, in the quantile decomposition analysis, I removed this conditionality and corrected for selection bias (both in terms of selection into labor force participation and into employment) using a probit-model based reweighting method proposed by DiNardo et al. (1996).

Another potential issue is omitted variable bias. In wage regressions, this can be particularly problematic because of the very large number of observed and unobserved factors that ultimately affect wages, including innate ability (which could also be correlated with education, pointing to endogeneity and potentially biasing the coefficients on education upward), and firm or job-specific characteristics (including employment in a 'superstar' firm versus a smaller firm in the same sector). Another omitted variable could be an individual's social network, which could help in the job search and match process (this can also be particularly important for the employment probability regressions). Omitted variable bias can lead to incorrect conclusions about the true relationships between the covariates and wages, and in terms of quantile regressions, it can distort our understanding about how covariate effects differ across different parts of the wage distribution. To address these types of biases, one could add instrumental variables: for instance, a variable that impacts an individual's race but not wages, such as surname-based instruments that estimate the frequency of certain surnames within a racial group, could be used as instruments for race. Changes in immigration policy that affected the racial composition of certain areas might also serve as potential instruments.

A final point worth reemphasizing is the lack of racial data for France and Germany, and the inconsistencies in the self-identified nature of the racial data for the UK, which makes interpretation of the results less than ideal. Even if we had captured all possible variables that could affect wage outcomes and corrected for selection issues, any potential "discrimination" or "unexplained" wage gap could still potentially be underrepresenting the real gap if it is truly driven by racial discrimination, or it could be partly attributed to "cultural" discrimination if the individuals with migrant backgrounds are not fully assimilating (or if the natives preconceive cultural differences that they believe will be problematic and so choose not to hire them).

7 Conclusions

The aim of this study was to determine whether and to what extent racial/ethnic minorities face discrimination in the French, German and British labor markets in terms of labor force participation, employment outcomes, wage outcomes and a ceiling that hinders upward mobility past a certain point.

Beyond the concept of social justice, this is important because discrimination-driven inequalities are a source of market failure that can have important implications for corporate profitability and economic growth – when equally productive individuals receive unequal pay or opportunities based on non-merit factors such as race, ethnicity or gender, it can lead to significant market inefficiencies.

Discriminatory practices can create barriers to entry for talented individuals from marginalized groups, which means employers may miss out on hiring potentially productive employees, while these employees are restricted to less suitable or lower-paid roles.

Discrimination can also cause wage distortions where some individuals are paid less than their productivity would warrant, distorting labor market signals that typically guide workers to the most productive and suitable roles, reducing overall market efficiency.

Corporations that engage in discriminatory practices may hire or promote less qualified individuals over more qualified candidates from marginalized groups, leading to inefficiencies in job performance and productivity.

Discrimination also limits economic mobility by preventing individuals from advancing based on their productivity and skills. This stagnation can result in a less dynamic and less flexible economy, reducing its ability to adapt to change and to grow.

Ultimately, discrimination-driven inequalities disrupt the optimal functioning of labor markets by preventing the most productive allocation of human resources. For businesses, this translates to inefficiencies, higher costs and potential losses in innovation and market competitiveness. On a broader scale, these inequalities impede economic growth by curbing productivity, perpetuating income disparities and limiting economic mobility. Addressing this issue is thus crucial not just for ethical reasons, but for fostering a more efficient, profitable and robust economy.

A Appendix

This appendix includes a more detailed breakdown of the racial categorizations and controls used for each country's models, as well as a more detailed breakdown of the racial sample sizes for the historical series. It also includes the full results for the pooled OLS models, which show coefficients for all the additional controls (excluding reference years for spacing reasons) used in the second ('exogenous') and third ('all controls') models for a broad view of the effects of other covariates.

FRANCE	2005-09	2010-14	2015-19
SecGen African	1,144	3,887	5,121
	0.3%	0.4%	0.5%
SecGen Maghreb	8,662	21,085	21,749
	2.1%	2.2%	2.3%
SecGen MidEast	790	2,440	2,807
	0.2%	0.3%	0.3%
SecGen Asian	529	1,895	2,090
	0.1%	0.2%	0.2%
SecGen Other	23,046	55,324	52,125
	5.6%	5.7%	5.5%
FirstGen African	3,231	12,713	13,123
	0.8%	1.3%	1.4%
FirstGen Maghreb	6,530	20,689	19,982
	1.6%	2.1%	2.1%
FirstGen MidEast	1,249	5,046	4,392
	0.3%	0.5%	0.5%
FirstGen Asian	835	2,554	2,067
	0.2%	0.3%	0.2%
FirstGen Other	10,521	36,261	34,870
	2.5%	3.7%	3.7%
Native	357,718	810,897	788,883
	86.4%	83.4%	83.3%

UK	2005-09	2010-14	2015-19
Black	4,242	4,195	5,022
	0.7%	0.7%	0.8%
South Asian	6,533	8,025	10,419
	1.0%	1.4%	1.7%
Asian	830	967	1,267
	0.1%	0.2%	0.2%
Mixed	2,476	3,280	4,182
	0.4%	0.6%	0.7%
Other (incl. Arabs)	806	913	1,029
	0.1%	0.2%	0.2%
White Immigrant	78,634	38,423	52,409
	12.2%	6.5%	8.4%
Black Immigrant	6,707	7,780	9,769
	1.0%	1.3%	1.6%
South Asian Immigrant	12,735	14,522	16,825
	2.0%	2.5%	2.7%
Asian Immigrant	5,331	6,028	7,355
	0.8%	1.0%	1.2%
Mixed Immigrant	1,196	1,148	1,450
	0.2%	0.2%	0.2%
Other Immigrant (incl. Arabs)	6,200	5,977	6,833
	1.0%	1.0%	1.1%
White	519,731	497,423	510,790
	80.5%	84.5%	81.4%

