Discussion Papers
Collana di
E-papers del Dipartimento di Economia e Management – Università di Pisa

Benedetti I., Regoli A.

Assessing job quality in the French labour market: decompositions of the native/migrant wage gap

Discussion Paper n. 241

2019

Discussion Paper n. 241, presentato: **Gennaio 2019**

Indirizzo dell'Autore:

Ilaria Benedetti
Dipartimento di Economia, Ingegneria, Società e Impresa, via del Paradiso 47, 01100, Viterbo - Italy
i.benedetti@unitus.it

Andrea Regoli
Dipartimento di studi Aziendali e Quantitativi, Via Generale Parisi 13, 80132, Napoli - Italy
andrea.regoli@uniparthenope.it

Si prega di citare così:
Benedetti, I., Regoli, A. (2019), "Assessing job quality in the French labour market: decompositions of the native/migrant wage gap", Discussion Papers del Dipartimento di Economia e Management – Università di Pisa, n. 241 (http://www.ec.unipi.it/ricerca/discussion-papers.html).

Discussion Paper
n. 241

Benedetti I., Regoli A.

Assessing job quality in the French labour market: decompositions of the native/migrant wage gap

Abstract

Having a job, and particularly having a job of good quality, is an important determinant of people's well-being. In many countries, inequality starts in the labour market. Indeed, changes in the distribution of wages are found to be the key factors behind recent inequality trends (ILO 2015).

A high level of inequality can create divisions within society, reduce opportunity and social mobility: it could weaken the social cohesion and reduce household consumptions with low rates of economic growth. All these issues can threaten the political stability. In this study, we contribute to the literature on immigrants in the French labour market by analysing the earnings differentials between workers born in France and workers born abroad. We used the wage indicator of job quality by using the 2013 French Working condition survey carried out by DARES (Directorate for Research, Studies and Statistics). Given the importance of the immigration phenomenon in the EU countries and in particular in the French labour market context, the aim of the paper is to explain the differences between immigrant and native workers in terms of wage by using decomposition techniques, controlling for a large set of covariates.

The decomposition methods allow us to decompose mean differences in two components: the "explained" and the "unexplained" part (the second one is often used as a measure for discrimination). In particular, as an extension to the classical decomposition method, proposed by Oaxaca (1973) and Blinder (1973), we applied the decomposition method proposed by Firpo et al. (2007, 2009) to consider the ways in which various characteristics of immigrants and natives affect the wage gap along the whole distribution of wages, at points other than the mean.

Keywords: Wage inequality, Rif-regression, Immigrant workers, Wage differential

JEL: J31, J61, C210

Assessing job quality in the French labour market: decompositions of the native/migrant wage gap

1.Introduction

In many countries, inequalities start in the labour market. Indeed, changes in the distribution of wages are found to be the key factors behind recent inequality trends (ILO 2015). Income is a decisive factor in determining many socio-economic outcomes. The degree to which income can provide a decent living is affected by personal (or personal) factors and work-related factors. Several studies have shown that higher levels of income are associated with better health conditions, higher educational attainment, greater civic participation and social cohesion (Aeberhardt et al., 2010a, 2010b). Among personal factors, the degree of income is affected also by the workers' country of origin.

The OECD report on Immigrants Integration (2015) estimated that in 2012 wages were more unevenly distributed within the immigrant population than in the native-born population. In the OECD countries, 16% of immigrants fall into the lowest income decile, the proportion is slightly higher in the European Union countries. In particular, the French situation is quite similar to the situation observed in Belgium, Finland and Czech Republic, where a quarter of the immigrant population is in the poorest decile.

A high level of inequality can create divisions within society, reduce opportunity and social mobility: it could weaken the social cohesion and reduce household consumptions with low rates of economic growth. All these issues can threaten the political stability. In this study, we contribute to the literature on immigrants in the French labour market by analysing the earnings differentials between workers born in France and workers born abroad. We used the wage as an indicator of job quality, with the aim of explaining the differences between immigrant and native workers in terms of wage by using decomposition techniques, controlling for a large set of covariates. The decomposition methods allow us to decompose mean differences in two components: the "explained" and the "unexplained" part (the second one is often used as a measure for discrimination). In particular, as an extension to the classical decomposition method, proposed by Oaxaca (1973) and Blinder (1973), we applied the decomposition method proposed by Firpo et al. (2007, 2009) to consider the ways in which various characteristics of immigrants and natives affect the wage gap along the whole distribution of wages, at points other than the mean.

The remainder of this paper is organised as follows. Section 2 reviews the literature on the determinants of wage inequalities among native and migrant workers. Section 3 describes the Recentered Influence Function regression method used in the analysis. Section 4 reports the data on 2013 French Working Conditions Survey, while section 5 presents the estimation results. Section 6 concludes the study.

2. Literature review: Assessing the determinants of wage inequality among native and migrant workers

There are many reasons why the labour market outcomes of immigrants tend to differ from those of native-born.

The fertility rate is on average higher for migrant than native women and migrants tend to marry more and earlier than native individuals (Algan et al. 2010). Unsurprisingly, being married and having children is negatively and significantly related to female labour force participation (Akgüç and Ferrer, 2015).

Education is crucial in influencing labour market outcomes. According to Dustmann and Glitz (2011), France is characterized by low-skilled immigrants. Two studies by Algan et al. (2010, 2010) report that on average France's immigrants have left school at an earlier age than the native-born counterpart. In another contribution, Algan et al. (2010) show that the young second-generation migrants perform worse than the older cohort. Regarding earnings, most of these works find that immigrants are less likely to be employed (Aeberhardt et al. 2010a, 2010b) and earn on average significantly less than natives do (Akgüç and Ferrer, 2015). In particular, immigrants from the Maghreb suffer from greater unemployment than other ethnic groups do (Meurs et al., 2006). Although immigrants are less likely to be employed and receive lower wages than natives, Langevin et al. (2017) and Martins and Pereira (2004) show that education plays a major role in explaining the employment and wage gaps.

To find a job in the public sector is less likely for immigrant than French natives, even when they have the same age, qualifications and profession (Berson, 2009). Al Ariss et al. (2013) demonstrated that most of the highly skilled ethnic minority workers interviewed obtain unskilled jobs because they face legal barriers in France. Compared to other EU countries, in France the rates of over-skilling substantially exceeded those of over-education (McGuinness and Byrne, 2015).

