ETHNIC GAPS IN EDUCATIONAL ATTAINMENT AND LABOR-MARKET OUTCOMES: EVIDENCE FROM FRANCE

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Abstract

We use data from the *Trajectoires et Origines* survey to analyze ethnic gaps in education and labor-market outcomes between second-generation immigrants and their French native counterparts. Altogether, our findings do point out the importance of family background in explaining lifelong ethnic inequalities. Precisely we have three main findings. First, we find that second-generation immigrants are on average less likely to experience education success than their native counterparts and that such education gap seems to be mainly rooted in ethnic differences in family backgrounds. Second, our data indicate that if second-generation immigrants have on average a lower probability of employment and lower wages than natives, both gaps are mainly explained by differences in education. Third, we find important heterogeneity across ethnic groups.

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1. Introduction

In the recent years, several European countries have experienced unprecedented flows of immigrants, mostly originated from Africa and Middle East. These recent immigration flows raise important questions about the economic assimilation of immigrants. To what extent are the OECD countries able to absorb these flows of immigration? Does it matter where immigrants come from in explaining differences in market outcomes?

An extensive literature has attempted to provide some answers to these questions by examining the differences between natives and immigrants in terms of employment (see, among others, Bevelander and Nielsen, 2001, for Sweeden ; Blau and Kahn, 2005, for the US; Meurs and Pailhé, 2010, and Aeberhardt et al. 2010a,b, for France), earnings (see, among others, Chiswisck 1978; Borjas, 1995 or Altonji and Blank, 1999, for the US; Constant and Massey 2003, for Germany; Longva and Raaum, 2003, for Norway, Aeberhardt and Pouget, 2010, and Aeberhardt et al. 2010a,b, for France) and educational attainment (see, among others, Card, DiNardo and Estes, 2000, for US evidence; Gang and Zimmermann, 2000, and Casey and Dustmann, 2008, for German data; Van Ours and Veenman, 2003, for the Netherlands;, 2010; Algan et al., 2010, for French, German and British evidence; Dustmann and Glitz, 2011, for evidence on OECD countries).

Most of these studies report that immigrants are *i*) less likely to be employed, *ii*) earn on average significantly less than natives and *iii*) do perform worse at school than the natives. However the existing literature also stresses the fact that the ethnic gaps tend to reduce over time. For instance, some studies reveal that second-generation youth tends to perform better academically than first-generation youth and performs as well or even better than natives (Rong and Grant, 1992; Kao and Tienda, 1995; Chiswick and DebBurman, 2004; Algan et al. 2010; Dustmann et al, 2010; Dustmann, 2012).[1] Empirical evidence also indicates that the younger the age at arrival the better language fluency and educational attainment (see, for instance, Bleakly and Chin, 2010, Domingues Dos Santos and Wolff, 2011).[2] There is also a strong support that differences of parental educational attainment between natives and

[1] For instance, Dustmann et al (2010) find that while minority groups start off at lower achievement outcomes at school entry, they tend to outperform British white children by the age of 16.

[2] Using the British school census, Dustman et al. (2010) compare educational outcomes between children from ethnic minority groups and native children from the age of 5 until the age of 16. The authors show that improvements in proficiency of the English language is the most important factor to explain why ethnic minorities improve relative to their British counterparts. Furthermore language proficiency would also impact social integration (see Bleakly and Chin, 2010).

immigrants are likely to reproduce in the next generation (see, among others, Chiswick, 1977, Borjas, 1993, Card et al. 2008, for the US, Gang and Zimmerman, 2000, for Germany; Van Ours and Veenman, 2001, for the Netherlands; Domingues Dos Santos and Wolff, 2011, for France). Finally, other studies put in evidence that socio-economic integration of immigrants is not uniform across ethnic groups. For instance, in France, it is documented that immigrants from Maghreb suffer more from unemployment than other ethnic groups (e.g. Meurs et al., 2006; Meurs and Pailhé, 2010). Other studies find that Muslim immigrants integrate less and more slowly than non Muslims, suggesting that Muslim immigrants face more difficulties in adapting within their host countries than other immigrant groups (see Bisin et al. 2008 for the UK and Constant et al. 2006 for Germany). Regarding educational attainment, some studies on the US find that Asians outperform other groups while Hispanic students perform worse compared to Asians and non-Hispanic Whites (Hirschman and Wong, 1986; Arias, 1986; Lee and Rong, 1988). Using a data set on immigrants living in France, Mitrut and Wolff (2014) find no difference in education between children of Muslim and non-Muslim immigrants but observe more within-family inequality in children's educational achievements among Muslims relative to non-Muslims.

In this paper, we attempt to contribute to this existing literature by examining both educational and labor-market inequalities between natives and second-generation immigrants in France. Precisely, our contribution to the existing literature is threefold.

A first originality of our study is to investigate the ethnic gaps over the life cycle. This sharply contrasts with previous studies that focus either on the labour-market outcomes or on educational attainment in isolation. Precisely we begin by examining the determinants of educational attainment and the educational ethnic gap underlining the central role of family background (e.g. parental education, family income and family structure) as key determinants of education. Then, we examine the determinants of employment and wages, shedding light on the employment and wages gaps existing between French natives and second-generation immigrants.[3] In particular we investigate the effect of belonging to a particular ethnic group on the probability of being employed and on the earnings. By taking this sequential approach, we can assess the effects of ethnic groups through three main channels: educational

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[3] Note that, for convenience, we consider as natives only those respondents whose parents were both born with French nationality, although from a legal point of view, immigrants' descendants born in France are also French natives as a result of the French *jus solis*.

attainment, employment and the level of wages. Possible endogeneity and selection issues need however to be addressed in looking at the effect of the ethnic groups over the life cycle. Indeed there may exist a potential selection bias in the estimation of wages due to the fact that wages are observed only for individuals who are employed. We control for this selection bias using the Heckman two-step procedure. In addition, estimates of employment and wages may suffer from an endogeneity bias due to the fact that the education explanatory variable may be correlated with the error term. While previous studies have attempted to control either for the selection bias or for the endogeneity bias, we account for both biases by estimating a bivariate probit model that consists of two simultaneous equations, one for the binary outcome "failure or not in education" and another for "being employed or not" followed by the Mincer equation.

A second originality of our paper is that we investigate the heterogeneity of socio-economic integration among ethnic groups by studying ethnic gaps for different ethnic minority groups of second-generation immigrants in France. This contrasts with most of the previous studies that have concentrated mostly on one ethnic group only. According to Chiswick (1988), there may exist at least three main factors to explain why ethnic groups may differ in their level of educational attainment. A first reason is that some ethnic groups may be over-represented among lower-classes individuals (Dos Santos and Wolff, 2011). This is consistent with Becker (1972) and Becker and Tomes (1986) showing that there may exist an intergenerational correlation in education because better off parents are more likely to invest in the education of their children, ceteris paribus. Consequently immigrants belonging to some ethnic groups with poor social background would provide less human and financial capital for the education of their children. Second, some communities may have stronger "taste" for schooling than others due to cultural, religious differences which may lead some ethnic groups to invest more in the schooling of their descendants (Chiswick, 1988; Dos Santos and Wolff, 2011, and Fryer and Torelli, 2010, for an empirical analysis of ethnic identities and 'Acting White'). Thirdly, members of some communities may be (un)consciously discriminated with regard to access to schooling, in their choices of their educational track (Losen and Orfield, 2002; Dos Santos and Wolff, 2011). For instance teachers may have lower expectations toward non-native students (Fryer and Levitt, 2004). Furthermore some communities may anticipate that the return of their investment in education

will be lower due to discrimination, which may incite them to invest less in their human capital skill (Altonji and Blank, 1999).[4]