Figure 11: Sample sizes by smaller batches of pooled years - men and women combined

FRANCE	
Native	French-born to French-born parents (includes 3rd+ generation migrants)
African	Sub-Saharan Africa
Maghreb	North Africa
Middle Eastern	Near and Middle East, Turkey
Asian	Laos, Vietnam, Cambodia + autres nationalités d'Asie
Other	Rest of world
GERMANY	
Native	German-born to German-born parents (includes 3rd+ generation migrants)
African	Sub-Saharan Africa
Middle Eastern	Near and Middle East, North Africa, Turkey
Asian	East Asia, Southeast Asia, South Asia (India, Pakistan, Bangladesh, Sri Lanka)
Latin American	Latin America, Caribbean
Other	North America, Oceania, Europe
UK	
White	White includes respondents in England, Wales and Scotland identifying themselves as 'White -Gypsy or Irish Traveller' and respondents in Scotland identifying themselves as 'White -Polish'
Black	Black/African/Caribbean/Black British
South Asian	India, Paksitan, Bangladesh
Asian	Rest of Asia
Mixed	Multiple ethnic groups
Other	Other includes respondents in Northern Ireland identifying themselves as 'Irish Traveller' and respondents in all UK countries identifying themselves as 'Arab'

First generation are those born in foreign country. Second generation are born in France/Germany to at least one parent born in foreign country.

Figure 12: Racial categorizations by country

UK racial self identification (2012-2017)	White	Black	South Asian	Asian	Mixed	Other
FirstGen African (excl. South Africa)	3,438	19,064	4,710	1,132	701	1,475
	11%	62%	15%	4%	2%	5%
FirstGen South African	5,749	436	174	35	215	153
	85%	6%	3%	1%	3%	2%
FirstGen South Asian	1,237	36	36,436	3,862	267	1,143
	3%	0%	85%	9%	1%	3%
FirstGen Middle Eastern	2,426	302	425	968	280	7,243
	21%	3%	4%	8%	2%	62%
FirstGen Asian	2,792	58	294	14,266	662	3,738
	13%	0%	1%	65%	3%	17%
FirstGen LatAm/Caribbean	1,528	5,783	84	128	578	1,237
	16%	62%	1%	1%	6%	13%

Figure 13: UK self categorization of race based on country of origin

FRANCE

Age, age squared
Potential experience (proxied using age and age left education)
Education level (secondary, tertiary, bachelors, masters, phd) - primary left out
Education field (business, stem, medicine, humanities, agriculture) - beauty school and misc. left out
Reference year

Industry: agriculture, industry/manufacturing, constuction, services - 'unknown' left out
Private sector
Whitecollar
Full-time

Cohabitating w/ partner
Number of children under 18

UK

Age left education (proxy for education)
Potential experience (proxied using age and age left education variables)
Reference year

Industry: agriculture, manufacturing, constuction, energy, banking - 'other services' left out
Private sector
Whitecollar
Full-time

Married

GERMANY

Age, age squared
Education level (secondary, tertiary, bachelors, masters, phd) - primary left out
Education field (business, stem, medicine, humanities, agriculture) - beauty school and misc. left out
Potential experience (proxied using age and age left education)
Reference year

Cohabiting w/ partner
Number of children in house

Figure 14: Controls by country

Table 1: France log monthly earnings outcomes - men

	Dependent variable:		
	log earnings		
	(1)	(2)	(3)
SecGen African	−0.224***	−0.086***	−0.042***
	(0.015)	(0.012)	(0.010)
SecGen Maghrebin	−0.108***	−0.061***	−0.034***
	(0.006)	(0.005)	(0.005)
SecGen MidEast	−0.138***	0.030*	0.048***
	(0.020)	(0.016)	(0.014)
SecGen Asian	−0.061***	−0.023	−0.003
	(0.021)	(0.017)	(0.015)
SecGen Other	0.012***	0.015***	0.013***
	(0.004)	(0.003)	(0.003)
FirstGen African	−0.191***	−0.255***	−0.195***
	(0.009)	(0.007)	(0.006)
FirstGen Maghrebin	−0.111***	−0.200***	−0.147***
	(0.006)	(0.005)	(0.005)
FirstGen MidEast	−0.097***	−0.143***	−0.085***
	(0.013)	(0.011)	(0.010)
FirstGen Asian	0.039**	−0.078***	−0.084***
	(0.019)	(0.016)	(0.014)
FirstGen Other	0.071***	−0.011**	0.013***
	(0.005)	(0.005)	(0.004)
Education - Secondary		0.096***	0.069***
		(0.004)	(0.003)
Education - Tertiary		0.335***	0.233***
		(0.004)	(0.004)
Education - Bachelors		0.432***	0.334***

Table 1 continued: France log earnings outcomes - men

	Dependent variable:		
	log earnings		
	(1)	(2)	(3)
		(0.005)	(0.005)
Education - Masters		0.719***	0.593***
		(0.005)	(0.004)
Education - PhD		0.741***	0.634***
		(0.008)	(0.007)
Education - business		0.041***	0.033***
		(0.003)	(0.003)
Education - stem		0.042***	0.020***
		(0.003)	(0.002)
Education - medicine		0.030***	0.047***
		(0.006)	(0.005)
Education - humanities		−0.077***	−0.046***
		(0.004)	(0.003)
Education - agriculture		−0.030***	−0.014***
		(0.003)	(0.003)
Age		0.042***	0.018***
		(0.001)	(0.001)
Ageˆ2		−0.0004***	−0.0001***
		(0.00001)	(0.00001)
Potential experience		0.078***	0.058***
		(0.001)	(0.001)
Experienceˆ2		−0.005***	−0.004***
		(0.0001)	(0.0001)
Experienceˆ3		0.0002***	0.0001***
		(0.00000)	(0.00000)