3. Methodology: the Recentered Influence Function regression

We investigate wage inequality in France by comparing the wage between native and immigrant workers. First, a raw estimate of this differential is obtained by a simple wage function (WF):

$$y_i = \beta_0 + \beta_1 F_i + \varepsilon_i \qquad (1)$$

where y_i is the wage of the i-th worker, F_i is a dummy variable for native status (migrant=m, native=n), and ε_i is the error component. The coefficient β_1 from a classical OLS regression provides a first estimate of the size of the gap in the average wage, though it does not allow us to control for other factors that may influence the wage level. For this reason, we adopt a "full" WF in order to obtain an adjusted estimate of the wage gap, controlling for a set of covariates x_{ik} (k=2, …, K) that include individual and work-related characteristics:

$$y_i = \beta_0 + \beta_1 F_i + \sum_{k=2}^{K} \beta_k x_{ik} + \varepsilon_i \tag{2}$$

Then we use the decomposition method proposed by Firpo et al. (2007, 2009) to consider the ways in which various characteristics of immigrants and natives affect the wage gap not only at the mean but over the whole wage distribution. Indeed, this method, built on earlier work by Di Nardo et al. (1995), goes beyond the decomposition at the mean, which is inherent in the standard Oaxaca-Blinder decomposition. The classical Oaxaca-Blinder (OB) method of decomposition (Oaxaca, 1973; Blinder, 1973) is based on the estimation of separate linear regression models in the two groups, that is:

$$y_{Fi} = x'_{Fi}\beta_F + \varepsilon_{Fi} \qquad \mathrm{F = n, m} \tag{3}$$

Since the mean of the response variable can be written as:

$$E(y_F) = E(x_F)'\beta_F \tag{4}$$

the mean outcome gap, expressed as:

$$E(y_n) - E(y_m) = E(x_n)'\beta_n - E(x_m)'\beta_m \tag{5}$$

can be easily decomposed in order to separate the effect due to differences in worker characteristics (endowments component) from the effect due to differences in the impacts of those endowments on wage outcome (returns components). To this purpose, the outcome distributions of the two actual groups are compared through a third (artificial) group, representing the counterfactual distribution, that shares its characteristics with one group and its WF coefficients with the other group. In this study, the counterfactual distribution has been defined by associating the endowments of migrant group with the returns of native group. In this way, the native group is chosen as a reference group with the assumption that the WF for native workers represents the reference, non-discriminatory model. Migrants coefficients, as well as coefficients from a pooled regression, could instead be taken as a reference (Oaxaca and Ransom, 1994).

With the native group coefficients as a reference, the mean (observed) outcome gap of equation (5) can be computed as follows:

$$\Delta_0^{\mu} = \bar{y}_n - \bar{y}_m = (\bar{x}_n - \bar{x}_m)'\hat{\beta}_n + \bar{x}'_m(\hat{\beta}_n - \hat{\beta}_m) = \Delta_x^{\mu} + \Delta_s^{\mu} \tag{6}$$

where $\bar{x}_n$ and $\bar{x}_m$ are the vectors of the group means of the endowments, while $\hat{\beta}_n$ and $\hat{\beta}_m$ are the least squares estimates of the coefficients of models (3). The explained effect Δ_x^{μ} accounts for differences in the distribution of K variables in the X matrix between the two groups, while the unexplained effect Δ_s^{μ} accounts for differences in the way the X characteristics influence the workers' wage.

In addition, the OB method allows us to obtain a detailed decomposition of the observed gap, in which the contribution of each single explanatory variable x_k (k=1,..,K) to the main effects is highlighted:

$$\Delta_n^{\mu} = \bar{y}_n - \bar{y}_m = \sum_{k=1}^{K}(\bar{x}_{nk} - \bar{x}_{mk})\hat{\beta}_{nk} + \left(\hat{\beta}_{n0} - \hat{\beta}_{m0}\right) + \sum_{k=1}^{K}\bar{x}_{nk}\left(\hat{\beta}_{nk} - \hat{\beta}_{mk}\right) = \Delta_X^{\mu} + \Delta_S^{\mu} \quad (7)$$

In the above equation, $(\bar{x}_{nk} - \bar{x}_{mk})\hat{\beta}_{nk}$ represents the effect due to the difference between the groups in the endowments of the k-th explanatory variable, whereas $\bar{x}_{nk}\left(\hat{\beta}_{nk} - \hat{\beta}_{mk}\right)$ is the contribution of the difference between the coefficients of the k-th explanatory variable in WF model. The term $\left(\hat{\beta}_{n0} - \hat{\beta}_{m0}\right)$ is the difference between the intercepts of the WF models; it represents the unexplained component for the base group. In the presence of categorical covariates, the detailed decomposition of the unexplained effect depends on the choice of the omitted group in the regression model, which gives rise to the "omitted group" problem (Fortin et al., 2011).

The estimation of the mean gap may conceal heterogeneous patterns in the gap across the whole distribution. If the objective is the evaluation of the impact of explanatory variables on the gap in different parts of the unconditional distribution of the outcome (for example, at each percentile) and not just on the mean outcome gap, an extension of the standard OB method should be implemented.

The Recentered Influence Function (RIF) regression method, developed by Firpo et al. (2009), allows us to perform Oaxaca-Blinder-like decomposition at chosen quantiles. This method requires the estimation of a RIF for every quantile of interest $Q\tau$:

$$RIF\left(y; \hat{Q}_t\right) = \hat{Q}_t + \frac{\tau - I(y \leq \hat{Q}_t)}{\hat{f}_y(Q_t)} \quad (8)$$

where $\hat{Q}_t$ is the sample τ-th quantile, $fy(Q\tau)$ is a standard nonparametric density estimator (i.e., a kernel), and I is an indicator function.

For every quantile, the estimated RIF is then regressed on the chosen covariates using a standard OLS estimator. The estimated coefficients capture the marginal impact of the covariates on the quantiles of the unconditional wage distribution. In other words, they provide information on the wage determinants among low-wage earners (at the lowest quantiles) as well as among high-wage earners (at the highest quantiles). In contrast, the classical OLS regression gives only information on the impact of the covariates for an average worker.