Another important originality of our study is the use of an original data set from the French survey *Trajectoires et Origines* (TeO) that provides rich information on familial and social background characteristics of second-generation immigrants in France to investigate differences in educational and labor market outcomes between native and other ethnic groups. This data set has been rarely used previously in other French studies to investigate ethnic gaps in both education and labour-market outcomes between second-generation immigrants. There are several interests of focusing one's attention on French immigration. First, France has been traditionally considered as a country of immigration. For instance, previous studies have documented that France was the country with the largest share of migrants in 1920 after the US and since the middle of the seventies the share of immigrants in the population has remained relatively stable with about 25% of the population who had some immigration background from the first, second, and third generation by early 2000s (Algan et al., 2012; Aeberhardt et al., 2010). Another important feature of French immigration is its diversity. Indeed previous studies have shown that the ethnic composition of the migrants has become increasingly diverse over the last decades (e.g. Algan et al., 2012). Furthermore another specificity of the French immigration is that it is mostly characterized by low-skilled immigrants, which differs from other countries such as Canada, the United Kingdom or Australia (Dustmann and Glitz, 2011). For instance, the living standards of individuals with immigrant parents in France are on average 14% lower than those of natives; this may be potentially a source of tension as shown by the French riots that occurred in 2005 in many poor suburbs of important cities where immigrants were overrepresented (e.g. Lombardo and Pujol, 2011; Aeberhardt et al., 2010).[5]

Despite all the interests of investigating the French immigration, the empirical analysis of the ethnic gaps in both educational attainment and labor market outcomes in France is surprisingly sparse. This sharply contrasts with the vast literature on racial discrimination and the social integration of immigrants in a number of other countries (see Altonji and Blank,

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[4]Note that in this current our data do not allow us to isolate the effect of each of these motives.

[5] In November 2005, a wave of violence swept through the suburbs of a number of French cities. Faced with this sudden rise in tension, some commentators underlined long-standing integration problems, including discrimination against minorities and the lack of job opportunities in the suburbs which are mainly populated by immigrants.

1999 and Borjas, 1999 for surveys). One likely explanation is that, until recently, information regarding ethnicity was not collected in French survey data. The French egalitarian ideal, which rejects any form of categorization into ethnic groups, is often evoked to explain that lack of ethnic information in French survey data and the reluctance of public authorities to provide valuable information on ethnicity. A few notable exceptions are the recent contributions of Laine and Okba (2005); Meurs et al. (2006); Dustmann et al. (2008), Aeberhardt and Pouget (2010), Aeberhardt et al. (2010a,b), Belzil and Poinas (2010), Algan et al., (2010), Domingues Dos Santos and Wolff (2011), Brinbaum et al., (2012), Akgüç and Ferrer (2015). These previous studies have shown that the educational attainment or the labor market outcomes of immigrant groups is generally worse than that of the native group.

Brinbaum et al. (2012) also uses TeO data to examine differences in education between natives, second-generation immigrants, and immigrants whose education in France began at the primary school level. Our approach differs from theirs as we focus on lifelong ethnic inequalities and study how educational differences translate into employment gaps and wage disparities. In a recent paper, Akgüç and Ferrer (2015) also investigate ethnic gaps in labor market outcomes using the Teo dataset.[6] The authors find that first-generation immigrants are less educated than the natives and that there is a significant wage gap. However our study sharply differs from this paper as we focus our attention on the comparison between second-generation immigrants and natives which allows us to compare individuals who have attended the same french educational system.

Our analysis is also related to the seminal papers of Aeberhardt and Pouget (2010) and Aeberhardt *et al.* (2010a). Aeberhardt and Pouget (2010) analyze national-origin wage differentials in France. They find that these wage gaps mostly reflect differences in the type of jobs individuals take up, according to their experience, background and education.[7] Using data from the "*Formation Qualification Professionnelle*" survey, Aeberhardt *et al*. (2010a) investigate the wage and employment gaps between French natives and French workers with at least one African parent. They conclude that the unexplained portion of the employment decomposition is much larger than that of the wage decomposition. Labor market discrimination in France is found to be more frequent at the hiring stage than in earnings. Our paper is also related to that of Belzil and Poinas (2010), who estimate a dynamic model of

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[6] It is important to notice here that we became aware of this study after starting writing our paper.
[7] A similar empirical analysis of "*Emploi en Continu*" data confirms these findings (see Aeberhardt *et al*., 2010b).

schooling choices and early access to permanent employment contracts in France. Using data from the "Generation 98" survey, Belzil and Poinas (2010) investigate the differences between second-generation immigrants and their French-native counterparts in terms of access to permanent employment contracts. Education is found to be the main determinant of permanent-employment differentials. After controlling for education and other observed characteristics, ethnic origin explains less than 6% of this employment gap. However, in contrast to Belzil and Poinas (2010) who only consider permanent employment contracts in the early career, we here also focus on the determinants of wages.

These studies mentioned above have controlled either for the endogeneity of education or for the sample selection issue (Sloane et al. 1999; Aeberhardt et al., 2010a,b; Akgüç and Ferrer, 2015). We depart from these works as we investigate the ethnic gaps over the life cycle with an attempt to account for both selection and endogeneity biases. We also investigate differences across various sub-populations of second-generation immigrants (North African, Sub-Saharan African, Turkish, Asian, Eastern European, Northern European and Southern European) while most previous studies mentioned above concentrate on one ethnic group only. For instance Aeberhardt et al. (2010) concentrate on African second-generation immigrants compared to French native.

To preview our findings, we show that: *i*) second-generation immigrants are on average less likely to experience education success than their French native counterparts and that such education gap seems to be mainly rooted in ethnic differences in family backgrounds; *ii*) second-generation immigrants are on average less likely to be employed and receive lower wages than French natives ; *iii*) a large part of the labor-market differences between French natives and second-generation immigrants can be attributed to differences in education; *iv*) we observe important heterogeneity across our various ethnic groups both in terms of educational attainment and labor market outcomes, which seems to be also mainly driven by differences in social and familial background.

The remainder of the paper is organized as follows. Section 2 presents the TeO survey and our sub-sample analysis. Section 3 then presents our main findings. Last, Section 4 discusses and concludes.

2. The dataset and methodology

2.1. Presentation of the data set

We use the data set TeO *Trajectoires et Origines: Enquête sur la diversité des populations de France*, collected jointly by INED (*Institut National des Études Démographiques*) and by INSEE (*Institut National de la Statistique et des Études Économiques*) between 2008 and 2009. This dataset is a unique survey conducted in France on ethnicity. It provides rich information on a variety of socio-demographic and socio-economic variables for individuals belonging to different groups of the French population that differ by their origin as well as information on their family members. Precisely, it considers French respondents whom parents are born French (natives), descendants of immigrants (second-generation immigrants), and immigrants (first-generation immigrants) from various origins, either from previous French colonies in Africa, individuals from Eastern, Northern, and Southern Europe as well as people from North and South America. The survey contains additional information about the migratory history, and the family and social context during both childhood and adulthood. TeO also provides valuable information related to educational attainment, labor force participation and earnings. The variables can be broadly organized into three main groups: family and social background (parents' statuses and education, siblings, and marital life) [8]; socio-economic outcomes (education, employment, and housing); and migratory history and ethnic belonging (ties to the home country, religion, languages, and ethnic identity). [9]

2.2. Sample procedure representativeness and non-responses

The survey sample includes 21,761 individuals either French-born natives, first-generation immigrants (born abroad and arrived to France at some point in their life) and

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[8] Note that one has to be careful in interpreting the role played by parents' education due to the fact that diploma of non-native parents is not always comparable to French native parents diplomas. Ideally a way to control for such differences would suppose considering third-generation immigrants. Unfortunately this information was not available in our database.