Table 1 continued: France log earnings outcomes - men

	Dependent variable:		
	log earnings		
	(1)	(2)	(3)
Experienceˆ4		-0.00000^{***}	-0.00000^{***}
		(0.00000)	(0.00000)
		(0.006)	(0.006)
White collar			0.175^{***}
			(0.002)
Full time			0.723^{***}
			(0.003)
Private sector			0.026^{***}
			(0.002)
Industry/Manufacturing			0.138^{***}
			(0.005)
Construction			0.113^{***}
			(0.005)
Services			0.044^{***}
			(0.005)
Constant	7.523^{***}	5.832^{***}	5.519^{***}
	(0.001)	(0.014)	(0.013)
Observations	325,056	321,673	319,495
R^2	0.005	0.353	0.500
Adjusted R^2	0.005	0.353	0.500
Residual Std. Error	0.537 (df = 325045)	0.433 (df = 321631)	0.380 (df = 319447)
F Statistic	159.274^{***} (df = 10; 325045)	$4{,}275.680^{***}$ (df = 41; 321631)	$6{,}788.044^{***}$ (df = 47; 319447)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: France log monthly earnings outcomes - women

	Dependent variable:		
	log earnings		
	(1)	(2)	(3)
SecGen African	-0.080^{***}	-0.001	-0.012
	(0.015)	(0.013)	(0.011)
SecGen Maghrebin	-0.053^{***}	-0.019^{***}	-0.019^{***}
	(0.007)	(0.006)	(0.005)
SecGen MidEast	-0.114^{***}	-0.019	0.003
	(0.021)	(0.018)	(0.015)
SecGen Asian	0.108^{***}	0.111^{***}	0.084^{***}
	(0.023)	(0.020)	(0.017)
SecGen Other	-0.015^{***}	-0.006	-0.007^{**}
	(0.005)	(0.004)	(0.003)
FirstGen African	-0.186^{***}	-0.164^{***}	-0.123^{***}
	(0.010)	(0.008)	(0.007)
FirstGen Maghreb	-0.180^{***}	-0.193^{***}	-0.145^{***}
	(0.009)	(0.008)	(0.006)
FirstGen MidEast	-0.198^{***}	-0.268^{***}	-0.190^{***}
	(0.020)	(0.018)	(0.015)
FirstGen Asian	0.076^{***}	0.011	-0.007
	(0.022)	(0.020)	(0.017)
FirstGen Other	-0.038^{***}	-0.102^{***}	-0.053^{***}
	(0.006)	(0.005)	(0.004)
Education - Secondary		0.144^{***}	0.117^{***}
		(0.005)	(0.004)
Education - Tertiary		0.442^{***}	0.359^{***}
		(0.005)	(0.004)
Education - Bachelors		0.559^{***}	0.446^{***}

Table 2 continued: France log earnings outcomes - women

	Dependent variable:		
	log earnings		
	(1)	(2)	(3)
		(0.006)	(0.005)
Education - Masters		0.777***	0.653***
		(0.006)	(0.005)
Education - PhD		0.881***	0.762***
		(0.010)	(0.008)
Education - business		0.056***	0.035***
		(0.004)	(0.003)
Education - stem		0.021***	0.006
		(0.004)	(0.004)
Education - medicine		0.116***	0.106***
		(0.004)	(0.004)
Education - humanities		−0.005	−0.014***
		(0.004)	(0.004)
Education - agriculture		−0.061***	−0.051***
		(0.005)	(0.005)
Age		0.044***	0.030***
		(0.001)	(0.001)
Ageˆ2		−0.0004***	−0.0002***
		(0.00001)	(0.00001)
Potential experience		0.070***	0.058***
		(0.001)	(0.001)
Experienceˆ2		−0.006***	−0.004***
		(0.0001)	(0.0001)
Experienceˆ3		0.0002***	0.0001***
		(0.00000)	(0.00000)

Table 2 continued: France log earnings outcomes - women

	Dependent variable:		
	log earnings		
	(1)	(2)	(3)
Experienceˆ4		−0.00000***	−0.00000***
		(0.00000)	(0.00000)
White collar			0.130***
			(0.003)
Full time			0.585***
			(0.002)
Private sector			−0.098***
			(0.002)
Industry/Manufacturing			0.212***
			(0.007)
Construction			0.104***
			(0.009)
Services			0.033***
			(0.007)
Constant	7.250***	5.517***	5.343***
	(0.001)	(0.018)	(0.016)
Observations	334,592	331,869	330,033
R^2	0.003	0.246	0.465
Adjusted R^2	0.003	0.246	0.465
Residual Std. Error	0.601 (df = 334581)	0.522 (df = 331827)	0.438 (df = 329985)
F Statistic	106.633*** (df = 10; 334581)	2,641.931*** (df = 41; 331827)	6,101.956*** (df = 47; 329985)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: UK log wage outcomes - men

