The heterogeneity of the ethnic employment gap [§]

Romain Aeberhardt[¶] Élise Coudin[‖] Roland Rathelot[**]

December 1, 2011

Preliminary version: Do not quote please

Abstract

This study provides new empirical evidence about the heterogeneity of ethnic employment gaps, for males on the French labor market. We present a method to study the heterogeneity of binary outcomes that allows for the inclusion of many covariates in the model. We find that both the raw and the unexplained employment differentials are larger for low-skill workers than for high-skill ones. One should though be careful not to conclude that the economic phenomenon underlying these empirical facts is intrinsically heterogeneous: we show that such results can be obtained in basic theoretical model in which the ratio of the hiring probabilities between the minority and the majority groups does not depend on workers' skills. We also build a theoretical model incorporating the idea of screening discrimination in a search-and-matching framework and show that the apparent heterogeneity of employment gaps is compatible, under some assumptions, with a homogenous discrimination process.

Keywords: discrimination, employment differentials, decomposition, statistical discrimination.
JEL: C14, C25, J70, J71.

[§]We would like to thank Pierre Cahuc, Laurent Davezies, Xavier D'Haultfœuille, Denis Fougère, Pauline Givord, Guy Laroque, Thomas Le Barbanchon, Sophie Osotimehin and Sébastien Roux for insightful remarks and the participants of the INSEE-DEEE, the CEE and the CREST-LMi seminars, the EEA and the EALE annual conferences for useful comments and discussions. Any opinions expressed here are those of the authors and not of any institution.

[¶]CREST (DARES)

[‖]CREST (ENSAE)

[**]CREST, Corresponding author. roland.rathelot@ensae.fr, CREST - Bâtiment MK2 Bureau 2020 - Timbre J310 - 15 Boulevard Gabriel Péri - 92245 Malakoff Cedex - France - Tel.: 33 1 41 17 60 36 - Fax.: 33 1 41 17 60 29

1 Introduction

In the United States as well as in Europe, there exist large ethnic differentials in wages and employment rates (Altonji and Blank, 1999; Algan, Dustmann, Glitz, and Manning, 2010). However, if the ethnic gaps in wages are large in magnitude, a major part of these can be explained by differences in human capital. In the US, Neal and Johnson (1996) have shown that an important part of the black-white wage differential among young adults can be traced to differences in verbal and mathematical skills measured by the AFQT.[1] Symmetrically, Aeberhardt, Fougère, Pouget, and Rathelot (2010) have shown for France that introducing a detailed description of the latest degree obtained wipes out the wage gap between French individuals of African origin and French individuals of French origin. While differences in human capital account for a large deal of the ethnic wage gap, there is no such evidence for employment gaps, as noted by Ritter and Taylor (2011). Somewhat paradoxically, the literature dealing with ethnic differentials on the labor market has focused on wage gaps, and has relatively neglected the issue of employment gaps.[2]

While average measures give a broad picture of labor market differentials, studying their heterogeneity is interesting for two reasons. First, the policy-makers might be interested in identifying who are the subgroups suffering from the highest gaps on the labor market. Second, because the economic phenomena underlying these differentials have not yet been entirely understood, obtaining new empirical facts may shed a new light on existing theoretical models and foster theoretical innovation. As it is the case for average measures, the heterogeneity of ethnic differentials on the labor market has mostly been studied on the wage dimension. On the one hand, there has been several empirical papers focusing on sub-populations, more often on high-skill workers (Black, Haviland, Sanders, and Taylor, 2006, 2008; Bjerk, 2007) than on low-skill ones (Chandra, 2000): to sum it up, ethnic wage gaps tend to be smaller for high-skill workers. On the other hand, the quantile literature on wage gaps has been burgeoning in the recent years, following the advances in econometrics (Fortin, Lemieux, and Firpo, 2011). Much less attention has been paid to ethnic employment differentials. To our knowledge, Johnson and Neal (1998) is the only contribution in which ethnic employment gaps are stratified according to individual skills: they find that “a college degree has a greater effect on the employment opportunities of black workers”, which means that lower ethnic employment gaps are expected among college graduates.

In this paper, we study the heterogeneity of the ethnic employment differential with respect to workers' skills. In line with most of the literature, we focus on males to avoid complex considerations about the relation between family and labor issues. First, we show the variation of the differences in employment probability between French workers with non-immigrant parents and French workers with at least one North-African-immigrant parent with age and a precise measure of the last obtained degree. We present a new

[1] See, for instance, Lang and Manove (2011) for a discussion of these results.

[2] Notable counter-examples include Flanagan (1976), Abowd and Killingsworth (1984), Cain and Finnie (1990), Welch (1990), Bound and Freeman (1992), Stratton (1993), Darity and Mason (1998), Fairlie and Sundstrom (1999) or Couch and Fairlie (2010).

method that allows us to analyze and easily plot the unexplained component of the employment gap, even when many covariates are included in the model. We find that the unexplained employment gap is large for low-skill workers and shrinks to zero for very high-skill ones. Besides the empirical and the methodological contributions, this paper brings a third, theoretical, contribution to interpret the empirical results. We show that our results are compatible with a model in which the ratio of hiring probabilities between minority and majority workers do not depend on skill.

Why should we investigate beyond the mean? Figure 1 brings a direct answer to this question. It reports the employment gaps between French with North African parents and French with French parents, by level of education (above) and by age (below). For each stratum, we isolate the component of the gap which is explained by other human capital differentials from the unexplained component. While the gap, whether raw or unexplained, does not exhibit a high degree of heterogeneity with respect to age, there are large differences with respect to education. More precisely, skilled workers experience lower employment gaps than unskilled ones.

[Insert here Figure 1]

While this type of figure may prove useful to motivate the study of employment gaps heterogeneity, it is difficult to push the analysis much further using this procedure. Indeed, as the number of subgroups increases, the number of observations per subgroup drops and so does the accuracy of the results. In other words, as soon as more than one dimension are included in the analysis (*e.g.* age and education), this approach will be prone to the curse of dimensionality. Our idea is to follow the idea of propensity-score or single-index techniques and to sum up all the covariates that require to be included in the analysis and to project it on one scalar only. We show that the ethnic gap is higher among individuals who have characteristics corresponding to lower employment probability.

How should we interpret the uncovered heterogeneity? It would be tempting to interpret it as the result of some asymmetric discriminatory behaviors, in which, for instance, low-skill workers are more prejudiced than high-skill ones. No such conclusion can be asserted based on our results. Within a basic theoretical framework in which hiring probabilities are allowed to differ across skill and ethnicity, we are able to test the null hypothesis that the ratio of the hiring probabilities in the two groups is constant across skills. Using our data and our empirical results, we show that the null hypothesis cannot be rejected, so that it is not possible to assert that the economic process underlying the heterogeneity is itself varying with the skill level.

Hiring probabilities are themselves endogenous parameters than may depend on more structural ones in a complex way. Therefore, it is difficult, without more assumptions, to make a direct link between the nature of the discrimination process and the ratio of the hiring probabilities of the two populations. In order to attempt to open the black box, we design an extension of the screening discrimination model by Cornell and Welch (1996) that we link to a simplified search-and-matching model. In this model, hiring probabilities are explicitely functions of structural parameters. In particular, we show that a homogenous discrimination process, in which the parameters underlying discrimination do not depend on the worker's skill, may, depending on the wage-setting parameters, lead to a constant ratio of hiring probabilities, that we proved compatible with our empirical facts.

This paper is organized as follows. Section 2 presents the data we use, the French Labor Force Survey (LFS) from 2005 to 2010, as well as some summary statistics on our populations. Then, we introduce our empirical methodology and provide our main empirical results, evidencing the heterogeneity of the ethnic employment gap. In Section 3, we present a basic theoretical framework to help interpret the empirical results. Section 4 goes one step further: we build a theoretical model of statistical discrimination to structurally ground our interpretation.

2 Empirical evidence

In this section, we start by documenting the differences between the two groups of interest. Then, we present the methodology that allows us to analyze the heterogeneity of the employment gaps and apply it to the ethnic gaps in France.

