Are immigrants' skills priced differently? Evidence from France

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Abstract

Over the last two decades, despite similar employment dynamics, immigrants and natives in France have experienced sharp differences in wage changes along the occupational wage distribution. Immigrants' wage growth has outperformed that of natives along the whole occupational wage distribution. We explain this pattern within a Roy-type wage setting and relate changes in the occupational wage distribution to changes in task-specific skill returns and task specialization choices. We show that immigrants wage growth performance is mostly explained by changes in immigrants' relative skill endowment, which allows them to move upward the occupational wage ladder. The sources of immigrants' relative wage performance are heterogeneous depending on the immigrant skill group. Among the least skilled, minimum wage changes over the period are a major determinant. Instead, wage performance of the most skilled immigrants is rather driven by the dynamics of their occupational choices.

JEL Codes: D12, J15, J21, J31, J61, O33

Keywords: Job polarization, tasks, immigrants, inequalities

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1 Introduction

Immigrants are an important component and the main source of workforce growth in most developed countries. Not surprisingly, immigration and immigrants are at the forefront of ongoing policy debates along various dimensions. One central and often contentious issue is how immigrants fare in societies of host countries. Understanding immigrants' success is of paramount importance for the design and the sustainability of migration policies. To a large extent, this success depends on immigrants' labor market integration, which is largely the outcome of immigrants' skills and how these skills are valued in their host country labor markets. These two aspects directly relate with immigrants' employment and wage performance. In this paper, we focus on the relative wage performance of immigrants in France over the last two decades.

A large literature analyzes the sources of wage inequality and relative wage dynamics between natives and immigrants. The focus has been on three different factors. The first one is human capital in a broad sense, *i.e.* including schooling, experience and language skills (see Katz and Murphy (1992), Algan et al. (2010), Kee (1995), Card (2005)).[1] A second factor refers to reservation wages. Whatever the labor market considered, immigrants are new comers. As a consequence, and beside human capital differences, they lack of host-country-specific labor market knowledge and other non directly productive valuable assets. These characteristics affect immigrants' outside option and put them in a lower bargaining position as compared to natives when they negotiate their wages with employers (see Nanos and Schluter (2012) for Germany, Moreno-Galbis and Tritah (2016) for 12 European countries, Gonzalez and Ortega (2008) for Spain, or the theoretical setups proposed by Ortega (2000) and Chassamboulli and Peri (2014)). A third factor is discrimination. Once differences in schooling, experience and reservation wages have been controlled for, an unexplained part of wage differential remains. This "migrant" effect is often attributed to discrimination (see Algan et al. (2010), Card (2005) or Kee (1995)).

In this paper, we tackle the issue of the differential wage dynamics between immigrants and natives through an alternative approach that focuses on tasks performed by natives and immigrants. Our approach is grounded on the recent and growing labor market literature, which places occupations and their task content as a key dimension through which labor demand shifts −due to technological change and globalization− have affected employment and wage dynamics over the last three decades.[2]

[1] The debate is centered, on the one hand, on the role of immigrants' origin country composition and changes in the supply of traditional measures of skills as well as their portability. On the other hand, the debate also focuses on the relative deterioration of immigrants' labor market outcomes upon arrival in the host country (Borjas (1995), Friedberg (2000), Card (2005) or Dustmann, Frattini, and Preston (2013)), as well as on the progressive convergence of immigrants' wages to those of natives with years of residence in the host country (see Chiswick (1978), Borjas (1994) or Borjas (1999) for the US, Chiswick, Lee, and Miller (2005) for Australia, Friedberg and Hunt (1995) for Israel or Lam and Liu (2002) for Hong Kong).

[2] See for instance Autor, Levy, and Murnane (2003), Autor, Levy, and Kearney (2006) for the US, Goos and Manning (2007) for the UK, Spitz-Oener (2006) for Germany, and Maurin and Thesmar (2004) for France. According to this literature the progressive replacement of labor input in routine tasks by machines has promoted a progressive polarization of employment between jobs intensive in non routine analytical-abstract tasks (located at the top of the wage distribution) and jobs intensive in non routine manual tasks (located at the bottom of the wage distribution), since routine task intensive jobs are located at the middle of the wage distribution.

A starting motivation of our paper lies on the contrasting pattern of immigrants and natives employment and wage dynamics. To see this, in Figure 1 (based on the French Labor Survey, LFS) occupations have been ranked in ascending order according to the median wage paid in each occupation to form 20 equal-sized (i.e. vigintiles) occupational employment groups. Following Autor and Dorn (2009) this grouping can be viewed as a skill ladder. The left hand side panel of Figure 1 displays the yearly average employment growth along that skill ladder and the right hand side the yearly average wage growth over the same skill ladder. These figures portray a situation in which, despite very similar employment dynamics (see left-hand side panel), natives and immigrants wage growth performance over the same skill ladder is strikingly different (see right-hand side panel).[3] Immigrants' wage growth has outperformed that of natives along the whole occupational wage distribution, and particularly at the tails of this distribution (*i.e.* highest and lowest paid occupations). Unlike for natives, immigrants' wage changes are more in line with changes in their employment structure. To understand this differential pattern of wage dynamics, we propose to go beyond traditional factors studied in the literature and to investigate the role of differences in workers' (unobserved) relative skill endowments, which we proxy using the task content of occupations.[4]

The inclusion of occupations and their task content in the migration literature is relatively recent. According to the seminal Roy (1951) model, occupational specialization is due to workers' self-selection based on comparative advantages. Following that line of inquiry, Peri and Sparber (2011a), Peri and Sparber (2011b), Peri and Sparber (2009) or D'Amuri and Peri (2014) underline that natives and immigrants differ in their relative skill endowments. In these studies, immigrants' and natives' unobserved skill endowment are assessed using the task requirement of occupations. We also build on this idea in this paper.[5] We assume that to perform the occupation-specific set of tasks, workers need a bundle of different skills whose importance depends on the type of tasks. Therefore, the nature of tasks performed by workers within occupations provides useful information about their skill endowments. While the exact set of tasks actually executed is not observed, we observe systematic variations across occupations in the degree of requirement for different types of tasks. This degree of requirement is measured using indices of task content for each occupation.

Provided workers in different occupations perform different tasks requiring different types and levels of skills we can relate differences in task specialization to differences in skill endowments. In this

[3]The divergent wage dynamics by nativity group is confirmed when estimating a quadratic equation which relates (log) wage changes to initial wages. Using a weighted least squares (weights equal native (respectively immigrant) employment in the occupation) we obtain:

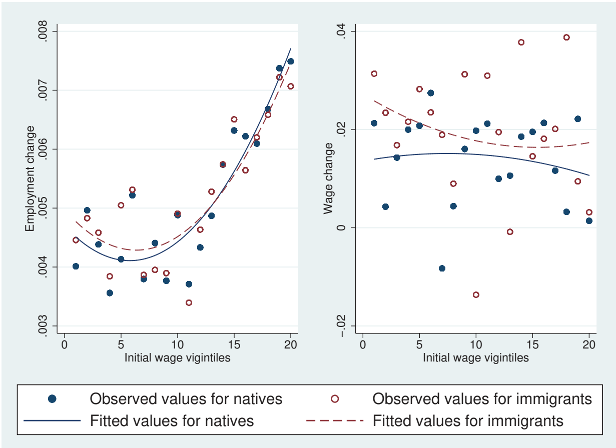
$$\begin{aligned} d(\log \text{wage}_{native}) &= -0.315 + 0.082 \cdot \log w_{1994} - 0.005 \cdot (\log w_{1994})^2 \\ d(\log \text{wage}_{immigrant}) &= 0.118 - 0.021 \cdot \log w_{1994} + 0.001 \cdot (\log w_{1994})^2 \end{aligned}$$

All coefficients are statistically different from zero.

[4]We implicitly assume here that immigrants and natives have different skill endowment if they are employed in occupations having different task content. Moreover, identical skills will be differently rewarded across nativity groups if these skills are implemented to perform different tasks.

[5]This is also similar to the employer or occupation specific skill weighted approach proposed by Lazear (2009) to study wage and employment mobility.

Figure 1: Average employment and wage growth over the 1994 median wage in the occupation. French LFS 1994-2012.



Notes: Occupations are ranked in the X-axis in ascending order according to their median hourly wage in 1994, computed on natives' workers, and then gathered within occupational wage vigintiles. The Y-axis in the left-hand side panel represents the average yearly employment growth between 1994 and 2012 by vigintile while on the right-hand side panel it represents the average yearly wage growth by vigintile over the same period.

setting the same set of skills may be differently rewarded across occupations depending on the task composition of occupations. Moreover, changes in returns to skills (or changes in task prices) will affect wage changes within and across occupations (Acemoglu and Autor (2011)). For instance, cognitive skills are less rewarded in occupations intensive in manual tasks (*e.g.* , movers) than in occupations relatively more intensive in analytical tasks (*e.g.* , actuaries). An increase in returns to cognitive skills is expected to have a greater impact in the latter occupations, increasing wage dispersion within occupations (between a good actuary and a mediocre actuary) and also across occupations (between an average actuary and an average mover).

In this paper, we assess how such changes in task-specific skill returns may have contributed to the differential wage dynamics between immigrants and natives. In fact, we expect that such changes may have contributed to the differential wage dynamics between immigrants and natives in two ways: (*i*) inducing different changes in the valuation of immigrants' and natives' skills. This arises in case of a different task specialization between natives and immigrants due to a different distribution across occupations (*i.e.* a "price effect"), (*ii*) promoting different occupational mobility (*i.e.* sorting) in case of different comparative advantages across nativity groups (*i.e.* a "quantity effect").

To date, and with the notable exception of Butcher and DiNardo (2002), there are very few analysis of immigrants' performance along the whole occupational wage distribution. Methodologically, our paper is closely related to Firpo, Fortin, and Lemieux (2011), which stands for the most systematic analysis measuring the contribution of occupations to changes in the wage distribution. Using the Current Population Survey (CPS) for 1988-90 and 2000-02, they show that both the level and the dispersion of wages across occupations have substantially changed over the 1990s, and that these changes are tightly related to the task content of occupations.[6]

For our purpose, we use the yearly French Labor Force Survey (LFS) between 1994 and 2012.[7] We proceed in two steps. First we quantify and qualify the "price effect". To do so, we analyze the wage dynamics of immigrants and natives along the wage distribution of detailed occupations, conditionally on the fixed set of tasks they are performing.[8] The implicit idea is that, given a set of individual characteristics (notably, age, education and duration of residence), individuals located in the same position of the wage distribution of an occupation at different moments of time are likely to have similar skills. Therefore, we can relate changes over time in occupation-specific wage deciles within and across occupations to changes in occupation-specific returns to skills, that is, we quantify the "price effect". Then we qualify this effect by assessing the contribution of differential returns to tasks (and/or skill endowments) to the relative wage dynamics of immigrants and natives (*i.e.* the "price effect"). We do so under the assumption that the task content of occupations can be related to workers' skill endowments. For instance, an occupation scoring high in the index of non-routine analytical tasks will require relatively more non-routine analytical skills than occupations having a lower score along that dimension. Therefore an increase in returns to non-routine analytical skill will have a greater impact on the former occupation, increasing both average wage and wage disparity within these occupations.