	Dependent variable:		
	log wage		
	(1)	(2)	(3)
Black	-0.050^{***}	-0.091^{***}	-0.062^{***}
	(0.010)	(0.009)	(0.008)
South Asian	-0.008	-0.036^{***}	-0.038^{***}
	(0.007)	(0.006)	(0.005)
Asian	0.101^{***}	0.053^{***}	0.033^{**}
	(0.017)	(0.015)	(0.014)
Mixed	-0.022^{**}	0.003	0.003
	(0.010)	(0.009)	(0.008)
Other	0.076^{***}	0.022	0.001
	(0.020)	(0.017)	(0.015)
White Immigrant	-0.049^{***}	-0.085^{***}	-0.031^{***}
	(0.002)	(0.002)	(0.002)
Black Immigrant	-0.154^{***}	-0.327^{***}	-0.189^{***}
	(0.007)	(0.006)	(0.005)
South Asian Immigrant	-0.055^{***}	-0.218^{***}	-0.116^{***}
	(0.005)	(0.004)	(0.004)
Asian Immigrant	-0.105^{***}	-0.267^{***}	-0.149^{***}
	(0.007)	(0.007)	(0.006)
Mixed Immigrant	0.028^{*}	-0.067^{***}	-0.022^{*}
	(0.016)	(0.014)	(0.013)
Other Immigrant	-0.117^{***}	-0.249^{***}	-0.124^{***}
	(0.007)	(0.006)	(0.006)
Education		0.078^{***}	0.048^{***}
		(0.0003)	(0.0003)
Potential experience		0.105^{***}	0.077^{***}

Table 3 continued: UK log wage outcomes - men

	Dependent variable:		
	log wage		
	(1)	(2)	(3)
		(0.001)	(0.001)
Experienceˆ2		−0.004***	−0.003***
		(0.0001)	(0.0001)
Experienceˆ3		0.0001***	0.0001***
		(0.00000)	(0.00000)
Experienceˆ4		−0.00000***	−0.00000***
		(0.00000)	(0.00000)
White collar			0.418***
			(0.001)
Full time			0.161***
			(0.002)
Private sector			−0.010***
			(0.001)
Agriculture industry			−0.143***
			(0.006)
Manufacturing industry			0.078***
			(0.002)
Construction industry			0.116***
			(0.002)
Banking industry			0.106***
			(0.002)
Constant	2.620***	0.292***	0.568***
	(0.001)	(0.008)	(0.008)
Observations	578,965	578,965	575,140
R^2	0.003	0.242	0.395

Table 3 continued: UK log wage outcomes - men

	Dependent variable:		
	log wage		
	(1)	(2)	(3)
Adjusted R^2	0.003	0.242	0.395
Residual Std. Error	0.534 (df = 578953)	0.466 (df = 578932)	0.416 (df = 575100)
F Statistic	134.720*** (df = 11; 578953)	5,771.085*** (df = 32; 578932)	9,635.119*** (df = 39; 575100)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: UK log wage outcomes - women

	Dependent variable:		
	log wage		
	(1)	(2)	(3)
Black	0.118***	0.140***	0.050***
	(0.007)	(0.010)	(0.007)
South Asian	0.072***	0.006	−0.011*
	(0.006)	(0.008)	(0.006)
Asian	0.197***	0.116***	0.036**
	(0.015)	(0.021)	(0.015)
Mixed	0.051***	0.064***	0.033***
	(0.008)	(0.011)	(0.008)
Other	0.098***	0.017	−0.014
	(0.017)	(0.023)	(0.016)
White Immigrant	−0.016***	−0.024***	−0.004*

Table 4 continued: UK log wage outcomes - women

	Dependent variable:		
	log wage		
	(1)	(2)	(3)
	(0.002)	(0.003)	(0.002)
Black Immigrant	−0.031***	−0.119***	−0.017***
	(0.005)	(0.008)	(0.005)
South Asian Immigrant	0.021***	−0.155***	−0.074***
	(0.005)	(0.007)	(0.005)
Asian Immigrant	−0.007	−0.171***	−0.070***
	(0.006)	(0.009)	(0.006)
Mixed Immigrant	0.076***	0.008	0.014
	(0.013)	(0.018)	(0.013)
Other Immigrant	−0.012*	−0.147***	−0.059***
	(0.007)	(0.010)	(0.007)
Education		0.089***	0.046***
		(0.0004)	(0.0003)
Potential experience		0.132***	0.089***
		(0.002)	(0.001)
Experienceˆ2		−0.009***	−0.005***
		(0.0001)	(0.0001)
Experienceˆ3		0.0003***	0.0001***
		(0.00000)	(0.00000)
Experienceˆ4		−0.00000***	−0.00000***
		(0.00000)	(0.00000)
White collar			0.462***
			(0.001)
Full time			0.748***
			(0.001)

Table 4 continued: UK log wage outcomes - women

	Dependent variable:		
	log wage		
	(1)	(2)	(3)
Private sector			-0.121^{***}
			(0.001)
Agriculture industry			-0.093^{***}
			(0.011)
Manufacturing industry			0.104^{***}
			(0.003)
Construction industry			-0.004
			(0.005)
Energy industry			0.210^{***}
			(0.007)
Banking industry			0.080^{***}
			(0.002)
Constant	2.431^{***}	3.255^{***}	3.443^{***}
	(0.001)	(0.012)	(0.009)
Observations	641,696	645,081	641,205
R^2	0.001	0.132	0.559
Adjusted R^2	0.001	0.132	0.559
Residual Std. Error	0.483 (df = 641684)	0.672 (df = 645048)	0.478 (df = 641164)
F Statistic	74.584^{***} (df = 11; 641684)	$3{,}059.818^{***}$ (df = 32; 645048)	$20{,}355.370^{***}$ (df = 40; 641164)

Note: *p<0.1; **p<0.05; ***p<0.01

References

Adida, C., Laitin, D., Valfort, M. (2016). "'One Muslim is Enough!' Evidence from a Field Experiment in France." *Annals of Economics and Statistics*, 121/122: 121–160.