[9] We acknowledge that the answers given by the participants when asked in retrospective may be subject to reliability. This question of reliability of self-reported schooling is however a general issue in the literature. Indeed research has generally found that the reliability of self-reported education is about 90% (Miller et al. 1995; Ashenfelter and Rouse, 1998; Angrist and Krueger, 1991). For instance Angrist and Krueger (1991) conclude that the reliability of self-reported schooling is 85-90 percent. According to Griliches (1977), measurement errors in schooling would lead to downward bias in the OLS estimates of the returns to schooling. Note however that such bias may be partially offset by a possible upward ability bias (Card, 2001).

second-generation immigrants (born in France, but who have at least one foreign born parent). The immigrant population is overrepresented in the database and weights are used through the analysis to produce nationally representative estimates. The survey is carried out during a two years period but individuals are interviewed only once. This is therefore not a panel data base. Following several previous studies, we choose to focus our attention on the French native and on the second-generation immigrants. Indeed including first-generation immigrants may be potentially problematic since it does not allow any comparisons *ceteris paribus* across groups given the fact that first generation in general did not go through the French education system. We also drop students, retired people as well as self-employed workers from the data analysis.[10] Finally we drop from the data analysis individuals with missing values for wages or labor-force status. Our final sample comprises 7939 individuals including 2737 natives and 5202 second-generation immigrants.[11] To investigate the differences across ethnic groups, we separate our final sample of second-generation immigrants into seven subgroups: North African (1422), Sub-Saharan African (481), Turkish (248), Asian (291), Southern European (2147), Northern European (351), Eastern European (262)[12]. When both parents are immigrants, but from two different areas, we retain the father's origin.

2.3. Econometric models, methodology and variables of interest

Our econometric models aim at investigating the determinants of *i*) educational attainment (captured either by the highest diploma obtained or by schooling failure/success)

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[10] We also choose to exclude self-employed workers from our data analysis because we cannot introduce them in our two-step Heckman procedure to measure wage discrimination. Indeed by definition, self-employed being their "own boss" have no reason to discriminate against themselves at the wage setting step. However we recognize that some individuals may choose self-employment because they are discriminated by employers. Nevertheless, in our dataset it seems that it is not the case since we do not observe significant differences in self-employment rates between natives and second-generation immigrants. Self-employed represent 6.24% of second-generation immigrants and 6.57% of natives. A similar concern regards the discouraged workers that are not considered here. Although we are able to identify these individuals in the survey, we do not consider them as a part of our population of interest because of the subjective aspect of this status. Furthermore, they only represent 1.52% of second-generation's and 5.76% of native's inactive population.

[11] Following the French Republican egalitarian principle, migrants' offsprings are not usually visible in national statistics. This was dealt with in the TeO survey by cross-checking with the 2007 French census and local registers to identify first-generation immigrants' children (in particular from birth certificates).

[12] We define the European sub-groups as follows. Southern Europe comprises Italy (36.46% of this sub-group), Portugal (32.67%), Spain (30.19%) and Greece (0.68%). Northern Europe contains Germany (43.02% of this sub-group), Belgium (32.48%), United Kingdom (9.40%); Netherlands (3.42%), Ireland (3.42%), Austria (3.13%), Luxembourg (2.28%), Denmark (1.71%), Sweden (1.14%). Eastern Europe contains all of the remainder of the European continent. Second-generation immigrants from America, Oceania and Middle East countries are dropped due to small cell sizes.

as well as the determinants of *ii*) employment and *iii*) hourly wages for both second-generation immigrants and their French native counterparts.

We follow our research agenda by presenting first the determinants of educational attainment. Then we examine the determinants of employment. In a third step, after having investigated the employment ethnic gap, we turn to the ethnic wage gap by using Mincer wage equations (Mincer, 1974). We estimate first each labor market outcome is isolation and then we account for selection issues. Indeed self-selection into work may potentially introduce bias in the estimation of wage equations. One has therefore to control for this selection bias by using a two-step Heckman procedure (Heckman, 1979). For the model to be identified, we require selection variables that affect the probability of employment, but not wages directly. Precisely we use standard instruments such as marital status (single man, single woman, working or non-working spouse) and the presence of at least one child (Aeberhardt et al., 2010a) that affect the probability of being employed or not but that should not impact the level of earnings. Finally in a fourth step we attempt to account for both the selection bias and the endogeneity bias at the same time. Indeed the models may also suffer from an endogeneity bias, due to the fact that the correlation between education and labor market outcomes (employment, earnings) may differ from the true causal effect of education. For instance, the education explanatory variable included in the Mincer wage equation may be correlated with the error term which may lead to a problem of endogeneity. Indeed, several authors have pointed out the fact that the earnings differential may also reflect differential ability between groups. Precisely, individuals who have a higher wage may also have a comparative advantage in schooling.[13] Thus failure to control for this correlation may yield an estimator of the effect of education on labour outcome that is upward-biased (Card, 2001). The most widely used methodology to estimate the true return to schooling when ability is not observed consists in using instrumental variables (IV) techniques (see Card, 2001 for an extensive review of the IV studies of the return to schooling).[14] Control for both the selection and the

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[13] This assumption is known as the signaling or the screening hypothesis (Arrow, 1973; Spence, 1974). For instance, suppose that some individuals with low unobserved ability receive lower earnings. If these individuals are more likely to be undereducated, this means that the disturbance of the individual's occupational selection process could be correlated with the error term in the wage equation. Consequently there may exist an endogeneity bias in the relationship between schooling and earnings due to the fact that ability is not taken into account and is therefore included in the error term. Ideally, one should control for individual ability in the estimates. Unfortunately, in most cases we cannot observe individual ability.

[14] We acknowledge that the IV methodology may however suffer from several limitations. A first limitation of the IV estimates is that they may be relatively imprecise such that measuring the magnitude of the ability bias in OLS estimates may be difficult (see Card, 2001 for a discussion of this point). In the words of Card (2001), "no

endogeneity biases is done by estimating a bivariate probit model that consists of two simultaneous equations, one for the binary outcome "failure or not in education" and another for "being employed or not". The estimation of this model by the log likelihood allows to obtain Inverse Mill's ratios that are then included in the wage equations (Cutillo and Di Pietro, 2005; Jones and Sari, 2015).

3. Results

In this section, we evaluate first the determinants of differences in education between ethnic groups (sub-section 3.1). Then, we investigate the ethnic gap in both employment and wages with an attempt to control for the potential selection bias (sub-section 3.2). Finally, we discuss the issue of endogeneity of education in section 3.3.

3.1. The determinants of educational achievement and educational gaps between ethnic groups.

In this sub-section, we first present some summary statistics and then show the results of estimations of the determinants of education.

3.1.1. Summary statistics

Table 1 describes the distribution of the highest diploma obtained by the respondent.[15] It indicates that second-generation immigrants are more likely to have left school without any qualifications and conversely are less likely to have a university degree. Nonetheless, schooling performance varies with respect to origins. Notably, Turkish origins have the worse performance as the fraction with no qualification is almost twice the one of natives. The Turkish origin is also the one which most follows a vocational curriculum. On the opposite, the Asian origin has the lowest fraction of people without any degree and outperforms other origins and natives at the University. This observation does not hold, however, for those of Sub-Saharan African and Asian origin. This is consistent with previous studies that find that

individual study is likely to be decisive in the debate over the magnitude of ability biases in OLS estimates of the return to schooling" (p. 1157). A second limitation of the IV methodology is that there are restrictive conditions for the choice of the instrumental variables. Indeed there are two important conditions for a valid IV and these conditions are not always verified. First, the instrumental variable must be a significant factor of education. Second, the instrument variables must be uncorrelated with any other determinants of the dependent variable such that for instance ability (exclusion restriction).

[15] Note that these figures should be interpreted with caution since the age structure varies widely between groups.

Asians outperform other groups in education (Hirschman and Wong, 1986; Arias, 1986; Lee and Rong, 1988).