In a second step, we relax the assumption of constant task composition and we study how immigrants and natives task distribution has evolved from 1994 to 2012. More precisely, we quantify and qualify the "quantity effect". To quantify it, we estimate immigrants' and natives' occupational choices when facing identical wage changes within and between-occupations (both depend on tasks' returns). To qualify it, we relate immigrants' and natives' sorting across occupations to task content. Specifically, we estimate an occupational choice model that relates the dynamics of immigrants' and natives' occupational choices to changes in between- and within-occupation wage changes first, and then to task content of occupations. The pattern of immigrants' and natives' occupational sorting across occupations allows us to characterize changes in relative skill endowments that drive immigrants' and natives' relative wage performance over time.

We find that immigrants wage growth performance is not related to the specific task they were performing. Instead, immigrants' wage growth performance over the period is rather due to their

[6] Goos and Manning (2007) show that the composition effect linked to changes in the distribution of occupations accounts for a substantial part of inequality increase in the United Kingdom. Acemoglu and Autor (2011) show evidence that changes in inter-occupation wage differentials are an important factor in the increased variance of U.S. wages since 1980.

[7] Individual French Social Security Data, DADS, does not contain information on the country of birth, education level or year of arrival in France by immigrants. Whereas matching the panel DADS with the French Census would allow us to obtain information on the educational level of the individual and his country of birth, the date of arrival only appears from 1999. Moreover, the DADS does not provide detailed information on occupations (42 occupations) while in the French LFS occupations are defined at the 4-digit level. We exploit heterogeneity across occupations so we need to have a fine definition.

[8] For an analysis on other European and OECD countries, see Dustmann and Glitz (2011) for OECD, Dustmann, Frattini, and Preston (2013) for the UK, Lehmer and Ludsteck (2015) for Germany, Rodríguez-Planas and Nollenberger (2014) for Spain. See Aleksynska and Tritah (2013) for a comparative perspective across Europe and Algan et al. (2010) for a comparison between France, Germany and UK.

occupational employment dynamics which differs from that of natives suggesting a divergence over time in comparative advantages, despite a similar distribution in terms of age and education. The immigrants' pattern of task specialization is a key driver of their relative wage change over the period. We also uncover specific sources of wage mobility along the skill distribution. Indeed, the wage growth premium of less and more skilled immigrants is explained by different factors. For the least skilled, changes in skill prices brought about by minimum wage changes appear as a dominant factor. Instead, changes in relative skill endowments and returns to skills are the main factor among more skilled immigrants.

The rest of the paper is organized as follows. Section 2 presents the data. In Section 3, we provide some motivating evidence regarding the importance of occupations in wage dynamics and occupational employment for immigrants and natives. In Section 4, we propose a conceptual setup to derive an empirical measure of returns to skills and present assumptions under which this measure can be econometrically identified. We develop the econometric approach and present the main results in Section 5. In Section 6, we provide some further robustness tests. Section 7 concludes. We relegate additional results to an extended appendix.

2 Data

2.1 The French Labor Force Survey

The French Labor Force Survey (LFS) was established as an annual survey in 1982. Redesigned in 2003, it is now a continuous survey providing quarterly data. Participation is compulsory and it covers private households in mainland France. All individuals in the household older than 15 are surveyed. The LFS provides detailed information on individual characteristics of the respondent and in particular on her country of birth. The latter information is used to identify natives and immigrants in this paper (see Appendix A.1 for more details).

The LFS provides information on wages and the occupation for each employed individual among a list of four digit detailed occupations such as "gardener", "messenger", "clerk in banking activities", or "financial manager". We exclude farmers, civil servants, the military and clergymen from the sample. Throughout the period, some jobs may have disappeared, while new ones have emerged. The French LFS modified the job classification in 2003 in order to take into account the changes in occupations. We pay attention to having a consistent definition of jobs throughout the 18 years of our sample. There are no new occupations that cannot be included in the pre-2003 classification. Overall we end up with 350 occupations consistently defined over the whole period.

2.2 The O*NET and EurOccupations databases

The O*NET index is provided by the Department of Labor's Occupational Information Network. For the United States, the O*NET database provides a detailed description of workers, occupations or jobs. We use information about occupation requirements that detail typical activities required across occupations to summarize the specific types of job behavior and tasks that may be performed within occupations.

The O*NET index is built according to the American Standard Occupational Classification (SOC). We assume that the task content of occupations is similar in the United States and in France, so we can use the O*NET classification to analyze the task content of French occupations.[9] The whole issue was to link the O*NET occupation classification with the French PCS-ESE classification. To do so, we build a mapping table from PCS-ESE to SOC 2010 using the EurOccupations database, which covers 1,594 occupational titles within the ISCO-08 classification.[10] We match the 412 PCS-ESE occupational classification for which there is at least a perfect pair with occupations described in the EurOccupations database. Finally, we use a mapping table from the ISCO-08 to the SOC-2010 classification to link PCS-ESE occupational classification with SOC-2010. By creating this mapping table, we can use the O*NET index to analyze the task content of French occupations.

Our classification of occupations by their task intensity follows Autor, Levy, and Murnane (2003) (see Appendix A.2 for a summary on the content of the task according to the authors). We break down the different tasks into three major categories, instead of five, as in Autor, Levy, and Murnane (2003). We provide below main skill requirements associated with each of the three categories:

i) Non-routine analytical-interactive tasks: analytical tasks are usually performed in technical or managerial occupations. They require cognitive capacity in which responsiveness, creativity, decision making and problem solving are important. In contrast, interactive tasks require communication skills, physical interaction and adaptability to certain types of situations.

ii) Non-routine manual tasks require specific knowledge and are considered as skilled manual tasks. These tasks are mostly performed by technicians or foremen.

iii) Routine tasks may be cognitive or manual. The formers are usually carried out by administrative or clerical occupations, such as secretaries and accounting officers, who perform repetitive tasks using an identified procedure. Manual routine tasks are performed by production operators such as handlers, machine operators, workers in packaging and transportation. These tasks can be seen as unskilled manual tasks.

O*NET provides information on the characteristics of nearly 900 occupations in its latest version. These characteristics are listed in seven broad categories : abilities, interest, knowledge, skills, work activities, work context, and work value. We focus on work activities which are closest to the notion of task. This file gives a score ranking from 0-100, for 41 different tasks, indicating the degree (or

[9]This hypothesis is based on the idea that two countries with the same level of development should have the same production function, as suggested by the traditional international trade theory.

[10]The EurOccupations project aimed at building a publicly available database containing the most common occupations in a multi-country data collection. The database includes a source list of 1,594 distinct occupational titles within the ISCO-08 classification, country-specific translations and a search tree to navigate through the database. It also provides a mapping table between the EurOccupations classification and the ISCO-08 classification, as well as a French translation of these occupations. We are very grateful to Professor Kea Tijdens for having allowed us to use this database.

point along a continuum) to which a particular descriptor is required or needed to perform the occupation. We divide these tasks into the three major groups described above and we normalize the index.[11] Because the O*NET database does not provide information on workers, we are unable to follow the evolution of task requirements within a given occupation.

3 Empirical Motivation

To assess the driving role of occupations in the dynamics of the wage differentials between individuals, we first implement a simple wage variance decomposition analysis for each nativity group. The results of this analysis, reported in Figure 2, reveal that wage differences between and within occupations account for a major part of total wage variance in both nativity groups.
To reach this conclusion we first remove for each nativity group the part of total wage variance ("Total" line) which is due to observable individual characteristics by considering the residual wage variance ("Residual" line), *i.e.* the variance of residuals from the following wage equation :

$$\ln w_{int} = \alpha_{nt} + \beta_{nt}\, \text{age} \times \text{educ} \times \text{resid}_{int} + \gamma_{nct}\, \text{country}_{inct} + \tilde{w}_{int},$$

where w_{int} stands for the hourly wage of an individual i from nativity group n (natives, immigrants) in year t, age $\times$ educ $\times$ resid$_{int}$ stands for the different individual cells (up to 72 for immigrants and 36 for natives) we define each year from the following groups : 9 age groups (from 15 to 60 years old using five-year intervals), 4 educational groups (less than Baccalaureate, Baccalaureate or equivalent, Baccalaureate plus two years, and higher degrees) and 2 levels for the residence duration (less than 10 years, more than 10 years). country$_{inct}$ contains a set of dummy variables for geographical origins of immigrants (a dummy for each of the 27 countries distinguished in the LFS). $\tilde{w}_{int}$ are the estimated residual wages, that we then decompose into between- and within-occupation components by relating them to a full set of occupation dummies as follows :

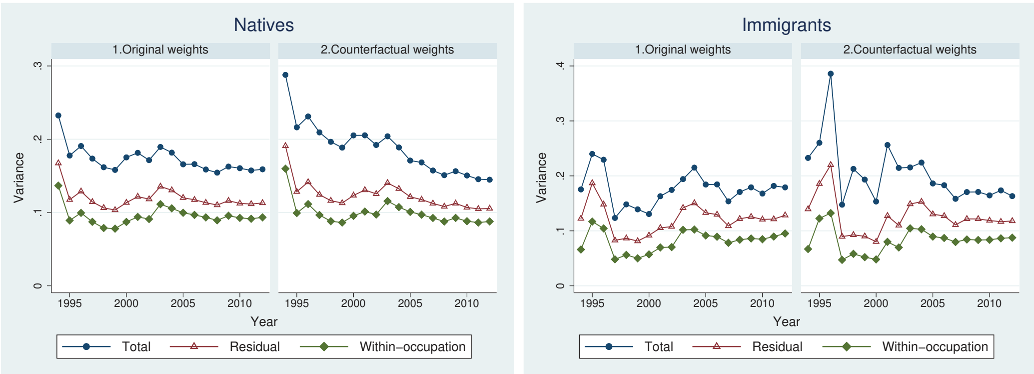
$$\tilde{w}_{int} = \theta_{njt}\, \text{occupation}_{injt} + \nu_{int},$$

where occupation$_{injt}$ stands for the j-th occupational dummy variable. ν_{int} is the part of the first-stage wage residual that is not explained by differences across occupations but rather by unobserved differences across individuals working in the same occupations (*i.e.* skill endowments, skill returns, unobserved abilities or reservation wages). The within-occupation residual wage variance ("Within-occupation" line) is obtained by computing for each year and for each nativity group the variance of ν_i, and represents the part of residual wage variance that is explained by wage disparities within occupations. Thus, the vertical distance between the residual wage variance and the within-occupation residual wage variance corresponds to the part of residual wage variance that is explained by differences between occupations, *e.g.* different task content and occupation-

[11] For instance, using a two digit classification of occupation; relatively to blue collars, professionnals (lawyers, doctors, etc.) perform tasks that are less non-routine manual (0.0789 vs 0.1589), more non-routine analytical and interactive (0.9106 vs 0.1795) and less routine intensive (0.1104 vs 0.1795).

specific skill returns. In contrast, the vertical distance between the x-axis and the within-occupation residual wage variance corresponds to the part of the residual wage variance explained by differences across individuals employed in the same occupation.