Advani, A., Ash, E., Cai, D., Rasul, I. (2021). "Race-Related Research in Economics and Other Social Sciences." *Center for Law and Economics Working Paper Series*, 6.

Aeberhardt, R., Fougère, D., Pouget, J., Rathelot, R. (2010a). "Wages and employment of French workers with African origin." *Journal of Population Economics*, 23(3):881–905.

Aeberhardt, R., Fougère, D., Pouget, J., Rathelot, R. (2010b). "L'emploi et les salaires des enfants d'immigrés." *Economie et statistique*, 433(1): 31–46.

Aigner, D., Cain, G. (1977). "Statistical Theories of Discrimination in Labor Markets." *ILR Review*, 30(2).

Albrecht, J., Bjorklund, A., Vroman, S. (2003). "Is there a glass ceiling in Sweden?" *Journal of Labor Economics*, 21(1): 145–177.

Alesina, A., Harnoss, J., Rapoport, H. (2016). "Birthplace diversity and economic prosperity." *Journal of Economic Growth*, 21(2): 101–138.

Alesina, A., Michalopoulos, S., Papaioannou, E. (2016). "Ethnic Inequality." *Journal of Political Economy*, 124(2).

Algan, Y., Dustmann, C., Glitz, A., Manning, A. (2010). "The economic situation of first- and second-generation immigrants in France, Germany, and the United Kingdom." *Economic Journal*, 120(542): F4–F30.

Altonji, J., Blank, R. (1999). "Gender and Race in the Labor Market." in *Handbook of Labor Economics, edited by Orley Ashenfelter and David E. Card* New York: Elsevier Science Press 3C: 3143–4259.

Angrist, J., Pischke, J.S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton University Press.

Arellano, M., Bonhomme, S. (2016). "Nonlinear panel data estimation via quantile regression." *The Econometrics Journal*, 19(3): C61–C94.

Arellano, M., Bonhomme, S. (2017a). "Quantile selection models with an application to understanding changes in wage inequality." *Econometrica*, 85(1): 1–28.

Arellano, M., Bonhomme, S. (2017b). "Sample Selection in Quantile Regression: A Survey." *CEMFI Working Paper*, 1702.

Arnoult, E., Ruault, M., Valat, E., Villedieu, P., Breda, T., et al. (2021). "Discrimination in hiring people of supposedly North African origin: What lessons from a large-scale correspondence test?" *Institut des Politiques Publiques.*

Arrow, K. (1972). "Some mathematical models of race discrimination in the labor market." in (A.H. ed.) *Racial Discrimination in Economic Life*, 187-204, Lexington, MA: D.C. Heath.

Baert, S. (2018). "Hiring Discrimination, and Overview of (Almost) All Correspondence Experiments Since 2005." in *Audit Studies: Behind the Scenes with Theory, Method, and Nuance*, edited by S. M. Gaddis. New York, NY: Springer International Publishing.

Bassett, G., Koenker, R. (1986). "Consistency of Regression Quantiles and Related Empirical Processes." *Econometric Theory*, 2(2): 191-201.

Beaman, J. (2017). *Citizen Outsider: Children of North African Immigrants in France.* Berkeley, CA: University of California Press.

Beauchemin, C., Hamel, C., Lesné, M., Simon, P. (2010). "Les discriminations : une question de minorités visible." *Population et Sociétés*, No. 466.

Beauchemin, C., Hamel, C., Simon, P. (2015). "Trajectoires et origine. Enquête sur la diversité des populations en France." Institut Nationale d'Études Démographiques (INED).

Becker, G.S. (1957 [1971]). *The Economics of Discrimination.* Chicago: University of Chicago Press.

Behagel, L., B. Crepon, le Barbanchon, T. (2011). "Évaluation de l'impact du CV anonyme."

Berthoud, R. (2000). "Ethnic employment penalties in Britain." *Journal of Ethnic Migration Studies*, 26:389–416.

Bertrand, M., Duflo, E. (2016). "Field Experiments of Discrimination." *National Bureau of Economic Research*, Working Paper 22014.

Blinder, A.S. (1973). "Wage discrimination: reduced form and structural estimates." *Journal of Human Resources*, 8(4): 436–55.

Bon-Maury, G., Bruneau, C., Dherbécourt, C., Diallo, A., Flamand, J., Gilles, C., Trannoy, A. (2016). "The Economic Cost of Discrimination." France Stratégie report, Paris.

Bonilla-Silva, E. (2006). *Racism without Racists: Color-Blind Racism and the Persistence of Racial Inequality.* Lanham, MD: Rowman and Littlefield.

Boutchenik, B., Coudin, E., Maillard, S. (2019) "Les méthodes de décomposition appliquées à l'analyse des inégalités." INSEE.

Brinbaum, Y. (2018). "Incorporation of Immigrants and Second Generations into the French Labour Market: Changes between Generations and the Role of Human Capital and Origins." *Social Inclusion*, 6(3): 104–118.

Buchinsky, M. (1998). "Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research." *Journal of Human Resources*, 33(1): 88–126.

Cain, G. (1986). "The Economic Analysis of Labor Market Discrimination: A Survey" in (O. Ash and R. Layard, eds.) *Handbook of Labor Economics*, 1: 693-785.

Carneiro, P., Heckman, J., and Masterov, D. (2005). "Labor Market Discrimination and Racial Differences in Premarket Factors." *Journal of Law and Economics*, 46(1).

Card, D., Lemieux, T. (1996). "Wage Dispersion, Returns to Skill and Black-White Wage Differentials." *Journal of Econometrics*.