In terms of native-immigrant wage gap estimation, the OLS regression compares the average wages for native and immigrant workers who share the same characteristics. By contrast, the RIF regression allows us to assess whether any difference in the wages between natives and immigrants with the same observed characteristics remains constant across wage levels or if instead it shrinks or grows. The properties of the RIF allow us to write the equivalent of the OB decomposition for any τ −th quantile Q_τ of the outcome distribution as follows:

$$\Delta_{\mathrm{n}}^{\tau}= \sum_{k=1}^{K}(\bar{x}_{nk} - \bar{x}_{mk})\hat{\beta}_{\mathrm{nk}}^{\tau} + \left(\hat{\beta}_{\mathrm{n0}}^{\tau} - \hat{\beta}_{\mathrm{m0}}^{\tau}\right) + \sum_{k=1}^{K}\bar{x}_{nk}\left(\hat{\beta}_{\mathrm{nk}}^{\tau} - \hat{\beta}_{\mathrm{mk}}^{\tau}\right) = \Delta_{X}^{\tau} + \Delta_{S}^{\tau} \quad (9)$$

where $\hat{\beta}_{\mathrm{Fk}}^{\tau}$ (F=n,m) is the estimated coefficient of the k-th explanatory variable in the unconditional quantile regression for each group.

4. Data: French Working Conditions Survey

We use data drawn from the 2013 wave of the French Working Conditions Survey, a French nationally representative dataset with information on workers' earnings. This survey represents the largest source for obtaining comparable statistics on income, job characteristics, job quality and living conditions at country level.

The Working Conditions Surveys have been organized and operated by Dares[1] since 1978, in collaboration with INSEE[2]. They are renewed every seven years: 1984, 1991, 1998, 2005 and finally 2013[3]. Respondents are asked about their perceived working conditions through face-to-face interviews. The survey units are all employed workers in every sector, including the civil service. The questions regarding job quality refer to a concrete description of the work, its organization and its conditions, from various angles: room for manoeuvre, cooperation, work rhythms, physical effort or risks. The first wave of the survey (carried out in the 1978) was focussed on the analysis of physically painful work. However, its scope was widened in the successive waves: in 1998 some questions have been introduced on work injuries and in 2005 questions on the prevention of work-related risks have been added.

The dataset contains, among the others, variables from the household questionnaire describing the characteristics of all interviewed individuals, their housing and their household. For the first time, in 2013, the survey covered four overseas departments (Martinique, Guyana, Guadeloupe and Reunion).

The last survey, carried out in 2013, has been conducted on a representative sample of 33,673 respondents aged 15 and over.

Bearing in mind the aims of our analysis, we focused on employees (i.e., anyone who receives compensation in the form of wage, salary, payment by result or in kind), aged 15–65, irrespective of their activity sector, excluding those employed in military occupations.

---

[1] DARES: Directorate for Research, Studies and Statistics (DARES) produces statistics and analyses useful to the Ministry in charge of labour, employment, vocational training and social dialogue and to economic and social actors (Social partners, regional councils, public employment service, economic and social press, etc.).

[2] INSEE: National Institute for Statistics and Economic Studies collects, produces, analyzes and disseminates information on the French economy and society.

[3] http://dares.travail-emploi.gouv.fr/dares-etudes-et-statistiques/enquetes-de-a-a-z/article/conditions-de-travail-edition-2013.

The key dependent variable in our analysis is the hourly wage of French workers[4]. This variable is used to evaluate the gap in the labour market between native and migrant workers. Country of birth is used to define migrant status: those born outside the French borders are classified as migrants and French-born individuals are classified as natives.

The final dataset, net of missing values in every investigated variable, includes 29,287workers, with 2,580 (8,81%) immigrants and 26,707 (91.19%) native born workers. The choice to consider only employees derives from differences in the personal and work characteristics of self-employed workers (Hamilton, 2000; Parker 2004; Castellano and Punzo 2013) and the different reported income.

With the aim of assessing whether the exclusion of self-employed people would lead to distortion from selection, we estimate the Heckman two-step selection model. In the first step, for the whole sample of workers we predict the probability of working as an employee vs. working as a self-employed by using the dummy for self-employed parents as an instrument. Then in the second step, we estimate the wage equation among the employees. At the 1% significance level, the results of the job satisfaction regression model rule out any significant correlation between the decision to work as an employee and the wage level. Thus, we can conclude that our analysis does not suffer from selection bias.

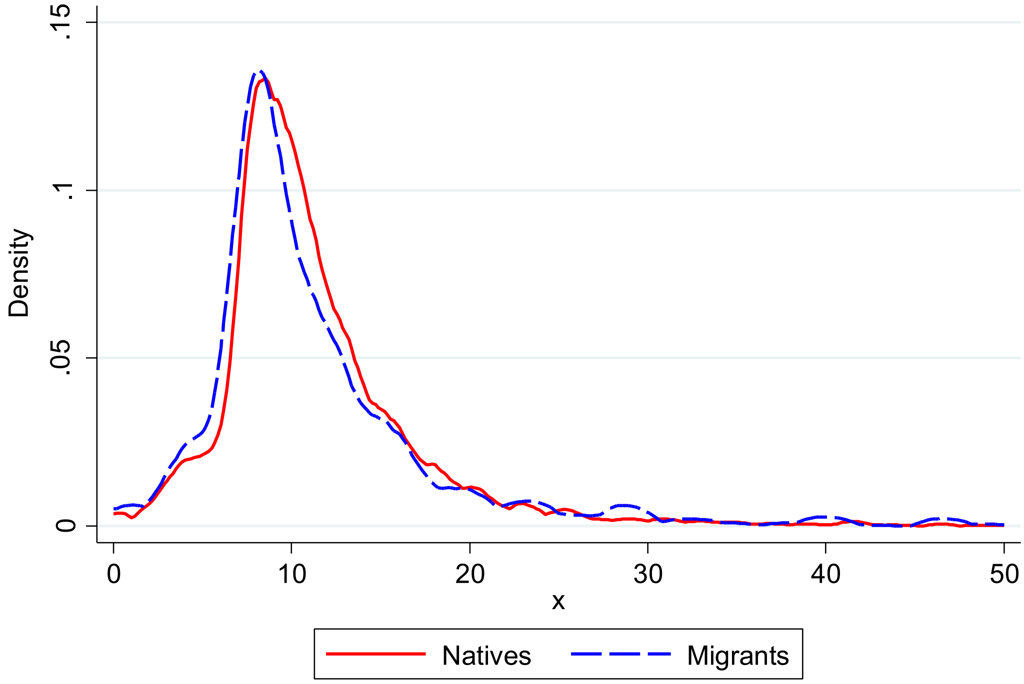
Considering unconditional hourly wages, kernel density[5] estimates for logged hourly wages are plotted in figure 1 to illustrate the wage distribution of natives and migrants. Generally, the density curve for natives has more "mass" to the right than the density curve for migrants, thus suggesting the presence of a wage gap to the disadvantage of migrant workers.