2.1 Summary statistics and decomposition of the mean

The analysis is conducted using the French Labor Force Survey (LFS), undertaken by INSEE. We use the data collected from 2005Q1 to 2010Q2 as, since 2005, the LFS contains information on the parents' nationalities at birth and countries of birth. The children of immigrants from a given country can therefore be identified as well as their own nationality at birth and country of birth. The LFS contains also a precise description of the individual status on the labor market as well as information on socio-demographic characteristics – age, gender, qualification, family characteristics. Around 70,000 individuals aged more than 15 are interviewed each quarter for six quarters in a row. We only keep the first observation for each individual. As we wish to avoid mixing labor-supply with labor-demand issues, we only keep males aged 15 to 50 who are not students. The population of interest, denoted population D, contains 3,049 French men aged 15-50, born in France or arrived before 5, with at least one parent born with the citizenship of a North African country. The reference population, denoted population F, contains 63,975 French men aged 15-50 whose both parents were born French in France. The main outcome is the employment status. The one reported in the LFS refers to the ILO definition: an individual is considered as working if he worked at least one hour during the week.

Tables 1 and 2 report descriptive statistics for both groups. First, French males of North African origin have characteristics associated with lower human capital. They are less likely to have reached the highest qualifications (for instance, 2% *vs.* 5% with a degree from a Grande École) and more likely to have no qualification at all (30% *vs.* 16%). They are also younger (25% between 25 and 30 years old *vs.* 17%). Finally, they experience more difficulties on the labor market. They are less often employed (65% *vs.* 86%) and more likely not to have ever worked (18% *vs.* 7%). Those who work are about twice less likely to be executive or professional and are also less likely to occupy technical or educational occupations (16% *vs.* 21%).

[Insert here Tables 1 and 2]

Tables 3 and 4 reports the results of the estimation of a logit model of employment, run on both the majority and the minority populations. Age and education are included in a detailed way in the model, and even interacted. Covariates related to family situation are excluded, as, especially for men, their endogeneity might severely bias the results.[3] Estimates on age and education have the expected signs. The employment probability increases steadily from the 15-25 to the 45-50 categories. Degrees higher than Bac+3, technical or health-oriented Bac+2 degrees, and scientific, technical or vocational Bac degrees increase the employment probability with respect to a General Bac degree with a major in Humanities.[4] Having no degree at all is significantly less favorable than holding the General Bac. The coefficients of the interaction between being aged 15-35 and the degree hold, which are introduced to capture potential changes of the labor-market values of some degrees over time, are mostly insignificant.

[Insert here Tables 3 and 4]

We carry on our comparison of groups D and F by performing a classical decomposition of the mean of the employment differential *à la* Oaxaca (1973) and Blinder (1973). We find that the average employment rate in the majority population is 86% while it is equal to 65% in the minority population. Using the estimates on population F, the counterfactual mean probability of employment for population D is equal to 81%. The raw gap of 22 percentage points (pp.) can be decomposed into two parts: 6 pp. are explained by the differences in observable characteristics while 16 pp. are not.

This result in means is however too synthetic to illustrate the full picture. As shown in Figure 1, differences by qualification exist, which does not appear in a decomposition of the mean. Hence we propose the following simple framework to study and illustrate employment gap heterogeneity.

2.2 The heterogeneity of the employment gap w.r.t. observables

Let Y be a binary outcome variable. Our goal is to analyze the observed gap in Y between two populations D and F. The raw outcome gap is to be decomposed into two terms. One part is explained by variations in observable characteristics, and the other one remains unexplained.

Let us consider the potential outcome model advocated by Rubin (1974). We are interested in the effect of a binary treatment T on the binary outcome Y. "Treatment" is to

[3]We tried to introduce them in alternative specifications and the results were not qualitatively altered.

[4]The *Baccalauréat*, abbreviated as *Bac*, is an academic qualification that French students take at the end of high school. The Bac is required to pursue post-secondary studies. Three main types of Baccalauréat exist: general, technical, and vocational. The notation "Bac+x" means a degree that requires x years of studies after the Baccalauréat.

be understood in a wide sense. Here, the treatment is the population group: $T_i = 0$ if individual i comes from group F, which is the reference/native population, and $T_i = 1$ if individual i comes from group D, which is potentially discriminated against. $Y_i(F)$ and $Y_i(D)$ are the two potential outcomes of individual i whether i receives or not the treatment, that is, whether i comes from population F or D, and we are interested in the difference between both outcomes. Unfortunately, only $Y_i = T_i Y_i(D) + (1 - T_i)Y_i(F)$ is observed.

The usual decomposition-of-the-mean approach (Oaxaca, 1973; Blinder, 1973) consists in estimating $E(Y_i(F)|X_i)$ on population F (for instance with a probit or logit model) and using the estimation results to predict $E(E(Y_i(F)|\ X_i, D)|D)$ on population D. The other terms, $E(E(Y_i(F)|X_i, F)|F)$ and $E(E(Y_i(D)|X_i, D)|D)$ are directly estimated by the empirical means in populations F and D. This decomposition is valid when individual observations are assumed to be independent and that there is no difference between the minority and the majority populations in unobservable abilities correlated with the outcome once conditioned on observables. The latter condition is a conditional independence assumption (CIA), and can be stated in a formalized way as:

Assumption 2.1. *Conditional independence assumption*

$$Y_i(F) \perp T_i|X_i,\ \forall i \tag{1}$$

Whether they explicitly state it or not, all studies which deal with wage or employment differentials between groups have to rely on such an ignorability assumption, conditional on observable characteristics. With this assumption, a quite natural way to study heterogeneity of employment gaps is to study $E(Y_i(F)|X_i = x, D) - E(Y_i(D)|X_i = x, D), \forall x$. The first term of this difference is estimated on population F and the second one on population D.[5]

In Figure 2, each dot represents an age $\times$ education cell. The position of the dot on the x-axis is given by the employment rate of the individuals of group F whose characteristics belong to the cell, while the position on the y-axis is given by the mean employment of individuals of group D that belong to the cell. The points to the right of the figure thus correspond to more experienced and more educated individuals who have a higher probability of employment. Under the CIA, this figure provides an empirical counterpart of $E(Y_i(D)|X_i, D)$ as a function of $E(Y_i(F)|X_i, D)$, where X contains age and education. In other terms, assuming the CIA holds, the graph shows the observed probability of employment in population D *versus* its counterfactual value if the same individuals belonged to population F. The above difference corresponds to the gap between the points and the line of equation $y = x$. According to this figure, $E(Y_i(D)|X_i, D)$ and $E(Y_i(F)|X_i, D)$ are very close for characteristics associated with high employment probability. As the

[5] Fortin, Lemieux, and Firpo (2011) provides an extensive discussion about the interpretation of decomposition methods using the treatment-effect literature. They also introduce a Conditional Independence/Ignorability Assumption.

employment probability decreases, that is for smaller values on the x-axis, this differential becomes wider.

[Insert here Figure 2]

Although this approach is theoretically sufficient to study the heterogeneity of employment gaps, the credibility of the CIA often requires to include a large number of covariates in the model. However, as more covariates are included, the number of individuals by cell is going to rapidly decrease, due to the curse of dimensionality. Unless an extremely large dataset is available, the preceding approach will thus be impossible to use when a large number of covariates is necessary to make reliable comparisons between groups.[6]

The curse of dimensionality is a well documented issue in empirical economics and especially in the matching litterature. The usual solution, as proposed by Rosenbaum and Rubin (1983), consists in conditioning by a propensity score instead of the full set of covariates. As it happens, a similar method also works here. The following proposition enables us to overcome the curse of dimensionality when studying the heterogeneity of unexplained employment gaps.

Proposition 2.2 (Consequence of the CIA with a binary outcome variable)**.**

$$Y_i(F) \perp T_i|X_i,\ \forall i \Rightarrow Y_i(F) \perp T_i|P(Y_i(F) = 1|X_i),\ \forall i.$$

Proof: Given that $Y(F)$ and T are two binary variables, they play a symmetrical role from a statistical point of view. Therefore, the property highlighted in Rosenbaum and Rubin (1983) can be applied to $Y(F)$ instead of T.