Cediey, E., Foroni, F. (2007). "Les discriminations à raison de 'l'origine' dans les embauches en France." Une enquête nationale par tests de discrimination selon la méthode du BIT. *Bureau International du Travail*, Genève.

Chernozhukov, V., Fernandez-Val, I., Melly, B. (2013). "Inference on counterfactual distributions." *Econometrica*, 81(6):2205–2268.

Combes, P., Decreuse, B., Laouenan, M., Trannoy, A. (2016). "Customer Discrimination and Employment Outcomes: Theory and Evidence from the French Labor Market." *Journal of Labor Economics*, 34(1):107-160.

CRE (2003). "Towards Racial Equality." *Commission for Racial Equality*, London.

Crul, M., Vermeulen, H. (2003). "The second generation in Europe." *International Migration Review*, 37(7): 965–986.

Cusset, P.Y. (2006). "Les statistiques 'ethniques' : premiers éléments de cadrage." *Centre d'Analyse Stratégique*, Colloque Statistiques 'ethniques'.

Daniel, W. (1968). *Racial Discrimination in England.* Penguin, London.

De Rudder, V., Vourc'h, F. (2006). "Les discriminations racistes dans le monde du travail" in Didier Fassin et Eric Fassin (dir.) *De la question sociale à la question raciale ? Représenter la société française.* La Découverte, Paris, 175–194.

Diehl, C. (2001). "Die Partizipation türkischer Migranten in Deutschland : Ergebnisse einer Gemeindestudie." *Zeitschrift für Ausländerrecht und Ausländerpolitik*, 21(1): 29–35.

Diehl, C., Schnell, R. (2006). "'Reactive ethnicity' or 'assimilation'? Statements, arguments and first empirical evidence for labor migrants in Germany." *International Migration Review*, 40(4): 786–816.

DiNardo, J., Fortin, N., Lemieux, T. (1996). "Labour market institutions and the distribution of wages, 1973-1992: a semiparametric approach." *Econometrica*, 64(5): 1001–1044.

Duguet, E., Leandri, N. L'Horty, Y., Petit, P. (2010). "Are young French job seekers of ethnic immigrant origin discriminated against? A controlled experiment in the Paris area." *Annales d'Economie et de Statistique*, 99-100:187–215.

Duguet, E., Du Parquet, L., L'Horty, Y., Petit, P. (2005). "New Evidence of Ethnic and Gender Discriminations in the French Labor Market Using Experimental Data: A Ranking Extension of Responses from Correspondence Tests." Working paper.

Escafré-Dublet, A., Guiraudon, V., Talpin, J. (2023). "Fighting discrimination in a hostile political environment: the case of "colour-blind" France." *Ethnic and Racial Studies*, 46(4): 667–685.

European Union (2019). "Being Black in the EU: Second European Union Minorities and Discrimination Survey." *European Union Agency for Fundamental Rights.*

Firth, M. (1981). "Racial Discrimination in the British Labor Market." *Industrial and Labor Relations Review*, 34(2): 265–72.

Fontaine, F. (2008). "Why are similar workers paid differently? The role of social networks." *Journal of Economic Dynamics and Control*, 32(12): 3960–3977.

Fortin, N., Lemieux, T., Firpo, S. (2010). "Decomposition Methods in Economics." *NBER*, Working Paper 16045.

Frickey, A., Primon, J.L. (2002). "Jeunes issus de l'immigration: les diplômes de l'enseignement supérieur ne garantissent un accès égal au marché du travail." *Formation Emploi*, 79:31-49.

Goldberg, A., Mourinho, D., Kulke, U. (1996). "Labour market discrimination against foreign workers in Germany." *Bureau International du Travail*, Genève.

Guryan, J., Charles, K. (2013). "Taste-Based or Statistical Discrimination: The Economics of Discrimination Returns to its Roots." *The Economic Journal*, 123(572).

Harari, Y. (2019). *21 Lessons for the 21st Century.* London, England: Vintage.

Heath, A.F., Cheung, S.Y. (2006). "Ethnic Penalties in the Labour Market: Employers and Discrimination." *Department for Work and Pensions*, Research Report, No. 341, published for the Department for Work and Pensions by Corporate Document Services, Leeds.

Heath, A.F., Cheung, S.Y. (2007). *Unequal Chances: Ethnic Minorities in Western Labour Markets.* Oxford, United Kingdom: Oxford University Press for the British Academy.

Heath, A.F., Di Stasio, V. (2019). "Racial Discrimination in Britain, 1969-2017: A Meta-Analysis of Field Experiments on Racial Discrimination in the British Labour Market." *British Journal of Sociology*, 70(5): 1774-1798.

Heath, A., Liebig, T., Simon, P. (2013). "Discrimination against Immigrants – Measurement, Incidence and Policy Instruments." *OECD* iLibrary.

Heath, A., Rothon, C., Kilpi, E. (2008). "The second generation in Western Europe: Education, unemployment, and educational attainment." *Annual Review of Sociology*, 34: 211–235.

Heckman, J. (1974). "Shadow prices, market wages and labor supply." *Econometrica*, 42:679–694.

Heckman, J. (1976). "The common structure of statistical models of truncation, sample selection, and limited dependent variables, and a simple estimator for such models." *Annals of Economic and Social Measurement*, 5:475–492.

Heckman, J. (1979). "Sample selection bias as a specification error." *Econometrica*, 47:153–161.

Heckman, J. (1998). "Detecting Discrimination." *Journal of Economic Perspectives*, 12(2):101–116.

Héran, F. (2002). "Les immigrés et leurs descendants dans le système statistique français: réflexions sur les pratiques et les principes" in *Immigration, marché du travail, intégration*, Commissariat Général du Plan: 117–133.