---

[4] The original income variable in the dataset is the monthly income. From an initial exploratory analysis, we noticed that out of the total of 30198 employees, 779 of them did not report their monthly income. We imputed the missing values through a regression analysis based on the observed data using as explanatory variables: gender, education, sector of activity, classification of occupation and type of contract. Through this procedure we reduced the number of missing values to 31. To turn the monthly income into hourly income., we used the information on the hours worked per day. However, even in this case we observed that 427 workers had not declared the weekly hours worked. So, we took into consideration the employment sector and the type of contract, thus estimating the average number of hours worked for each sector and type of contract, and we replaced the missing number of hours by the mean. Finally, we calculated the hourly income as (monthly income)/(4.3*hourly worked hours).

[5] Kernel density estimators approximate the density f(x) from observations on x. The data are divided into nonoverlapping intervals, and counts are made of the number of data points within each interval.

Figure1: Hourly wage (kernel density estimates) for migrant and native workers



Source: Data Elaboration from FLS 2013

Using French Labour Force data, we are able to explore the factors influencing the earning differential using the set of explanatory variables listed in table 1. Descriptive statistics for native and migrant workers are reported in table 2.

Table 1: Explanatory variables used

Personal characteristics	
Name	Description
Native status	=1 for native-born; =0 for foreign-born
Gender	=1 for male; =0 for female
Marital status	=1 for not married; =0 for married or in a civil union
Age	=1 for16-30; =2 for 31-40; =3 for 41-50; 4=for >50;
Educational level	=1 for lower secondary; =2 for upper secondary; =3 for tertiary
Health status	=1 for fair, bad or very bad health; =0 for good or very good health
Limitations due to chronic illnesses or disabilities	=1 for yes; =0 for no limitations
With children	=1 yes; =0 no
Work-related characteristics	
Name	Description
Sector in employment	=1for agriculture; =2 for industry; =3 for construction, 4=for tertiary sector
International standard of occupation	=1 for high skilled non-manual; =2 for high skilled manual, =3for low skilled non-manual, =4 for low skilled manual;
Contract type	=1 for permanent contract; =0 for fixed term contract
Full-time worker	=1 for full-time worker; =0 for part-time worker
Firm size	=1 for small size (<50); =0 for big size (≥50)
Union membership	=1 for yes; =0 for no

Table2: Descriptive statistics for migrant and native born workers

	Native		Migrant			
	Mean	s.d.	Mean	s.d.	diff	sig.
Male	0.515	0.500	0.530	0.499	-0.014	
Not married	0.523	0.499	0.396	0.489	0.127	***
16-30 years old	0.231	0.422	0.152	0.359	0.079	***
31-40 years old	0.258	0.437	0.261	0.439	-0.003	
41-50 years old	0.256	0.436	0.243	0.429	0.013	
51-65 years old	0.255	0.436	0.344	0.475	-0.089	***
Primary education	0.406	0.491	0.448	0.497	-0.042	***
Secondary education	0.336	0.473	0.256	0.437	0.080	***
Tertiary education	0.258	0.438	0.296	0.457	-0.038	**
No good health status	0.233	0.423	0.283	0.451	-0.050	***
Chronic limitations	0.107	0.309	0.119	0.324	-0.012	
With children	0.537	0.499	0.597	0.491	-0.061	***
Agriculture	0.011	0.106	0.015	0.123	-0.004	
Industry	0.171	0.377	0.124	0.330	0.047	***
Construction	0.066	0.248	0.092	0.289	-0.026	***
Tertiary sector	0.751	0.432	0.769	0.422	-0.017	***
Full-time worker	0.825	0.380	0.820	0.384	0.005	
High skilled non manual	0.467	0.499	0.396	0.489	0.071	***
High skilled manual	0.248	0.432	0.247	0.432	0.000	
Low skilled non manual	0.196	0.397	0.206	0.404	-0.010	
Low skilled manual	0.090	0.286	0.150	0.358	-0.061	***
Permanent contract	0.868	0.338	0.839	0.368	0.030	**
Small firm size	0.681	0.466	0.666	0.472	0.015	
Union membership	0.166	0.372	0.159	0.366	0.007	

Note: * p<0.10; ** p<0.05; ***p<0.01.
Source: Elaborations from the French Working Conditions Survey, 2013

Immigrants are more likely than natives to have both a primary and a tertiary educational attainment. Furthermore, immigrants are less frequently hired on "standard" contracts (83,9% versus 86,8%). Compared with natives, a higher proportion of migrants is employed in construction sector (9,2% versus 6,6%) and a smaller proportion employed in the industry sector (12,4% versus 17,1%). These results are in line with the anatomy of the French labour Market (Le Barbanchon and Malherbet, 2013). Finally, immigrants are with a lower degree involved in high skilled non-manual occupations (39,6% versus 46,7%) and tend to declare worse health conditions (11,9% versus 10,7%), as compared to French-born workers.