Although they share some similarities, the method proposed here is different from the classical conditioning using a propensity score. Indeed, a propensity score measures the propensity to be treated, which would be conceptually somewhat hard to maintain in case of the treatment being the ethnicity. The framework used here differs from that: the employability index p measures the propensity to be employed, that is the propensity of a positive outcome.

Proposition (2.2) reduces the dimension of X to a single one:

$$p_i = P(Y_i(F) = 1|X_i) = E(Y_i(F)|p_i).$$

Under the CIA, proposition (2.2) entails

$$E(Y_i(F)|p_i, D) - E(Y_i(D)|p_i, D) = E(Y_i(F)|p_i) - E(Y_i(D)|p_i).$$

A natural way of studying the heterogeneity of employment gaps is thus to study the counterfactual probability of employment as a function of p. The first step consists in estimating the counterfactual probability of employment as a function of the observables:

[6] To maintain a sufficient number of observation per cell in figure 2, the education covariate was indeed grouped into 8 positions instead of 21.

$p = P(Y(F) = 1|X)$. This is done with the same logit model as in section 2.1. In a second step, it is possible to compute a counterfactual probability of employment for each individual of population D: $p_i = P(Y_i(F) = 1|X_i)$. The third step consists in estimating $E(Y(D)|p)$ (which is a function of p). This is done by computing the empirical average of $Y_i(D)$ for all individuals of D whose counterfactual probability of employment is equal to p. Because this probability is continuous, this is done using kernel methods. Figure 3 displays the estimate of the counterfactual probability of employment with the specification detailed in Tables 3 and 4.

[Insert here Figure 3]

Interestingly, figures 2 and 3 share similarities, and the main two comments remain. First, the unexplained employment gap is sizable for most individuals of the population of interest. Second, the unexplained employment gap seems to decrease steadily for higher employability levels. Such a graph could remind of a sticky-floor story in which the individuals whose characteristics tend to drive them away from employment suffer more from their ethnic background than the ones with higher qualifications. In fact, as detailed later in this paper, the link between differences in employment gaps and heterogenous discrimination is not so straigthforward. The next section proposes to interpret these empirical findings at the light of theory.

3 Testing for the homogeneity of discrimination

In the previous section, we showed that the unexplained ethnic employment gap is not constant with respect to individual characteristics. Can we conclude from this descriptive approach that the economic mechanisms underlying these gaps are heterogenous? For instance, it would be tempting to infer from the previous figures that discrimination is higher for men whose age and qualification are associated with higher unemployment. The idea of this section is to add some theoretical structure to the data and to test whether a homogenous discriminatory phenomenon is compatible with the previous empirical results.

The hiring process is assumed to have two stages. In a first stage, firms and individuals randomly meet: this meeting process is assumed to be blind with respect to ethnicity. In a second stage, firms assess individuals' productivities and decide to hire them or not. Being hired conditional on having met occurs with probability p_F (resp. p_D) for the majority (resp. minority) group. We show that, at the steady-state of this model, the heterogeneity of ethnic employment gaps comes down to the heterogeneity of the ratio between hiring probabilities p_D/p_F.

3.1 The theoretical framework: Beveridge curves on segmented markets

Individuals are assumed to differ in two dimensions: an observable component x of their productivity and their ethnic group. One can think of x as the summary of qualification, age, and any other observable characteristics relevant to the firm. When posting job vacancies, firms are assumed to target explicitely candidates with characteristics x. This means that only candidates x will apply for jobs x. For each segment x of the labor market, the meeting process between firms opening vacancies and unemployed workers, is modeled as usual, using a matching framework, *à la* Diamond, Mortensen and Pissarides (see, for instance, Pissarides, 2000). $U(x)$ jobseekers compete for $V(x)$ jobs and the unemployment rate for individuals of characteristics x is denoted as $u(x) = U(x)/L(x)$ where $L(x)$ is the labor force with characteristics x. The meeting function is the function $M(V(x), U(x))$ of the number of vacancies and jobseekers. $M(.,.)$ is assumed homogenous of degree one. The probability for a firm to meet a candidate is thus equal to $M(1, U/V) = m(\theta)$, where $\theta = v/u = V/U$ is the tightness parameter.[7] The probability for a jobseeker to meet an employer is equal to $\theta m(\theta)$. We denote by q the exogenous separation rate.

Combining the Beveridge curves. We assume, for simplicity, that there are no inflows into, nor outflows from the populations and that q, θ and $m(.)$ do not depend on ethnicity. The Beveridge curves for both populations write:

$$u_F = \frac{q}{q + p_F\theta m(\theta)} \quad \text{and} \quad u_D = \frac{q}{q + p_D\theta m(\theta)}$$

which leads to the following relation:

$$\frac{1}{u_D} - 1 = \frac{p_D}{p_F}(\frac{1}{u_F} - 1)$$

or, equivalently, using the employment rate $e_. = 1 - u_.$:

$$e_D = \frac{1}{1 + \frac{p_F}{p_D}\left(\frac{1}{e_F} - 1\right)} \tag{2}$$

Thus, the heterogeneity in x comes down to that of p_D/p_F only. Indeed, despite the fact that q, θ and $m(.)$ potentially depend on x, they cancel out in the last relation.

Homogenous discrimination (*i.e.* unrelated to characteristics). One way to model a homogenous discriminatory behavior is to assume that the ratio of the hiring probabilities p_D/p_F does not depend on x. Under this assumption, Equation 2 implies that the only source of heterogeneity of e_D w.r.t. to the observables x is linked to the one of e_F. Figure 5(a) displays an illustrative example with $p_D/p_F = 0.6$ and x varying so that the employment rate e_F covers all the segment $(0, 1)$. This employment level e_F refers both to the employment level of a worker from the reference population and to the potential employment level of the minority worker in a world with no hiring differentials.

It is clear in this example that, although p_D/p_F is held constant, the employment gap between the minority and the majority populations differs across the employment level e_F. Figure 5(b) illustrates what happens when the disadvantage in terms of hiring probabilities decreases with the counterfactual employment probability (*i.e.* p_D/p_F increases with e_F). In both cases, the employment gap is larger in the middle of the graph and cancels out at the top as in Figure 3.

[7] U, V, θ and all variables of the model which are not structural parameters depend on x. We omit it when it is not ambiguous for the sake of lisibility.

3.2 Empirical application: testing for the homogeneity of discrimination

Building on the previous structure, we wish to test whether p_D/p_F varies with e_F in the data. Equation (2) may be written as:

$$e_D(x) = \frac{1}{1+\exp(\rho(x)+\delta(x))} \text{ and } e_F(x) = \frac{1}{1+\exp(\rho(x))}$$

with $\rho(x) = \log(p_F\theta m(\theta))$ and $\delta(x) = \log\frac{p_D}{p_F}$ functions of x, the skills which are related to e_F. This entails a logistic relationship between $e_F(x)$ and $\rho(x)$, and similarly between e_D and $\rho(x)+\delta(x)$.

If $\Lambda(.)$ denotes the logistic function and if we use the observables X (age and education) to proxy the skills x, we have

$$P[Y(F)=1|X] = \Lambda(\rho(X))$$
$$P[Y(D)=1|X] = \Lambda(\rho(X)+\delta(X))$$

We wish to test the two following null hypotheses:

- $H_{01}:\ \delta(X)=0$ corresponds to the absence of discrimination.
- $H_{02}:\ \delta(X)=cst$ corresponds to a constant p_D/p_F.

In order to perform the tests, we consider the two following statistical models, in which a linear index is assumed:

$$P[Y_i=1|X_i,T_i] = \Lambda(X_i\beta + \delta 1\{T_i=D\}) \quad (3)$$
$$P[Y_i=1|X_i,T_i] = \Lambda(X_i\beta^F + (X_i\beta^D)1\{T_i=D\}) \quad (4)$$

We start by estimating (3) and we find $\hat{\delta} = -0.95$ with standard deviation of 0.04. The negative sign of δ corresponds to the fact that minority individuals are less employed than majority ones. The Student p-value being lower than 2e-16, we can confidently reject the null H_{01}. The numerical value of the estimate $\hat{\delta}$ leads to an estimate of $\widehat{p_D/p_F} = 0.39$. Some elements of interpretation of this result will be provided in the next section.