Figure 2: Variance decomposition analysis by nativity group. France 1994-2012



Notes: The vertical distance between the Total line and the Residual line corresponds to wage disparities explained by age, education, residence duration and origin country differences. The vertical distance between the Residual line and the Within-occupation line corresponds to the part of the residual wage variance that is explained by differences between occupations. The vertical distance between the X-axis and the Within-occupation line corresponds to the part of residual wage variance that is explained by wage disparities within occupations. In the panels "Original weights" we use the sample weights provided by the LFS. In the panels "Counterfactual weights" we reweight each nativity group so that the age-education-years of residence composition is constant over all years.

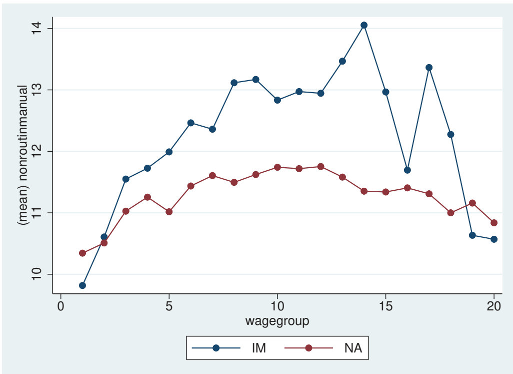
Wage differences within and between occupations keep a major place in total wage variance once we remove the mechanical effect coming from changes in the composition of observable characteristics on residual wages (*i.e.* composition effects), by reweighting each nativity sample so as to get the same composition in terms of age, education and residence duration[12] (see "Counterfactual weights" panels in Figure 2). Thus, quantitatively, occupations appear as a relevant unit of analysis for examining wage differentials between individuals and their evolutions over time. It is increasingly true as the role of observable characteristics tends to decrease over time for both immigrants and natives (particularly when considering constant-population composition). Moreover, the bulk of residual wage differences occurs within occupations. Therefore, it seems that workers performing similar tasks get paid differently. The importance of these differences in explaining total wage disparities has also increased from the beginning to the end of the period. We show below that this pattern is consistent with changes in returns to skills within occupations.

Unfortunately, we do not observe immigrants' and natives' returns to skills but only their occupational choices. Figure 1 in the introduction, shows that, in spite of having the same productivity (measured by the median wage), immigrants and natives display different wage dynamics between

[12]As explained in appendix B, we reweight our sample by $\omega^a_{ct} = \Psi_{ct}\,\omega_{ct}$, where ω_{ct} is the original sample weight of cell c and period t and Ψ_{ct} is the reweighting factor we estimate for each cell c at period t. More precisely, $\Psi_{ct} = \frac{\eta_c}{\eta_{ct}}$, where η_c is the share of workers (natives or immigrants) in the age-education cell c over the whole considered period (1994-2012) and η_{ct} is the share of workers (natives or immigrants) in the age-education cell c in period t.

1994 and 2012. As task prices have evolved differently, a different initial pattern of specialization across tasks could explain the different wage dynamics experienced by immigrants and natives. Figures 3, 4 and 5 reveal that indeed immigrants and natives differ in their task specialization. In these figures, individuals have been ranked in an ascending order in 5 percentiles wage group (20 groups) estimated on the wage distribution of natives in the initial baseline period. Individuals in the same group (whether natives or immigrants) have similar level of productivity, though not necessarily similar skill composition. For each nativity group we report on y-axis the average intensities of non-routine manual, routine and non-routine analytical-interactive tasks of their occupations.[13] Different average task intensities reflect different distribution across occupations (and thus across tasks) for immigrants and natives that are in the same location within the (native) wage distribution.

Figure 3: Intensity, along the skill distribution, of immigrants and natives occupational employment in non-routine manual tasks in 1994



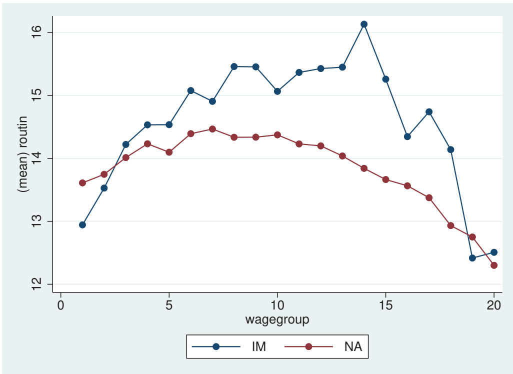
Notes: Observations for the immigrants and natives sample are ranked in the X-axis according to their wage vigintile group (20 groups) computed over the wage distribution of natives in 1994. The Y-axis represents the weighted average of immigrants and natives occupational employment intensity in non-routine manual task within each vigintile group. The weights are equal to the share of each occupation in the total employment of the corresponding wage vigintile group, computed separately for immigrants and natives.

Figure 3 reveals that for an identical location in the wage distribution, immigrants are more specialized in manual tasks. The gap in the degree of manual specialization becomes particularly large at the middle of the distribution, but it sharply drops at the top of it. Figure 4 portrays a similar picture regarding routine cognitive-manual tasks. In this case, natives are slightly more specialized than immigrants in routine tasks at the bottom of the wage distribution. The situation is reversed beyond the third vigintile. The gap increases progressively as we move up in the distribution and

[13]These task indices are computed separately for natives and immigrants as weighted average across occupations of a given task type with weights equal to the share of immigrants or natives workers employed in each occupation in 1994. The average intensity for each task k in year 1994 is equal to $Task_{k1994} = \sum_j^J share_{j1994} * Task_{jk}$ where $share_{j1994}$ is equal to the share of occupation j in total natives or immigrants employment and $Task_{jk}$ is the intensity of occupation j in task k, where k is either (1) non-routine analytical interactive, (2) non-routine manual or (3) routine cognitive or manual task.

then sharply falls at the top of it. The pattern of specialization is the opposite for non-routine analytical-interactive tasks (see Figure 5). Throughout the wage distribution natives are more specialized than immigrants in this task category. The gap between the two nativity groups remains fairly stable along the wage distribution and is only slightly reduced at the top of it.

Figure 4: Intensity, along the skill distribution, of immigrants and natives occupational employment in routine manual tasks in 1994



Notes: Observations for the immigrants and natives sample are ranked in the X-axis according to their wage vigintile group (20 groups) computed over the wage distribution of natives in 1994. The Y-axis represents the weighted average of immigrants and natives occupational employment intensity in routine cognitive-manual tasks within each vigintile group. The weights are equal to the share of each occupation in the total employment of the corresponding wage vigintile group, computed separately for immigrants and natives.

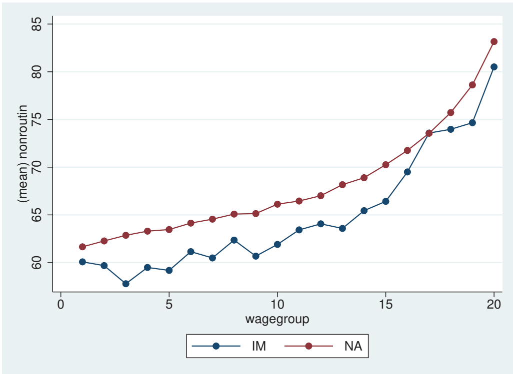
The different pattern of task specialization across nativity groups revealed by Figures 3, 4 and 5, stands for the first potential explanation to the different wage dynamics between immigrants and natives displayed in Figure 1. Specifically, immigrants' and natives' returns to skills may have evolved differently in spite of facing identical changes in returns to tasks over the recent decades because of their different initial task specialization. This is what we call the "price effect".

Differences in task specialization also suggest that immigrants and natives may differ in their relative skill endowments. If this is the case, immigrants and natives may have reacted differently to changes in returns to tasks/skills, *i.e.* they have experienced a different occupational sorting. This is a second potential explanation to the differential wage dynamics between immigrants and natives that we investigate. We refer to the dynamics of sorting across occupations (*i.e.* tasks) following a change in task returns as the "quantity effect".

To assess the relevance of this second and complementary explanation we report in Figure 6 the yearly evolution of the average task intensity of immigrants' and natives' occupational employment. As previously the average task index is a weighted sum of a given type of task index computed across occupational employment distribution, with weights equal to the yearly share of each occupation in total employment of immigrants or natives.[14] Along the period 1994-2012, both immigrants

[14]The average intensity for each task k in year t is equal to $Task_{kt} = \sum_j^J share_{jt} * Task_{jk}$ where $share_{jt}$ is equal to the share of occupation j in total natives or immigrants employment and $Task_{jk}$ is the intensity of occupation j

Figure 5: Intensity, along the skill distribution, of immigrants and natives occupational employment in non-routine analytical-interactive tasks in 1994

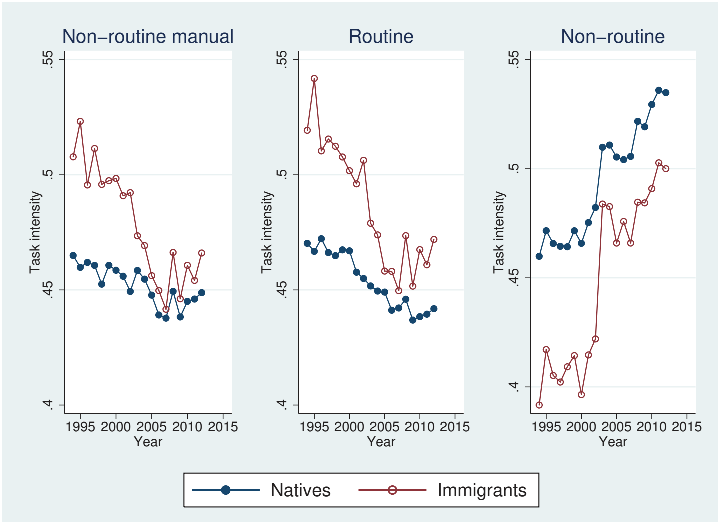


Notes: Observations for the immigrants and natives sample are ranked in the X-axis according to their wage vigintile group (20 groups) computed over the wage distribution of natives in 1994. The Y-axis represents the weighted average of immigrants and natives occupational employment intensity in non-routine analytical-interactive tasks within each vigintile group. The weights are equal to the share of each occupation in the total employment of the corresponding wage vigintile group, computed separately for immigrants and natives.

and natives have moved away from non-routine manual and routine task-intensive occupations (concentrated in the first half of the wage distribution) towards occupations intensive in non-routine analytical and interactive tasks (concentrated in the second half of the wage distribution). Consistently with results displayed in Figure 1, natives and immigrants have reacted in the same direction following price incitations (*i.e.* changes in returns to tasks). However, the dynamics has been clearly more pronounced for immigrants. Overall, Figure 6 suggests that occupational sorting induced by changes in returns to tasks, has contributed to a convergence in the tasks performed by immigrants and natives, even if differences persist. The pace of immigrants task sorting portrayed in Figure 6 may have contributed to their more favorable wage growth over the period.
Immigrants and natives do not seem to be equally distributed across occupations (*i.e.* tasks) along the wage distribution, suggesting that both nativity groups may differ in their skill endowments. Due to globalization and technological change, returns to tasks have been strongly altered over the past decades. These price changes should have affected differently the wage dynamics of immigrants and natives, in two possible ways: (*i*) different returns to skills between immigrants and natives due to a different initial specialization across tasks ("price effect"); (*ii*) a different pattern of sorting across tasks (*i.e.* occupations) if immigrants and natives differ in their relative skill endowments ("quantity effect"). We will quantify and qualify the relative importance of these two effects in the econometric analysis. In the next section, we present a simple conceptual framework which we use to derive an empirical definition of returns to skills across tasks, and to discuss our econometric approach.

in task k, where k is either (1) non-routine analytical interactive, (2) non-routine manual or (3) routine cognitive or manual task.

