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The heterogeneity of ethnic employment gaps[§]

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Abstract

This paper investigates the heterogeneity of ethnic employment gaps using a new single-index based approach. Instead of stratifying our sample by age or education, we study ethnic employment gaps along a continuous measure of employability, the employment probability minority workers would have if their characteristics were priced as in the majority group. We apply this method to French males, comparing those whose parents are North African immigrants and those with native parents. We find that both the raw and the unexplained ethnic employment differentials are larger for low-employability workers than for high-employability ones. We show in a theoretical framework that this heterogeneity can be accounted for by homogeneous underlying mechanisms and is not evidence for, say, heterogeneous discrimination. Finally, we discuss our main empirical findings in the light of simple taste-based vs. statistical discrimination models.

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

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[¶]Aeberhardt and Coudin: CREST; Rathelot: University of Warwick

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). If the ethnic gaps in wages are large in magnitude, a major part of these can be explained by differentials in workers' characteristics.[1] In contrast, a large part of ethnic employment gaps remains unexplained by skill differentials, as stressed by Ritter and Taylor (2011). In the French case, Aeberhardt, Fougère, Pouget, and Rathelot (2010) study ethnic wage gaps between French individuals of African origin and French individual of French origin correcting for employment selection. They find that a detailed description of the latest obtained degree, together with age, accounts for the entire wage gap, but only for a third of the unemployment gap. Despite these empirical facts, both empirical and theoretical literatures dealing with ethnic differentials on the labor market have focused on wage gaps and the issue of employment gaps has been relatively neglected (see Charles and Guryan, 2011; Lang and Lehmann, 2011).[2]

This paper aims to develop a new empirical framework to study the heterogeneity of ethnic employment gaps, and provides results using French data. While average measures give a broad picture of labor market differentials, studying their heterogeneity is interesting for two reasons. First, policy-makers may 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. Several empirical papers focus on sub-populations, high-skill (Black, Haviland, Sanders, and Taylor, 2006, 2008; Bjerk, 2007) or low-skill workers (Chandra, 2000): ethnic wage gaps tend to be smaller for high-skill workers.[3] Much less attention has been paid to ethnic

[1] Neal and Johnson (1996) stress the roles of verbal and mathematical skills and Black, Haviland, Sanders, and Taylor (2006) those of detailed degrees and fields of specialization for highly educated workers.See also Lang and Manove (2011) for a discussion.

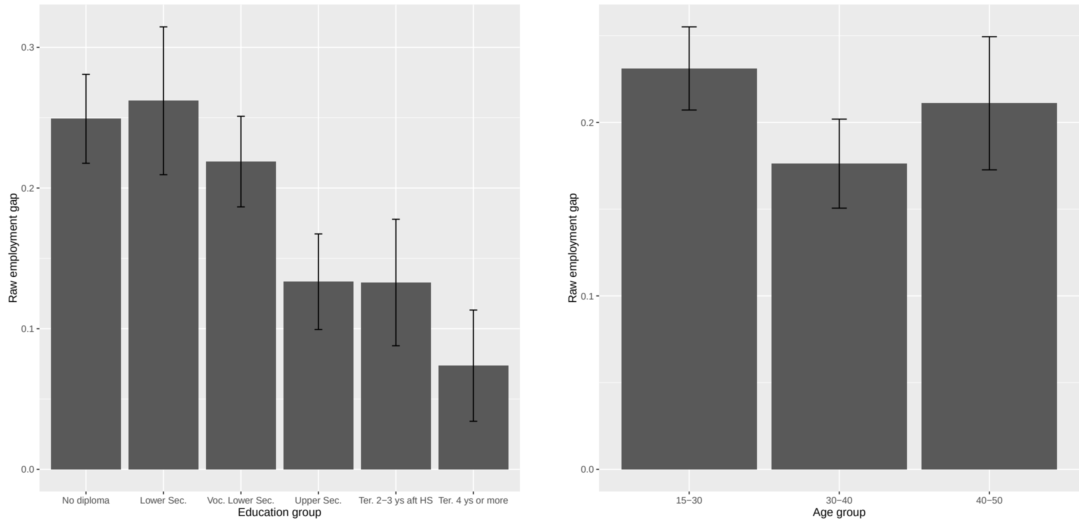
[2] Notable counter-examples include Flanagan (1976), Abowd and Killingsworth (1984), Cain and Finnie (1990), Welch (1990), Bound and Freeman (1992), Stratton (1993), Darity and Mason (1998), Fairlie and Sundstrom (1999) or Couch and Fairlie (2010).

[3] Other papers make use of the decomposition technique developed in (Fortin, Lemieux,

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.

Figure 1 reports the raw employment gaps between French men with North African parents and French men with French parents, by level of education (left) and by age (right) and provides some preliminary evidence about the heterogeneity of ethnic employment gaps. There are large differences with respect to education: highly educated workers experience lower employment gaps than less-educated ones. The gap also looks slightly lower for middle-aged workers.

Figure 1: Ethnic employment gap by education (left) and age (right) for male workers



Source: Labor Force Survey 2005-2011 (INSEE).

Notes: Raw difference between the employment rates in the majority and the minority groups, within each age or education subsample. Confidence intervals with 95% coverage level are reported in brackets.

Pushing the analysis beyond a few subgroups is difficult. As the number of sub-

and Firpo, 2011): Heywood and Parent (2012) focus on performance pay jobs and show that Black/White wage differentials grow with earnings, whereas in non-performance pay jobs, those differentials go to zero.

groups increases, the precision of the results drops. Our approach is to sum up all the relevant covariates into a single index. We estimate a model of employment on the majority population and use parameter estimates to predict for all individuals a continuous measure of *employability*, which is the employment probability as predicted from a worker's characteristics if those were valued as in the majority group. Then, we study the ethnic employment gaps along this score, comparing majority and minority workers with similar employability. The approach relies on a conditional independence assumption (CIA), which amounts to assuming that majority and minority workers do not have systematic different unobservable determinants of employment. As far as we know, the approach we propose is new. Studies in the treatment effect literature usually analyze treatment heterogeneity along treatment probability (i.e. propensity score) or use subgroup analyses (i.e. along one-dimensional X). Our approach is in contrast related to the growing interest on studying heterogeneous treatment effects across other dimensions. Another contribution of this text is to study transitions into and from employment along employability.

Applying this approach to French men with North African and native origins, we document that the unexplained employment gap is large for workers with low employability and decreases with employability. We decompose this gap between hiring and exit gaps and find that both play important roles in explaining the employment gap, but exit gaps seem to matter more than hiring gaps for most of workers. We also document that the ratio of exit rates between the minority and the majority seems to be clearly constant along the employability score. For the ratio of hiring rates, point estimates suggest that the hiring rate ratio increases for low levels of employability and then decreases for higher ones but we cannot statistically reject that it is in fact constant.

Finally, we interpret these empirical results in light of theory. A simple inflow-outflow model shows that, even when hiring and exit rate ratios are constant, employment gaps can be heterogeneous. Then, we investigate which hiring discrimination mechanisms may help us in explaining our empirical findings. Our ambition is purely illustrative and we do not pretend to provide formal tests about which discrimination types are at stake. We develop a screening model in a taste-based vs. a statistical discrimination framework. We find that the shape of the hiring rate ratio curve found in the empirical part is easiest to reconcile with a model of statistical discrimination where minority applicants have a noisier signal than majority ones. In a last theoretical part, we provide two frameworks in which exit rates can differ across ethnic groups. Adding a second signal draw while the worker is on the job can generate ethnic gaps in exit rates in the case of statistical discrimination. Alternatively, a search model with risk-averse workers predicts that minority workers are more likely to accept jobs with higher exit rates.

Our study is related to a recent literature that aims at understanding the channels underlying ethnic differentials in France. The results obtained by Tô (2014) on the heterogeneity of the ethnic wage gap suggest the existence of statistical discrimination.[4] In contrast, Adida, Laitin, and Valfort (2014) provide evidence that anti-Muslim discrimination in France is at least partly taste-based, and Combes, Decreuse, Laouénan, and Trannoy (2014) find evidence in favor of customer discrimination against African immigrants. Finally, using a correspondence study, Edo, Jacquemet, and Yannelis (2014) find that large unexplained gaps remain in hiring probabilities once statistical discrimination related to language ability is accounted for.

The remainder of the paper is organized as follows. Section 2 presents the French Labor Force Survey (LFS) from 2005 to 2011, as well as some summary statistics. In Section 3, we introduce the empirical methodology. Section 4 provides the main empirical results, which evidence the heterogeneity of the ethnic employment gap. In Section 5, we discuss our empirical findings in the light of classical theoretical frameworks.

2 Data and descriptive statistics

The analysis is conducted using the French Labor Force Survey (LFS), undertaken by INSEE. We use the data collected from 2005Q1 to 2011Q4 as, since 2005 only, 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 parents' nationality at birth, and parents' country of birth.

[4] Gobillon, Meurs, and Roux (2015) develop a different method to account for observables in the analysis of wage gaps along the distribution of wages, which could be applied to ethnic gaps.

The LFS also contains 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.

As we wish to focus on labor-demand issues, we only keep males aged 15 to 50 who are not students. The minority population, denoted population D, contains 3,626 French men aged 15-50, born in France, with at least one parent born with the citizenship of a North African country. The majority population, denoted population F, contains 79,055 French men aged 15-50 whose both parents were born French in France. Employment status corresponding to the ILO definition is reported in the LFS: an individual is considered as working if he worked at least one hour during the week. The empirical analysis will first consider as the outcome the employment status: for this part of the analysis, we only keep the first observation of each individual. Then, we examine quarterly transitions into and from employment. For this second part, we use all observations (there is a maximum of six) available for each individual.