Then, we test H_{02} by a nullity (LR) test of β^D (constant excluded), in model (4). The LR statistic equals 76.5 and has to be compared to critical values from a χ^2 with 67 degrees of freedom (the number of covariates but the constant). The p-value corresponding to H_{02} is equal .18, so that we cannot reject the constancy of δ.

Figure 6 provides a graphical representation by exploiting the estimation results of model (4) and leads to the same conclusions. For each individual in the minority sample, it reports on the y-axis, the empirical difference $\delta_i = \log(P[Y_i=1|X_i=x_i,D_i=1]) - \log(P[Y_i=1|X_i=x_i,D_i=0])$, and on the x-axis, $\log(P[Y_i=1|X_i=x_i,D_i=0])$, computed with the estimates of model (4). In short, Figure 6 relates δ_i, the empirical counterpart of δ for individual i, to the corresponding $\Lambda(\rho_i)$. It is a way to illustrate how p_D/p_F varies with

e_F. The absence of discrimination would correspond to the points being spread symmetrically around the horizontal line $y = 0$. In our case, the points are centered around a horizontal line $y = -0.95$, which conforts the hypothesis that δ is constant as a function of e_F. Figure 6 also reports the δ horizontal line with δ estimated in model (3), and the regression line of the scatter plot. Boths lines are very close to each other.

[Insert here Figure 6]

In this section, we showed that, in a simple model based on a Beveridge curve, a homogenous discriminatory behavior is compatible with heterogenous employment gaps. In our case, we were not able to reject the null hypothesis that the ratio of hiring probabilities p_D/p_F is constant with respect to observable characteristics. In the next section, we attempt to ground p_D/p_F theoretically, using a more structural model of discrimination.

4 A statistical-discrimination model of the heterogeneity of employment gaps

Two recent reviews of existing discrimination theory and empirics, Charles and Guryan (2011) and Lang and Lehmann (2011), highlight that most of the literature focuses on models that reproduce empirical facts on wages rather than on employment. To our knowledge, no existing model specifically attempts to reproduce the kind of heterogeneity in employment gaps that was uncovered in the previous sections. Still, existing models are not entirely silent on the issue.

In an employer-discrimination model *à la* Becker (1957), the parameter p_D/p_F can be given a straightforward sense. Let us consider that there are two types of firms: the first ones are indifferent between hiring a majority and a minority worker whereas the second ones are prejudiced against minority workers and would only hire majority workers. In this context, if firms discovered the ethnic origin of the applicant only when they met, p_D/p_F would represent the fraction of non-prejudiced firms. Unfortunately, as noted in Lang and Lehmann (2011), taste-based discrimination models have difficulties explaining employment gaps without relying on values of their structural parameters that would seem quite impossible. Here, in order to match the data, the fraction of discriminating firms would be more than 60 %, which seems extremely high.

In the remaining of this section, we develop a simple model of statistical discrimination that can generate the type of employment gaps described previously. We build upon the idea of *screening discrimination* introduced by Cornell and Welch (1996) and incorporate it into a search-and-matching model that includes a Beveridge curve, in line with the previous section.

4.1 General setup

We focus here on predictions concerning the heterogeneity of employment gaps rather than on predictions about wages, therefore some features of the model are willingly left simple.

In particular, we keep the assumption of a segmented labor market along some observable characteristics x of the individuals. The firms capture all the surplus and offer an exogenous wage $w(x)$ which ensures that individuals enter the labor market. Unemployed workers and firms meet randomly and the hiring takes place if the worker succeeds in a screening process. There is no on-the-job search and matches split exogenously at a rate $q(x)$.

Beside x, productivity has a hidden component π. These two are the only relevant quantities for the hiring of a given candidate. For simplicity, we assume that π is match-specific (for instance, it can be that a personality trait can be appreciated in a firm but not in another one). We assume that both majority and minority candidates share the same distribution of π conditional on x: a uniform on $(0, 1)$. π is unknown to the candidate and the recruiting firm can only observe a proxy $\hat{\pi}$ of π, through a screening process. Using the same idea as in Cornell and Welch (1996), we assume that the screening process is more efficient for candidates of the majority group than it is for minority workers. However, we depart from their framework for the hiring decision rule, because we want it to fit into a continuous time search-and-matching model. Instead of assuming that the recruiting firm chooses the best applicant in a pool of workers, we assume that it fixes a threshold, meets applicants continuously, and hires the first one who scores above the threshold. This threshold is determined through maximization of the firm's profit. The firm trades off between the cost of keeping the vacancy open (h) and the potential improvement of the quality of the match. If the threshold is set to a high value, the vacancy will be open for a longer time on average but the expected productivity of the hired worker will also be higher. The interest rate is denoted r.

4.2 The screening process

The screening process consists in a sequence of tests. Cornell and Welch (1996) use a discrete setting in which some of the tests are informative and others are not. An informative test is modeled as the result of a Bernoulli draw of probability π. With n informative tests and a uniform prior distribution, the expected value of π for a candidate with $S_n \leq n$ successes is $\hat{\pi} = (S_n + 1)/(n + 2)$. The most important here is that the variance of the posterior distribution of $\hat{\pi}$ is increasing in the number of informative tests n. Discrimination occurs with the additional assumption that the number of informative tests is lower for minority than for majority workers. In this case, the variance of the proxy will also be higher for majority workers so that they will more often achieve high proxies but also low proxies. Therefore, depending on the threshold, this framework can generate statistical discrimination: while prior distributions are identical, posterior distributions differ.

To keep the analysis simple, we assume that n is close to infinity for majority workers, so that the proxy $\hat{\pi}$ is equal to π (perfect information). For minority workers, only a finite number n of tests are informative, so that the variance of the proxy will be lower than the one of π.

In this framework, the key notions, which will be used in the firms' decision strategy, are the probability for the firms to meet a worker whose signal $\hat{\pi}$ will be above the threshold, and the expected value of π given that the signal is above the threshold.

For majority workers, $\pi = \hat{\pi}$ and for any threshold $C \in (0,1)$,

$$E(\pi|\pi > C, F) = \frac{1+C}{2} \quad \text{and} \quad P(\hat{\pi} > C|F) = 1 - C. \tag{5}$$

For minority workers, since the signal is discrete, we need only consider discrete values $K \in \{0, ..., n\}$ for the threshold of the signal $\hat{\pi}$:[8]

$$E(\pi|S_n \geq K, D) = \frac{1}{2}\left(1 + \frac{K}{n+2}\right) \quad \text{and} \quad P(S_n \geq K|D) = 1 - \frac{K}{n+1} \tag{6}$$

4.3 The demand side and the matching process

We now turn to the demand side of the model and determine the optimal threshold for the firm. First, we express the firm's profit, when a vacancy is open (Π^v) and when an employee occupies the job (Π^e). Firms set a threshold C^* (resp. K^*) above which a worker they meet from the majority (resp. minority) population is hired. The choice of C^* (resp. K^*) is such that the expected profits for a vacancy is maximum, taking as given the tightness $\theta(x)$ and the wage $w(x)$. We call λ the fraction of the minority population.

$$\begin{aligned} r\Pi^v &= -h + m(\theta)\left[(1-\lambda)P(\pi > C)E(\Pi^e|\pi > C)\right. \\ &\quad \left. + \lambda P(S_n \geq K)E(\Pi^e|S_n \geq K) - \Pi^v\right] \qquad (7) \\ r\Pi^e &= y(\pi) - w + q\left(\Pi^v - \Pi^e\right) \qquad (8) \end{aligned}$$

We recall that $m(\theta)$ is the probability for the firm to meet a condidate, h is the cost for keeping an open vacancy, q is the exogenous exit rate, and r the interest rate.
We assume that $y(\pi, x) = \alpha(x)\pi$.[9] This means that the output of the job is the product of a productive function of the observed skills, $\alpha(x)$, and the match specific productivity π, on which the firm gets some information $\hat{\pi}$ through the screening process. The following reasoning is conditional on x, (segmented markets) so we write $y(\pi)$, and α for simplicity. We also assume that there is free entry on the market so that $\Pi^v = 0$.