Figure 6: Yearly task intensity of immigrants and natives occupational employment from 1994 to 2012



Notes: The X-axis stands for years (period 1994-2012). The Y-axis represents the average intensity for each task k in year t: $Task_{kt} = \sum_j^J share_{jt} * Task_{jk}$ where $share_{jt}$ is equal to the share of occupation j in total natives or immigrants employment and $Task_{jk}$ is the intensity of occupation j in task k =(1) non-routine analytical interactive, (2) non-routine manual or (3) routine cognitive or manual task.

4 Conceptual framework

We consider a perfectly competitive environment with exogenous wages. The production side employs labor, measured in efficiency units, as a unique production input using a linear technology (*i.e.* marginal productivity of labor equals unity). At the competitive equilibrium the price of the produced good will then equal the wage per efficient unit of labor.

On the labor supply side individuals differ on their relative skill endowments. To simplify, we focus on a particular skill S (*e.g.* cognitive skills) which is heterogeneously distributed across individuals within the interval $[\underline{S}, \overline{S}]$. We normalize to unity the remaining skill bundle (*e.g.* manual skills) and we assume that it is homogeneously distributed across workers.[15]

4.1 The occupation specific production function

The earning capacity of an individual endowed with a relative skill S_i will depend on her occupation. Indeed, task composition and relative task intensity differ across occupations. As a consequence, each occupation requires more or less quantity of S to produce one efficient unity of labor. Since wages are defined by efficient units of labor, the earning capacity of an individual endowed with S_i varies depending on the task composition of her occupation. More precisely, we consider 3 occupation categories : (i) those highly intensive in skill S (denoted H); (ii) those requiring both

[15]This simplification is consistent with our econometric approach where we look at the partial effect of a task dimension keeping constant other measures of task intensity. We therefore focus on relative task or skill intensity.

skills and in which tasks performed have a middle requirement in skill S (denoted M); and (iii) those weakly intensive in tasks requiring skill S (denoted L).
For a given relative skill endowment S_i the quantity of efficient units of labor, s_{ij}, provided by individual i depends on her occupation according to:[16]

$$s_{ij} = \begin{cases} e^{\beta_L + \gamma_{Lt} S_i} & \text{for } j = L \\ e^{\beta_M + \gamma_{Mt} S_i} & \text{for } j = M \\ e^{\gamma_{Ht} S_i} & \text{for } j = H \end{cases}$$

Since we assume a linear technology, s_{ij} is also the quantity of potential output produced by a worker in each occupation. The coefficients β_j and γ_{jt} are respectively the contributions of the general skill bundle and skill S to the production of efficient units of labor in each type of job. The ratio γ_{jt}/β_j measures the relative intensity of occupation j in tasks requiring skill type S. Parameters β_j and γ_{jt} are proportional to the earning capacity of a worker in a particular occupation. Moreover, we assume that $\gamma_{Ht} > \gamma_{Mt} > \gamma_{Lt}$ and $\beta_L > \beta_M$. The earning capacity of skills S will then be the highest in H occupations and the lowest in L occupations, while for the complementary skill bundle we assume the opposite, its earning capacity is the highest in L jobs. Similarly to Gibbons et al. (2005) these differential weights generate a sorting of workers based on their comparative advantage.

4.2 Workers' earnings

Wages per efficient unit of labor differ from one occupation to another and returns to an identical skill endowment differ depending on the task composition of an occupation. Therefore a worker with a quantity of efficient labor equal to s_{ij} will earn a different wage depending on her occupation. Workers are paid the value of their marginal product. The wage perceived by a worker in each occupation is equal to $W_{ijt} = s_{ijt} \times p_{jt}$, for $j = L, M, H$, where p_{jt} stands for the time-varying price index of the specific goods or services provided by the occupation. With the log-specification:

$$\begin{aligned} \ln(W_{iLt}) \equiv \omega_{iLt} &= \ln(p_{Lt}) + \beta_L + \gamma_{Lt} S_i \\ \ln(W_{iMt}) \equiv \omega_{iMt} &= \ln(p_{Mt}) + \beta_M + \gamma_{Mt} S_i \\ \ln(W_{iHt}) \equiv \omega_{iHt} &= \ln(p_{Ht}) + \gamma_{Ht} S_i \end{aligned} \tag{1}$$

where p_{jt} and γ_{jt} are allowed to change over time. In this setting, conditional on a distribution of skills, the dynamics of wages (within and across occupation) and workers occupational sorting will depend on occupation specific price changes $p_j\prime s$, and changes in occupation specific skill returns $\gamma_j' s$.

[16] The exponential specification is consistent Heckman and Sedlacek (1985)'s or Firpo et al. (2013) linear factor formulation of log wages.

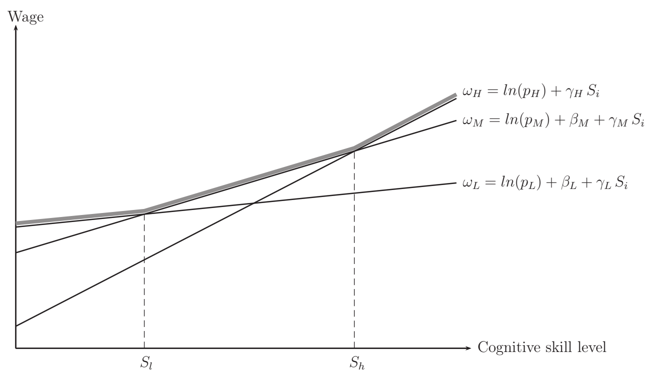
4.3 Workers' sorting across occupations

Income maximization implies that each worker chooses the job offering the highest wage given her relative skill endowment:

$$W^*_{ijt} = \underset{j=L,M,H}{\arg\max} \{W_{iLt}, W_{iMt}, W_{iHt}\} \tag{2}$$

We illustrate in Figure 7 one pattern of workers' sorting across the three occupations. Those with the lowest endowment of S allocate towards L occupations, where the earning capacity of skill S is the lowest and the earning capacity of the complementary bundle of skills is the highest. Workers with a medium endowment of S choose M occupations, and those with the highest endowment in S allocate towards H occupations.

Figure 7: Wages and skill returns



Within a given type of occupation, workers are heterogeneous in terms of their skill endowments. As a result, they are also earning different wages. Since workers' earning capacity is a monotonic transformation of their skill endowments, a worker position in the wage distribution within an occupation corresponds to her position in the relative skill endowment distribution of the occupation. We will rely on this rank-order preservation assumption in our econometric approach.

4.4 The dynamics of occupational wages

4.4.1 Parameters' identification

Using this basic conceptual framework, we characterize the factors driving the dynamics of wage disparities. Individual (log) wages in a particular occupation $j = L, M, H$ are given by $\omega_{ijt} = \ln(W_{ijt}) = ln(p_{jt}) + \beta_j + \gamma_{jt} S_i$. Under the assumption of constant skill distribution, that is, under the assumption that there is no sorting of workers across occupations following changes in returns to skills, we can estimate the part of the wage dynamics corresponding to the "price effect". In our simplified Roy-type wage setting we distinguish between two determinants of wage dynamics: (i) returns to skills (γ_{jt}), and (ii) a demand/supply effect inducing a change in the price of the corresponding good or service (p_{jt}). This effect is driven by potential changes in the demand for the good/service and/or potential technological changes in the production process of the good/service. The demand/supply effect induces wages to evolve across occupations shifting the whole wage distribution up or down. Changes in returns to skills induce wages to evolve both within and across occupations. Occupations characterized by decreasing returns to skills will be characterized by a wage contraction and, at the same time, will move downward in the occupational wage ladder. In contrast, occupations characterized by increasing returns to skills will be characterized by greater wage inequality and, at the same time, will move upward in the occupational wage ladder.

Because we do not have individual longitudinal data but simply a pool of cross sections[17], we assume that individuals' position in the wage distribution within a particular occupation corresponds to their position on the relative skill endowment distribution. Moreover, when interpreting our results, we will assume that, conditional on a set of observable characteristics, the skill distribution within an occupation remains constant over time.[18] Therefore, we will use counterfactual weights to ensure that the age-education composition (and also the residence duration composition when working with immigrants) within every occupation is identical across periods. Under the hypothesis that the relative skill distribution within an occupation is constant, we can denote F_j the time invariant distribution of efficient units of labor, s_{ij}, in an occupation $j = L, M, H$. With a suitable normalization, the q^{th} quintile of the distribution of wages can be written as:

$$\omega_{jt}^q = \overline{\omega}_{jt} + \gamma_{jt} F_j^{-1}(q), \tag{3}$$

where $\overline{\omega}_{jt} = ln(p_{jt}) + \beta_j + \gamma_{jt}\overline{S}_{ij}$ is equal to the average (log) wage. The wage at quintile q equals the average wage in the occupation plus the marginal skill return γ_{jt} multiplied by the skill level at the corresponding quintile. Taking differences over time leads to:

$$\Delta\omega_{jt}^q = \Delta\overline{\omega}_{jt} + F_j^{-1}(q)\Delta\gamma_{jt}, \tag{4}$$

Solving for $F_j^{-1}(q)$ in (3) at the base period gives $F_j^{-1}(q) = \frac{\omega_{j0}^q - \overline{\omega}_{j0}}{\gamma_{j0}}$. Replacing in the difference equation yields:

$$\Delta\omega_{jt}^q \;=\; \Delta\overline{\omega}_{jt} + \frac{\omega_{j0}^q - \overline{\omega}_{j0}}{\gamma_{j0}}\Delta\gamma_{jt} \;=\; \Delta\overline{\omega}_{jt} + \frac{\Delta\gamma_{jt}}{\gamma_{j0}}(\omega_{j0}^q - \overline{\omega}_{j0}) \;=\; a_j + b_j(\omega_{j0}^q - \overline{\omega}_{j0}), \tag{5}$$

where $(\omega_{j0}^q - \overline{\omega}_{j0})$ is simply a normalization (quintiles are written in deviation from occupation average wage in the base period).

Under the hypothesis of time invariant skill distribution within occupations, we can exploit decile-specific wage changes within each occupation to identify two synthetic measures of the dynamics

[17] The French database resulting from matching individual social security data ("Déclaration Annuelle Données Sociales") with the French Census fails to provide some of the information we require for our analysis. For example, the arrival date of the immigrant in France is only available from 1999 (and not always provided) and, specially problematic, occupations are not consistently reported.

[18] A similar assumption is for instance exploited by Acemoglu and Autor (2011) to infer the impact of changes in task prices on wage inequality.

of wage distribution (*i.e.* "price effect") across and within occupations:

- Changes in the average wage of the occupation: the term $a_j = \Delta\overline{\omega}_{jt} = \Delta\ln(p_{jt}) + \overline{S}_{ij}\Delta\gamma_{jt}$, corresponds to the occupation-specific average wage growth. This dimension of wage growth will vary across occupations due to different changes in the market price of occupation-specific goods and services and/or due to changes in the returns to skills used to perform the set of occupation-specific tasks. Immigrants and natives could experience different average wage growth along this dimension owing to their different task distribution, (*i.e.* occupational distribution) and/or different skill endowments within occupations.