The human-capital attributes observed in the data are the age (or the potential experience) and education. Ability measures, such as IQ or AFQT scores, are not available in this dataset. However, education is described in a precise way: both the level and the field of the highest degree obtained are provided. We build 20 categories of education combining the highest degree's level and major (see Table 1). We also rely on parents' occupations or former occupations, which are likely to be correlated with some dimensions of unobserved ability.[5]

Table 1 reports descriptive statistics for both groups. First, minority workers are less educated: 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 (29% *vs.* 15%). They are also younger (49% less than 30 years old *vs.* 33%). Second, they experience more difficulties on the labor market. They are less often employed (64% *vs.* 87%) and much 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

[5] See 3.4 for a discussion on the choice of the covariates.

or educational occupations (16% *vs.* 21%). Finally, minority individuals come from less advantaged backgrounds. Their fathers were more often blue-collars, less often professionals, technicians or office workers, than those of the majority. Their mothers did not work at all more often.

[Insert here Table 1]

Table 2 reports the estimation results of a logit model of employment on the majority group. Age and education are included in the model in a detailed way, and are interacted. We also include the parents' current occupations (or former for those who are retired) to control for family backgrounds.

Covariates related to family situation are excluded, as their endogeneity might bias the results.[6] Estimates on age and education have the expected signs. The employment probability increases steadily from the 15-25 to the 45-50 categories. Terciary education degrees (either general, vocational or technical) and vocational upper secondary (high school) degrees increase the employment probability with respect to a general upper secondary (high-school) degree in Humanities. Having no degree at all is, as expected, significantly less favorable than having completed high school. 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 Table 2]

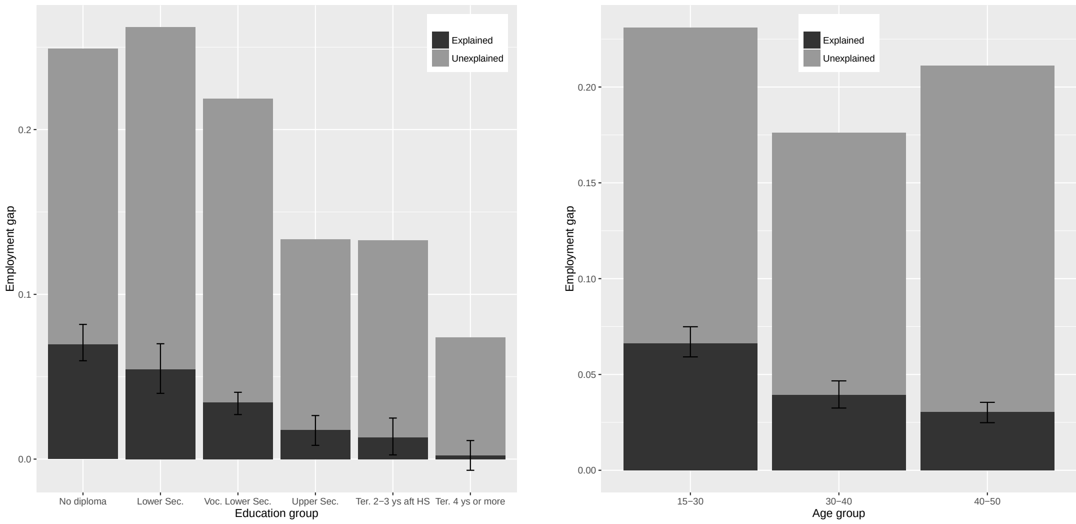
We carry out the comparison of groups D and F by performing a classical decomposition of the mean of the employment differential *à la* Oaxaca (1973) and Blinder (1973). The average employment rate in the majority population is 87% while it is equal to 64% in the minority population. In this decomposition as well as in the remainder of the text, we consider the majority group as the reference group. Using the returns estimated on population F, the counterfactual mean employment probability for population D is equal to 81%. The raw gap of 22 percentage points (pp.) can then be decomposed into two parts: 6.5 pp. (30%) are explained by the differences in observable characteristics while 15.5 pp. (70%)

[6] We tried to introduce them in alternative specifications and results were not qualitatively affected.

are not.

Using the same specification, we can repeat the exercise by subgroup defined either by the highest degree achieved or by age (Figure 2). Compared to Figure 1, Figure 2 adds a decomposition with respect to observables (parental socio-economic backgroup as well as remaining heterogeneity in education and age). We find that ethnic employment differentials are not homogeneous and vary by age and education. More educated and middle-aged groups seem to experience a lower employment gap, both in raw terms and after controlling for differences in observable characteristics.

Figure 2: Explained and unexplained components of the ethnic employment gap by education (left) and age (right)

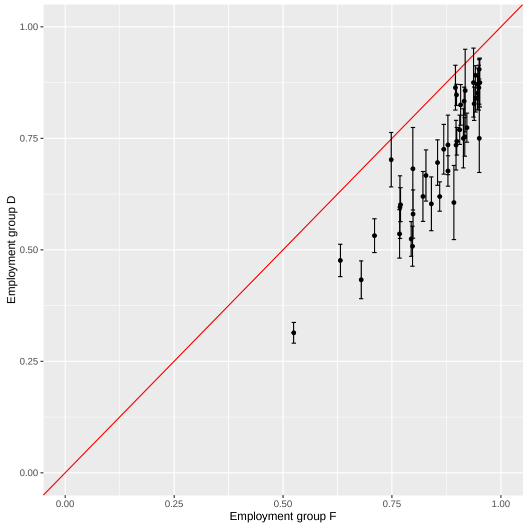


Source: Labor Force Survey 2005-2011 (INSEE).

Notes: The decomposition of employment gaps into explained and unexplained is based on Blinder-Oaxaca decomposition, using parental socio-economic background, age and education as workers' characteristics. Confidence intervals with 95% coverage level for the explained part of the gap are reported in brackets.

In Figure 3, each dot represents an age × 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 correspond to more experienced and more educated individuals who have a higher probability of employment. The overall message is that, for subgroups characterised by higher levels of employment, the ethnic employment gap is lower.

Figure 3: 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 2005-2011 (INSEE).

Notes: Education is given by the last obtained degree (in 8 positions) while age is given in 6 positions, for a total of 48 cells.

One drawback of this figure is that cutting the sample into subgroups increases the noise within each cell.[7] The following section presents a statistical framework to study the heterogeneity of employment gaps and introduces a new single-index-based method that allows us to obtain results that are less affected by noise.

3 Methodology

3.1 Discrimination in a potential outcome framework

We use the potential outcome model of Rubin (1974). Let Y_i be a binary outcome variable, here, the employment status, and X_i the characteristics of individual i.

[7]To maintain a sufficient number of observations per cell in Figure 3, the education covariate was grouped into 8 positions instead of 21.

We want to understand how the binary variable T_i affects the binary outcome Y_i. In our case, T denotes the population group: $T_i = F$ if individual i comes from group F, the majority population, and $T_i = D$ if individual i comes from the minority group D. $Y_i(F)$ and $Y_i(D)$ are the two potential outcomes of individual i whether i comes from population F or D, and we are interested in the difference between both outcomes. Unfortunately, only $Y_i = T_iY_i(D) + (1 - T_i)Y_i(F)$ 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 return estimates 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 corresponding empirical means in populations F and D. This decomposition can be interpreted when there is no difference between the minority and the majority populations in unobservable abilities correlated with the outcome once conditioned on observables. This conditional independence assumption (CIA) can be stated as $Y_i(F) \perp T_i|X_i,\ \forall i$. 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 natural way to study the heterogeneity of employment gaps is to study $E(Y_i(F)|X_i = x, D) - E(Y_i(D)|X_i = x, D), \forall x$, which is called the conditional average treatment effect, see e.g. Imbens and Wooldridge (2009). Under the CIA, the first term of this difference is equal to $E(Y_i|X_i = x, F)$ and can be estimated on population F.[8] Figure 3 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, 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. Although this approach is theoretically sufficient to study the hetero-

[8]See also Fortin, Lemieux, and Firpo (2011) for an extensive discussion about the interpretation of decomposition methods under the CIA.

geneity of employment gaps, the credibility of the CIA often requires to include a large number of covariates in the model.

As more covariates are included, the number of individuals by cell rapidly decreases and the preceding approach leads to very imprecise conditional gap estimates between groups. The usual solution was proposed by Rosenbaum and Rubin (1983) and consists in conditioning on the propensity score rather than on the full set of covariates. Studying the heterogeneity of the treatment effect along the propensity score makes sense in cases when individuals select themselves into the treatment (based on some unobservables) as one may expect then that two individuals with similar scores would benefit from the treatment in similar proportions.

3.2 Employment gaps along the employability score

A more natural dimension to study the heterogeneity of the ethnic employment gap is the outcome probability line $e_F(X) = P(Y(F) = 1|X)$, that we hereafter call for simplicity the employability score. Worker i's employability score is equal to $e_{F_i} = P(Y_i(F) = 1|X_i)$, where i's characteristics are priced as in the reference population F. Employability score is a single-index-based measure that sums up all X in one dimension. One can interpret the employability as a measure for the workers' proximity to employment when individual characteristics are valued as in the majority group.

Our theoretical contribution is actually more general. We show that in case of a binary outcome and under the CIA, the outcome probability score (employability) provides, as the propensity score, a unidimensional score that summarizes the CIA (see proof A.1 in the Appendix):

$$Y(F) \perp T|X, \forall i \Rightarrow Y(F) \perp T|e_F(X), \forall i$$

which entails

$$E(Y(F)|e_F, D) - E(Y(D)|e_F, D) = E(Y|e_F, F) - E(Y|e_F, D), \forall i$$

This provides a statistical justification for the choice of the employability as the conditioning variable.[9]

[9] One may also note that the information about the heterogeneity of treatment along the employability score is not redundant with the one along the propensity score. See Appendix B for a discussion of similarities and differences between the propensity and employability scores.