Optimal threshold C^* for the reference population. For the reference population, the firm will set the threshold C^* to maximize $P(\pi > C)E(y(\pi) - w|\pi > C)/(r+q)$ in Equation 7. Using Equation 5, this is equivalent to maximizing $(1-C)(\alpha(1+C)/2 - w)$. The maximum is obtained in $C^* = w/\alpha$ and we suppose that the parameters are such that $C^* \in (0,1)$.

[8] See appendix for computations.

[9] Note that the output depends on x and π, while the wage depends only on x. This is obviously a simplifying assumption that should be relaxed if the model had other purposes than just being illustrative. A wage that depends on x and not on π may occur when wages are set at a collective level and not at the individual one.

Optimal threshold K^* for the minority population. The problem is slightly more complex in this case because the firm does not observe the exact productivity and the optimization is done on a discrete set. We assume the number of informative draws n to be given. The firms will choose a threshold in terms of number of successes K to maximize:

$$P(S_n \geq K)E(\Pi^e(\pi)|S_n \geq K)$$

Using the definition of C^*, Π^e can be rewritten as $\Pi^e = \alpha(\pi - C^*)/(r+q)$ and the above expression is now equal to

$$\begin{aligned}
&\frac{\alpha}{r+q}\left(1-\frac{K}{n+1}\right)\left(\frac{1}{2}\left(1+\frac{K}{n+2}\right)-C^*\right)\\
=&\frac{\alpha}{r+q}\left[\frac{1}{2}\left(1-\frac{K(K+1)}{(n+1)(n+2)}\right)-C^*(1-\frac{K}{n+1})\right]
\end{aligned}$$

When a firm chooses a threshold $K+1$ instead of K, the gain in the expression within brackets is $C^*/(n+1)$ and the loss is $(K+1)/[(n+1)(n+2)]$. Therefore, firms choose the threshold K^*, such that

$$\frac{K^*}{n+2} < C^* \leq \frac{K^*+1}{n+2}.$$

In this case, by denoting the hiring probabilities, conditional on meeting, for a minority individual $p_D = P[S_n > K^*|D]$, and for an individual from the reference population $p_F = P[\pi > C^*|F]$, we have

$$p_D = 1 - \frac{K^*}{n+1}, \quad \text{and} \quad \frac{p_D}{p_F} = \frac{1-K^*/(n+1)}{1-C^*}$$

Figure 7 illustrates this for $n=2$: if $C^* < 1/4$, then the firms will set no threshold and $p_D = 1$. If $1/4 < C^* < 1/2$, the firms will put a threshold at $S_n \geq 1$ and $p_D = 2/3$. If $1/2 < C^* < 3/4$, then the firms will only hire the individuals for whom $S_n = 2$ and $p_D = 1/3$. If $C^* > 3/4$, then firms will never hire individuals from the minority population. Overall, with $n=2$, if $1/4 < C^* < 1/3$ or $1/2 < C^* < 2/3$, we are in a situation in which $p_F > p_D$.

Let us now compare the structural parameters coming from different markets segmented by x. For each market, $C^*(x) = w(x)/\alpha(x)$. The higher this threshold the more selective employers are during the hiring process, given the observed skill-induced wage the worker is offered, and her observed skill-induced productivity. If the wage is high with respect to the skill-induced productivity α, the threshold will be high: the firm will be more demanding concerning the match-specific component of productivity. On the contrary, if the wage is low with respect to the observed skill-induced productivity, the firm will be less selective when hiring.

When C^* does not depend on x, that is, when the wage is a constant share of the skill-dependent component of productivity, then p_D/p_F will be constant with respect to x. The coefficient of proportionality between α and w may be related to the workers negociation power in the branch or the sector. When skilled and unskilled workers have the same bargaining power, p_D/p_F will be constant with respect to workers' observed skills.

In contrast, say that skilled workers have more bargaining power than unskilled ones. Then w/α and p_D/p_F increase with x. In this case, employers are going to be more selective about the unobserved productivity of skilled workers, as their wages are more important relative to their skill-induced productivity.

To sum up, we made the following assumptions:

- Markets are segmented according to a set of observable characteristics x, namely education and experience.
- On each market, firms open vacancies and have no means to discriminate *ex ante* on the grounds of ethnicity; therefore, the probabilities for minority or majority workers to meet an employer are identical.
- Firms perfectly observe the match-specific component of productivity in the reference population but they observe only a noisy signal in the minority population.

They lead to the following main results:

- Some combinations of the structural parameters imply that $p_D < p_F$, which is consistent with our empirical observations.
- The ratio p_D/p_F can be constant or not, depending on the way the wage depends on x.
- p_D/p_F is constant, for instance, when the ratio between the wage and the observed skill-induced productivity does not depend on skills. This is likely to occur when high skilled and low skilled workers have the same bargaining power.

This simple model based on statistical discrimination is therefore compatible with our empirical findings: for some values of the structural parameters, one will observe a negative employment gap against the minority population. The discriminatory process is entirely homogenous, as the screening process is identical whatever the level x of the considered market segment. In this case, however, depending on the wage-setting pattern with respect to x, the ratio p_D/p_F need not be constant. There are however some combinations of parameters which entail a constant ratio, consistent with the empirical findings of the previous section.

5 Concluding remarks

In this paper, we show that the ethnic unexplained employment gap concerning French males of North African origin is sizable for low-skill individuals and decreases steadily to become much smaller for the high-skill ones. This result is in line with previous work based on subgroup analysis, but it goes further in the sense that the method we introduce allows us to describe this heterogeneity in a more systematic way.

We also show that much care should be taken in the interpretation of these findings. It would be tempting to jump to the conclusion that low-skill minority workers are more discriminated against than high-skill ones. On the contrary, we show that these differences are in fact compatible with a theoretical framework in which the ratio of the hiring probabilities between the majority and the minority group does not depend on skill. Moreover, we embed a statistical-discrimination model in a search-and-matching framework to analyze the hiring probabilities as a function of structural parameters. Using this model, we show that it is possible to interpret a constant ratio of the hiring probabilities as the result of a statistical discrimination process in which all minority workers are treated equally regardless of their skill level.

However, for sake of simplicity, the theoretical model which we develop here focuses mainly on reproducing the employment gap heterogeneity whereas the wage part is voluntarily left simple. Future work could be devoted to developing discrimination models that incorporate both recent findings on wage and employment gap heterogeneities.

References

Abowd, J. M., and M. Killingsworth (1984): "Do Minority/White Unemployment Differences Really Exist?," *Journal of Business and Economics Statistics*, 2, 64–72.

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

Algan, Y., C. Dustmann, A. Glitz, and A. Manning (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., and R. Blank (1999): "Race and Gender in the Labor Market," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 3C, pp. 3143–3259. Elsevier, Amsterdam.

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

Bjerk, D. (2007): "The Differing Nature of Black-White Wage Inequality Across Occupational Sectors," *Journal of Human Resources*, 42(2).

Black, D., A. Haviland, S. Sanders, and L. Taylor (2006): "Why Do Minority Men Earn Less? A Study of Wage Differentials Among the Highly Educated," *The Review of Economics and Statistics*, 88(1), 300–313.

Black, D. A., A. M. Haviland, S. G. Sanders, and L. J. Taylor (2008): "Gender Wage Disparities among the Highly Educated," *Journal of Human Resources*, 43(3), 630–659.

Blinder, A. (1973): "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of Human Resources*, 8(4), 436–455.

Bound, J., and R. B. Freeman (1992): "What Went Wrong? The Erosion of Relative Earnings and Employment among Young Black Men in the 1980s," *The Quarterly Journal of Economics*, 107(1), 201–32.

Cain, G. G., and R. E. Finnie (1990): "The Black-White Difference in Youth Employment: Evidence for Demand-Side Factors," *Journal of Labor Economics*, 8(1), S364–95.

Chandra, A. (2000): "Labor-Market Dropouts and the Racial Wage Gap: 1940-1990," *American Economic Review: Papers and Proceedings*, 90(2), 333–338.

Charles, K. K., and J. Guryan (2011): "Studying Discrimination: Fundamental Challenges and Recent Progress," *Annual Review of Economics*, 3, 479–511.

Cornell, B., and I. Welch (1996): "Culture, Information, and Screening Discrimination," *Journal of Political Economy*, 104(3), 542–71.