Huber, M., Melly, B. (2015). "A Test of the Conditional Independence Assumption in Sample Selection Models." *Journal of Applied Econometrics*, 30(7):1144–1168.

Jowell, R., Prescott-Clarke, P. (1970). "Racial Discrimination and White-collar Workers in Britain." *Race and Class*, 11(4): 397–417.

Kaas, L., Manger, C. (2012). "Ethnic Discrimination in Germany's Labour Market: A Field Experiment." *German Economic Review*, 13:1–20.

Kesler, C., Safi, M. (2018). "Immigrants in the labour markets of France and the United Kingdom: Integration models, institutional variations, and ethnic inequalities." *Migration Studies*, 6(2): 225–250.

Khattab, N., Modood, T. (2015). "Both Ethnic and Religious: Explaining Employment Penalties across 14 Ethno-religious Groups in the United Kingdom." *Journal for the Scientific Study of Religion*, 54: 501–22.

Kislev, E. (2017). "Deciphering the 'Ethnic Penalty' of Immigrants in Western Europe: A Cross-Classified Multilevel Analysis." *Social Indicators Research*, 134(2): 725–745.

Koenker, R., Bassett Jr, G. (1978). "Regression quantiles." *Econometrica: Journal of the Econometric Society*, 33–50.

Koenker, R. (2005). "Quantile Regression." *Cambridge University Press.*

Koopmans, R., Veit, S., R. Yemane (2019). "Taste or statistics? A correspondence study of ethnic, racial and religious labour market discrimination in Germany." *Ethnic and Racial Studies*, 42(16): 233–252.

Lang, K., Lehmann, J.Y.K. (2012). "Racial discrimination in the labor market: theory and empirics." *Journal of Economic Literature*, 50(4): 959–1006.

Lang, K., Manove, M., Dickens, W. (2005). "Racial Discrimination in Labor Markets with Posted Wage Offers." *American Economic Review.*.

Langevin, G., Masclet, D., Moizeau, F., Peterle, E. (2017). "Ethnic gaps in educational attainment and labor-market outcomes: evidence from France." *Education Economics, Taylor and Francis Journals*, 25(1): 84–111.

Lee, W. Roemer, L., Van der Straeten, K. (2006). "Racism, Xenophobia, Distribution." *Journal of the European Economic Association*, 4(2-3): 446–454.

Lefranc, A., Pistolesi, N., Trannoy, A. (2009). "Equality of opportunity and luck: Definitions and testable conditions, with an application to income in France." *Journal of Public Economics*, 93(11-12): 1189–1207.

Li, Y., Heath, A.F., et al. (2010). "Struggling onto the Ladder, Climbing the Rungs: Employment and Class Position of Minority Ethnic Groups in Britain." in Stillwell, J. (Ed.) *Spatial and Social Disparities.*

Lin, N. (2000). "Inequality in Social Capital." *Contemporary Sociology*, 29(6): 785–795.

Machado, J.A., Mata, J. (2005). "Counterfactual decomposition of changes in wage distributions using quantile regression." *Journal of Applied Econometrics*, 20(4):445–465.

Maurin, E., Navarrete, N. (2022). "Behind the Veil: the Effect of Banning the Islamic Veil in Schools." Working Paper.

Melly, B. (2005). "Decomposition of differences in distribution using quantile regression." *Labour Economics*, 12(4):577–590.

Melly, B. (2006). "Estimation of counterfactual distributions using quantile regression." *Swiss Institute for International Economics and Applied Economic Research.*

Meurs, D., Pailhe, A., Simon, P. (2006). "The persistence of intergenerational inequalities linked to immigration: labour market outcomes for immigrants and their descendants in France." *Population*, 61(5): 645–682.

Mincer, J. (1974). "Schooling, experience, and earnings." *Human Behavior and Social Institutions*, No. 2.

Neuman, S., Oaxaca, R. (2004). "Wage decompositions with selectivity corrected wage equations: a methodological note." *Journal of Economic Inequality*, 2(1): 3–10.

Neumark, D. (2018). "Experimental Research on Labor Market Discrimination." *Journal of Economic Literature*, 56:799–866.

Noon, M. (1993). "Racial Discrimination in Speculative Application: Evidence from the UK's Top 100 Firms." *Human Resource Management Journal*, 3: 35–47.

Oaxaca, R. (1973). "Male-female wage differentials in urban labor markets." *International Economic Review*.

OECD (2007). "Jobs for Immigrants (Vol. 1.): Labour Market Integration in Australia, Denmark, Germany and Sweden." *OECD Publishing*, Paris.

OECD (2008a). "Jobs for Immigrants (Vol. 2.): Labour Market Integration in Belgium, France, the Netherlands and Portugal." *OECD Publishing*, Paris.

OECD (2008b). "The Price of Prejudice: Labour Market Discrimination on the Grounds of Gender and Ethnicity" in OECD Employment Outlook 2008. *OECD Publishing*, Paris.

Pager, D., Quillian, L. (2005). "Walking the Talk? What Employers Say Versus What They Do." *American Sociological Review*, 70(3): 55–80.

Pager, D., Bonikowski, B., Western, B. (2009). "Discrimination in a Low-Wage Labor Market: A Field Experiment." *American Sociological Review*, 74(7): 77–99.

Pager, D. (2007). "The Use of Field Experiments for Studies of Employment Discrimination: Contributions, Critiques, and Directions for the Future." *Annals of the American Academy of Political and Social Science*, 609: 104–33.

Pager, D., Karafin, D. (2009). "Bayesian Bigot? Statistical Discrimination, Stereotypes, and Employer Decision Making." *Annals of the American Academy of Political and Social Science*, 621: 70–93.