Note that our approach is related to the growing interest on studying heterogeneous treatment effects across other dimensions. Athey and Imbens (2015), amongst others, apply machine learning methods to determine the sub-groups (and the x) for whom the treatment has the strongest effects, and enhance heterogeneous treatment estimation. As reviewed by Imbens and Wooldridge (2009), Dehejia (2005), Manski (2000, 2002, 2004), Hirano and Porter (2005) develop decision-making approaches in which administrators of programs decide to assign new individuals to a treatment or a control groups based on how much the latter are likely to benefit from the program given some prior information.

3.3 Estimation in practice

The first step consists in estimating employability score $e_F = P(Y(F) = 1|X)$ as a function of the observables, using the logit model presented in section 2. In a second step, we compute the employability score of each individual of population D: $e_{F_i} = P(Y_i(F) = 1|X_i)$. The third step consists in estimating $E(Y(D)|e_F)$, which is a function of e_F, for the whole range of values taken by e_F in the ethnic minority. Because e_F is continuous, $E(Y(D)|e_F)$ is estimated using smoothing methods: we use cubic splines and check that the main results hold when other methods (splines with other degrees of freedom, lowess, kernel smoothing) are used.[10]

3.4 Should we believe in the CIA in our case?

A potential limitation of decomposition methods like the one used here is their reliance on the CIA. We have to assume that there are no ethnic differentials in unobserved determinants of employment once we condition on detailed measures of age, education and parents' occupation.

This assumption is questionable if some dimensions of employability are not accounted for by the covariates included in the analysis. Immigrants could indeed have lower-quality social networks, which would be detrimental to the hiring of

[10] Xie, Brand, and Jann (2012) also use a nonparametric method to estimate heterogeneous treatment effects. They match control units to treated ones based on the propensity score and then estimate treatment effects as a function of the propensity score by fitting a non-parametric model.

their children. Further, minority workers may have more difficulties to signal their skills than majority workers.[11] While we cannot reject this possibility, it is worth noting that children of migrants from Southern Europe, who have socio-economic backgrounds comparable to North-African migrants, do not suffer from any differential on the labor market, once education and age are taken into account (Rathelot, 2014).

Some papers have also argued that ethnic groups may have different labor-supply behaviors for cultural reasons, as evidenced for females in the U.S. by Fernandez and Fogli (2009). In the case of France, decomposing employment gaps for females provide results that are similar to those on males (Aeberhardt and Rathelot, 2013). If cultural transmission were a substantial driver of the employment, we would have expected to see much larger raw and unexplained gaps for females.

One strand of the literature has attempted to deal with these issues by including some kind of IQ measure among covariates (Neal and Johnson, 1996; Lang and Manove, 2011). Arcidiacono, Bayer, and Hizmo (2010) use alternatively the AFQT at 12 and the father's education as measures of unobserved ability when explaining ethnic wage gaps of college and high-school graduates in the U.S. and find similar results with both measures.[12] In our data, there is no IQ measure but we observe both parents' occupations. While we have no evidence that the result obtained by Arcidiacono, Bayer, and Hizmo (2010) would hold in the case of France, we expect that including parents' occupations will mitigate potential deviations to the CIA.

In the case of France, Aeberhardt, Fougère, Pouget, and Rathelot (2010) show that controlling for the same covariates as the ones we use in this study explains the entire ethnic wage gap (but not the employment gap), even when selection issues are accounted for. This result can be considered as additional suggestive evidence that the covariates used here can do a decent job making the CIA hold.

[11]Note that ethnic gaps in skill-signalling quality are likely to be larger for low-skill workers (lower employability), than for high-skill workers (higher employability), see Arcidiacono, Bayer, and Hizmo (2010)

[12]See also Black, Devereux, and Salvanes (2009) for evidence on inter-generational transmission of IQ scores.

4 Empirical findings

4.1 The ethnic employment gap along employability

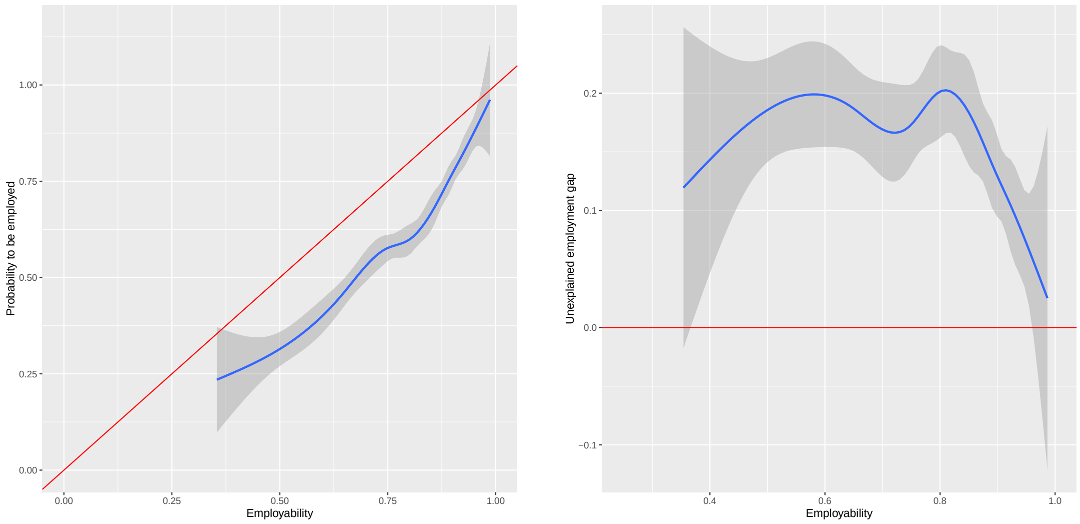
Figure 4 displays the estimate of $E(Y(D)|e_F)$, where the employability $e_F(X)$ is estimated using the specification detailed in Table 2. The ethnic gap can be read as the difference between the curve and the 45-degree line in the left panel, and is directly shown as $e_F - E(Y(D)|e_F)$ in the right panel. This gap can be interpreted as net of composition effects: under the CIA, it is the unexplained/residual gap that remains once differences in observables have been accounted for. From Figure 4, we note that the unexplained employment gap is sizable for most individuals of the minority population. The overall pattern is hump-shaped with lower gaps for both very high and lower employability. While the pattern of the point estimates looks broadly increasing when the employability score is lower than .5, confidence intervals are too large to allow us to be too assertive. Between .6 and .8, the gap is roughly stable, between 15 and 20 percentage points. For workers with employability scores above .8, the gap frankly decreases with employability (**Finding 1**). This concerns half of the minority workers and three majority workers out of four, see Figure 5, which reports the distribution of minority and majority workers along the employability line. For employability scores above .95, the point estimate of the employment gap becomes small in magnitude (below 5 percentage points) and insignificant, although the confidence intervals are also too large to allow us to conclude that the gap converges to zero.

4.2 Ethnic differentials in the flows from and into employment

Differences in employment rates can be linked to differences in the hiring rates or in the exit rates. In this section, we analyze the levels of ethnic differentials regarding inflow and outflow rates and their heterogeneity along the employability score.

The share of employed people moving quarterly out of employment is quite low: 2.7% in the majority group. The raw ethnic gap in the outflow rate is relatively high, 4 percentage points, which means that the exit rate is overall 3 times higher in the minority than in the majority group. The unexplained gap is still quite sub-

Figure 4: Average employment probability for the individuals with North African parents and unexplained employment gap, as a function of the employability score.



Source: Labor Force Survey 2005-2011 (INSEE).

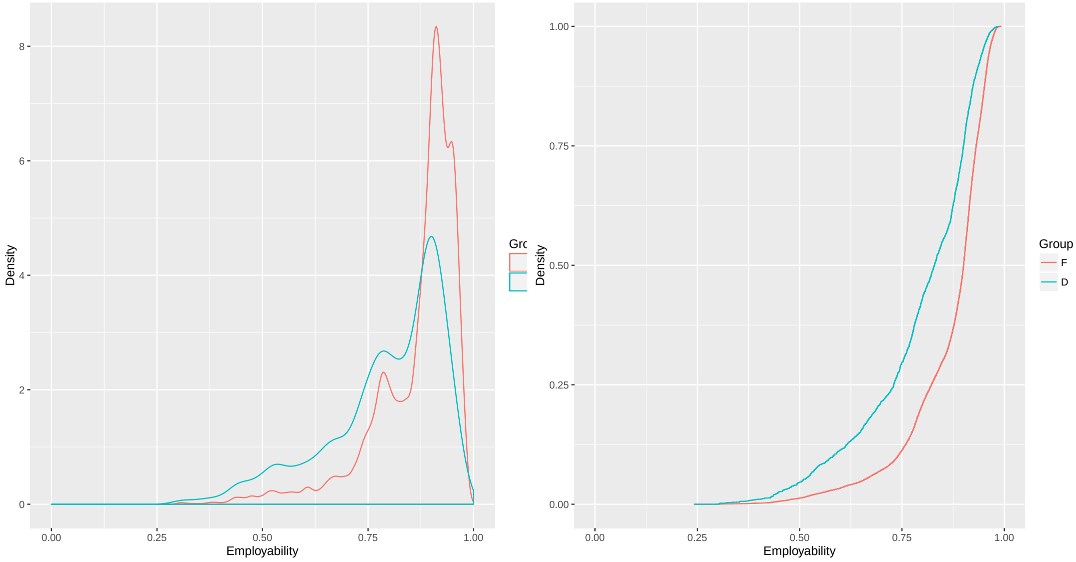
Notes: Predicted employment probabilities are based on the estimation of a logit on the majority population. The employment probability in the minority group is smoothed using cubic splines with 7 degrees of freedom.

stantial, around 2.5 percentage points. The share of non-employed people moving quarterly into employment is equal to 19.8% in the majority group and is 7.2 percentage points lower in the minority group. The unexplained gap is around 5 percentage points.