5. Results

5.1 Results from OLS regressions

We start our analysis with the estimation of WF models using classical OLS regression for the entire sample of workers, then the inclusion of the dummy variable on native status allows us to assess the gap in wage between natives and migrants while controlling for the effects of other factors. Different models are estimated: the first model (m1) includes the native status dummy alone, thus producing an estimate of the raw average gap; in the second model (m2), we insert the personal characteristics and finally, in the full model (m3), we included all the variables. The dependent variable is the logarithm of the hourly wage, so that the estimated coefficients express the percentage increase or decrease in wage that would result from a change in the corresponding covariate. In other words, each coefficient expresses the relative difference in wage with respect to the reference category for the corresponding dummy covariate, holding all other variables in the model constant. The results of OLS regression (table 3) show that the observed average gap in wage between natives and migrants is 0.065 (m1). Therefore, on average, the natives' wage is about 6.5% higher than the migrants' wage. As expected, demographic characteristics turn out to be significantly correlated with wage (m2): the native-migrant gap rises from 6.5% to 10% when we control for the individual characteristics. Conversely, the gap decreases, though it remains statistically significant, after controlling for work-related characteristics (m3). The results suggest that individual and work-related covariates impact differently on the wages of native and migrant workers: the personal characteristics seem to favour more the migrants than the natives whereas the opposite is true for the work-related characteristics.

Table 3: OLS regressions for all workers

	(m1)		(m2)		(m3)	
	coeff	sig.	coeff	sig.	coeff	sig.
Native	0.065	**	0.109	***	0.061	**
Male			0.179	***	0.094	***
Not married			-0.040	**	-0.030	
Age (ref. >51 years old)						
16-30 years old			-0.467	***	-0.323	***
31-40 years old			-0.252	***	-0.191	***
41-50 years old			-0.123	***	-0.093	***
Education (ref. tertiary edu)						
Primary education			-0.487	***	-0.270	***
Secondary education			-0.257	***	-0.149	***
No good health status			-0.062	***	-0.053	***
Chronic limitations			-0.063	**	-0.054	**
With children			0.050	**	0.036	
Sector (ref. Tertiary)						
Agriculture					-0.118	**
Industry					0.056	***
Construction					0.052	*
Full-time worker					0.158	***
Occupation (ref. High skilled no manual)						
High skilled manual					-0.217	***
Low skilled non-manual					-0.216	***
Low skilled manual					-0.330	***
Permanent contract					0.265	***
Small firm size					0.080	***
Union membership					0.058	***
Constant	2.228	***	2.595	***	2.195	***
Number of observations	26695		26695		26695	

Note: * p<0.10; ** p<0.05; ***p<0.01.
Source: Elaborations from the French Working Conditions Survey, 2013

5.2 Results from RIF regressions

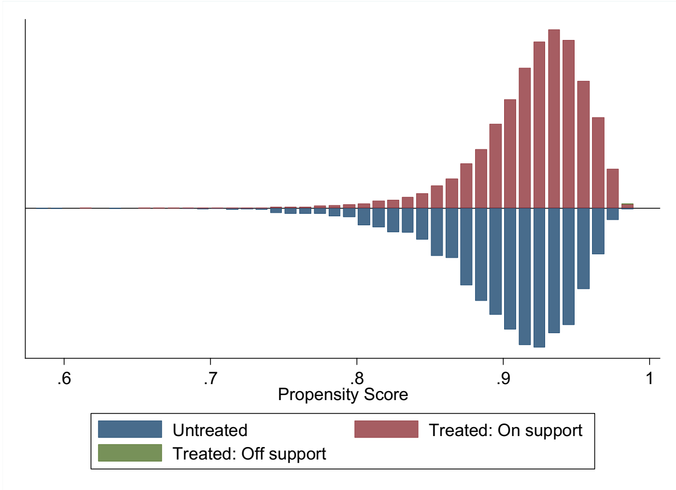
In this section, we provide a detailed descriptive picture of the native-migrant difference in the wage levels in France and we decompose this difference into a part that is due to differences in socioeconomic characteristics and a part that is due to differences in coefficients. The latter will be interpreted as a gap in wage function and might be expressed, for example, by a different effect of education on wage between native and migrant workers. In this study we refer to the economic treatment of workers: in fact, there are discriminations both in the access to employment and, once a job is obtained, in the access to particular positions.

We compare the standard Oaxaca-Blinder decomposition of the mean outcome differential through linear regression models with the decomposition of the gap at selected percentiles through quantile regression models using the Recentered Influence Function. The oaxaca command of STATA has been used to this aim (Jann, 2008).

A common support assumption is needed for the identification of the model parameters (Bryson et al., 2002). It requires that the values of the covariates should not be different for the two groups of workers: as long as native workers are observed with a given set of characteristics, the same set of characteristics should be observed among the immigrant workers (Heckman et.al., 1997). The simple solution to this issue is to estimate the pay gap only on the observations where the characteristics of native and immigrant workers are comparable, i.e. within the common support. It means that for each immigrant worker, a native worker must be found with similar characteristics. Empirically a probit model is estimated and the propensity score (that is the probability to be immigrant given a set of observed characteristics) is computed.

The graphical analysis (figure 2) stresses that the distributions of the propensity scores for the two groups of workers overlap almost completely. Indeed, few observations are out of the common support.

Figure 2: Propensity score graph



Source: Our elaboration from French Working Conditions Survey, 2013

Table 4 reports the results of the decomposition analysis for the wage function model specified at 10th, 25th, 50th, 75th and 90th centile and for the mean decomposition (OLS). Specifically, it underlines the decomposition effects due to characteristics and coefficients and the raw differential.

Our empirical results indicate that the native-migrant wage difference assumes a positive value till the median of the distribution, which entails a disadvantage for migrant workers among the low to medium earners. From the 75th centile onwards the gap becomes not significant, meaning that migrant high-income earners fill the gap. Furthermore, we can see that the native-migrant wage differences are mainly due to differences in the coefficients rather than to differences in observable characteristics. Indeed, the characteristics component is never significant whereas the coefficients effect is responsible for the very large part of the observed gap (ranging from 80% to 91% in the low half of the distribution).