Couch, K. A., and R. Fairlie (2010): "Last Hired, First Fired? Black-White Unemployment and the Business Cycle," *Demography*, 47(1), 227–247.

Darity, William A, J., and P. L. Mason (1998): "Evidence on Discrimination in Employment: Codes of Color, Codes of Gender," *Journal of Economic Perspectives*, 12(2), 63–90.

Fairlie, R. W., and W. Sundstrom (1999): "The Emergence, Persistence and Recent Widening of the Racial Unemployment Gap," *Industrial and Labor Relations Review*, 52, 252–270.

Flanagan, R. J. (1976): "On the Stability of the Racial Unemployment Differential," *American Economic Review*, 66(2), 302–08.

Fortin, N., T. Lemieux, and S. Firpo (2011): "Decomposition Methods in Economics," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 4, chap. 1, pp. 1–102. Elsevier, Amsterdam.

Johnson, W. R., and D. Neal (1998): "Basic Skills and the Black-White Earnings Gap," in *The Black-White Test Score Gap*, ed. by C. Jencks, and M. Philips, pp. 480–500. Brooking Institution.

Lang, K., and J.-Y. K. Lehmann (2011): "Racial Discrimination in the Labor Market: Theory and Empirics," *Journal of Economic Literature*, p. forthcoming.

Lang, K., and M. Manove (2011): "Education and Labor Market Discrimination," *American Economic Review*, 101(4), 1467–96.

Neal, D. A., and W. R. Johnson (1996): "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 104(5), 869–95.

Oaxaca, R. (1973): "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 14(3), 693–709.

Pissarides, C. A. (2000): *Equilibrium Unemployment Theory*. MIT Press.

Ritter, J. A., and L. J. Taylor (2011): "Racial Disparity in Unemployment," *Review of Economics and Statistics*, 93, 30–42.

Rosenbaum, P. R., and D. B. Rubin (1983): "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41–55.

Rubin, D. (1974): "Estimating Causal Effects of Treatments in Randomized and Non-randomized Studies," *Journal of Educational Psychology*, 66, 688–701.

Stratton, L. S. (1993): "Racial differences in men's unemployment," *Industrial and Labor Relations Review*, 46(3), 451–463.

Welch, F. (1990): "The Employment of Black Men," *Journal of Labor Economics*, 8(1), S26–74.

Table 1: Summary Statistics

Variables	Men	
	France	North Africa
Diploma		
Medicine doctorate	0.01	0.00
Master degree and above	0.04	0.02
Grandes Ecoles	0.05	0.02
Univ.: Bac+4, Science-Industry	0.01	0.00
Univ.: Bac+4, other	0.02	0.02
Univ.: Bac+3, Science-Industry	0.01	0.01
Univ.: Bac+3, other	0.02	0.02
Univ.: Bac+2	0.02	0.01
Tech.: Bac+2, Industry	0.06	0.04
Tech.: Bac+2, other	0.05	0.04
Health: Bac+2	0.01	0.00
Bac: Science	0.03	0.03
Bac: Humanities	0.03	0.04
Bac: Technical, Industry	0.02	0.01
Bac: Technical, other	0.02	0.03
Bac: Vocational, Industry	0.06	0.04
Bac: Vocational, other	0.02	0.03
Bac-2: Vocational, Industry	0.26	0.19
Bac-2: Vocational, other	0.04	0.06
Lower Sec. Educ. Deg.	0.08	0.10
No diploma	0.16	0.30
Age		
15-25	0.17	0.24
25-30	0.17	0.25
30-35	0.16	0.19
35-40	0.17	0.14
40-45	0.17	0.11
45-50	0.17	0.07
Nobs	63975	3049

Source: Labor Force Survey 2005-2010 (Insee).
Notes: 7% of French men whose parents were both born French never worked, while it is the case for 18% of French men who were born in France (or who arrived before 5) and for whom at least one parent had the citizenship of a North African country at birth.

Table 2: Summary Statistics (continued)

Variables	Men	
	France	North Africa
Labor Market Situation		
Employed	0.86	0.65
Full-time when employed	0.95	0.93
Occupation (current or last if not employed)		
Executive, Professional	0.21	0.12
Technical, Education	0.21	0.16
Clerical, Sales, Service Worker	0.13	0.15
Factory Operator	0.38	0.39
Never worked	0.07	0.18
Socio-demographic		
Couple	0.75	0.71
Working spouse	0.48	0.23
No child	0.52	0.53
1 child	0.21	0.20
2 children	0.20	0.17
3+ children	0.08	0.09
Youngest child less than 3	0.12	0.16
Nobs	63975	3049

Source: Labor Force Survey 2005-2010 (Insee).
Notes: 7% of French men whose parents were both born French never worked, while it is the case for 18% of French men who were born in France (or who arrived before 5) and for whom at least one parent had the citizenship of a North African country at birth.

Table 3: Employment Logit estimation

Individuals from ... population	Majority	Minority
Education. *Ref: Bac, Humanities*		
Master degree and above	0.76 ***	0.23
	(0.17)	(0.90)
Medicine doctorate	1.51 ***	0.42
	(0.40)	(1.17)
Grandes Ecoles	0.54 ***	1.18
	(0.15)	(1.14)
Univ.: Bac+4, Science-Industry	1.09 **	13.78
	(0.43)	(1024.26)
Univ.: Bac+4, other	0.31	−0.90
	(0.19)	(0.72)
Univ.: Bac+3, Science-Industry	1.61 ***	−0.28
	(0.52)	(1.21)
Univ.: Bac+3, other	0.64 ***	−0.39
	(0.20)	(0.81)
Univ: Bac+2	0.21	−0.39
	(0.19)	(0.93)
Tech.: Bac+2, Industry	0.90 ***	0.06
	(0.16)	(0.73)
Tech.: Bac+2, other	0.58 ***	0.39
	(0.16)	(0.78)
Health: Bac+2	1.36 ***	13.81
	(0.40)	(720.31)
Bac: Science	0.10	−1.37**
	(0.17)	(0.68)
Bac: Technical, Industry	0.53 ***	13.80
	(0.20)	(593.08)
Bac: Technical, other	0.25	−0.29
	(0.19)	(0.93)
Bac: Vocational, Industry	0.84 ***	0.19
	(0.18)	(0.73)
Bac: Vocational, other	0.27	1.03
	(0.23)	(1.14)
Bac-2: Vocational, Industry	0.14	−0.64
	(0.11)	(0.51)
Bac-2: Vocational, other	−0.05	0.07
	(0.14)	(0.64)
Lower Sec. Educ. Deg.	−0.16	−0.70
	(0.12)	(0.56)
No diploma	−0.91***	−1.50***
	(0.11)	(0.50)
Age. *Ref: 40-45*		
15-25	−1.32***	−1.10***
	(0.06)	(0.19)
25-30	−0.80***	−0.50***
	(0.06)	(0.19)
30-35	−0.40***	−0.03
	(0.06)	(0.20)
35-40	−0.11**	0.08
	(0.05)	(0.18)
45-50	−0.04	0.17
	(0.05)	(0.21)
N	63975	3049

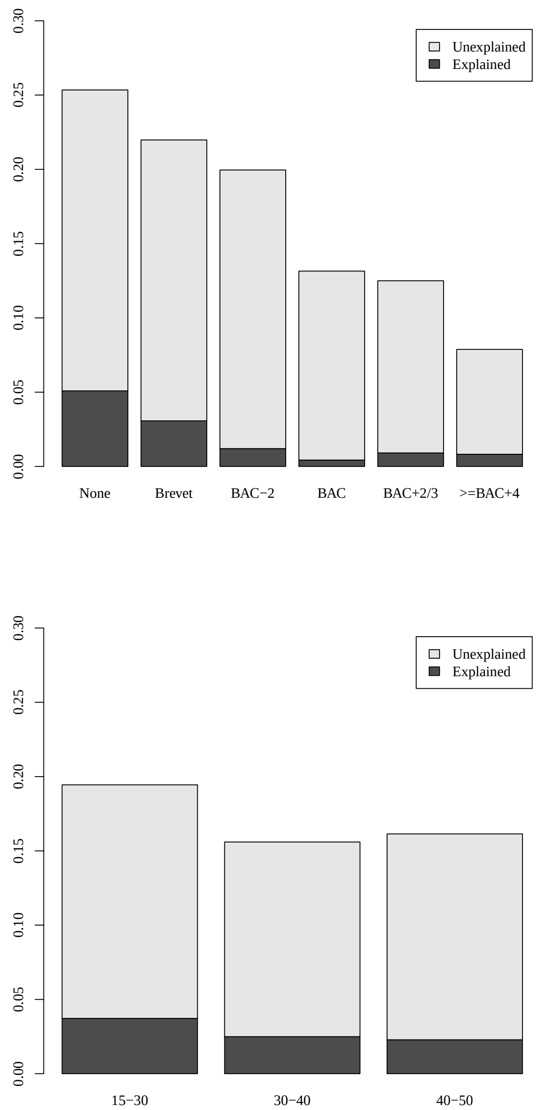
Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Dummies for quarters are also included in the model but their coefficients are omitted for readibility. * means 10%-significant, ** means 5%-significant and *** means 1%-significant. Asymptotic standard errors are reported in parentheses.