[Table 1 : about here]

3.1.2. The Determinants of Educational Attainment

Table 2 reports results from estimates on the determinants of education. Table 2 consists of two panels. The left panel reports findings of two ordered probit models of highest qualification (columns 1 and 2). The right panel which we will discuss later shows the findings of two probit models of schooling failure (columns 3 and 4). Column (1) and (3) only control for demographic variables such as ethnic origin, gender and age. Column (2) and (4) add several variables related to parental background. The choice of ordered probit models to estimate educational attainment is justified since our data provide an ordered categorical information regarding the level of education. Precisely the level of diploma denoted by S is defined as follows : 'no education' ($S=0$), 'junior high school' ($S=1$), 'vocational studies' ($S=2$), 'high school' ($S=3$), 'college' ($S=4$) and 'university' ($S=5$). This model takes into account the discreteness of the data. Let's assume that there exists a continuous latent variable S^*_{ij} corresponding to educational attainment of individual i belonging to ethnic group j:

$$S^*_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 \omega_j + \gamma_{ij}. \tag{1}$$

Given the various categories, we suppose that $S^* \leq \mu_1$ when $S=0$, $\mu_1 < S^* \leq \mu_2$ when $S=1$, $\mu_2 < S^* \leq \mu_3$ when S=2, … and $\mu_5 < S^*$ when S=5. The different parameters μ correspond to a set of threshold levels which will be estimated jointly with the coefficients, with μ_1 being normalized to zero. Assuming that γ is normally distributed, the corresponding is a standard ordered probit model. ω_j are fixed effects for each ethnic group j. Considering French natives as the omitted category, we set $\omega_{France} = 0$. γ_{ij} is an error term which is assumed to follow a normal distribution with parameters $(0, \sigma_u)$. X_{ij} is the full vector of characteristics that are thought to affect education. X_{ij} includes demographic variables such as gender, age, age squared, as well as variables controlling for the familial background (parents' education, parental social and health difficulties) and the family structure (number of siblings, being the only child, the rank among siblings, being in a single-parent family).

Concerning the role of the familial background, much work has shown that family income is an important determinant of child school success (Haveman and Wolfe, 1995; Plug and

Vijverberg, 2005).[16] For instance some previous studies have shown that children from poor families have greater difficulty in pursuing their education as their parents face credit constraints in financing their children's education. As our data do not contain information on parental income, we use the occupation of both the father and the mother during the individual's childhood to proxy for the household financial situation. Beyond these financial aspects, parental education may be also an important determinant of educational attainment, suggesting an intergenerational correlation in education. Such correlation may reflect some ability being transferred genetically to children. It may also reflect the transmission of informal human capital and preferences. It can reasonably be argued that highly-educated parents will place greater value on education, and may therefore be more likely to encourage their children to pursue further education. Furthermore, educated parents may also help their offspring in their schoolwork (e.g. by having books around the house) which may reduce the cost of acquiring education (see for instance Ermisch and Francesconi, 2001). We also include variables related to parental social and health difficulties such as parents' related problems of alcohol, violence or money. Finally we also account for family structure by including variables related to the number of siblings, being the only child, the rank among siblings, being in a single-parent family. Siblings' role may be unclear since well-educated elder siblings may provide positive externalities on younger ones whereas having more brothers or sisters might also hamper education via the scarcity of resources (both money and time) in larger families (e.g. Blundell *et al*. 1997). Furthermore, some research has shown that being in a single-parent family during childhood has a negative impact on education (e.g. Haveman and Wolfe, 1995). Following Belzil and Poinas (2010), we use the highest qualification as the attainment variable (to be estimated by an ordered probit model). Alternatively we also estimate the probability of schooling failure (defined as no diploma).[17]

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[16] Recently, economists have shown that the existence of a positive relationship between parental income and children's school outcomes may be biased if parental ability is ignored. Plug and Vijverberg (2005) show however that this bias may be overestimated. They appeal to a sample of adopted children, which offers genetically-unbiased estimates, and find that family income still has a significant effect.

[17] Following most of the existing studies we used ordered probit models to estimate the highest grade attained (e.g. Drèze and Kingdon, 2001). A possible limitation of this approach is that errors are supposed to be homoscedastic which does not sit comfortably with the possibility of heterogeneous responses that depend on unobservables. Alternatively, we may have run a multinomial choice model incorporating six education levels. However, such models are computationally more complex and would suppose that IIA property holds which is not necessarily the case. We also compare our findings obtained with ordered probit models with those obtained by a simple probit model where the dependent variable is "schooling success/failure". We also run OLS models, logit ordered models as well as logit models (available upon request) that provide very similar findings.

Column (1) shows that women have better education outcomes than do men. This result is consistent with previous research on gender gap in education (see for instance, Siahaan *et al.*, 2014). Furthermore, our findings indicate that most of the non-native groups perform on average worse than natives. However, there exist important differences across ethnic groups. For instance, those individuals from Sub-Saharan Africa, Asia and Eastern Europe are not significantly different from French natives. In contrast, the North African, Southern Europe and Turkish origin variables attract negative and significant coefficients, suggesting that these individuals are less likely to experience education success. These results are corroborated by previous findings. For instance, using the French database "Passage to Retirement of Immigrants", Attias-Donfut and Wolff (2009) observe important differences across ethnic groups and that the Turkish group performs worse than other ethnic groups. The authors stress that this relies essentially on the bad performance of girls. Interestingly an additional estimate (available upon request) that includes an interaction variable Turkish group*gender also confirms that Turkish girls perform worse in our data. Ethnographic and sociological studies on Turkish immigrants in France explain this gender difference on educational attainment by the fact that (i) Turkish families may favor endogamous marriages which often lead girls to end up school, and that (ii) families may have ambivalent attitudes towards education as it is also seen as a way to emancipate from religious values (see references in Attias-Donfut and Wolff, 2009; see also Domingues Dos Santos and Wolff, 2011).

Column (2) reports rather different findings. Interestingly after controlling for family background, we no longer find a negative effect of origin on education: instead second-generation immigrants are more likely than French natives to obtain better education outcomes. Most of the ethnic-origin coefficients are now significantly positive (except for Turkey and Eastern Europe, which are not different from French natives). This result is consistent with the existing literature. For instance Brinbaum *et al*. (2012) obtain a similar result showing that ethnic origin is no longer significant as a predictor of schooling failure after controlling for family background. Using US data (the 1940 and 1970 Censuses and 1994-1996 Current Population Surveys), Card *et al*. (2000) also find that after controlling for several variables, second-generation immigrants are on average more educated than the children of comparable US-born parents. This result is also consistent with Dustmann *et al*. (2012) who find in the context of a comparative analysis that the test-score gap between

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children born to immigrants and natives is substantially reduced in most countries when controls for parental characteristics, school and peer quality, and the language spoken in school are introduced.

To check the robustness of our findings we also ran alternative models on the determinants of schooling failure. These estimates are shown in the right panel of Table 2 (columns (3) and (4)). They reports similar findings. The notable exceptions are that the coefficients associated to the Asians and the Southern Europe are no more significant in column (4), indicating that these ethnic groups do perform as well as natives in terms of schooling failure.

Childhood environment thus seems to be a key determinant of education. Parental education and family income are strongly correlated with child education. In addition, having a single parent is associated with worse education outcomes. The negative impact of the number of siblings on education can reflect that having more siblings implies fewer available resources per child. Last, in line with the results of Goux and Maurin (2005), the availability of a separate room for homework is positively associated with education outcomes. This can be seen as additional evidence for the importance of educational resources.