Table 4: Aggregate decomposition of the native/migrant wage gap

		q10	**q25**	**q50**	**q75**	**q90**	**OLS**
Characteristics	coeff.	0.014	0.006	0.005	-0.007	-0.03	0.001
	%	20%	9%	9%	-54%	41%	2%
	sig						
Coefficients	coeff.	0.058	0.059	0.053	0.02	-0.044	0.063
	%	80%	91%	91%	154%	59%	98%
	sig	(**)	(***)	(***)			(**)
Raw gap	coeff.	0.071	0.065	0.058	0.013	-0.074	0.065
	%	100%	100%	100%	100%	100%	100%
	sig	(***)	(***)	(***)			(**)

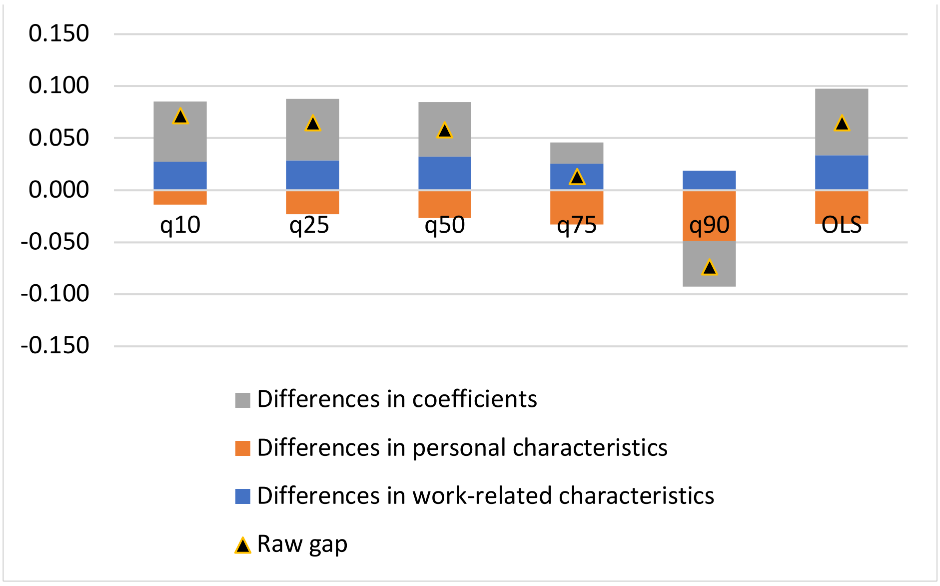
Note: * p<0.10; ** p<0.05; ***p<0.01
Source: Elaborations from the French Working Conditions Survey, 2013

In summary, where the migrants' wage is significantly lower than natives' wage, the gap is due to differences in the wage structure between the two groups. With the caution dictated by the still limited number of covariates, this effect can be identified as an approximation of the discrimination suffered by migrants in the labor market in terms of remuneration. The characteristics' component is offset by two forces having opposite direction. This appears evident when we divide the set of characteristics into two subsets, the former including the personal characteristics and the latter the work-related characteristics. Figure 3 shows the results of the wage decomposition where the characteristics effect is split up into the above-mentioned components.

The dark blue bars represent the native-migrant differences in the wage returns related to differences in the work characteristics, such as sector and occupation. The orange bars represent the native-migrant differences in wage return related to differences in the personal characteristics, such as age, educational level and civil status. The grey bars represent the coefficients effects. The last symbol, the black triangle, is the sum of the values represented by the three bars previously explained; it corresponds to the raw gap. The sign of the raw gap is positive and significant till the median value, then it became insignificant.

Across the whole distribution, the effect due to the differences in the personal characteristics has a negative sign. This means that if the only differences between migrant and native workers were differences in personal characteristics, the wage gap would reverse to the advantage of migrant workers. Conversely, the effect due to the differences in the work characteristics has a positive sign, which confirms that migrant workers are penalized in the comparison with native workers (for working more often than natives in agriculture and construction and for having the lowest occupations). For the very large part of the distribution the total effect explained by both sets of characteristics balances out.

Figure 3: Personal, work related characteristics and coefficients effect in the native-migrant workers wage gap decomposition



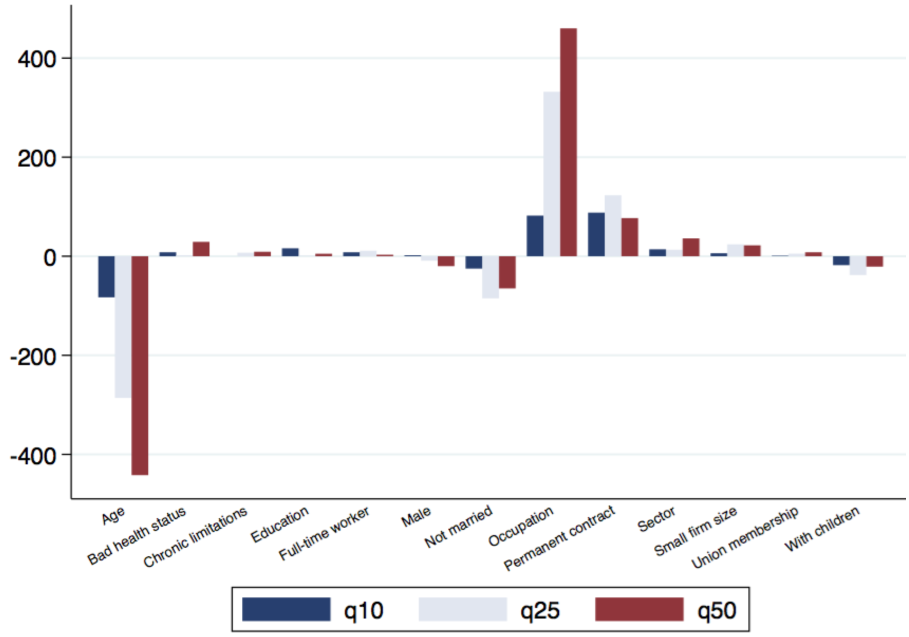
Source: Our elaboration from French Working Conditions Survey, 2013

As for the detailed decomposition of the characteristics and coefficients effect, table 5 shows the impact of the covariates and the corresponding percent share. For covariates with more than two categories, the impact results from the sum of the effects associated with every category. From the descriptive analysis of the differences between the samples of natives and migrant workers (see Table 2 above), we know that migrant workers are penalized in the comparison with native workers for having higher share of primary education, for having the lowest occupations and for having a lower share of permanent contract: these characteristics entail a lower wage level. Therefore, if the migrants could fill the gap in the above listed characteristics, they would see an improvement in their working conditions. Conversely, migrants benefit more than natives for having a lower share of workers in the class age 16-30, for having a lower share of not married individuals, for having a lower level of secondary education and for having a higher share of children. Therefore, if they had the same characteristics as the natives, their gap would increase further.