Figure 6 displays how the transition rates from and into employment vary with employability. As suggested by the average results, there are sizable ethnic differentials in both the hiring and the exit rates, at least when employability exceeds .5 for hiring rates, and when it remains below .95 for exit rates.

Overall, for both groups, the hiring rates are increasing with employability while the exit rates are decreasing. We now examine the ratios of hiring/exit rates between the two groups. Figure 7 replicates Figure 6 with rescaled majority rates to ease comparisons with minority ones: in the left panel the majority hiring rate is divided by 1.5, in the right panel, the majority exit rate is multiplied by 1.6. Although we cannot statistically reject that it is constant along the employability score, the general shape of the curve given by point estimates suggests that, if

Figure 5: Distribution of the employability score in both groups: empirical probability and cumulative distribution functions



Source: Labor Force Survey 2005-2011 (INSEE).

Notes: The employability score is based on the estimation of a logit on the majority population.

anything, the hiring rates ratio may increase up to an employability score of .8 and may decrease above (**Finding 2**) Results are more clear-cut concerning the exit rates ratio. The ratio between the minority and the majority exit rates appears to be constant with employability (**Finding 3**).

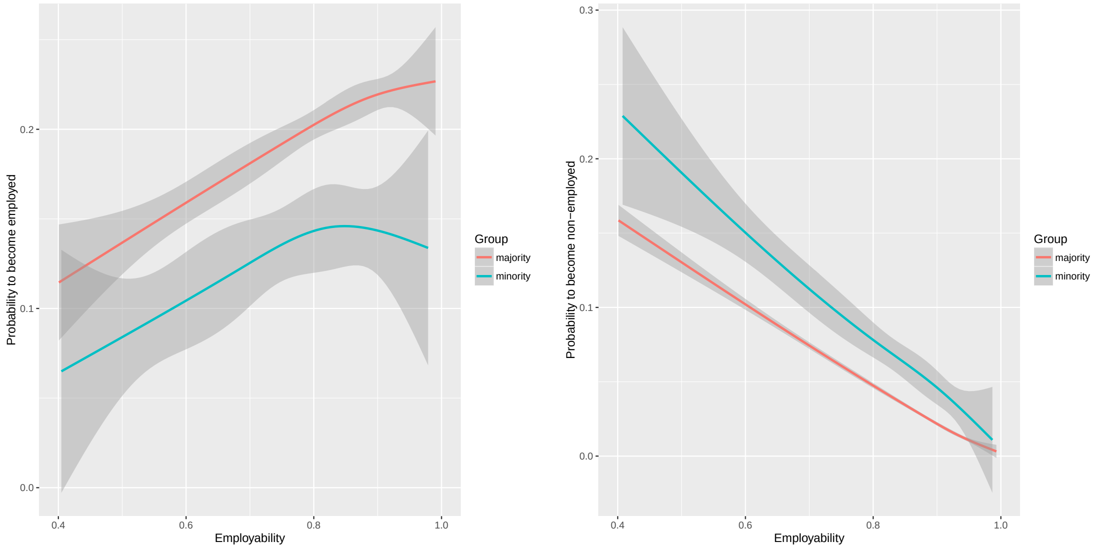
4.3 The contributions of inflows and outflows to employment gaps

Are the results on the flows consistent with the ones on the employment rates? In order to answer this question, we have to add some structure to the data. Suppose that individuals, given their characteristics, have a specific hiring rate h and exit rate q. Then, at the steady state, their employment probability will be:

$$e = \frac{h}{h+q}$$

We can compare the average employment rate observed in the data and the steady-state rate based on the average values of the hiring and exit rates. In the majority group, the employment rate is equal to 87% while the steady-state rate would be

Figure 6: Hiring rate h (left) and exit rate q (right) as a function of the employment score



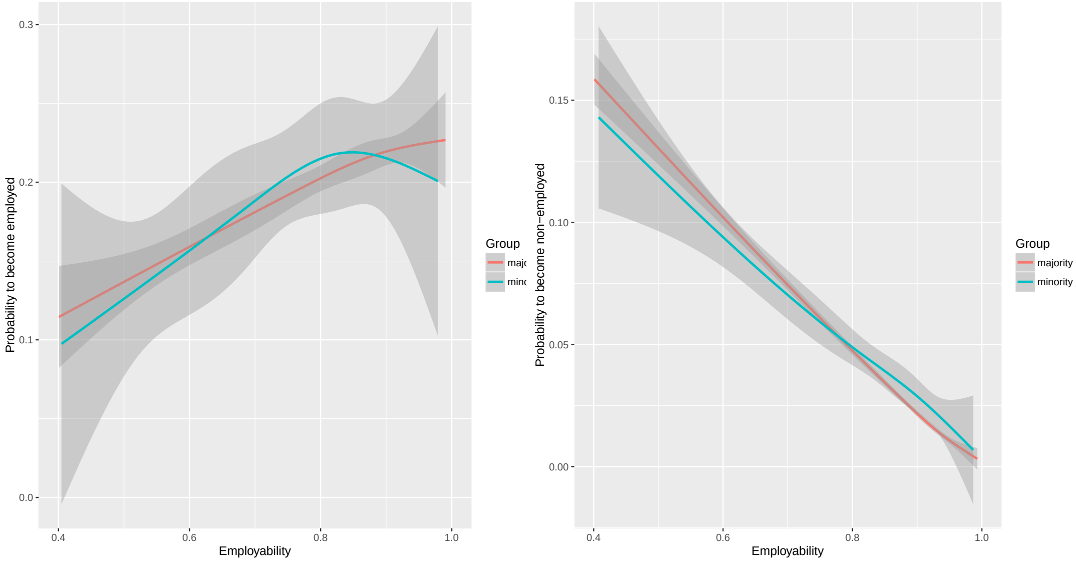
Source: Labor Force Survey 2005-2011 (INSEE).

Notes: The employability score is based on the estimation of a logit on the majority population. The hiring and exit probabilities in the minority group are smoothed using cubic splines with 4 degrees of freedom.

88% (based on an average hiring rate equal to 0.198 and an average exit rate equal to 0.027). In the minority group, the employment rate is equal to 64% while the steady-state rate would be 65% (based on an average hiring rate equal to 0.125 and an average exit rate equal to 0.067). Interestingly, the employment rates in the data are really close to the steady-state values predicted using the hiring and exit rates.

Now, we disentangle the contribution of inflows and outflows to the total ethnic employment gap by a simple counterfactual exercise. Keeping the hiring rate at the level of the majority group and plugging the minority exit rate leads to a counterfactual steady-state employment rate of 75%, 14 percentage points lower than the steady-state employment rate in the majority. Conversely, keeping the exit rate of the majority group and plugging the minority hiring rate leads to a counterfactual rate of 82%, only 6 percentage points less than the steady-state rate in the majority. The ethnic differentials in exit rates seem to explain a larger

Figure 7: Hiring rate h (left) and exit rate q (right) as a function of the employment score: majority hiring rate deflated by 50% and majority exit rate inflated by 60%



Source: Labor Force Survey 2005-2011 (INSEE).

Notes: Employability is based on the estimation of a logit on the majority population. The hiring and exit probabilities in the minority group are smoothed using cubic splines with 4 degrees of freedom.

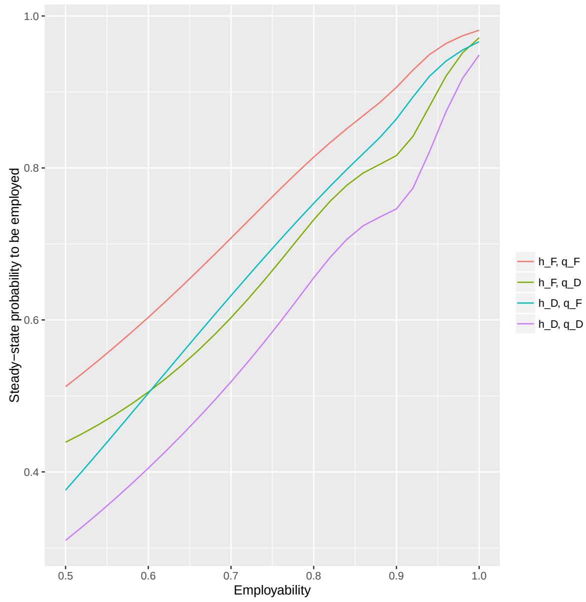
part of the raw employment gap than those in hiring rates.

Finally, we can perform the same counterfactual exercise conditional on employability. Figure 8 shows the predicted steady-state employment probability $h/(q+h)$ at each level of employability, isolating the contributions of the hiring and of the exit rates. Both differentials in hiring and exit rates seem to importantly contribute to the employment gap at each level of employability. Exit rates seem to contribute a little more for higher levels of employability whereas gaps in hiring rates contribute more for lower levels. As 90% of the minority workers have an employability score above .6 (see Figure 8), differentials in exit rates are, for most of workers, more important than differentials in hiring rates to explain ethnic employment gaps (**Finding 4**).

4.4 Summary of the empirical findings

Our empirical analysis leads to the following main findings:

Figure 8: Steady-state employment probability as a function of the employability score



Source: Labor Force Survey 2005-2011 (INSEE).

Notes: The employability score is based on the estimation of a logit on the majority population. The steady-state employment probabilities in the minority group are computed mixing the values of the hiring and exit rates in both groups, for each level of employability, before being smoothed using cubic splines with 4 degrees of freedom.

1. The employment gap tends to decrease with employability, especially for workers above the median of employability (**Finding 1**).