Phelps, E.S. (1972). "The Statistical Theory of Racism and Sexism." *American Economic Review*, 62(4): 659–661.

Piketty, T. (2022). *Mesurer le racisme, vaincre les discriminations*, Ed. du Seuil, Libelle.

Platt, J. (2005). "The intergenerational social mobility of minority ethnic groups." *Sociology*, 36: 445–461.

Quillian, L. (1995). "Prejudice as a Response to Perceived Group Threat: Population Composition and Anti-Immigrant and Racial Prejudice in Europe." *American Sociological Review*, 60: 586–611.

Quillian, L. (2006). "New Approaches to Understanding Racial Prejudice and Discrimination." *Annual Review of Sociology*, 32: 299–328.

Quillian, L. et al. (2019). "Do Some Countries Discriminate More Than Others? Evidence from 97 Field Experiments of Racial Discrimination in Hiring." *Sociological Science*, 6: 467–496.

Quillian, L., Pager, D., Hexel, O., Midtbøen, A. (2017). "Meta-analysis of Field Experiments Shows No Change in Racial Discrimination in Hiring over Time." The Proceedings of the National Academy of Sciences of the United States of America.

Riach, P.A., Rich, J. (2002). "Field Experiments of Discrimination in the Market Place." *The Economic Journal*, 112: 480–518.

Richard, J.L. (2013). "Unemployment of people of foreign origin in France: The role of discrimination" in "Immigration and the Life Course" special issue *Journal of Canadian Studies in Population*, 40(1-2): 75–88.

Richard, J.L. (2013). "Unemployment of people of foreign origin in France: The role of discrimination" in "Immigration and the Life Course" special issue *Journal of Canadian Studies in Population*, 40(1-2): 75–88.

Safi, M., Simon, P. (2014). "Les discriminations ethniques et raciales dans l'enquête Trajectoires et Origines: représentations, expériences subjectives et situations vécues." *Economie et Statistique*, No 464-465-466.

Schmaus, M., Kristen, C. (2022) "Foreign Accents in the Early Hiring Process: A Field Experiment on Accent-Related Ethnic Discrimination in Germany." *International Migration Review*, 56(2): 562–593.

Semyonov, M., Raijman, R., Gorodzeisky, A. (2006). "The Rise of Anti-Foreigner Sentiment in European Societies, 1988–2000." *American Sociological Review*, 71:426–449.

Silberman, R., Fournier, I. (1999). "Les enfants d'immigrés sur le marché du travail: les mécanismes d'une discrimination sélective." *Formation/Emploi*, 65:31–55.

Silberman, R., Fournier, I. (2006). "Les secondes générations sur le marché du travail en France : une pénalité ethnique ancrée dans le temps. Contribution à la théorie de l'assimilation segmentée." *Revue française de sociologie*, 47(2): 243–292.

Silberman, R., Fournier, I. (2007). "Is French society truly assimilative? Immigrant parents and offspring on the French labour market." in Heath & Cheung 2007, 221-269.

Simon, P. (2003). "France and the unknown second generation." *International Migration Review*, 37(4): 1091–1119.

Simon, P., Clément, M. (2006a). "Comment décrire la diversité des origines en France? Une enquête exploratoire sur les perceptions des salariés et des étudiants." *Population et Sociétés*, 425.

Simon, P., Clément, M. (2006b). "Rapport de l'enquête 'Mesure de la diversité.'" *Institut Nationale d'Études Démographiques (INED).*

Simon, P. (2008). "The Choice of Ignorance: The Debate on Ethnic and Racial Statistics in France." *French Politics, Culture & Society*, 26-1:7–31.

Strabac, Z., and Listhaug, O. (2008). "Anti-Muslim prejudice in Europe: A multilevel analysis of survey data from 30 countries." *Social Science Research*, 37(1): 268–86.

Tilcsik, A., et al. (2020). "Statistical Discrimination and the Rationalization of Stereotypes." *American Sociological Review*, 86(1).

Tucci, I. (2008). "Les descendants des immigrés en France et en Allemagne: des destins contrastés. Participation au marché de travail, formes d'appartenance et modes de mise à distance sociale." Sociologie. *Ecole des Hautes Etudes en Sciences Sociales (EHESS); Humboldt Universität Berlin*, Doctoral dissertation.

Valfort, M. (2015). "Religious Discrimination in Hiring: A Reality." *Institut Montaigne report*, Paris.

Vourc'h, F., De Rudder, V., Tripier, M. (1999). "Foreigners and immigrants in the French labour market: structural inequality and discrimination" in John Wrench, Andrea Rea and Nouria Ouali, *Migrants, Ethnic Minorities and the Labour Market: Integration and exclusion in Europe*, Macmillian Press, London, 72–92.

Wood, M., Hales, J., Purdon, S., Sejersen, T., Hayllar, O. (2009). "A Test for Racial Discrimination in Recruitment Practice in British Cities." *Research Report 607*, London: DWP.

Worbs, S. (2003). “The second generation in Germany: between school and labor market.” *International Migration Review*, 37: 1011–1038.

Wrench, J., Rea, A., Ouali, N. (1999). *Migrants, ethnic minorities and the labour market: integration and exclusion in Europe*, Macmillan Press Ltd.

Wrench, J. (2011). “Data on discrimination in EU countries: statistics, research and the drive for comparability.” *Ethnic and Racial Studies*, 34: 1715-1730.

Zschirnt, E., Ruedin, D. (2016). “Ethnic Discrimination in Hiring Decisions: A Meta-analysis of Correspondence Tests 1990–2015.” *Journal of Ethnic and Migration Studies*, 42: 1115–1134.