Additionally, Figure 4 allows for a comparison of the effects of the covariates. For covariates with more than two categories, the impact results from the sum of the effects associated with every category. Considering the opposite sign with respect to the raw differential, the main effect is given by age, marital status and presence of children at home. Considering the same sign with respect to the raw differential, the main effect is given by occupation, permanent contract, sector and bad health status.

As for the detailed decomposition of the unexplained effect for categorical covariates with more than two categories, the results depend arbitrarily on the choice of the reference group (Oaxaca and Ransom, 1999). For these reasons, we do not comment further these findings.

Figure 4: Detailed decomposition of the native/migrant gap in the wage gap: estimated effect of the covariates for q10, q25 and q50 (as a % of the total characteristics component)



Source: Our elaboration from French Working Conditions Survey, 2013

Table 5: Detailed decomposition of the native/migrant gap in the wage gap: characteristic and coefficient effects

Characteristics	q10		q25		q50		q75		q90		OLS	
	coef.	%	coef.	%	coef.	%	coef.	%	coef.	%	coef.	%
Male	0.000	2%	-0.001	-9%	-0.001	-20%	-0.002	25%	-0.003	10%	-0.001	-99%
Not married	-0.003	-25%	-0.005	-85%	-0.003	-65%	-0.004	54%	-0.002	8%	-0.004	-281%
Age	-0.011	-83%	-0.016	-286%	-0.024	-442%	-0.026	356%	-0.036	120%	-0.027	-1890%
Education	0.002	16%	0.000	1%	0.000	5%	-0.002	20%	-0.004	15%	0.000	13%
Sector	0.002	14%	0.001	13%	0.002	36%	0.002	-25%	0.003	-10%	0.002	136%
Full-time worker	0.001	8%	0.001	11%	0.000	3%	0.000	1%	0.000	0%	0.001	57%
Occupation	0.011	82%	0.019	332%	0.025	460%	0.020	-266%	0.014	-48%	0.022	1534%
Permanent contract	0.012	88%	0.007	123%	0.004	77%	0.002	-31%	0.001	-2%	0.008	537%
Small firm size	0.001	6%	0.001	24%	0.001	22%	0.001	-18%	0.001	-4%	0.001	71%
Union membership	0.000	1%	0.000	5%	0.000	8%	0.000	-4%	0.000	0%	0.000	25%
Bad health status	0.001	8%	0.000	2%	0.002	29%	0.002	-25%	0.002	-5%	0.002	165%
Chronic limitations	0.000	0%	0.000	7%	0.000	9%	0.000	-1%	0.000	0%	0.000	25%
With children	-0.002	-18%	-0.002	-38%	-0.001	-21%	-0.001	16%	-0.005	16%	-0.003	-192%
Total	0.014	100%	0.006	100%	0.005	100%	-0.007	100%	-0.030	100%	0.001	100%
Coefficients	q10		q25		q50		q75		q90		OLS	
	coef.	%	coef.	%	coef.	%	coef.	%	coef.	%	coef.	%
Male	-0.039	-67%	-0.011	-19%	0.003	5%	-0.031	-156%	0.017	-38%	0.030	47%
Not married	-0.007	-13%	-0.014	-24%	-0.005	-9%	-0.034	-170%	-0.030	67%	-0.006	-9%
Age	-0.018	-31%	-0.017	-29%	-0.057	-109%	-0.066	-326%	-0.088	200%	-0.051	-80%
Education	-0.081	-140%	-0.059	-100%	-0.061	-116%	-0.026	-129%	0.008	-19%	-0.053	-84%
Sector	0.005	9%	-0.008	-14%	-0.002	-3%	0.014	70%	0.045	-103%	0.011	17%
Full-time worker	-0.027	-47%	-0.022	-37%	-0.034	-65%	0.035	175%	0.077	-175%	-0.061	-96%
Occupation	0.055	96%	0.012	20%	0.056	107%	0.179	886%	0.168	-382%	0.068	106%
Permanent contract	0.096	167%	0.097	164%	-0.006	-12%	-0.056	-276%	-0.113	257%	-0.029	-46%
Small firm size	-0.063	-110%	-0.017	-29%	-0.033	-62%	-0.042	-206%	-0.037	83%	-0.081	-128%
Union membership	-0.003	-5%	-0.004	-7%	-0.003	-6%	0.004	20%	-0.009	20%	-0.007	-11%
Bad health status	-0.002	-3%	0.015	25%	-0.004	-7%	-0.027	-134%	-0.009	21%	0.020	31%
Chronic limitations	0.009	15%	0.003	5%	0.010	20%	0.022	109%	0.022	-49%	0.027	43%
With children	0.052	90%	0.021	35%	0.008	16%	-0.005	-23%	0.037	-85%	0.055	87%
Constant	0.081	140%	0.065	110%	0.179	341%	0.052	258%	-0.133	303%	0.141	223%
Total	0.058	100%	0.059	100%	0.053	100%	0.020	100%	-0.044	100%	0.063	100%

Note: * p<0.10; ** p<0.05; ***p<0.01 – Source: Our elaborations from the French Working Conditions Survey, 2013

6. Conclusions

Integration of immigrants in their host countries has become a crucial policy issue. The aim of this paper is to explore the native-migrant workers wage differential in the French labour market context based on data from the 2013 French Working Conditions Survey.

The results indicate that on average native employees earned more than migrant employees. Immigrants tend to have different characteristics than their native-born counterparts. Regarding human capital, the immigrants group tend to cluster at the highest and the lowest levels of education. Regarding demographic characteristics, there are differences in the characteristics of their families: immigrants in France are more likely to be married than natives. Without expectation, the immigrant groups have a higher share of presence of children in the household than natives. These patterns in the demographic characteristics affect employment and earnings, since being married and having children tend to have a detrimental effect on the labour market outcomes, especially in the lower part of the income distribution. Also, the job characteristics are quite different between migrants and native-born workers, which have implications for inequalities. Immigrants group in the French context is relatively unlike to work in the tertiary sector, whereas they have a higher share of workers involved in the construction sector. Not surprisingly, immigrants group is more likely than native-born workers to have a temporary contract and a low skilled occupation.

We applied the decomposition method proposed by Firpo et al. (2007, 2009) in order to take into account the ways in which various characteristics of immigrants and natives affect the wage gap along the whole distribution of wages, at different points other than the mean.