2. Hiring rates are increasing with employability. The ethnic differential in hiring rates is around 5 percentage points and the ratio between the majority and the minority rates is roughly constant with employability, around 1.6 (**Finding 2**).

3. Exit rates are decreasing with employability. The ethnic differential in exit rates is around 5 percentage points and the ratio between the minority and the majority rates is constant with employability, around 1.5 (**Finding 3**).

4. While both the ethnic differentials in hiring and exit rates play a role in explaining the employment gap, differentials in exit rates seem to matter more, for most of workers (**Finding 4**).

5 Interpretation

In this section, we interpret our empirical results in light of theoretical models. First, we develop the inflow-outflow model evoked above to show that the heterogeneity of the employment gap is compatible with a very simple model in which the underlying process generating the differences between groups is homogeneous (**Findings 1, 2 and 3**). Second, we investigate whether, if one was ready to interpret the unexplained employment gaps as the result of hiring discrimination, **Findings 1 and 2** could be helpful to learn about the type of discrimination. Third, we present two simple theoretical frameworks to explain how ethnic gaps in exit rates (**Findings 3 and 4**) can be generated.

5.1 Constant ratios of flow rates lead to heterogeneous employment gaps

Using the same inflow-outflow model as before, we can combine the following two equations,

$$e_F = \frac{h_F}{q_F + h_F} \quad \text{and} \quad e_D = \frac{h_D}{q_D + h_D}$$

leading to a relationship between the steady-state employment rate in the minority group and (steady-state) employability:

$$e_D = \frac{1}{1 + \frac{q_D}{q_F}\frac{h_F}{h_D}\left(\frac{1}{e_F} - 1\right)}.$$

As discussed above, our data are consistent with the fact that ratios $\frac{q_D}{q_F}$ and $\frac{h_F}{h_D}$ are roughly constant. Constant ratios in inflow and outflow rates, lead to a simplified form for the relationship between the minority employment rate and their employability:

$$e_D = \frac{1}{1 + \alpha\left(\frac{1}{e_F} - 1\right)}$$

where the parameter α, according to our rough estimates based on the curves, would be around 2.4.

We can perform a more formal test of α being constant. Without loss of generality, we can rewrite $e_F(x) = \frac{1}{1+\exp(\rho(x))}$ where x denotes the linear index of characteristics and $\rho(x) = \log(h_F/q_F)$, and $e_D(x) = \frac{1}{1+\exp(\rho(x)+\zeta(x))}$ where $\zeta(x) = \log(h_D/q_D q_F/h_F)$. Exploiting the logit form of these expressions, we estimate

$P[Y_i = 1|X_i, T_i] = \Lambda(X_i\beta^F + (X_i\beta^D)\mathbf{1}\{T_i = D\})$. In this model ζ (or equivalently α) being constant corresponds to $\beta^D_{-0} = 0$ (constant excluded). We perform a LR test of this condition and find a p-value of .09 meaning that the null hypothesis of a constant α cannot be rejected at a conventional level.

While this framework is silent about the mechanisms that generate the differences between minority and majority groups in terms of hiring and exit rates, it is useful to understand that homogeneous mechanisms (i.e. leading to constant ratios) are empirically consistent with heterogeneous employment rates along the employability score (Figure 9). In other terms, even if high-skill minority workers face the same amount of hiring discrimination as low-skill ones, as measured by h_D/h_F, the resulting employment gap will be ultimately lower for the former than for the latter. In this framework, **Findings 1**, **2** and **3** are consistent with each other.

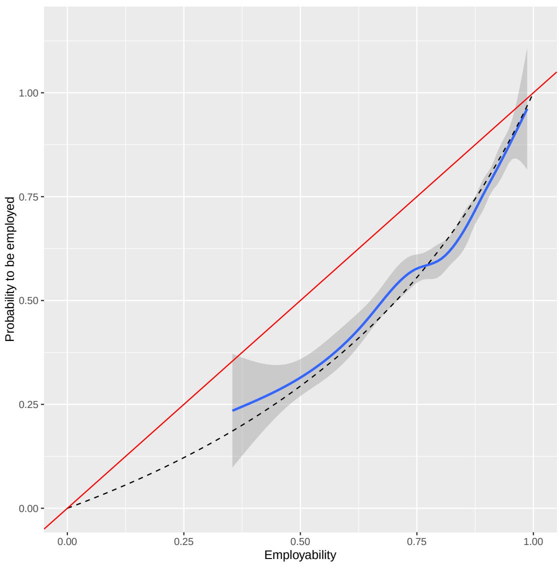
The rest of this section is more prospective. We derive simple setups in which different types of discrimination are at stake in order to compare their predictions to our empirical findings. Our ambition is not to provide statistical tests about discrimination type but only to illustrate our empirical findings.

5.2 What can we learn about the type of hiring discrimination from our empirical findings?

Our main insight regarding the type of discrimination comes from a screening framework at the hiring stage that leads to predictions on the hiring rates ratio h_D/h_F as a function of the employability score e_F.

In this framework, productivity is only partially observed and the screening mechanism goes as follows. A worker belonging to group $T = D, F$, has quality y, and $x = E(y|X)$ sums up the information on quality provided by his observable characteristics. x is observed both by the econometrician and employers. y can be rewritten as $y = x + \varepsilon$, where ε is the unobservable part of quality and is assumed to be normally distributed as a $\mathcal{N}(0, \omega^2)$ in both groups. When employers screen applicants for a given job, they observe a signal $\tilde{\varepsilon} = \varepsilon + \eta$. η is a screening error assumed to be independent of ε and its distribution is assumed to depend on the worker's group. The screening error is distributed as a $\mathcal{N}(0, \sigma_F^2)$ in group F and

Figure 9: Constant ratio of inflow/outflow rates and the heterogeneity of the ethnic employment gap



Source: Labor Force Survey 2005-2011 (INSEE).

Notes: Predicted employment probabilities are based on the estimation of a logit on the majority population. The employment probability in the minority group is smoothed using cubic splines with 7 degrees of freedom. The dotted line corresponds to the equation:

$$e_D = \frac{1}{1 + \alpha\left(\frac{1}{e_F} - 1\right)} \quad \text{with} \quad \alpha = 2.4$$

a $\mathcal{N}(-\mu, \sigma_D^2)$ in group D. Based on the observation of x, T and $\tilde{\varepsilon}$, risk-neutral employers formulate the best guess for an applicant's quality (see proof A.2 in Appendix):

$$\hat{y}_T(x) \doteq E[y|x, T, \tilde{\varepsilon}] = x + \tilde{\varepsilon}\left(\frac{\omega^2}{\sigma_T^2 + \omega^2}\right)$$

If $\mu > 0$, employers make a systematic error on the assessment of the productivity of minority workers (which is only plausible if, at the equilibrium, they do not have the opportunity to refine this prior very often). This is a simple case of statistical discrimination, which we call hereafter statistical discrimination in means. The distribution of η depends on the group T and we assume that $\sigma_D > \sigma_F$. For instance, this will be the case if the screening process is less precise for minority than for majority applicants because employers mainly belong to the majority group. $\sigma_D > \sigma_F$ thus generates statistical discrimination in variances. With either $\mu > 0$ or $\sigma_D > \sigma_F$, minority workers will pass the cut less often than the ones from the majority.

We assume that employers are willing to hire all job seekers whose expected productivity is above a given threshold $\underline{c}$, which we assume to be constant with x for simplicity. In this framework, taste-based discrimination can be modelled as a utility loss δ for employers. They require therefore a threshold $\underline{c}_D$ for minority applicants, which is higher than $\underline{c}$ and determined by:

$$E(\hat{y}|\hat{y} > \underline{c}_D, x) - E(\hat{y}|\hat{y} > \underline{c}, x) = \delta$$

Considering separately each of the three discrimination mechanisms, we obtain theoretical predictions about how the ratio of the hiring rates h_D/h_F varies with x, (see proofs A.3-A.6 in Appendix).

1. **Taste-based discrimination or statistical discrimination in means.** If $\sigma_D = \sigma_F = \sigma$ and either $\delta > 0$ or $\mu > 0$ then h_D/h_F increases with x.

2. **Pure statistical discrimination in variances.** If $\delta = 0$, $\mu = 0$ and σ_D/σ_F is constant with x, h_D/h_F increases in x up to a certain threshold and decreases with x above.

3. **Productivity and employability.** If q is constant or decreases in x, then the employment probability e_F increases in x

The first two results provide predictions about how h_D/h_F varies with observable productivity, under the polar cases of pure taste-based or statistical discrimination. The third result shows that these relationships hold when employability is used instead of productivity.

Many papers in the literature assume that the screening process is likely to be more efficient as the skill level of the worker increases (see Arcidiacono, Bayer, and Hizmo, 2010 or Lang and Manove, 2011), so that both σ_F and σ_D would decrease with x. To avoid any strong stance on how the ratio should vary with x, we assume, for the second result, that σ_D/σ_F is constant with x but have to acknowledge that the empirical literature is silent about this, so far.

Our first theoretical prediction states that in simple models of taste-based discrimination or statistical discrimination on the means, the hiring ratio h_D/h_F should be increasing. The second one states that in a simple statistical discrimination framework in which the variance of the signal differ across ethnic groups, this same ratio should increase at lower levels of x and decrease above a certain threshold. While our empirical result do not allow us to exclude any of these two patterns, we note that the point estimates of the hiring rates are compatible with the increasing-then-decreasing-ratio story.

This exercise should not be taken as formal evidence in favor of statistical discrimination on the signalling variance, as it is probably possible to construct other models of discrimination that would lead to different predictions in terms of how the ratio varies with productivity. However, we think that it is illustrative of the fact that studying the heterogeneity of labor-market differentials might provide additional testable predictions about the mechanisms underlying discrimination.