Altogether these findings show the importance of the family and social background. Thus one may legitimately wonder whether the observed differences across ethnic groups may be partly explained by differences in family and social background. First, it might be conjectured that (some) migrant descendants may be more likely to have unfavorable family backgrounds than natives. Second, one may also reasonably conjecture that some family backgrounds may have a more negative impact on migrant descendants than they would on natives. To investigate whether the impact of family background differs across ethnic groups, we ran complementary regressions with interactions between respondents' ethnic origin and family and social background (number of siblings, separate room, family structure and parental education). In these regressions (which are available upon request) none of these interaction variables are significant or robust to specification changes, suggesting that family background has a similar effect across ethnic groups. The size, structure and wealth of the family are of the same central importance in predicting education outcomes for all ethnic groups. In addition to check whether second-generation immigrants are more likely to suffer from unfavorable family and social backgrounds, we test whether there are significant differences in our family and social backgrounds variables between each ethnic groups and French natives. Table 3 shows that ethnic-origin groups are significantly different from

French natives with respect to their family background. This may explain why ethnic-origin groups have worse educational outcomes than do French natives. We first see that North African, Southern European and Turkish parents are less educated than are French parents. Second, second-generation immigrants from North African, Sub-Saharan African, Eastern Europe and Turkish parents have fewer opportunities to do their homework in a separate room. Notably, the number of Eastern-European descendants who benefited from a separate room is almost 30 percentage points lower than their French counterparts. For the three other ethnic groups, the difference is at least 8 percentage points. Sub-Saharan and North African (respectively Asian and Turkish) second-generation immigrants live in families with on average two siblings (respectively 0.8 siblings) more than French families. Third, Table 3 indicates that Sub-Saharan, Southern and Eastern European origin respondents were brought up less frequently by both parents in a couple. In particular, the percentage of Sub-Saharan individuals reared by both parents in a couple is 14.6 points lower than the figure for French natives. This may be a major cause of the low performance of Sub-Saharans as we find that the probability of schooling failure is raised by 10.3% when the child is reared by a mother only (see column 4 in Table 2). North African, Southern-European and Turkish parents are also on average less educated. Finally, Northern-European immigrants are not significantly different from natives, except for the fact that their parents were more often in a couple relationship.

[Table 3 : about here]

To provide further evidence of the extent of the ethnic educational gap and to check whether natives and ethnic groups with comparable characteristics are equally likely to succeed in schooling, we use the Blinder-Oaxaca decomposition method (Oaxaca, 1973, Blinder, 1974). Precisely, we expand the Blinder-Oaxaca decomposition technique to non-linear regressions in order to decompose the gross ethnic difference in schooling failure/success (see for instance Bauer and Sinning, 2008, or Aeberhardt et al., 2010a, for the use of the decomposition method for non-linear models and Chaudhuri and Roy, 2009, for the use of the decomposition method in the context of schooling).[18] The main attraction of the Aeberhardt et al. (2010a) method is that it does not involve the calculation of coefficients for

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[18] For computational reasons we consider here schooling failure/success rather than education attainment.

the minority groups. Due to the small cell sizes of immigrant-origin groups, separate regressions may yield inaccurate coefficient estimates. Using the decomposition technique, we attempt to decompose the gross ethnic difference in schooling failure/success into a component explained by differences in characteristics between the native and a particular ethnic group and the unexplained component. The unexplained component is conventionally regarded in the literature as the extent of ethnic discrimination (Oaxaca, 1973, Blinder, 1974). However in the context of education, it is probably better to refer to the term differential treatment rather than discrimination. Indeed there may exist several factors included in the unexplained component and all of these factors are not necessarily related to discrimination. Among these factors, it may be argued that parents may value education differently according to the ethnic group (Chiswick, 1988; Dos Santos and Wolff, 2011). The residual gap may also result from lower expectations on the part of parents or of teachers toward non-native students due to anticipated labour market discrimination against non-native (Fryer and Levitt, 2004). Finally, the residual gap may reflect the existence of discriminatory treatment. Indeed there is now a growing literature on discriminatory behavior in education evaluating the impact of teachers' behavior on the gap between natives and ethnic groups. For instance, Dee (2005) provides evidence of taste based discrimination, observing that the student's odds of being seen as inattentive increases significantly by at least 33 percent when the teacher is not of the same ethnic group. In the same vein, Ouazad (2014) underlines that teachers give better assessments to pupils of their own ethic group.[19]

The decomposition of the educational gap between natives and second-generation immigrants from group j is given by:

$$F_{ij} = 1_{F_{ij}^* > 0} \tag{2}$$

$$F_{ij}^* = G_{ij}.\alpha + \omega_j + u_{ij} \tag{3}$$

where F_{ij} is the schooling failure probability associated with the latent variable, F_{ij}^*. G_{ij} is a vector of the observable determinants of educational attainment, and ω_j is a group j fixed effect. The error term u_{ij} is assumed to follow a normal distribution with parameters (0,1). The probability of schooling failure is expressed as :

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[19] These results suggest that the ethnicity of both the teacher and the pupil seems to matter. Unfortunately the TeO survey does not include data regarding the characteristics of the teachers. However one may reasonably assume that the majority of teachers belong to the native group.

$$Prob(F_{ij} = 1) = Prob(F_{ij}^* > 0) = Prob(u_{ij} > -(G_{ij}.\alpha + \omega_j)) = \Phi(G_{ij}.\alpha + \omega_j) \quad (4)$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

Decomposition methods allow us to separate the schooling failure gap between two groups into a part resulting from differences in observable characteristics such as demographics or family background and a residual part. The decomposition of the schooling failure gap between natives and second-generation immigrants from group j is given by:

$$E[F_{if}] - E[F_{ij}] = \underbrace{E_{G_f}[E(F_{if}|G_i)] - E_{G_j}[E(F_{if}|G_i)]}_{Explained\ part}$$

$$+ \underbrace{E_{G_j}[E(F_{if}|G_i)] - E_{G_j}[E(F_{ij}|G_i)]}_{Residual\ gap} \quad (5)$$

The explained part consists of the difference between French natives' schooling failure and the estimated failure of second-generation immigrants from group j, when both groups have similar returns to characteristics. This part of the educational gap results from differences in characteristics only. On the other hand, the residual gap consists of the part of schooling gap attributed to differences in the return to characteristics.

Following Aeberhardt *et al.* (2010a,b), we use simple empirical counterparts to carry out this decomposition[20].

$$\frac{1}{N_f}\Sigma_{i\epsilon f} F_i \xrightarrow{a.s} E_{G_f}[E(F_{if}|G_i)] \quad (6)$$

$$\frac{1}{N_j}\Sigma_{i\epsilon j} F_i \xrightarrow{a.s} E_{G_j}[E(F_{ij}|G_i)] \quad (7)$$

$$\frac{1}{N_j}\Sigma_{i\epsilon j} \Phi(G_i.\alpha_f) \xrightarrow{a.s} E_{G_j}[E(F_{if}|G_i)] \quad (8)$$

Equations (6) and (7) are the simple arithmetical means of schooling failure levels in groups f and j. Equation (8) implies calculating the coefficients α_f in a previous regression on the French native population only, and applying them to second-generation immigrants from group j. Although this method does not lead to an exact decomposition, it has been shown to yield more precise estimates than the usual approach (Aeberhardt *et al.*, 2010a,b).

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[20] Note that they firstly use this method to decompose the ethnic employment gap and that we also implement it in such case in the following 3.2.2 sub-section of this paper.

Table 4 shows the results of these educational-gap decompositions between French natives and second-generation immigrants. The procedure is applied with and without control for family background in order to assess its impact on schooling failure. We use the same covariates as in the regressions (3) and (4) shown in Table 2, apart for the ethnic group dummies.

[Table 4 : about here]

With no control for family background, the explained part of the educational gap is negative and the unexplained component is higher than the total educational gap for all ethnic groups (except for Asian and Eastern Europeans). The very high unexplained component indicates the presence of differential treatment for these ethnic groups compared to natives. The negative explained component indicates that due to better characteristics the schooling success of these ethnic groups should be higher. For eastern Europeans, the educational gap is explained by both different characteristics (42%) and differential treatment (58%). Northern Europeans succeed more than natives, which does not seem to be explained by better characteristics but rather by differential treatment in their favor as shown by the unexplained component that is higher than the total educational gap.