Table 4: Employment Logit estimation (continued)

Individuals from . . . population	Majority	Minority
Education interacted with age		
*15-35 * Bac: Other*	0.25 * (0.14)	−0.33 (0.57)
*15-35 * Master degree and above*	−0.22 (0.17)	0.05 (0.85)
*15-35 * Medicine doctorate*	−0.29 (0.55)	−0.49 (1.54)
*15-35 * Grandes Ecoles*	0.40 *** (0.15)	−1.19 (1.12)
*15-35 * Univ.: Bac+4, Science-Industry*	−0.11 (0.46)	−12.73 (1024.26)
*15-35 * Univ.: Bac+4, other*	−0.02 (0.20)	1.55 ** (0.74)
*15-35 * Univ.: Bac+3, Science-Industry*	−0.08 (0.62)	14.45 (717.63)
*15-35 * Univ.: Bac+3, other*	−0.18 (0.22)	0.67 (0.81)
*15-35 * Univ: Bac+2*	0.17 (0.22)	−0.59 (0.91)
*15-35 * Tech.: Bac+2, Industry*	0.17 (0.16)	0.30 (0.64)
*15-35 * Tech.: Bac+2, other*	−0.02 (0.14)	−0.44 (0.67)
*15-35 * Health: Bac+2*	0.45 (0.53)	0.20 (850.75)
*15-35 * Bac: Science*	0.21 (0.16)	1.09 * (0.57)
*15-35 * Bac: Technical, Industry*	−0.10 (0.20)	−13.82 (593.08)
*15-35 * Bac: Technical, other*	−0.13 (0.19)	−0.20 (0.84)
*15-35 * Bac: Vocational, Industry*	0.23 (0.17)	0.07 (0.62)
*15-35 * Bac: Vocational, other*	−0.14 (0.23)	−0.93 (1.09)
*15-35 * Bac-2: Vocational, Industry*	0.26 *** (0.07)	−0.03 (0.24)
*15-35 * Bac-2: Vocational, other*	−0.02 (0.12)	−0.77 (0.48)
*15-35 * Lower Sec. Educ. Deg.*	−0.09 (0.09)	−0.24 (0.34)
N	63975	3049

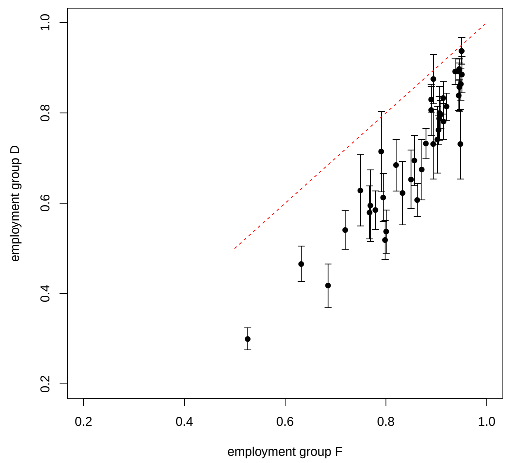
Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Dummies for quarters are also included in the model but their coefficients are omitted for readibility. * means 10%-significant, ** means 5%-significant and *** means 1%-significant. Asymptotic standard errors are reported in parentheses.

Figure 1: Explained and unexplained components of the employment differential stratifying by, row (1): education, row (2): age



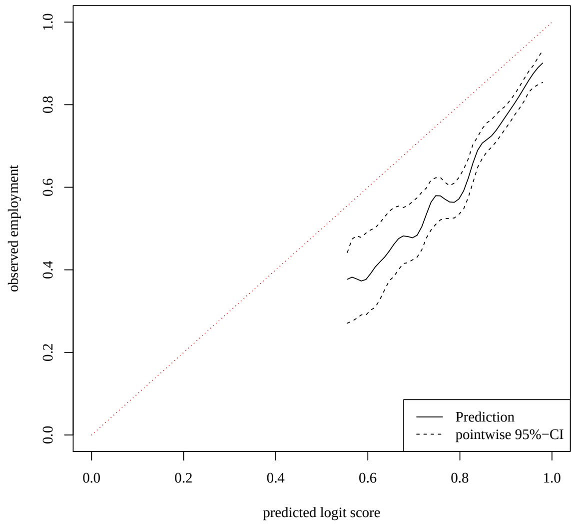
Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Predicted employment probabilities are based on the estimation of a logit model on the reference population.

Figure 2: Employment rates in the population with North African parents with respect to employment rates in the population with French parents, per education×age cells



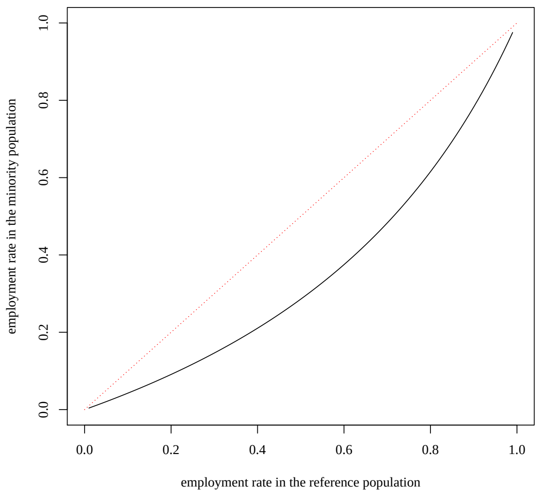
Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Education is given by the last obtained degree (in 8 positions) while age is given in 6 positions. There are thus 48 cells.

Figure 3: Average employment probability for the individuals with North African parents conditional on predicted employability score, kernel estimates.

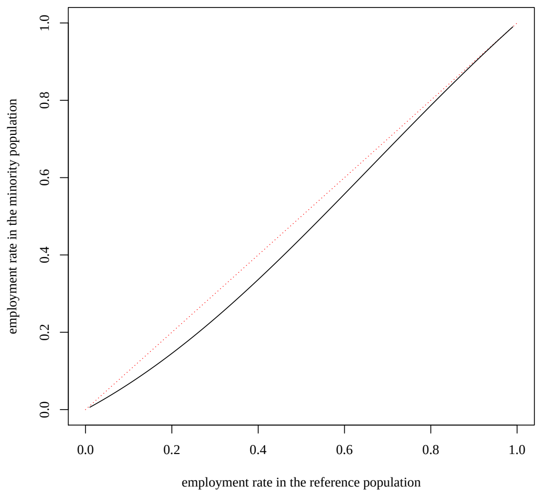


Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Confidence intervals are 95% pointwise confidence intervals obtained by bootstrap on the full sample. Predicted employment probabilities are based on the estimation of a logit on the reference population. Gaussian kernel estimates with bandwidth $h = .05$.