5.3 Micro-founding the ethnic gap in exit rates

In this section, we review two theoretical frameworks that may help explain differentials in exit rates (**Finding 3**).

5.3.1 Two-stage screening model

Here, we explicitly model the destruction of the job match in the screening model developped above. It is usual in the matching literature to endogenize the timing of the match destruction by assuming that the productivity varies according to some random process and that the match does not survive under a certain threshold. If productivity is perfectly observed, an obvious modeling choice is to have the random process depend on ethnicity. More interestingly, when productivity is not perfectly observed and employers learn about employees over time, new information about the worker's productivity can lead to a dismissal. As minority workers' initial signals are more noisy, new signals are more likely to reveal very low productivity. Therefore, the revelation of information about productivity can result in a higher termination rate for minority workers.

To understand under which conditions this may happen, we add a second stage to the screening framework in which a new signal is drawn. After a given period of time, which may depend across matches, employers observe a second draw of ε. This draw is used to refine their prior about the worker's quality and may reveal that some of the workers are not qualified enough for the job. Workers whose revised expected quality do not meet the new threshold are dismissed.

In the presence of statistical discrimination, minority workers are more often misclassified than majority workers. Thus, the exit rate of minority workers will be higher than the one of majority workers. In the presence of taste-based discrimination (without statistical discrimination), misclassification is comparable across groups and there should be no difference in the exit rates of minority and majority workers (see proof A.7 in Appendix). The ethnic gap in the exit rates observed in that data (**Finding 3**) would lead us to favor that statistical discrimination rather than taste-based discrimination only is involved in the employers' hiring behaviors.

5.3.2 Search model with risk aversion

Ethnic exit rate gaps also appear in frameworks with worker risk aversion. Indeed, one of the most obvious reasons why minority workers would face a higher exit rate is that they have more insecure jobs, which will have on average shorter durations. If workers are risk-averse, the uncertainty about the duration of the job is a dimension that workers will trade off with wages. Workers that are discriminated against may have a higher probability to accept a job with a lower wage but also a job of shorter duration.

In the usual job-search model, workers are risk neutral and their exit rate is exogenous. Introducing variable exit rates across jobs would leave the job-acceptance behavior unchanged in that framework. Therefore, we introduce risk aversion in the search model, and following Pratt (1964); Pissarides (1974); Nachman (1975), we model it in a simple way by introducing a risk-premium term $p(q)$ (increasing in q).[13] Denoting wages as w, the discount rate as r, the present expected utility associated to a job as V_e and the present expected utility associated to unemployment as V_u, the flow of utility of a worker in a job with wage w and exit rate q will be equal to:

$$rV_e(w,q) = w - p(q) + q(V_u - V_e(w,q))$$

In this context, we can define a reservation utility, and job seekers will only take offers such $w - p(q) > rV_u$. Assume that the minority population faces a lower arrival rate of job offers, the minority workers will accept, on average, jobs with a higher exit rate, even if they face the same distribution of wage and exit rate offers. In this framework, the differences in exit rates come directly from the differences in the hiring rates.

6 Concluding comments

In this paper, we describe the heterogeneity of ethnic employment gaps along a continuous dimension: employability, that measures the counterfactual employment probability minority workers would have if their observable skills, namely education and age, were priced as the majority workers' ones. Under a classical conditional independence assumption, our empirical strategy enables us to document unexplained (net-of-composition-effects) ethnic employment gaps along the employability score. We apply this method to the ethnic employment gap concerning French men of North African origin. We find that minority workers with lower

[13] $p(q)$ can have a broader sense than just a risk premium and can be seen as a general cost of insecurity. Having a less secure job can have actual consequences: more difficulty to rent a property or to get a loan.

employability suffer from large unexplained gaps, around 20 percentage points. The unexplained gap decreases unambiguously with employability, to be lower than 5 percentage points at the highest employability scores.

A second empirical contribution is to decompose quarterly transition rates into and from employment: we document how they vary with employability and whether entry or exit matter most to explain employment gaps. We find that, in both groups, hiring rates increase with employability while exit rates decrease with employability. The ratio between the minority and the majority exit rates is clearly constant along the employability score, whereas point estimates for the ratio of hiring rates suggest that it increases for low levels of employability and then decreases for higher ones but we cannot statistically reject that the ratio is in fact constant. Finally, we find that ethnic differentials both in hiring and in exit rates matter for employment gaps, but exit differentials seem to matter more for most of workers.

Simple labor-market models can be used to provide a first interpretation of these results. First, we show that the heterogeneity of the employment gaps do not need to come from heterogenous mechanisms, say, differential discrimination, which would be harsher towards low-employability than high-employability workers. We can generate the pattern of the heterogeneity through a simple inflow-outflow framework in which the ratio of hiring and exit rates are constant. This would for instance be the case if minority workers received say half as many offers as the majority ones.

Then, we investigate whether the new empirical results on the hiring and exit rates can help separate the different sources of discrimination. In a simple screening framework at the hiring stage, we compare the predictions that arise when we introduce statistical or taste-based discrimination. Neither the precision of our empirical results nor the simplicity of our theoretical framework allow us to draw definite conclusions. However, we note that the predictions given by this simple model with statistical discrimination (on the variance of the screening error) matches our point estimates for the pattern of the ratio of hiring rates across ethnic groups, which is increasing then decreasing with employability. More research would be needed to assess the validity of the assumptions of the model and to obtain more precise empirical estimates.

Finally, we provide two simple frameworks to understand ethnic gaps in exit rates, which have not attracted a lot of attention in the literature about ethnic labor-market gaps. We show that differentials in exit rates can be the consequence of noisier signals for minority workers at the hiring stage (compatible with the existence of statistical discrimination). In a search model, the combination of workers' risk aversion and discrimination at the hiring stage can also generate gaps in exit rates when workers self-select into jobs that have a higher probability to be destroyed.

Compliance with Ethical Standards: The authors declare that they have no conflict of interest.

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Table 1: Summary Statistics

Variables	Men	
	France	North Africa
Education		
Medicine doctorate	0.01	0.00
University (general): Master deg. and above	0.04	0.02
Grandes Ecoles (general): Master deg.	0.05	0.02
University (general): Bachelor's deg. (4 years after HS), Science or Industry	0.01	0.00
University (general): Bachelor's deg. (4 years after HS), Other	0.02	0.01
University (general): Bachelor's deg. (3 years after HS), Science or Industry	0.01	0.01
University (general): Bachelor's deg. (3 years after HS), Other	0.02	0.02
University (general): Short-cycle Tertiary Education (2 years after HS)	0.01	0.01
Technical: Short-cycle Tertiary Education (2 years after HS), Industry	0.06	0.03
Technical: Short-cycle Tertiary Education (2 years after HS), Other	0.05	0.04
Health (vocational): Short-cycle Tertiary Education (2 years after HS)	0.01	0.00
High School (general): Upper Secondary Education , Science	0.03	0.02
High School (general): Upper Secondary Education, Humanities	0.03	0.04
High School (technical): Upper Secondary Education, Industry	0.02	0.01
High School (technical): Upper Secondary Education, other	0.02	0.03
High School (vocational): Upper Secondary Education, Industry	0.07	0.05
High School (vocational): Upper Secondary Education, other	0.02	0.03
Basic (vocational): Lower Secondary Education, (apprenticeship), Industry	0.20	0.14
Basic (vocational): Lower Secondary Education, (school), Industry	0.06	0.04
Basic (vocational): Lower Secondary Education, (apprenticeship), other	0.03	0.04
Basic (vocational): Lower Secondary Education, (school), other	0.01	0.02
Basic (general): Lower Secondary Education deg.	0.07	0.10
No diploma	0.15	0.29
Age		
15-25	0.17	0.24
25-30	0.16	0.25
30-35	0.16	0.20
35-40	0.17	0.15
40-45	0.17	0.10
45-50	0.18	0.06
Labor Market Situation		
Employed	0.87	0.64
Full-time when employed	0.95	0.92
Occupation (current or last if not employed)		
Executive, Professional	0.16	0.07
Technical, Education	0.21	0.16
Clerical, Sales, Service Worker	0.13	0.16
Factory Operator	0.36	0.39
Never worked	0.07	0.18
Socio-demographic		
Couple	0.75	0.70
Working spouse	0.48	0.23
No child	0.51	0.54
1 child	0.21	0.20
2 children	0.20	0.17
3+ children	0.08	0.09
Youngest child less than 3	0.13	0.16
Mother's occupation		
Unknown	0.02	0.02
Cultivator	0.05	0.00
Retail, Craft	0.04	0.01
Professionals	0.03	0.01
Technicians	0.12	0.03
Office workers	0.32	0.23
Blue workers	0.10	0.08
Does not work	0.32	0.62
Father's occupation		
Unknown	0.05	0.08
Cultivator	0.07	0.00
Retail, Craft	0.11	0.08
Professionals	0.11	0.02
Technicians	0.16	0.05
Office workers	0.11	0.06
Blue workers	0.38	0.66
Does not work	0.02	0.05
Nobs	79,055	3626

Source: Labor Force Survey 2005-2011 (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 and for whom at least one parent had the citizenship of a North African country at birth.