- Changes in wage disparities within the occupation: the term $b_j = \frac{\Delta\gamma_{jt}}{\gamma_{j0}}$ captures the within-occupation component of wage dynamics due to changes in the returns to skills. Specifically, it measures how changes in returns to skills have impacted wage differences between workers employed in the same occupation but having different levels of skills, as measured by the occupation-specific quintile. Since returns to skills vary across tasks, immigrants and natives will experience different average returns to skills due to their different task distribution, *i.e.* occupational distribution.

Under the assumption that the relative skill distribution within occupations does not change over time, there is a clear positive correlation between average wage changes across occupations and wage changes within occupations, *i.e.* $Cov(a_j, b_j) > 0$, since both dimensions depend on returns to skills.

4.4.2 Identification issues

Our identification strategy of the "price effect" strongly relies on the hypothesis of time-invariant skill distribution within occupations, [19] since otherwise we are not able to identify the between- and within-occupation components. This assumption is clearly inconsistent with the sorting behavior of workers across occupations, based on their comparative advantages. Selective job choices will be driven by both price changes and changes in the relative contribution of skills (resulting for instance from globalization or technological changes). The "quantity effect" refers to the part of the wage dynamics driven by the differential sorting of immigrants and natives across occupations following similar changes in price and skill returns. This section explains the "quantity effect" in more detail.

At the equilibrium, the mapping of abilities into efficient units of labor and the optimal decision rule (2) define two thresholds:

(*i*) $S_{lt} = \frac{\ln(p_{Lt}/p_{Mt})+\beta_L-\beta_M}{\gamma_{Mt}-\gamma_{Lt}}$, which corresponds to the skill level such that $W_{iLt} = W_{iMt}$, and

(*ii*) $S_{ht} = \frac{\ln(p_{Mt}/p_{Ht})+\beta_M}{\gamma_{Ht}-\gamma_{Mt}}$, which stands for the skill level such that $W_{iHt} = W_{iMt}$.

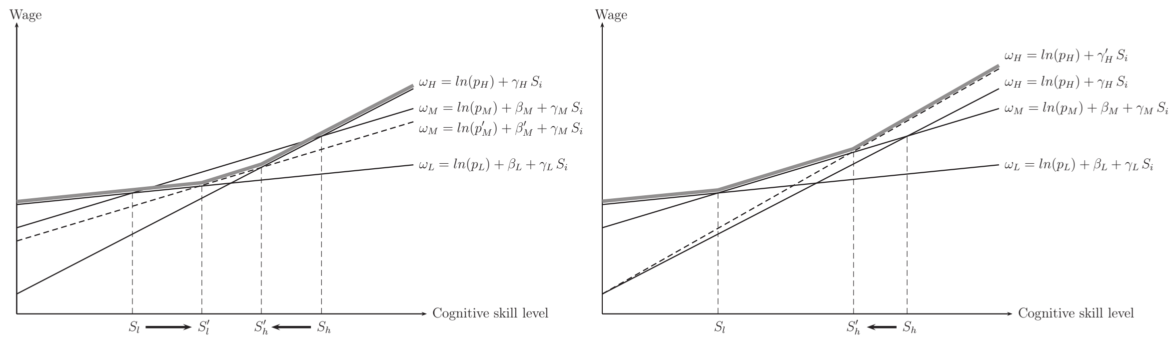
[19] This hypothesis will be translated into a counterfactual reweighting procedure in our econometric approach.

As shown by Figure 7:

$$\begin{aligned} \text{all } i \text{ with } S_i &< S_{lt} \text{ choose the L occupation,} \\ \text{all } i \text{ with } \ S_{lt} < S_i &< S_{ht} \text{ choose the M occupation,} \\ \text{all } i \text{ with } S_i &> S_{ht} \text{ choose the H occupation.} \end{aligned}$$

Any exogenous variation in the price p_{jt}, or any technological change modifying the relative contribution of skills to efficient units of labor, will trigger a change in these threshold values and thus workers' reallocation across occupations, since the unitary price of their skills will be modified. For instance, a decrease in p_{Mt} (see left-hand side panel of Figure 8) increases S_{lt} and decreases S_{ht}. Workers reallocate away from M occupations towards L and H occupations. In M occupations, the lowest skilled workers (those with a weak comparative advantage in M relatively to L occupations) reallocate towards L occupations while the highest skilled workers (those with a weak comparative advantage in M relatively to H occupations) reallocate towards H occupations. As a result, the labor share of occupations at the upper and lower ends of the skill distribution is expanding while that in the middle is contracting. Wage distribution will get more concentrated in M occupations and will widen in H and L even though returns to skills and/or skill prices have not changed in these two occupations. Similarly if returns to cognitive skills (γ_H) increase in H-type occupations (see right-hand side panel of Figure 8) there will be a decrease in S_{ht}, the highest skilled workers in M reallocate towards H jobs and thus there is an increase in wage dispersion within H-jobs. Again wage distribution will get more concentrated in M occupations.

Figure 8: Wages and skill returns



Endogenous selective sorting of workers across occupations suggests that the skill distribution within-occupations will not be fixed over time as we have assumed in order to identify $\Delta\gamma_{jt}$ and Δp_{jt}. Therefore, we cannot simply compare average wage and wage dispersion changes to infer the role of changes in returns to skills. Moreover, the direction of the bias is unclear. Depending on the exact distribution of S skills, stayers in M occupations can be on average less or more skilled than movers. For instance, if M occupations are intensive in routine tasks and H and L occupations are respectively intensive in non-routine abstract and non-routine manual tasks, following a decrease in the price of goods and services intensive in routine tasks, we will overestimate the importance of wage changes in L occupations (since new comers are relatively more skilled), and underestimate wage changes in H occupations (since new comers are relatively less skilled).

To control for worker sorting, we would need to follow workers over time as in the recent contribution of Cortes (2016), to distinguish stayers from movers. Here, we only have successive cross sectional data. Therefore, and following Acemoglu and Autor (2011), we will be able to control for selection only on observable characteristics, that is we will be measuring wage changes that occur among individual being similar with respect to a fixed set of observable characteristics. We will be using counterfactual weights to compare wage changes along the wage distribution of every occupation for workers having the same observable skill distribution within occupations, which we take to be equal to that of the baseline period (i.e., before the change in task returns). Moreover, in order to focus on occupation-specific skills and not on general skills, whose returns may have changed, we will rely on residual wage changes as in Autor, Katz, and Kearney (2008).[20] This is important for instance if some occupations attract more educated workers and the return to education rises over time, we will otherwise measure the mechanical effect of rising returns to education instead of occupation-specific skill returns.

To estimate the "quantity effect" we relax the assumption of fixed task (skill) distribution. We estimate a conditional logit model that allow us to assess whether immigrants and natives, facing similar changes in task prices and skill returns, have followed different sorting pattern across jobs and thus tasks (i.e. at the beginning and end of the period). This approach allow us to draw conclusions on the potential contribution of workers' selective mobility across tasks on wage dynamics.

5 Results

5.1 The price effect

In this section we first quantify the "price effect" and then we qualify it. To quantify the "price effect" we characterize changes in wages between and within occupations using two occupation-specific parameters estimated separately on each nativity group under the assumption that the relative skill distribution within each occupation is constant. We focus on males' residual wage changes,[21] between the periods 1994-96 and 2010-12.[22] Focusing on long difference helps to limit

[20] Interestingly, we find that within- and between-occupation wage changes are positively correlated only once we focus on changes in residual wages, *i.e.* the part of wages which is not explained by observable characteristics (age, education, and residence duration and origin country in addition for immigrants). This suggests that sorting across occupations based on observable characteristics is important in our setting.

[21] Excluding females allows to simplify the analysis because this avoids dealing with gender specificities in labor supply choices.

[22] Data prior to 1993 are difficult to use because of a substantial change in the French Industry Classification (NAF), that prevents us from having an unequivocal correspondence between the industry codes before and after 1993. This is a problem in our case because some jobs are defined in a specific industry. The Labor Force Survey 2012 were the most recent available data at the time of writing this paper. Note also that each period corresponds to the final part of a crisis: the nineties crisis for period 1994-1996 and the recent economic crisis for period 2010-2012.

the influence of short-term variations and thus to identify long-term effects of changes in prices and skill returns on wage changes. In addition, using long differences instead of year-to-year changes avoids some serial correlation issues, which would lead the estimated standard errors to be understated (see Bertrand, Duflo, and Mullainathan (2004)). Moreover, in order to increase the number of observations per occupation, each of the two periods for which we are computing long differences includes three years of data. This was necessary since we are using a detailed definition of occupations (four digits).[23]

In a second step, we compare immigrants and natives wage growth performance within and across occupations conditional on a fixed task specialization. That is we estimate the "price effect" and how these "price effect" may be attributed to the specific tasks performed by immigrants and natives. We implement the whole procedure with alternative sampling weights in order to control for changes in population composition that may affect changes in the structure of residual wages between periods 1994-96 and 2010-12. We use the reweighting strategy suggested by Lemieux (2002), to remove from occupational wage changes the part that results from changes in the population composition in terms of age, education and duration of residence within occupations.

In section 5.2, we will relax the assumption of constant task distribution to look at the role of differential sorting across occupations as a second channel affecting wage dynamics ("quantity effect"). We analyze immigrants' and natives' occupational choices given the observed change in returns to skills between periods 0 and 1.

5.1.1 Quantifying the "price effect": the between- and within-occupation components

We first recover residual wages $\tilde{w}_{int}$ in the same way as in our variance decomposition analysis (see Section 3) but this time separately at each period ($t = 0, 1$). By construction, residual wages measure wage disparities which are orthogonal to other worker observable characteristics (age, education, residence duration, origin country). Working with these residual wages allows us to control for wage disparities between workers which are not specifically related to their occupation. Next, we gather these residuals by deciles within each occupation to form occupation specific residual wage distribution (9 deciles per occupations). Second, we summarize changes in this occupation specific residual wage distribution into two components: a between-occupation and a within-occupation component. For this we estimate the occupation-specific intercept (between effect) a_j and slope (within effect) b_j in equation (5). Specifically, we estimate a linear relationship between the residual wage change at each occupation-specific decile q, $\Delta\tilde{w}_j^q$, and the corresponding level of the wage decile q at the base period ($t = 0$), $\tilde{w}_{j0}^q$:

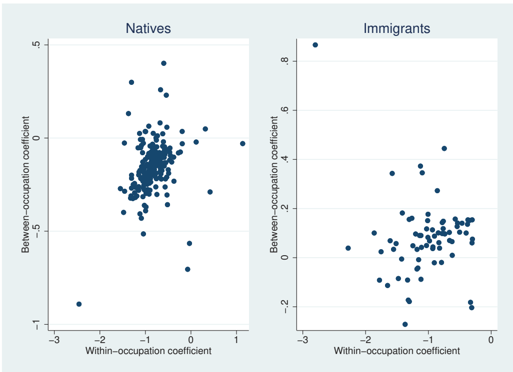
$$\Delta\tilde{w}_j^q = a_j + b_j\,\tilde{w}_{j0}^q + \lambda^q + \upsilon_j^q, \tag{6}$$

where υ_j^q is an idiosyncratic error term. We also consider a decile-specific error component, λ^q, rep-

[23]Otherwise, when working with immigrants, we would not have enough observations per occupation and per period.

resenting a generic change in the returns to skills, this is common component across all occupations but specific to a wage decile.[24] To compute wage deciles changes (*e.g.* between the 4th decile of medical secretaries in period 1 and the 4th decile of medical secretaries in period 0) requires a sufficient number of observation in each occupation.[25] Overall we are left with 229 occupations for natives and 146 occupations for immigrants. In the specification (6) we interpret the distance between wage deciles within an occupation as differences in occupation-specific skill levels. Therefore, the parameter b_j tells us whether and to what extent wages of more skilled workers in an occupation have evolve more favorably than those of less skilled workers within the same occupation. The parameter b_j is a synthetic measure of changes in occupation-specific returns to skills, its value is higher in occupations more intensive in skills (or tasks) whose returns have increased (for instance, cognitive skills). The parameter a_j is a measure of overall occupation-specific wage growth. These two summary statistics measure the overall shift in the occupational wage distribution and are both affected by changes in occupation-specific returns to skills, $\Delta\gamma_{jt}$. In addition, the intercept a_j depends also on changes in the price of occupation-specific good and services, which are not directly related to changes in returns to skills.