Figure 4: Employment probabilities for discriminated and reference groups

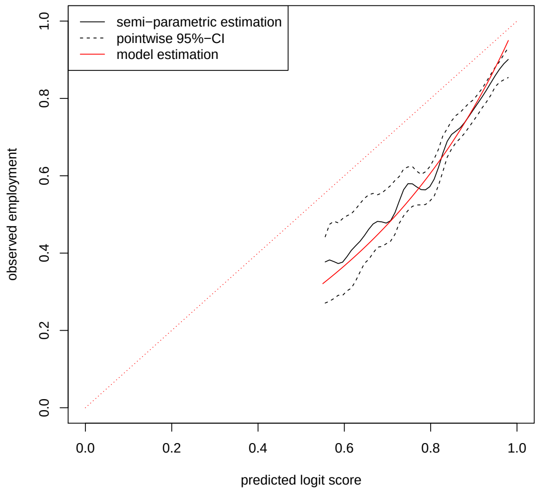


(a) p_D/p_F constant equal to 0.6



(b) p_D/p_F increasing with e_F

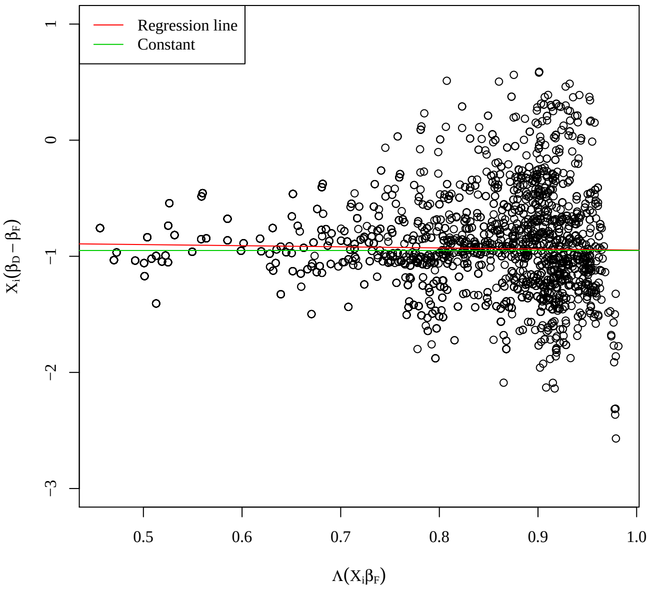
Figure 5: Estimation of the theoretical model vs. semi-parametric estimation



Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Confidence intervals are 95% pointwise confidence intervals obtained by bootstrap on the full sample. Predicted employment probabilities are based on the estimation of a logit on the reference population. Gaussian kernel estimates with bandwidth $h = .05$. The red curve corresponds to:

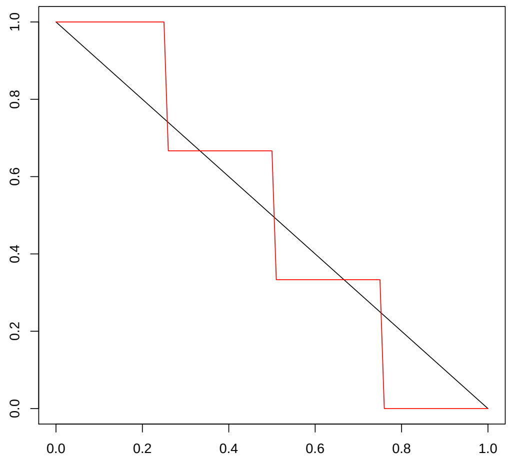
$$e_D = \frac{1}{1 + \frac{p_F}{p_D}\left(\frac{1}{e_F} - 1\right)} \quad \text{with} \quad \frac{p_D}{p_F} = 0.39$$

Figure 6: Empirical evidence on p_D/p_F as a function of e_F



Source: Labor Force Survey 2005-2010 (INSEE).
Notes: Each dot corresponds to an individual in the minority sample. The x-coordinate is $\log(P[Y_i = 1|X_i = x_i, D_i = 0])$, and the y-coordinate is the empirical difference $\delta_i = \log(P[Y_i = 1|X_i = x_i, D_i = 1]) - \log(P[Y_i = 1|X_i = x_i, D_i = 0])$. Both are computed with the estimates of model (4). This illustrates how p_D/p_F varies with e_F. The absence of discrimination would correspond to the points being spread symmetrically around the horizontal line $y = 0$. In our case, the points are centered around a horizontal line $y = -0.95$ (green line), which conforts the hypothesis that δ is constant as a function of e_F. The figure also reports the regression line of the scatter plot (red line).

Figure 7: Hiring probabilities in the majority (straight line) and the minority (steps) groups once a match has occurred, as a function of the optimal threshold in the majority group



Source: Labor Force Survey 2005-2010 (INSEE).
Notes: p_F (black straight line) and p_D (red steps) as a function of C^*. Information is perfect for the majority group but the number of informative draws for the minority group is $n = 2$. If $C^* < 1/4$, then the firms will set no threshold and $p_D = 1$. If $1/4 < C^* < 1/2$, the firms will put a threshold at $S_n \geq 1$ and $p_D = 2/3$. If $1/2 < C^* < 3/4$, then the firms will only hire the individuals for whom $S_n = 2$ and $p_D = 1/3$. If $C^* > 3/4$, then firms will never hire individuals from the minority population. Overall, with $n = 2$, if $1/4 < C^* < 1/3$ or $1/2 < C^* < 2/3$, we are in a situation in which $p_F > p_D$.

Calculations for the screening process

For majority workers, the calculations are quite straightforward since the signal $\hat{\pi}$ corresponds to the real productivity π. Recalling that $\pi \sim \mathcal{U}(0,1)$, for any $C \in (0,1)$,

$$P(\pi > C) = \int_C^1 d\pi = 1 - C \quad \text{and} \quad E(\pi|\pi > C) = \frac{\int_C^1 \pi d\pi}{P(\pi > C)} = \frac{1+C}{2}$$

For the minority group, the calculations are slightly different since the productivity π is not observed but only a proxy of it.[10] Let S_n be the number of successes in a series of n independent Bernoulli draws of probability π.
First, since the underlying distribution of π is uniform on $(0,1)$, the distribution of S_n, unconditional on π, is discrete with $n+1$ points of support $(0,\dots,n)$ of equal probability $1/(n+1)$.

Proof:
For $k \in \{0,\dots,n-1\}$

$$\begin{aligned}
P(S_n = k+1) &= \int_0^1 P(S_n = k+1|\pi)d\pi \\
&= \int_0^1 \binom{n}{k+1} \pi^{k+1}(1-\pi)^{(n-k-1)} d\pi \\
&= \binom{n}{k+1}\left[-\frac{\pi^{k+1}(1-\pi)^{n-k}}{n-k}\right]_0^1 + \int_0^1 \binom{n}{k+1}\frac{k+1}{n-k}\pi^k(1-\pi)^{(n-k)}d\pi \\
&= 0 + P(S_n = k) \\
&= P(S_n = 0) \\
&= \frac{1}{n+1}
\end{aligned}$$

Moreover, as noted in Cornell and Welch (1996),

$$E(\pi|S_n = k) = \frac{k+1}{n+2}$$

Proof:
Bayes formula implies:

$$\begin{aligned}
f_{\pi|S_n=k}(\pi) &\propto P(S_n = k|\pi)f(\pi) \\
&\propto \pi^k(1-\pi)^{n-k}, \quad \pi \in (0,1)
\end{aligned}$$

The previous calculations lead to:

$$\int_0^1 \pi^k(1-\pi)^{(n-k)}d\pi = \frac{1}{(n+1)\binom{n}{k}} \quad \text{and} \quad \int_0^1 \pi^{k+1}(1-\pi)^{(n-k)}d\pi = \frac{1}{(n+2)\binom{n+1}{k+1}}$$

[10] The following results are already stated in Cornell and Welch (1996) but we provide the calculations here for sake of clarity.

And therefore,

$$E(\pi|S_n = k) = \frac{(n+1)\binom{n}{k}}{(n+2)\binom{k+1}{n+1}} = \frac{k+1}{n+2}$$

Finally,

$$\begin{aligned}
E(\pi|S_n \geq K) &= \sum_{k=K+1}^{n} \left(E(\pi|S_n = k) \frac{P(S_n = k)}{P(S_n \geq k)} \right) \\
&= \frac{1}{n-K+1} \sum_{k=K}^{n} \frac{k+1}{n+2} \\
&= \frac{1}{2} \left(1 + \frac{K}{n+2} \right)
\end{aligned}$$