Table 2: Employment Logit estimation

Education. *Ref: Upper Sec. Education, Humanities*		Age. *Ref: 40-45*	
Master degree and above	1.39 *** (0.39)	*15-25*	−1.19*** (0.14)
Medicine doctorate	0.41 *** (0.11)	*25-30*	−0.64*** (0.14)
Grandes Ecoles: Master deg.	0.77 *** (0.12)	*30-35*	−0.28** (0.14)
Bachelor's deg. (4 years after HS), Science or Industry	1.16 *** (0.32)	*35-40*	−0.13*** (0.04)
Bachelor's deg. (4 years after HS), Other	0.29 ** (0.14)	*45-50*	−0.03 (0.04)
Bachelor's deg. (3 years after HS), Science or Industry	1.06 *** (0.19)	Mother's occupation. *Ref: Blue-collar*	
Bachelor's deg. (3 years after HS), Other	0.24 ** (0.12)	*Unknown*	−0.25*** (0.06)
Short-cycle Tertiary Ed. (2 years after HS)	0.14 (0.16)	*Cultivator*	0.46 *** (0.11)
Tec. Short-cycle Ter. Ed. (2 years after HS), Ind.	0.74 *** (0.11)	*Retail, Craft*	0.19 *** (0.06)
Tec. Short-cycle Ter. Ed. (2 years after HS), Other	0.39 *** (0.10)	*Professional*	−0.08 (0.06)
Short-cycle Ter. Ed. (2 years after HS), Health	1.58 *** (0.33)	*Technician*	−0.09** (0.04)
Upper Sec. Ed., Science	0.19 * (0.11)	*Office Worker*	−0.03 (0.05)
Upper Sec. Ed., Industry	0.28 ** (0.12)	*Does not work*	−0.58*** (0.08)
Tec. Up. Sec. Ed., Other	−0.10 (0.11)	*35-50 * Unknown*	0.06 (0.10)
Voc. Up. Sec. Ed., Industry	0.82 *** (0.10)	*35-50 * Cultivator*	0.14 (0.16)
Voc. Up. Sec. Ed., Other	−0.07 (0.11)	*35-50 * Retail, Craft*	−0.02 (0.09)
Voc. Lo. Sec. Ed., (appr.), Ind.	0.19 ** (0.08)	*35-50 * Professional*	−0.08 (0.09)
Voc. Lo. Sec. Ed., (school), Ind.	0.13 (0.10)	*35-50 * Technician*	0.10 (0.07)
Voc. Lo. Sec. Ed., (appr.), Other	−0.13 (0.11)	*35-50 * Office Worker*	0.03 (0.08)
Voc. Lo. Sec. Ed., (school), Other	−0.37*** (0.14)	*35-50 * Does not work*	0.33 ** (0.16)
Lower Sec. Ed.	−0.44*** (0.08)	Father's occupation. *Ref: Blue-collar*	
No diploma	−1.06*** (0.08)	*Unknown*	0.02 (0.11)
*35-50 * Upper Sec. Ed., Humanities*	−0.08 (0.13)	*Cultivator*	0.14 (0.15)
*35-50 * Master deg.*	0.08 (0.52)	*Retail, Craft*	−0.04 (0.09)
*35-50 * Medicine doctorate*	0.43 *** (0.16)	*Professional*	−0.10 (0.09)
*35-50 * Grandes Ecoles: Master deg.*	−0.10 (0.14)	*Technician*	−0.13** (0.06)
*35-50 * Bachelor's deg. (4 ys after HS), Sc. or Ind.*	0.06 (0.50)	*Office Worker*	0.02 (0.05)
*35-50 * Bachelor's deg. (4 ys after HS), Other*	0.46 ** (0.21)	*Does not work*	−0.29*** (0.05)
*35-50 * Bachelor's deg. (3 ys after HS), Sc. or Ind.*	0.27 (0.45)	*35-50 * Unknown*	−0.21 (0.17)
*35-50 * Bachelor's deg. (3 ys after HS), Other*	−0.11 (0.17)	*35-50 * Cultivator*	−0.01 (0.20)
*35-50 * Short-cycle Ter. Ed. (2 ys after HS)*	−0.05 (0.21)	*35-50 * Retail, Craft*	−0.00 (0.14)
*35-50 * Tec. Sh.-cyc. Ter. Ed. (2 ys after HS), Ind.*	0.14 (0.14)	*35-50 * Professional*	−0.28* (0.17)
*35-50 * Tec. Sh.-cyc. Ter. Ed. (2 ys after HS), Oth.*	0.05 (0.13)	*35-50 * Technician*	0.03 (0.10)
*35-50 * Short-cycle Ter. Ed. (2 ys after HS), Health*	−0.33 (0.47)	*35-50 * Office Worker*	0.06 (0.08)
*35-50 * Upper Sec. Ed., Sc.*	−0.10 (0.16)	*35-50 * Does not work*	0.28 *** (0.08)
*35-50 * Tec. Up. Sec. Ed., Ind.*	0.19 (0.19)		
*35-50 * Tec. Up. Sec. Ed., Oth.*	0.20 (0.18)		
*35-50 * Voc. Up. Sec. Ed., Ind.*	−0.19 (0.14)		
*35-50 * Voc. Up. Sec. Ed., Oth.*	0.15 (0.19)		
*35-50 * Voc. Lo. Sec. Ed. (appr.) , Ind.*	−0.23*** (0.07)		
*35-50 * Voc. Lo. Sec. Ed. (school), Ind.*	−0.09 (0.11)		
*35-50 * Voc. Lo. Sec. Ed. (appr.), Oth.*	−0.01 (0.13)		
*35-50 * Voc. Lo. Sec. Ed. (school), Oth.*	0.14 (0.19)		
N		79,055	

Source: Labor Force Survey 2005-2011 (INSEE).
Notes: Dummies for calendar quarters (27 without the reference) interacted with dummies for age lower than and greater than 35 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.

A Appendix: Proofs

A.1 Consequence of the CIA: $Y(F) \perp T | p(X)$

Rosenbaum and Rubin (1983) prove that:

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

Following exactly their reasoning, it is possible to prove that, for any random variables A_i, B_i taking values in $\{0, 1\}$:

$$A_i \perp B_i | X_i,\ \forall i \Rightarrow A_i \perp B_i | P(A_i = 1 | X_i),\ \forall i.$$

Rosenbaum and Rubin (1983) consider $A_i = T_i$ and $B_i = Y_i(F)$. The proof finishes by taking $A_i = Y_i(F)$ and $B_i = T_i$. $\square$

A.2 Employer's best guess: $\hat{y}_T(x) \doteq E[y|\tilde{y}, x, T] = x + \tilde{\varepsilon}\left(\frac{\omega^2}{\sigma_T^2 + \omega^2}\right)$

This point is derived from Aigner and Cain (1977). Employers' best guess, given x, T and $\tilde{y}$ is:

$$\hat{y}_T(x) = E[y|\tilde{y}, x, T] = E[x + \varepsilon | \varepsilon + \eta, x, T] = x + E[\varepsilon | \varepsilon + \eta, T]$$

The last equality holding because $x \perp \varepsilon$.
The result follows then from:

$$E[\varepsilon | \varepsilon + \eta, T] = \frac{\omega^2}{\omega^2 + \sigma_T^2}(\varepsilon + \eta) = \frac{\omega^2}{\omega^2 + \sigma_T^2}(\tilde{y} - x)$$

This equation implies that $\hat{y}_T(x) \sim N(x, \omega^4/(\sigma_T^2 + \omega^2))$.

$\square$

A.3 Point 1, Section 5, taste-based discrimination

To offset a utility loss δ, employers set up a cutoff $\underline{c}_D > \underline{c}$ such that:

$$E(\hat{y}|\hat{y} > \underline{c}_D, x) - E(\hat{y}|\hat{y} > \underline{c}, x) = \delta$$

Condition $\hat{y} > \gamma$, ($\gamma = \underline{c}$, or $\gamma = \underline{c}_D$) is equivalent to:

$$\frac{\sqrt{\sigma^2 + \omega^2}}{\omega^2}(\hat{y} - x) > \frac{\sqrt{\sigma^2 + \omega^2}}{\omega^2}(\gamma - x)$$

We define $c = (\underline{c} - x)\frac{\sqrt{\omega^2+\sigma^2}}{\omega^2}$, $c_D = (\underline{c}_D - x)\frac{\sqrt{\omega^2+\sigma^2}}{\omega^2}$, $u = (\hat{y} - x)\frac{\sqrt{\omega^2+\sigma^2}}{\omega^2} \sim \mathcal{N}(0, 1)$ and we denote $\lambda(.) = \varphi(.)/\Phi(.)$, with φ and Φ corresponding respectively to the probability distribution function and the cumulative distribution function of a $\mathcal{N}(0,1)$. With these notations $E(u|u>\gamma,x)=\lambda(\gamma)$.

The thresholds c and c_D are such that:

$$\lambda(-c_D)-\lambda(-c)=\delta\frac{\sqrt{\sigma^2+\omega^2}}{\omega^2}\doteq\tilde{\delta}$$

If δ does not depend on x, differentiating this equation with respect to x leads to:

$$-c_D'(x)\lambda'(-c_D(x))=-c'(x)\lambda'(-c(x)) \tag{1}$$

Given that λ'/λ is decreasing and that $c_D>c$, we have that:

$$\frac{\lambda'(-c_D)}{\lambda(-c_D)}>\frac{\lambda'(-c)}{\lambda(-c)} \tag{2}$$

Combining equations (1) and (2), and given that $\lambda'<0$, we obtain:

$$\lambda(-c_D)(-c_D'(x))>\lambda(-c)(-c'(x)) \tag{3}$$

The ratio of hiring probabilities is equal to:

$$\frac{h_D}{h_F}=\frac{P(u>c_D)}{P(u>c)}=\frac{\Phi(-c_D)}{\Phi(-c)}$$

Differentiating the ratio of employment probabilities by x, we show that the sign of the derivative is the same as the one of:

$$\lambda(-c_D)(-c_D'(x))-\lambda(-c)(-c'(x))$$

From equation (3), we find that the ratio h_D/h_F should be increasing.