When controlling for family background, the unexplained part of the educational gap decreases for all ethnic groups, indicating that the family background is a major determinant of ethnic differences in schooling failure/success. For Eastern European the residual gap almost disappears. For North and Sub-Saharan Africans, the predicted gap attributed to characteristics when controlling for family background becomes positive and is larger than the observed gap. This implies that their return to their characteristics is higher compared to those of natives. For Turkish and Southern Europeans, the residual gap decreases but still remains positive suggesting the persistence of a differential treatment for these ethnic groups. Finally, Table 4 indicates that Northern Europeans still succeed significantly more than natives after controlling for family background. However this difference remains mostly unexplained.

3.2. The determinants of labor-market outcomes

We now go one step further and consider the ethnic gap in labor-market outcomes (employment and wages). After presenting some summary statistics, we investigate the

determinants of both employment and wages. We first estimate employment regressions and appeal to the methods popularized by Oaxaca (1973) and Blinder (1973) to decompose the employment gap into a structural part resulting from differences in observable characteristics and a residual part resulting from differences in the return to these same characteristics. We then consider the differences in wages across ethnic groups. Following Aeberhardt *et al.* (2010a), we correct for the potential selection bias due to wages only being observed for the employed. This correction is effected *via* a two-step Heckman procedure.

3.2.1. Summary statistics

Table 5 presents the descriptive statistics regarding employment status and hourly wages among ethnic groups in our sample. Table 5 indicates that there are considerable employment and wage differences between second-generation immigrants and French natives, but also between immigrant groups. Second-generation immigrants with North-African, Sub-Saharan African and Turkish parents are less likely to be in employment than are natives and receive lower wages on average[21]. Southern-European immigrant descendants have a lower (but not significantly so) employment probability but earn on average higher wages. Remarkably, Northern-European immigrant descendants perform better than do the French regarding both employment and wages. Last, Table 5 reveals that the children of Asian parents suffer less from lower employment than do some other immigrant-origin groups.[22]

[Tables 5 and 6: about here]

Table 6 provides additional information regarding the wage ethnic gap. It reveals important heterogeneity across ethnic groups. Table 6 shows that for North and Sub-Saharan Africans, the wage gap increases both with the level of diploma and the ranking in the occupation (from the lowest to the highest paid professions). For Turkish, Asian and Southern Europeans, the wage gap is highly significant only for the highest paid occupations and/or for those who have a high diploma. Northern Europeans receive a wage premium but this seems to be the case only for employees and workers. As a whole, this Table also shows that wage inequalities

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[21] For instance, when considering North Africans who earn the smallest wages, the average monthly wage differential amounts to 261 euros.

[22] Weighted hourly wage means are compared via a t-test. We use the Rao and Scott (1984) second-order correction of the Pearson χ^2-test to analyze employment differences. We here consider the 10% significance threshold.

mainly arise for high-skilled occupations whereas they are reduced for low skilled-ones. A possible explanation that is evoked in the literature is the potential impact of the minimum wage legislation on the reduction of wage and earnings inequalities (see the empirical analysis of Aeberhardt, Givord and Marbot, 2012).

3.2.2. The determinants of the ethnic employment gap

To provide more formal evidence of an ethnic employment gap, we ran employment regressions. Let the employment function for individual i in ethnic group j be given by

$$L_{ij} = 1_{L_{ij}^* > 0} \tag{9}$$

$$L_{ij}^* = H_{ij}.\alpha + \omega_j + \varepsilon_{ij} \tag{10}$$

where L_{ij} is a dummy variable corresponding to employment, L_{ij}^* is the associated latent variable, H_{ij} is a vector of the determinants of employment, and ω_j is a group j fixed effect. The error term ε_{ij} is assumed to follow a normal distribution with parameters (0,1). The probability of employment is expressed as :

$$Prob(L_{ij} = 1) = Prob(L_{ij}^* > 0) = Prob(\varepsilon_{ij} > -(H_{ij}.\alpha + \omega_j)) = \Phi(H_{ij}.\alpha + \omega_j) \tag{11}$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

Table 7 shows the results from weighted[23] probit estimations of employment. To emphasize the role of education in ethnic employment gaps, we run estimates with and without the education variables.

[Table 7 : about here]

Column (1) shows the estimated coefficients without controls for education. Columns (2) and (3) report similar estimates with a control for schooling failure and educational degree, respectively. We include a number of individual characteristics as well as variables for the familial structure. Column (1) shows that North African, Sub-Saharan African and Turkish have a significantly lower probability of employment than do natives. In sharp contrast,

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[23] We use the pweight command in Stata10 to include weights in our models.

Northern-European descendants perform significantly better than do French natives, with an employment probability which is 7.96 percentage points higher. The insignificant coefficients on the Asian and Southern or Eastern European variables show that there is no employment difference between these groups and French natives. Controlling for educational degree in column (3) makes the coefficients on the Turkish variable insignificant. The employment probability gap for individuals of North-African origin rather than French origin drops from 7.91 to 5.99 percentage points in column (3). The results in Table 7 thus show that the ethnic employment gap is strongly reduced by controlling for education.

To provide further evidence of the extent of the ethnic employment gap, we use the decomposition method for non-linear estimates previously presented in sub-section 3.2.1. Given equation (11), the decomposition of the employment gap between natives and second-generation immigrants from group j is given by:

$$E[L_{if}] - E[L_{ij}] = \underbrace{E_{H_f}[E(L_{if}|H_i)] - E_{H_j}[E(L_{if}|H_i)]}_{Explained\ part}$$

$$+ \underbrace{E_{H_j}[E(L_{if}|H_i)] - E_{H_j}[E(L_{ij}|H_i)]}_{Residual\ gap} \tag{12}$$

Implementing empirical counterparts (Aeberhardt *et al*. 2010a,b), leads to

$$\frac{1}{N_f}\sum_{i\epsilon f} L_i \xrightarrow{a.s} E_{H_f}[E(L_{if}|Hi)] \tag{13}$$

$$\frac{1}{N_j}\sum_{i\epsilon j} L_i \xrightarrow{a.s} E_{H_j}[E(L_{ij}|Hi)] \tag{14}$$

the simple arithmetical means of employment levels in groups f (13) and j (14) and

$$\frac{1}{N_j}\sum_{i\epsilon j} \Phi(H_i.\alpha_f) \xrightarrow{a.s} E_{H_j}[E(L_{if}|Hi)] \tag{15}$$

the expected employment probability of second generations if their characteristics were treated as those of natives by the labor market.

Table 8 shows the results of the employment-gap decompositions between French natives and second-generation immigrants. The procedure is applied with and without control for

education in order to assess its impact on employment access. In the left panel, there are no education controls.[24]

[Table 8 : about here]

With no education controls, second-generation immigrants from North Africa, Sub-Saharan Africa, Eastern Europe or Turkey face a considerable residual employment gap. However, controlling for education sharply reduces this gap. Again, education is a major determinant of ethnic differences in employment. There remains nonetheless a substantial residual gap which may reflect, amongst many other phenomena, discrimination (Section 4 further discusses that the residual gap may not only reflect discrimination).

3.2.3. Wage differentials between ethnic groups and correction for the selection bias

After having investigated the employment ethnic gap, we now turn to the ethnic wage gap by using Mincer wage equations (Mincer, 1974). The Mincer equation is of the form:

$$logw_{ij}^* = \beta_0 \ + \ \beta_1 \, X_{ij} \ + \ \beta_2 \omega_j \ + \beta_3 S_{ij} + \mu_{ij} \qquad (16)$$

where the dependent variable $logw_{ij}^*$ is the log hourly wage of individual i belonging to ethnic group j; X_{ij} is a vector of the determinants of market wages; S_{ij} corresponds to years of schooling and ω_j is a parameter specific to ethnic group j. Alternatively we can also estimate a Mincer equation by replacing the continuous educational attainment variable by a dummy for schooling failure or by a series of dummy variables corresponding to discrete educational levels (Psacharopoulos and Patrinos, 2004).[25]

$$\log w_{ij} = \alpha + \beta \, X_{ij} \ + \ b_1 S_{ij1} + b_2 S_{ij2} + b_3 S_{ij3} + b_4 S_{ij4} + b_5 S_{ij5} + \delta_j + \mu_{ij} \qquad (17)$$

The Mincer wage equations can be easily estimated using OLS. However one problem by estimating this equation is that the estimates may suffer from a potential selection bias due to the fact that wages are observed only for those individuals who are employed and those individuals may have different (un)observables characteristics compared to unemployed

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[24] We use the same covariates as in the regressions in Table 5, apart for the ethnic group dummies.