Figure 9: Between- and within-occupation coefficients with constant labor force composition.



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 9 wage deciles. Age*education composition within occupations is kept constant and equal to that of natives in period 1994-1996 for both immigrants and natives. For immigrants, their duration of residence composition is also kept constant and equal to that observed in 1994-1996.

In Figure 9 we display the relationship between both components of residual wage changes. We have used counterfactual weights to insure time invariant population-composition across and within nativity groups for each occupation. We compute the counterfactual weights using as a reference for both nativity groups the age-education composition of natives in the occupation in period 0.

[24]This would capture for instance the effect of some labor market institutions (minimum wage, occupation level wage negotiations) which will affect more the bottom wage deciles of all occupations.

[25]In fact, each wage decile needs to be separately observed in each period. This requires at least 10 observations per period for each occupation and nativity group.

This baseline composition is exogenous to changes in tasks prices and skill returns which occurs over the period. Additionally, for immigrants, the composition in terms of residence duration is the same as in period 0 (see Appendix B for a detailed explanation).[26] Interestingly, we observe a positive correlation between the two components of residual wage changes: occupations with higher overall wage growth are also those where wage gaps between more and less skilled workers (*i.e.* high and low wage deciles) widened the most (*i.e.* larger skill returns). This is perfectly consistent with the Roy-type wage setting we outline in our conceptual framework. As changes in average wage and wage dispersion within occupations are both dependent on changes in occupation-specific returns to skills, the two components are therefore positively correlated *i.e.* $Cov(a_j, b_j) > 0$.

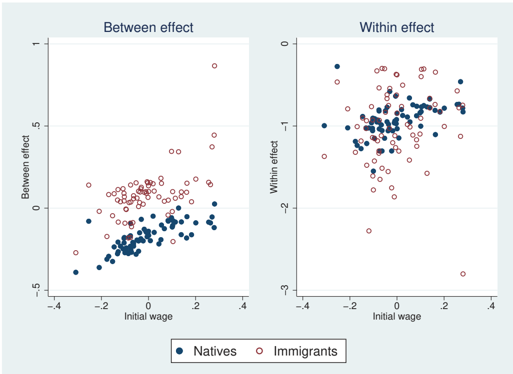
Where are the most rewarded skills located in the occupational wage distribution? We gathered interesting insights on this question by looking at Figure 10 (as well as in Figure 18 in Appendix C). The X-axis represents an occupational wage or skill ladder (we rank occupations according to the natives residual mean wage in period 0). We can see that for both immigrants and natives occupational wage growth (*i.e.* between effect) is higher in better paid (more skilled) occupations and it is actually higher for immigrants. Therefore, changes in occupational level wage growth have contributed to greater wage inequality. As can be seen on the right-hand panel of Figure 10 (*i.e.* within effect), this pattern has been only partially driven by increasing returns to skills along the skill ladder, though the profile seems to be more erratic for immigrants than for natives.

Overall, immigrants' wage growth clearly outperforms that of natives across the whole occupational wage ladder. At first glance, immigrants' better relative average wage performance is rather due to their skill endowments rather than their different returns to skills. Indeed, Figure 10 shows that wage growth has been higher for immigrants than natives in most occupations. At the same time, there is no clear pattern of differential return to skills within occupations between immigrants and natives. Overall immigrants wage growth performance seems to be related to their more favorable skill endowments within occupations. To see this, note that the wage growth premium of immigrants relatively to natives within an occupation is equal to: $\Delta\bar{\omega}_{jt}^{IM} - \Delta\bar{\omega}_{jt}^{NA} = \Delta\gamma_{jt} * (\bar{S}_j^{IM} - \bar{S}_j^{NA})$, where $(\bar{S}_j^{IM} - \bar{S}_j^{NA})$ is the difference in skill endowments in occupation j between immigrants and natives.[27] As we shall see in the econometric analysis, part of this more favorable skill endowment may be related to their specific age and education, but also to other dimensions which are not measurable such as occupation specific skills which we relate to the task content of occupations. In the next section, we formally test the assumption that immigrants have enjoyed a wage growth premium over the period and we try to qualify the "price effect" by relating between- and within-occupation wage changes to the specific task performed by immigrants.

[26] The estimated between- and within-occupation components arising when residual wages are obtained working with the standard Mincer equation are available from the authors upon request.

[27] One systematic source of skill disparity between immigrants and natives may be due to the fact that immigrants are over-educated within occupations relatively to natives. This has been shown across European countries by Aleksynska and Tritah (2013). While Chiswick and Miller (2010) have shown that this over-education explains the better wage performance of immigrants in low skilled occupations.

Figure 10: The Between and Within occupation wage growth components for natives and immigrants (Reweighted sample)



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation wage growth components have been computed using residual wage deciles. In the X-axis occupations are ranked according to their median wage computed over the wage distribution of natives residual wage in the baseline period (1994-96). The age*education composition within occupations is kept constant and equal to that of natives in the baseline period for both immigrants and natives. For immigrants residence duration composition is also kept equal to that observed in the baseline.

5.1.2 Qualifying the "price effect": the role of tasks

As suggested by our Roy conceptual framework, workers within the same occupation, despite identical observable characteristics (*i.e.* age, education and duration of residence in host country) do not necessarily have the same (multidimensional) skill endowment. Therefore, even if returns to skills/tasks are identical for all workers employed in the same occupation, two workers with different skill endowments can experience different wage changes even though they perform the same tasks. In this case, returns to skills/tasks could differently contribute to wage changes within and across occupations for individuals differing in their relative skill endowment. For instance, immigrant and native actuaries may earn the same wage in a base period. However, immigrant actuaries may have a higher level of analytical skills (as compared to their communication skills) while natives have a medium level of analytical skills (as compared to their communication skills). Following an increase in returns to analytical skills, wage growth among all actuaries relatively to other occupations will increase. Nevertheless, wage growth among immigrant actuaries will outperform that of natives because of their relatively better endowment in analytical skills, whose relative returns have increased the most. Unfortunately, we do not observe workers' skills but only the task content of their occupations. By relating occupations' wage dynamics to their task content, by nativity group, we will be able to test wether immigrants and natives have different returns to tasks and consequently different skill endowments.[28]

[28]Note though that a significantly different contribution of returns to tasks to between- or/and within-occupation wage changes could be suggestive of either discrimination (*i.e.* identical skill endowments are differently rewarded)

From the quantification of the price effect in the previous section, we collect as many estimations of $(a_j,\, b_j)$ as there are occupations employing both immigrants and natives. Then, we assess the average wage growth premium enjoyed by immigrants and to what extent this premium is due to the task content of occupations employing immigrants and natives. We qualify the "price effect" by estimating the following reduced-form relationships on the pooled sample of immigrants and natives occupations:

$$\widehat{a_{ji}} = \gamma_0 + \gamma_1 \text{Immigrant}_i + \sum_{k=1}^{3} \gamma_{jk} TC_{jk} + \sum_{k=1}^{3} \beta_{jk} \text{Immigrant}_i \times TC_{jk} + \mu_{ij}, \tag{7}$$

$$\widehat{b_{ji}} = \delta_0 + \delta_1 \text{Immigrant}_i + \sum_{h=1}^{3} \delta_{jh} TC_{jh} + \sum_{h=1}^{3} \alpha_{jh} \text{Immigrant}_i \times TC_{jh} + \nu_{ij}, \tag{8}$$

where Immigrant_i is a dummy variable taking the value 1 if the component has been estimated on the sample of immigrants, TC_{jk} is the task intensity index for each occupation j and task category $k =$ (1) non-routine analytical or interactive, (2) routine cognitive or manual, and (3) non-routine manual. Note that task intensity indices are normalized across occupations[29] and estimations are weighted using the size of the nativity group in the occupation. Coefficients γ_{jk} and δ_{jh} measure the contribution of each task to natives' wage changes across and within occupations $(\widehat{a_j}, \widehat{b_j})$, while interaction coefficients, β_{jk} and α_{jh}, capture the differential impact for immigrants.[30]

Beside technological changes, labor demand may evolve due to changes in the national output mix, which may affect occupations differently due to the specific initial distribution across sectors. Given that immigrants and natives, within the same occupation, may be employed in different sectors, they will be differently impacted by these changes independently on their relative skill endowments. To mitigate this effect, we add to our regressions an occupation-specific labor demand shift index *à la* Bartik (1991), which is constructed from the distribution of occupations across sectors in 1994-1996 and takes into account changes in the industrial composition between periods 1994-1996 and 2010-2012.[31]

Estimations take into account workers' sorting on observable characteristics to get rid-off differential

or a differential skill endowment between natives and immigrants (*i.e.* returns to skills are identical but the skill endowment differs across both nativity groups). Distinguishing these two explanations is beyond the scope of this paper.

[29] We define the "normalized" task intensity index by occupation as:

$$TC_{jk}^{norm} = \frac{TC_{jk} - \min[TC_k]}{\max[TC_k] - \min[TC_k]} \tag{9}$$

where $\min[TC_k]$ corresponds to the minimum value observed for the task index k across all considered occupations and $\max[TC_k]$ corresponds to its maximum value.

[30] Parameter estimates of the above equations when working separately with the native and the immigrant sample are available from the authors upon request.