The gap varies significantly along the wage distribution: it ranges between 6-7% to the disadvantage of migrant workers in the lower half of the distribution, namely among the low-medium earners, whereas it cancels out at the highest percentiles. Results of the decomposition show that the portion of the wage gap accounted by differences in the wage structure (coefficients effect) outweighs the share attributable to differences in personal characteristics (endowments effect).

Specifically, the characteristics' component is offset by two forces having opposite direction. The effect due to the differences in personal characteristics (age, education, marital status, health conditions) has a negative sign, which means that if the only differences between migrant and native workers were differences in these characteristics, the wage gap would reverse to the advantage of migrant workers. Conversely, the effect due to the differences in the work characteristics (such as sector, occupation, type of contract) has a positive sign, which confirms that migrant workers are penalized in the comparison with native workers for working more often than natives in agriculture and construction and for having the lowest occupations. This result points to the issue of access to employment by migrant workers, in particular to those occupations that could assure higher wages and better working conditions in general.

References

Aeberhardt, R., D. Fougère, J. Pouget, and R. Rathelot. (2010a). “Wages and Employment of French Workers with African Origin”. Journal of Population Economics 23 (3): 881–905. doi:10.1007/s00148-009-0266-3.

Aeberhardt, R., D. Fougère, J. Pouget, and R. Rathelot. (2010b). “L’emploi et les salaires des enfants d’immigrés”. Economie et statistique 433 (1): 31–46. doi:10.3406/estat.2010.8084;

Akgüç, M. and Ferrer, A. M. (2015). “Educational Attainment and Labor Market Performance: An Analysis of Immigrants in France”. Human Resource Management, 24:6, 1236-1256, DOI: 10.1080/09585192.2012.709190;

Al Ariss, A., Vassilopoulou, J., Özbilgin, M. F. and Game, A. (2013). “Understanding career experiences of skilled minority ethnic workers in France and Germany”. The International Journal of Human Resource Management, 24(6), 1236-1256;

Algan, Y., Dustmann, C., Glitz, A., and Manning, A. (2010). “The economic situation of first and second-generation immigrants in France, Germany and the United Kingdom”. The Economic Journal, 120(542);

Algan, Y., Landais, C. and Senik, C. (2010). “Cultural integration in France. Cultural integration of immigrants in Europe”. http://econ. sciences-po. fr/sites/default/files/file/yann% 20algan/France.pdf;

Berson, Clemence. (2009). “Private vs. Public Sector: Discrimination against Second-Generation Immigrants in France”. Documents de travail du Centre d'Economie de la Sorbonne. 59R - ISSN: 1955-611X - Version 2009. <halshs-00423944v2>;

Blinder AS. (1973). “Wage discrimination: reduced form and structural estimates”. Journal of Human Resources 8: 436–455;

Bryson, A., Dorsett, R. and Purdon, S. (2002). The use of propensity score matching in the evaluation of active labour market policies;

Castellano, R., Punzo, G. (2013). “The role of family background in the heterogeneity of self-employment in some transition countries”. Transit. Stud. Rev. 20(1), 79–88;

Di Nardo, J., Fortin, N. M. and Lemieux, T. (1995). “Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach (No. 5093)”. National bureau of economic research;

Dustmann, C. and A. Glitz (2011). "Migration and Education," in Handbook of the Economics of education, Volume 4, edited by E. S. Hanushek, S. Machin, and L. Woessmann, Elsevier;

Firpo, S., Fortin, N. and Lemieux, T. (2007). “Decomposing wage distributions using recentered influence function regressions”. University of British Columbia (June);

Firpo, S., Fortin N.M., Lemieux T., (2009). “Unconditional Quantile Regressions”. Econometrica 77(3), 953-973;

Fortin, N., Lemieux, T. and Firpo, S. (2011). "Decomposition methods in economics". Handbook of labor economics, 4, 1-102;

Hamilton, B. H. (2000). "Does entrepreneurship pay? An empirical analysis of the returns to self-employment". Journal of Political economy, 108(3), 604-631;

Heckman, J. (1974). "Shadow prices, market wages, and labor supply". Econometrica: journal of the econometric society, 679-694;

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The review of economic studies, 64(4), 605-654;

International Labour organization (ILO). 2015. World employment and social outlook: Trends 2015. Geneva;

Jann, B. (2008). "The Blinder-Oaxaca decomposition for linear regression models". The Stata Journal, 8(4), 453-479;

Langevin, G., Masclet, D., Moizeau, F., Peterle, E., (2017). "Ethnic gaps in educational attainment and labor-market outcomes: evidence from France". Education Economics, 25:1, 84-111, DOI: 10.1080/09645292.2016.1183591;

Le Barbanchon, T., and Malherbet, F. (2013). "An anatomy of the French labour market. Country case study on labour market segmentation". ILO Employment Working Paper, 142;

Martins, P. S., and Pereira, P. T. (2004). "Does education reduce wage inequality?" Quantile regression evidence from 16 countries. Labour economics, 11(3), 355-371;

McGuinness, S. and Byrne, D. (2015). "Born abroad and educated here: examining the impacts of education and skill mismatch among immigrant graduates in Europe". IZA Journal of Migration, 4(1), 17;

Meurs, D., Pailhé, A. and Simon, P. (2006). "The persistence of intergenerational inequalities linked to immigration: Labour market outcomes for immigrants and their descendants in France". Population, 61(5-6), 645-682;

Oaxaca RL. (1973). Male–female wage differentials in urban labor markets. International Economic Review 14: 693–709;

Oaxaca R.L., Ransom M.R. (1999). "Identification in detailed wage decompositions". Review of Economics and Statistics, 81: 154–157;

Organisation for Economic Co-operation and Development/European Union (OECD/European Union). (2015). Indicators of Immigrant Integration 2015: Settling In, Paris, OECD;

Organisation for Economic Co-operation and Development/European Union (OECD/European Union), (2015). In it together: Why less Inequality Benefits all. Paris, OECD. 21th May 2015. http://dx.doi.org/10.1787/9789264235120-en;

Parker, S.C. (2004). The Economics of Self-Employment and Entrepreneurship. Cambridge University Press, Cambridge.