A.4 Point 1, Section 5, statistical discrimination in means

In this case, $\hat{y}_D=\hat{y}_F=x+\tilde{\varepsilon}\frac{\omega^2}{\sigma^2+\omega^2}$. Condition $\hat{y}>\underline{c}$ is equivalent to:

$$\frac{\sqrt{\sigma^2+\omega^2}}{\omega^2}(\hat{y}-x)>\frac{\sqrt{\sigma^2+\omega^2}}{\omega^2}(\underline{c}-x)$$

We define $c=(\underline{c}-x)\frac{\sqrt{\omega^2+\sigma^2}}{\omega^2}$. In this case, transformed unobservables $u=(\hat{y}-x)\frac{\sqrt{\omega^2+\sigma^2}}{\omega^2}$ are distributed in a $\mathcal{N}(0,1)$ in group F and $\mathcal{N}(-\mu,1)$ in group D. We denote $\lambda(.)=\varphi(.)/\Phi(.)$, with φ and Φ corresponding to the probability distribution function and the cumulative distribution function of a $\mathcal{N}(0,1)$.

Then:

$$\frac{h_D}{h_F} = \frac{P(u_D > c(x))}{P(u_F > c(x))} = \frac{\Phi(-c(x) - \mu)}{\Phi(-c(x))}$$

Differentiating the ratio of employment probabilities by x, and using that $c' < 0$, we find that the sign of the derivative is the same as the one of:

$$\lambda(-c(x) - \mu) - \lambda(-c)$$

Because $-c(x) - \mu < -c(x)$, and $\lambda' < 0$, we have $\lambda(-c(x) - \mu) > \lambda(-c)$, so that the ratio h_D/h_F is increasing.

A.5 Point 2, Section 5

Condition $\hat{y}_T > \underline{c}$ is equivalent to:

$$\frac{\sqrt{\sigma_T^2 + \omega^2}}{\omega^2}(\hat{y}_T - x) > \frac{\sqrt{\sigma_T^2 + \omega^2}}{\omega^2}(\underline{c} - x)$$

or, denoting $u_T = \frac{\sqrt{\sigma_T^2+\omega^2}}{\omega^2}(\hat{y}_T - x)$, with $T = D, F$, $c(x) = \frac{\sqrt{\sigma_F^2+\omega^2}}{\omega^2}(\underline{c} - x)$ and $k = \frac{\sqrt{\sigma_D^2+\omega^2}}{\sqrt{\sigma_F^2+\omega^2}} > 1$, so that $h_F = P(u_F > c)$ and $h_D = P(u_D > kc)$.
Because u_D and $u_F \sim \mathcal{N}(0,1)$,

$$\frac{h_D}{h_F} = \frac{P(u_D > kc(x))}{P(u_F > c(x))} = \frac{\Phi(-kc(x))}{\Phi(-c(x))}$$

First consider the situation when σ_D and σ_F do not vary with x. The derivative of $\frac{h_D}{h_F}$ with respect to x is positive iff:

$$\Phi(-kc(x))\varphi(-c(x))c'(x) > k\Phi(-c(x))\varphi(-kc(x))c'(x)$$

and as $c'(x) = -\frac{\sqrt{\sigma_F^2+\omega^2}}{\omega^2} < 0$, this is equivalent to:

$$\Phi(-kc(x))\varphi(-c(x)) < k\Phi(-c(x))\varphi(-kc(x))$$

Noting $\lambda(.) = \varphi(.)/\Phi(.)$, this is itself equivalent to:

$$\lambda(-c(x)) < k\lambda(-kc(x))$$

If $c > 0$, that is $x < \underline{c}$, we have as $k > 1$, $-kc(x) < -c(x)$, and as $\lambda(.)$ is positive and decreasing, $\lambda(-c(x)) < k\lambda(-kc(x))$. Therefore, $\frac{h_D}{h_F}$ is increasing in x.

If $c < 0$, that is if $x > \underline{c}$, conclusion depends on the value of k: $\frac{h_D}{h_F}$ increases in x iff $\lambda(-c(x)) < k\lambda(-kc(x))$ and $\frac{h_D}{h_F}$ decreases in x iff $\lambda(-c(x)) > k\lambda(-kc(x))$. Simulations show that $\forall k > 1$ there exists a (unique) $-c_0$ such that $\forall - c < -c_0, \quad \lambda(-c(x)) < k\lambda(-kc(x))$ and $\forall - c > -c_0, \quad \lambda(-c(x)) > k\lambda(-kc(x))$ (more details available upon request). So, $\frac{h_D}{h_F}$ increases with x up to a certain threshold and then decreases. The threshold depends on the employer cut-off $\underline{c}$ and on the screening error variance ratio k. $\square$

A.6 Point 3, Section 5

Consider the inflow-outflow equation with e, h and q being functions of x:

$$e(x) = \frac{h(x)}{h(x) + q(x)}.$$

Taking the derivative with respect to x leads to:

$$e'(x) = \frac{h'(x)q(x) - q'(x)h(x)}{(h(x) + q(x))^2}$$

with the previous notations, $h(x) = P(u > c(x)) = \Phi(-c(x))$ which is increasing in x. Therefore, it suffices for e to be increasing in x, that q be non increasing in x. $\square$

A.7 Two-stage screening model

The two-stage screening model corresponds to drawing u_1, u_2 in a bivariate normal distribution such that $u_1, u_2 \sim \mathcal{N}(0, 1)$ and $cov(u_1, u_2) = \rho_T = \frac{\omega^2}{\omega^2 + \sigma_T^2}$.
Writing $u_2 = \rho_T u_1 + \nu$, with $V(\nu) = \sqrt{1 - \rho_T^2}$ leads to

$$P(u_2 > c | u_1 > c) = \frac{P\left(\frac{\nu}{\sqrt{1-\rho_T^2}} > \frac{c - \rho_T u_1}{\sqrt{1-\rho_T^2}} \quad \& \quad u_1 > c\right)}{P(u_1 > c)}.$$

With the previous notations, it follows that:

$$P(u_2 > c | u_1 > c) = \frac{\int_c^\infty \Phi\left(\frac{\rho_T u - c}{\sqrt{1-\rho_T^2}}\right) \varphi(u)}{\Phi(-c)}.$$

The denominator does not depend on ρ_T, and $\frac{\rho_T u - c}{\sqrt{1-\rho_T^2}}$ is increasing in ρ_T as long as $u > \rho_T c$ (which is the case here). $P(u_2 > c | u_1 > c)$ is thus increasing in ρ_T, and therefore decreasing in σ_T. Minority workers are more likely to be dismissed than majority ones.

$\square$

B Appendix: Similarities and differences between the propensity and employability scores

The employability score shares similarities with the propensity score but it differs from it. Note first that the employability score is not a balancing score in the sense defined by Rosenbaum and Rubin (1983). In general, we do not have $X \perp T|p(X)$. To see this, just consider two populations $T = 0$ and $T = 1$, and a unique explanatory variable X with values 0 and 1, and taking value 1 with probability q if $T = 0$ and probability $1-q$ if $T = 1$ ($q \neq 1-q$). Assume also that employment Y is such that $P(Y|X,T) = 1/2$ independent of T and X. It follows that $T \not\perp X|P(Y|X) = 1/2$.

Even if the employability score is not a balancing score, $Y(F) \perp T|p(X)$ entails that conditional treatment effects are identified at any value of $p(X)$. So the employability score provides a different dimension of analysis that is not redundant with nor cannot be summarized in general by the propensity score.

Further, applying the same reasoning as Rosenbaum and Rubin (1983) on $p(X)$ instead of on the propensity score, we can define balancing scores relative to Y, instead of balancing scores relative to T. Let b_Y be a balancing score relative to Y, b_Y is such that $X \perp Y|b_Y(X)$. Theorem 2 of Rosenbaum and Rubin (1983) says that the propensity score $e(X) = P(T = 1|X)$ is the coarsest balancing score in the sense that if b_T is a balancing score (relative to T), then $e = f(b_T)$ for some function f. Considering now Y instead of T, it follows that $p(X) = P(Y = 1|X)$ is the coarsest balancing score relative to Y.

Theorem 3 of Rosenbaum and Rubin (1983) says that if treatment assignment is strongly ignorable given X, then it is strongly ignorable given any balancing score $b_T(X)$, which holds in particular for the propensity score $e(X)$. Considering again Y instead of T, treatment assignment is also ignorable given any balancing score relative to Y, $b_Y(X)$, in particular given the employability $p(X)$.

To justify even more the use of the employability, we show next that it is, with the propensity score, the only other unidimensional score that could lead to the previous results in a general way. It may happen, that in specific situations, other unidimensional scores could summarize the CIA and be good candidates for a conditional analysis, but the only ones that can work on a general basis are the propensity score and the employability. To see that, it is sufficient to find an example in which they are the only valid scores (in the above sense).

Assume that there is one single covariate X, and that Y is such that $P(Y = 1|X) = \Lambda(X)$, with $\Lambda(x) = \exp(x)/(1 + \exp(x))$, and T is such that $P(T = 1|X) = 1 - \Lambda(X)$.

Imagine that there is some function g such that $Y \perp T|g(X)$ but g is neither a balancing score relative to Y nor to T: $X \not\perp T|g(X)$ and $X \not\perp Y|g(X)$. This means that there exist $x_1 < x_2$, such that $g(x_1) = g(x_2) = \gamma$ but $P(Y = 1|x_1) \neq P(Y = 1|x_2)$. Given the specific form of Y and T, this also means that $P(T = 1|x_1) \neq P(T = 1|x_2)$.

Assume without loss of generality that $g = \gamma \Rightarrow x \in (x_1, x_2)$ and that X follows a non informative distribution. It follows that $P(Y = 1|T = 0, g = \gamma) < P(Y = 1|T = 1, g = \gamma)$. Indeed, with $T = 0$, it is more likely that $x = x_1$ than $x = x_2$. This contradicts the fact that $Y \perp T|g(X)$. Therefore, in general, the only scores b that are such that $Y \perp T|b(X)$ are balancing scores relative to Y or T.