[31] We define as follows the labor demand shift indicator for occupation j and origin i: $\text{DemandShift}_{ji} = \sum_s \left[\frac{N_{sji0}}{N_{ji0}} \cdot \Delta N_{si}\right]$, where N_{sji0} stands for the number of employees in sector s, occupation j from origin i in period 0 (base period). N_{ji0} represents the total number of employees in occupation j from origin i in period 0. ΔN_{si} is the variation in the number of employees from origin i in sector s. In order to obtain the labor demand shift associated with an occupation, we must sum shifts over all sectors s composing the occupation j.

composition effects between immigrants and natives. We consider three different weighting schemes as described in the Appendix B. In the baseline scenario, we use the LFS original population sample weights; populations are therefore representative of their specific nativity group in each period. Next, we consider the weighting scheme 1, which insures a constant population composition within occupations for each nativity group separately. In that case, population in each nativity group is representative (along observable characteristics) of the baseline population of each occupation. Age*education composition is kept constant within occupations as the base period. We therefore focus on the sub-population which is the most likely to work in an occupation before the shift in skill returns (our conceptual framework highlights that this is the right population to consider to identify the between and within wage components). Lately, the weighting scheme 2 insures that within occupations the population composition is not time varying and is the same for both nativity groups, taking as a reference group the native population of each occupation in the base period. Age*education within each cell is kept constant and similar to that of natives in the the base period. This latter weighting scheme controls for different composition effects across nativity groups and over time. Additionally, for immigrants, wage residuals and weights are computed with and without controlling for residence duration (see notes at the bottom of Table 1).[32] Controlling for residence duration is important if some occupations are experiencing inflows of new immigrants, that may lack country non-observable specific human capital. Estimations that use the weighting scheme 2 and control for residence duration (columns 5 and 10 in all subsequent tables) are the most consistent with the assumption of constant population composition within occupations in our Roy-type framework. Depending on the scenario, the sample size varies from 248 to 144 observations (*i.e.* 72 occupations per nativity group).

To assess the sources of differential wage changes within and across occupations, we successively introduce the immigrant variable indicator (see Table 1), the task indices (see Table 2) and their interactions (see Table 3). The results we present in Table 1 confirm those of Figure 10 : across occupations, immigrants' relative wage growth outperformed that of natives by 26% over the 20 years. This is quite substantial given that we control for observable characteristics such as age, education and residence duration. This high relative wage performance is robust to differences in observable characteristics between immigrants and natives within occupations. The immigrant wage growth effect is almost twice when ignoring their observable specific characteristics (see coefficient difference between columns 4 and 5 in Table 1). This is an expected result that can be interpreted as follows: immigrants are on average younger and also very often over-educated. If over the period returns to education have increased while returns to experience have decreased then this could explain the specific wage growth premium associated with their age and education. Indeed, immigrants' more favorable returns to skills, *i.e.* within-occupation effect, are entirely due to their specific characteristics (see coefficient change between column 9 and column 10), which also

[32]More precisely, in weighting scheme 1, age*education*(residence duration) composition is kept constant within occupations as the base period. In weighting scheme 2, immigrants' residence duration is kept constant within each occupation, and age*education within each (occupation*residence duration) cell is kept constant and similar to that of natives in the the base period. We consider two levels of residence duration, below 10 years and above 10 years.

explain almost half of their wage growth performance across occupations.

We add in Table 2 the task content of occupations. The immigrants' wage growth premium (*i.e.* coefficient associated to the variable Immigrant) does not seem to be driven by specific returns to skills associated with non-routine analytical, routine and manual tasks. This is indeed an expected result given the shape of Figure 10: immigrants' wage growth premium occurs across the whole occupational wage distribution. Interestingly, coefficients associated with tasks reveal that returns to skills have increased in occupations which are more intensive in non-routine tasks (analytical-interactive and manual) and have decreased in occupations more intensive in routine tasks. In other words, returns to non-routine skills (analytical-interactive and manual) have positively influenced average wage growth in occupations, while returns to routine skills have had rather a negative influence.

So far, we have not taken into account the possibility of heterogenous effects of occupational task content (and thus of occupation-specific skills) in explaining differences in average wage and returns to skills between immigrants and natives. This heterogeneity is important if immigrants' and natives' skill endowment was initially different or changes differently over time, which could explain significant different returns to the tasks they perform within occupations. To test this heterogeneity, occupational task indices are interacted with the immigrant dummy. Estimates in Table 3 reveal that most differences in task-specific returns to skills are indeed due to differences in observable skill endowments related to age, education and residence duration. The immigrants' wage growth premium is barely affected when considering potential heterogenous effects in task-specific returns to skills. There is virtually no immigrant-specific return to skill that arises as significantly different from that of natives when considering changes in occupational average wages (*i.e.* between-occupation wage changes). This suggests that immigrants wage growth performance is not related to their specific skills in performing some tasks.

Conclusions are though modified when considering changes in returns to skills (*i.e.* within-occupation wage changes).[33] Once composition effects have been controlled for (column 10), we find that in occupations requiring non-routine manual skills, immigrants wages have been compressing, while they have contributed to wage dispersion among natives. This pattern is likely to result from changes in skill endowment of immigrants and natives in non-routine manual occupations.[34] Indeed we will

[33] To test the robustness of this result, we propose in Appendix D an alternative strategy, which consists in regressing the immigrant-native gaps in estimated between- and within-occupation components over the task indices:

$$\begin{aligned}\widehat{a_I} - \widehat{a_N} &= \gamma_0 + \gamma_1\,\text{DemandShift}_j + \sum_{k=1}^{3}\gamma_{jk}TC_{jk}^{norm} + \mu_j \\ \widehat{b_I} - \widehat{b_N} &= \delta_0 + \delta_1\,\text{DemandShift}_j + \sum_{k=1}^{3}\delta_{jk}TC_{jk}^{norm} + \nu_j\end{aligned}$$

where TC_{jk} stands again for the task content measure within each occupation k = (1) non-routine analytical or interactive, (2) routine cognitive or manual, and (3) non-routine manual. Results in Table 7 in Appendix D are consistent with estimations presented in Table 3.

[34] Note that whether the initial skill endowment is the same or not for natives and immigrants, the negative and significant coefficient associated with the variable "Img· Non routine manual" (compared to the positive and significant coefficient associated with "Non routine manual") can only arise if there is a divergent change in the

Table 1: Immigrant effect in the between- and within-occupation wage changes, from 1994-96 to 2010-12. Pooled sample.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	0.271***	0.279***	0.498***	0.434***	0.260***	-0.0855**	0.150***	0.134***	0.249***	-0.0157
	(0.0202)	(0.0185)	(0.0153)	(0.0208)	(0.0160)	(0.0393)	(0.0433)	(0.0373)	(0.0442)	(0.0438)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	250	186	180	164	146	250	186	180	164	146
R-squared	0.371	0.517	0.798	0.715	0.555	0.014	0.047	0.047	0.124	0.001

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment at the occupation of the corresponding nativity group. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 origin country dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*residence duration categories. In the weighting scenario Weight 1 population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10), control for population composition effects includes immigrants' residence duration.

show in the next section that immigrants specialization in non routine manual task has decreased over the period (see also Figure 6). If this occurs within an age and education group, this may lead to wage compression in these occupations among immigrants.

To summarize, as suggested by Figure 10, immigrants' average wage growth across occupations has outperformed that of natives. Their more favorable wage dynamics seems to be related to specific changes in their relative skill endowment. We then investigate a complementary explanation of immigrants' wage performance based on their occupational sorting, that is, we complement the analysis of the "price effect" with an analysis of the "quantity effect". To do so we relax then the assumption of constant relative skill (and tasks) distribution within occupations along time and analyze the dynamics occupational sorting by workers, which actually relates to changes in their comparative advantages across tasks and thus to changes in their relative skill endowment.

5.2 The quantity effect

Given the estimated changes in returns to skills, how immigrants' and natives' occupational choices have been modified? Estimations of the price effect have been implemented under the assumption of time invariant skill distribution within occupations. Evidently, this is an unrealistic hypothesis, since changes in returns to skills are likely to modify both individual's decisions on skill acquisition and on occupational choices. Different occupational choices between immigrants and natives, while facing identical changes in returns to skills, will be suggestive of different changes in their respective skill endowments. The specific pattern of occupational sorting may explain immigrants' relatively higher wage growth across the occupational wage distribution. For instance, if they are moving from middle routine task-intensive occupations towards analytical task-intensive occupations at a higher pace than natives, this will drive up their relative wage growth. To capture the differential pattern

relative skill endowment of immigrants versus natives.

Table 2: Immigrant and task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12. Pooled sample.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	0.278***	0.283***	0.502***	0.439***	0.262***	-0.0661*	0.161***	0.145***	0.262***	-0.00658
	(0.0170)	(0.0172)	(0.0140)	(0.0205)	(0.0135)	(0.0378)	(0.0434)	(0.0373)	(0.0458)	(0.0456)
Non-routine analytical-interactive	0.175***	0.121***	0.110**	0.132***	0.0780**	0.344***	0.407***	0.336***	0.394***	0.287**
	(0.0431)	(0.0432)	(0.0424)	(0.0458)	(0.0394)	(0.100)	(0.119)	(0.113)	(0.131)	(0.136)
Routine manual-cognitive	-0.277***	-0.187***	-0.179***	-0.149***	-0.171***	-0.524***	-0.340**	-0.404***	-0.292*	-0.403***
	(0.0598)	(0.0514)	(0.0492)	(0.0529)	(0.0506)	(0.141)	(0.151)	(0.140)	(0.158)	(0.153)
Non-routine manual	0.311***	0.227***	0.208***	0.192***	0.259***	0.225**	0.114	0.211**	0.119	0.294***
	(0.0532)	(0.0466)	(0.0446)	(0.0482)	(0.0462)	(0.102)	(0.114)	(0.0993)	(0.115)	(0.101)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	248	184	178	162	144	248	184	178	162	144
R-squared	0.526	0.619	0.841	0.766	0.685	0.183	0.183	0.191	0.229	0.104

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment at the occupation of the corresponding nativity group. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 origin country dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

Table 3: Task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12. Natives vs. Immigrants.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrant	0.209***	0.244***	0.492***	0.438***	0.240***	-0.0477	0.217	0.188	0.432***	0.104
	(0.0571)	(0.0510)	(0.0452)	(0.0614)	(0.0506)	(0.113)	(0.146)	(0.158)	(0.158)	(0.192)
Non-routine analytical-interactive	0.159***	0.115**	0.0920*	0.124**	0.0667	0.353***	0.410***	0.341***	0.419***	0.290*
	(0.0484)	(0.0469)	(0.0471)	(0.0478)	(0.0450)	(0.114)	(0.135)	(0.129)	(0.149)	(0.154)
Routine manual-cognitive	-0.272***	-0.183***	-0.191***	-0.159***	-0.180***	-0.581***	-0.449***	-0.471***	-0.396**	-0.456***
	(0.0688)	(0.0581)	(0.0558)	(0.0588)	(0.0591)	(0.161)	(0.169)	(0.161)	(0.178)	(0.174)
Non-routine manual	0.302***	0.219***	0.228***	0.205***	0.269***	0.272**	0.219*	0.275**	0.230*	0.363***
	(0.0597)	(0.0503)	(0.0502)	(0.0509)	(0.0531)	(0.112)	(0.119)	(0.108)	(0.119)	(0.111)
Img*Non-routine analytical-interactive	0.130	0.0460	0.144	0.0598	0.0830	-0.109	-0.0888	-0.0859	-0.262	-0.0519
	(0.0976)	(0.131)	(0.102)	(0.182)	(0.0786)	(0.220)	(0.276)	(0.250)	(0.304)	(0.308)
Img*Routine manual-cognitive	-0.0642	-0.0424	0.0701	0.0667	0.0549	0.433*	0.809***	0.501*	0.812***	0.418
	(0.113)	(0.126)	(0.116)	(0.156)	(0.0922)	(0.251)	(0.279)	(0.270)	(0.276)	(0.331)
Img*Non-routine manual	0.0869	0.0787	-0.158	-0.110	-0.0737	-0.382*	-0.849***	-0.518**	-0.928***	-0.580**
	(0.117)	(0.142)	(0.107)	(0.181)	(0.0914)	(0.222)	(0.314)	(0.248)	(0.317)	(0.291)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	248	184	178	162	144	248	184	178	162	144
R-squared	0.530	0.621	0.845	0.767	0.687	0.190	0.212	0.205	0.266	0.120

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

of occupational sorting between immigrants and natives, we will first quantify the "quantity effect" by relating occupational choices to the two components of wage changes previously estimated for each occupation. This will allow us to test whether immigrants and natives have made different occupational choices when facing identical wage changes. In other words, we will compare the "quantity effect" across nativity groups. In a second step, we qualify the occupational sorting of immigrants and natives (*i.e.* the "quantity effect"), by relating occupational choices to the task content of occupations. We propose to conduct both analysis through the estimation of an occupational choice model.