[25] According to several authors using dummies has the advantage of reducing measurement errors due to the fact that the errors in reported schooling may be probably mean regressive (see Card, 1999 for a discussion; also Kane et al, 1997; Psacharopoulos and Patrinos, 2004).

workers. Following Aeberhardt *et al.* (2010a,b), we thus control for selection using the Heckman two-step procedure.[26] Let the employment function for individual i in ethnic group j be

$$L_{ij}^* = H_{ij}.\alpha + \omega_j + \varepsilon_{ij} \tag{18}$$

where H_{ij} includes some of the characteristics in X_{ij} plus a set of instruments for being employed. Indeed for the model to be identified, we require selection variables, *i.e.* variables that affect the probability of employment, but not wages directly. We use standard instruments (Aeberhardt *et al.*, 2010a) such as marital status (single man, single woman, working or non-working spouse) and the presence of at least one child. These significantly affect the probability of employment (Table 5) and can thus be considered as valid.

The presence of possible correlation ρ between the error terms of our two equations implies potential bias. We estimate the wage equation for the employed, which is expressed as

$$logw_{ij}|L_{ij}^* > 0 = X_{ij}.\beta + \omega_j + \rho.\sigma_u.\lambda_{ij} \tag{19}$$

$$\lambda_{ij} = \frac{\phi(H_{ij}.\alpha + \omega_j)}{\Phi(H_{ij}.\alpha + \omega_j)} \tag{20}$$

where $\phi(.)$ is the standard normal density distribution function, $\Phi(.)$ is the standard cumulative normal distribution and λ_{ij} is the inverse Mills ratio. We can thus test for selection bias ($\rho \neq 0$) and correct it.

Table 7 reports wage-equation estimates using two different econometric methods: the right panel (models 1-4) reports simple weighted OLS regression results while estimates shown in the left panel (models 5-6) control for selection bias. In column (1) age has a positive effect on wages. The effect of age is however non-linear, as shown by the negative coefficient on the age squared variable. The negative and highly significant coefficients on "North-African" and "Sub-Saharan African" origin in column (1) indicate a significant ethnic wage gap. Consistent with previous work, we also see a significant gender gap in wages.[27]

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[26] We appeal to maximum-likelihood estimators, which are known to be more efficient than the original two-step procedure (Puhani, 2000).

[27] Controlling for occupations allows us to capture specific wage formation process. However, it could lead to underestimate the level of discrimination as the access to a particular occupation may result from discriminatory behaviors.

Unsurprisingly, models (2) and (3) indicate that education is an important determinant of wages. Controlling for educational degree (column 3), the ethnic wage gap persists but is less significant and smaller in size. Turkish origin attracts a positive coefficient in column (3) when controlling for education, and Asian and European second-generation immigrants do not significantly differ from French natives in terms of wages.

Columns (4)-(6) are analogous to columns (1)-(3) but control for selection bias.[28] The "Sub-Saharan African" variable is no more significant while the "North-African" origin variable is less significant in column (4) compared to column (1). After controlling for education in columns (5) and (6) this latter variable becomes insignificant. Finally, the positive coefficient on the "Turkish" variable shows that Turkish second-generation immigrants benefit from a wage premium relative to natives after controlling for education.

Overall, these results show that, with the exception of those of Turkish origin, ethnic wage gaps completely disappear after controlling for both selection bias and education. These findings generalize previous findings obtained by Aeberhardt *et al.* (2010a,b) and shed light on the heterogeneity between different immigrant types.

To investigate in further details the extent of ethnic wage gap, we resort again to the decomposition methodology proposed by Aeberhardt *et al.* (2010a).[29] This counterfactual

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[28] That the inverse Mills ratio is insignificant in some estimates does not necessarily imply that there is no selection bias within each ethnic group. It is due to the selection bias being different with respect to both its extent and nature between natives and second-generation immigrants. When we run regressions for each subgroup, we obtain a Mill's ratio which is significantly positive for natives and significantly negative for second-generation immigrants. This is the reason why we observe an insignificant Mill's ratio in the whole sample estimation.

[29] Despite all the advantages associated with the Blinder Oaxaca (BO) approach, we acknowledge that this methodology may potentially suffer from some limitations. We thank an anonymous referee for this helpful remark. A first limitation is that the wage gap is estimated around the mean value of the total population and thus it provides no clues about the distribution of the differences in earnings (e.g. Jenkins, 1994). A second limitation is that the relationship between characteristics and earnings is not necessarily linear (e.g. Heckman, Lochner and Todd, 2003). Another limitation of this approach is that it may under estimate labor market discrimination by not taking into account the effects of the feedback from labour market discrimination on the differences in the selected individual characteristics', (Oaxaca 1973, p.708). In other words, some differences in individual characteristics such as differences in human capital for instance may also reflect discrimination (Oaxaca, 1973, Grimshaw et al. 2002). For example some differences in human capital levels could reflect the fact that individuals invest less in human capital due to anticipated lower returns, which is itself influenced by current discrimination (Grimshaw et al. 2002). Furthermore discrimination may be blurred with omitted variable bias, which makes it impossible to truly separate discrimination from other factors. Finally, the Blinder-Oaxaca approach fails to restrict its comparison to comparable individuals, which is likely to substantially upwardly bias the estimators for unexplained differences in pay (e.g. Barsky et. al. 2002).

approach, inspired by standard decomposition techniques (Oaxaca, 1973; Blinder, 1973), only requires the estimation of wages for French natives. We use two simple counterfactuals to decompose the wage gap between French natives f and the second-generation group j:

$$w_j^* = \sum_{i \in j} \left(\frac{\Phi(H_i.\hat{\alpha}_f)}{\sum_i \Phi(H_i.\hat{\alpha}_f)} \right) \left(X_i.\hat{\beta}_f + \hat{\rho}_f.\hat{\sigma}_f.\frac{\phi(H_i.\hat{\alpha}_f)}{\Phi(H_i.\hat{\alpha}_f)} \right) \tag{21}$$

$$w_j^{**} = \sum_{i \in j} \left(\frac{L_i}{\sum_i L_i} \right) \left(X_i.\hat{\beta}_f + \hat{\rho}_f.\hat{\sigma}_f.\frac{\phi(H_i.\hat{\alpha}_f)}{\Phi(H_i.\hat{\alpha}_f)} \right) \tag{22}$$

The first counterfactual w_j^* corresponds to the average wage that an individual from group j could expect if he was selected and paid in the same way as those in the French native group. The second counterfactual w_j^{**} represents the average wage that an employed individual from group j could expect if he was paid in the same way as French natives.

The decomposition of the wage gap between French natives f and second-generation group j is then written as follows

$$\bar{w}_f - \bar{w}_j = \underbrace{\bar{w}_f - w_j^*}_{Explained\ part} + \underbrace{w_j^* - w_j^{**}}_{Selectivity} + \underbrace{w_j^{**} - \bar{w}_j}_{Residual\ gap} \tag{23}$$

Table 10 presents the ethnic wage gap decomposition results. The wage gap is expressed here as the difference in the log hourly wage between French natives and second-generation immigrants. As noted above, we decompose these gaps into three components. The first corresponds to the proportion explained by differences in observed characteristics between the two groups. The second represents the differences between the two groups in terms of selection. The third shows the residual gap, *i.e.* the proportion of the gap which is neither explained by observed characteristics nor by selection. The table shows each component as a percentage of the initial raw gap. Again, controlling for education reduces the residual part and increases the explained part of the wage gap. Overall, these and previous findings suggest that education differences between ethnic groups are particularly important in explaining employment and wage gaps.

[Table 10 : about here]

3.3. Control for the endogeneity bias

In the previous section we have considered Mincer equations with a control for the selection bias. However as mentioned above, estimates of determiannts of labor outcomes (employmnent and earnings) may also suffer from another bias, namely the endogeneity bias, that we need to control for. To account for both the selection and the endogeneity biases, we follow Cutillo and Di Pietro (2005) and Jones and Sari (2015) and estimate in a first step a bivariate probit model that consists of two simultaneous equations, one for the binary outcome "schooling failure" and another for "being employed or not" (Cutillo and Di Pietro, 2005; Jones and Sari, 2015). For computational reasons, we focus our attention on schooling failure instead of educational attainment. Indeed this would have supposed to resort to linear probability models on educational attainment that suffer from several important limitations (see Horrace and Oaxaca, 2006; Black et al. 2005). Precisely, we consider the bivariate probit model as follows:

$$
\begin{cases}
S^*_{ij} = \gamma Z'_{ijS} + \omega_j + \zeta_{ij} \\
L^*_{ij} = \alpha Z'_{ijL} + \omega_j + \varepsilon_{ij}
\end{cases}
\tag{24}
$$

where S^*_{ij} and L^*_{ij} are the latent variables associated to the probability of schooling success/failure and the probability of employment, respectively; Z_{ijL} is a set of individual characteristics influencing the probability of being employed; Z_{ijS} includes some of the characteristics included in Z_{ijL} plus a set of instruments for educational success; ω_j is a group j fixed effect. In addition, it is also necessary to have some instrumental variables that influence employment but not wages, which means that these variables should be included in Z_{ijL} but not in X_{ij} in equation (16). As mentioned in the previous sub-section, these variables include the marital status as well as the spouse's occupation. Finally the identification of the model requires that Z_{ijS} includes at least one instrumental variable that explains the probability of educational success but neither the probability of being employed nor the level of earnings. In other words this means that these instrumental variables should not be included neither in Z_{ijL} nor in X_{ij}, i.e. the vector of characteristics that are thought to affect wages. Our potential candidates as instrumental variables included in Z_{ijS} are the presence of a separate room for the kid, the number of siblings (see Angrist and Krueger, 1991)ˈ family size and/or birth order (Black et al. 2005).[30] The error terms ζ_{ij} and ε_{ij} are assumed to follow a

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[30] According to the literature greater family size may negatively affect child outcomes through resource dilution (Becker, 1960). Note that this effect may be partly offset by a positive effect of family size: a higher family size

normal distribution. The estimation of this model by the log likelihood allows to construct Inverse Mill's ratios that will be included in a second step in the wage equations.

In a second step, after having estimated the bivariate probit model, we estimate the determinants of wages:

$$logw_{ij}|L_{ij}^* > 0 = X_{ij1}.\beta_1 + \omega_j + a_1.\lambda_{ijs} + a_2.\lambda_{ijL} \tag{25}$$

where λ_{ijS} and λ_{ijL} are the Inverse Mill's ratios and the a's their coefficients.

Our findings are shown in Table 11. Columns (1) and (2) reports the findings on the determinants of schooling failure and employment, respectively. Column (3) of table 11 reports estimate on the determinants of wages after controlling for both the selection and the endogeneity biases.

Overall, these results shown in Table 9 confirm our previous findings. Column (1) of Table 11 reports very similar findings to those shown in column (4) of Table 2 on the determinants of schooling failure. Similarly, column (2) of Table 11 provides similar findings to those reported in column (3) of Table 7. Finally, column (3) of Table 11 confirms our previous findings, i.e. the fact that none of the origin variables is significant except the Turkish variable that captures a positive and significant coefficient, indicating that Turkish second-generation immigrants benefit from a wage premium relative to natives.[31]

[Table 11 :about here]

4. Discussion and conclusions

Using data from the French *Trajectoires et Origines* survey, we have investigated the determinants of the ethnic gaps in education and labor-market outcomes between natives and second-generation immigrants. To our knowledge, this dataset is the only one providing

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may help stabilizing marriages and thus decrease the probability of education failure. Empirical evidence tends to confirm the existence of a negative correlation between large families and low education level. Using data on the entire population of Norway, Black et al. (2005) found a negative relationship between family size and children education. However this effect becomes negligible when the authors include indicators for birth order and use of twin births as an instrument. Furthermore the authors observe a significant and negative birth order effect on children education.

[31] We also run separate estimates on the wages for those who succeed/failed in school (available upon request). These additional estimates indicate that only Turkish second-generation immigrants who succeeded at school benefit from a wage premium relative to natives.

accurate information on the life-course of second-generation immigrants in France. We have three main findings.

First, we find that childhood environment is a key determinant of education. Controlling for family background knocks out the negative effect of ethnic origin on education. It becomes even positive suggesting that educational achievement of children of immigrants is the result of the parents' strong value on education (see Siahaan *et al.* 2014). This result also echoes the explanations found in the sociology of education literature that immigrants believe more than natives that education is a vehicle for social mobility (see for instance, Kao and Tienda, 1995). For that reason, they would invest more into education. Another explanation is that second-generation immigrants may anticipate that they will be discriminated in the future on the job market and hence invest more in education to counteract this potential future discrimination. This sharply contrasts with the idea that second-generation immigrants would under-invest in education because they suffer from discrimination at school or because they anticipate lower returns on the labor market (see for instance the theoretical setups in Lundberg and Startz, 1983; Keane and Wolpin, 2000).[32]

Another important finding is that education plays a prominent role in explaining both the employment and wage gaps between French natives and second-generation immigrants. Although we find that second-generation immigrants are less likely to be employed and receive lower wages than do natives we show nevertheless that education plays a major role in explaining both the employment and wage gaps. Controlling for education the ethnic employment gap is strongly reduced. Concerning the wage gap, after controlling education as well as for selection and endogeneity biases the ethnic wage gaps disappear and we even observe a wage premium for Turkish second-generation immigrants who succeeded in schooling relative to natives.

A third important finding of this study is the existence of an important heterogeneity across ethnic groups in term of educational attainment but also in term of employment and wages. These differences seem to be mainly driven by familial background differences.

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[32] In these models, negative prior beliefs about members of a particular group may become self-fulfilling in equilibrium (Lundberg and Startz, 1983). This may occur for example if individuals of a particular group under-invest in human capital due to anticipated discriminatory treatment and therefore a lower return to education.

Altogether our data indicate that childhood environment seems to be a key determinant of life-course success, as it affects education which itself generates labor-force outcomes. Our result on the impact of family background on educational attainment, which in turn is key for labor market integration, is in line with the findings of existing work emphasizing the role of "premarket" factors in adult earnings inequality (see Todd and Wolpin, 2007).

Our findings suggest that targeting the education gap via family-oriented policies may be efficient in reducing ethnic gaps in the labor market.[33] Education policies such as early-childhood education, kindergarten, homework assistance, and so on, which act as a counterweight to aspects of family background, may help to attenuate these education gaps. Nevertheless the existence of a residual ethnic employment gap after controlling for educational attainment tends to suggest that apart from education other non-unobservable factors such as discrimination at the hiring stage seem to play a non-negligible role in explaining ethnic labor-market outcomes. Future research will help to further determine the precise impact of discrimination in determining outcomes on the French labor market.

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[33] We should however be cautious in our interpretation of the residual employment gap. Indeed this latter may not necessarily reflect only discrimination, but may also come from unobserved differences in ability, attitudes, or preferences. Unfortunately, one main limitation of this study is that it does not allow us to disentangle these different effects from a pure discrimination effect. This is however a general difficulty in most survey data without accurate information on discrimination at the hiring stage. Recent developments in field and laboratory experiments have shown that the experimental method is a valuable tool for the circumvention of this difficulty (See Riach and Rich, 2002, for an exhaustive survey of field experiments).

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