Our occupational choice model (based on the theoretical setup presented in section 4) can easily be framed within probabilistic or random utility choice model. For this, we suppose that when choosing their occupation, beside income potentials related to their relative skill endowment, individuals take into account some stochastic and idiosyncratic characteristics of occupations, which we assume are distributed independently of workers' skill endowments. Then, individuals choose from a variety of occupations their best option, taking into account income potential associated to each option and their specific characteristics. The indirect utility that a worker i derives from choosing an occupation j depends on her potential earning in the occupation, which we assume is a linear function of individual characteristics X_i, occupation-specific characteristics Z_j (occupation-specific returns to skills), and an idiosyncratic stochastic component:

$$U_{ij}^* = \beta_i X_i + \gamma_{ij} Z_j + \varepsilon_{ij} \tag{10}$$

An individual will choose among J occupations the one that yields the highest utility. We assume that the effects of occupation-specific characteristics on individual utility (γ_{ij}) vary across individuals, owing for instance to their specific skill endowments.[35] An individual will choose occupation j if $U_{ij}^* > U_{ik}^*\ \forall k \neq j$.

We define $U_{ij} = 1$ if individual i chooses occupation j and $U_{ij} = 0$ otherwise. Assuming that the disturbance term is iid and follows a Type-I extreme value distribution[36], we can estimate this random utility model using McFadden (1974)'s conditional logit:

$$\Pr(U_{ij} = 1) = \frac{\exp\{\beta_i X_i + \gamma_{ij} Z_j\}}{\sum_{j=1}^{J} \exp\{\beta_i X_i + \gamma_{ij} Z_j\}} \tag{11}$$

Terms that do not vary across alternatives and are specific to the individual (*i.e.* X_i) are irrelevant and fall out of the probability. Therefore, we cannot estimate the effect of individual characteristics on the occupational choice (β) since they are invariant to the choice. However, we can estimate the effect on occupational choice of occupational characteristics (γ), and also their interactions with

[35] In this setting, γ_{ij} can be thought as the vector of individual skill endowments and Z_j as a vector denoting the sensitivity of the occupation to each skill component of γ_{ij}.

[36] We should invoke here the independence of irrelevant alternatives (IAA) assumption. Choices are then independent from irrelevant alternatives and therefore the omission of a choice does not significantly alter estimates.

individual characteristics. To track the effect of changes in occupation-specific characteristics, we allow the effects to vary over time by interacting each characteristic with a dummy variable Year, equal to one in 2010-12. Therefore, we interpret the coefficients from a dynamic point of view, with respect to the base period (1994-1996). Coefficients associated with these interaction terms capture the change relatively to the base period in the probability of choosing an occupation relatively to its characteristics.

5.2.1 Measuring the "quantity effect": occupational choices in case of wage change

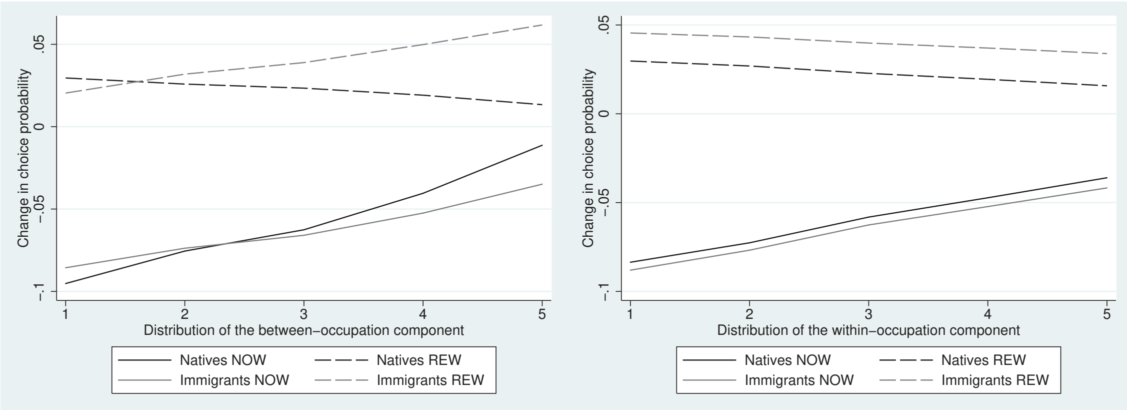
Let us first start estimating the pure "quantity effect", which relates the occupational choice to the between- and within-occupation components of wage changes. In Figure 11, the left-hand (right-hand) side panel displays on the X-axis the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of the between- (within-) occupation component of wage changes.[37] The Y-axis represents the variation in the probability of choosing an occupation located at the corresponding percentile of the specific component of wage changes. An upward profile along the distribution of the between- (within-) occupation component indicates that occupations where the average wage (wage dispersion) has relatively more increased are more likely to be chosen over time. In contrast, a downward probability choice profile in one of the two panels indicates that occupations in which the corresponding component has relatively more increased are less likely to be chosen over time. The NOW curves represent the results for the observed population sample, *i.e.* without controlling for composition effects related to age, education and residence duration. The REW curves represent the results with a reweighted sample representing a constant population composition over time and across nativity groups (*i.e.* same age-education-residence duration composition in both periods for immigrants and natives).

Figure 11 reveals in the left-hand side panel that occupations with higher wage growth are increasingly likely to be chosen by both immigrants and natives. Though, this sorting of natives in such occupations is entirely due to their skill upgrading in terms of age and education. When removing composition effects, we find instead that the probability of natives to choose occupations with higher wage growth has decreased. In contrast, at similar and constant population composition, we still observe a higher probability of immigrants to choose such occupations. In the right-hand side panel of Figure 11, we observe that both immigrants and natives are more likely to choose occupations with a greater rise in wage dispersion. However, for both nativity groups, this pattern is mostly explained by changes in the composition of the nativity group. At constant and identical population composition, we find instead that both immigrants and natives are slightly less likely to choose occupations whose wage dispersion has more increased. Interestingly, this pattern of occupational sorting is similar for immigrants and natives. Overall, immigrants' and natives' occupational choices have reacted in a similar way to changes in returns to skills. Therefore, their differential wage dynamics cannot been explained by different occupational choices following identical changes

[37] The between- and within-occupation components we consider here are those estimated on the sample of natives while removing age-education composition effects.

in returns to skills. It seems rather that immigrants and natives have responded differently to changes in the average wage level of occupations. Immigrants have evidently sorted relatively more than natives into occupations with higher average wage growth.

Figure 11: Change in the probability of choosing an occupation depending on the wage changes between 1994-1996 and 2010-2012



5.2.2 Qualifying the "quantity effect": the role of tasks

Next we qualify the differential sorting of natives and immigrants by relating the occupational choice to the task content of occupations. This allows us to characterize the occupational choices of both nativity groups when facing identical changes in task-specific returns to skills. These different occupational choices (would) result from different changes in comparative advantages across nativity groups, which are related with different changes in their skill endowment.[38] We control at the same time for the share of minimum wage earners in occupations to take into account variations across occupations in the probability to be exposed to a minimum wage change. Immigrants and natives may be differentially attracted by occupations whose wage changes are tightly related to minimum wage changes if, owing to some specific characteristics, they have different propensities to be minimum wage earners. This feature is particularly relevant to consider in the French context, where the minimum wage level has experienced a sharp increase over the period. Although we control for the effects of minimum wage changes to produce the different estimates reported below, we report the results related specifically to this feature in Section 6, where we analyze in more detail how minimum wage changes have altered the "price effect" and the "quantity effect".

We again interact these occupational characteristics with the dummy variable Year to capture the dynamics in occupational choices with respect to the base period (1994-1996). Coefficients associated with the interaction terms (Year $\times$ Task$_j$) capture the change relatively to the base

[38]Our approach is similar to that adopted in the microeconomic literature on revealed preferences. Taking as given changes in returns to skills, we infer about immigrants' and natives' changes in relative skill endowment by looking at their differential reaction to changes in the pricing of skills.

period in the probability of choosing an occupation relatively more intensive in a specific task (*i.e.* we condition on the value for all the other tasks).[39]

Figures 12, 13 and 14 display on the X-axis the 10th, 25th, 50th, 75th and 90th percentiles of the intensity index distribution for a particular task and on the Y-axis the variation in the probability of choosing an occupation located at the corresponding percentile of this specific task dimension. These graphs portray the time pattern of occupational sorting of immigrants and natives along each task intensity distribution. An upward profile in Figures 12, 13 and 14, along the task intensity index distribution indicates that occupations relatively more intensive in the corresponding task are increasingly likely to be chosen over time. Alternatively, a downward probability choice profile indicates that occupations relatively more intensive in the corresponding task are less likely to be chosen over time. These graphs show the type of tasks in which immigrants and natives are increasingly concentrated and therefore reveal how the pattern of their comparative advantages has evolved over time. Again, NOW curves represent the results for the observed population sample while REW curves consider a constant population composition over time and across nativity groups. This later effect will reveal whether differences in occupational mobility are due to genuine different comparative advantages in task-specific skills within age*education skill group or occur due to standard differences in observable age*education characteristics.[40]

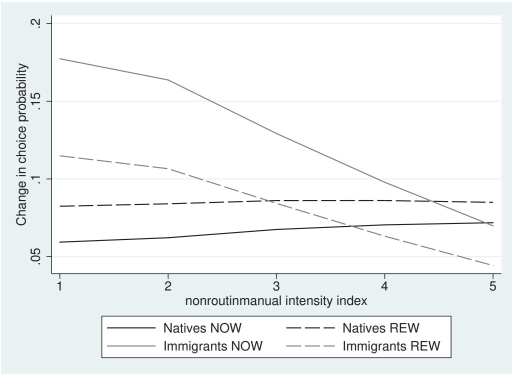
Figure 12 displays the predicted change (from 1994 to 2012) in the conditional choice probability of an occupation along the distribution of the non-routine manual task index. The probability that immigrants choose an occupation which is relatively more intensive in non-routine manual tasks has declined over time. Instead, natives show a weakly increasing pattern in their probability to choose occupations which are relatively more non-routine manual intensive. Controlling for changes and differences in population-composition does not affect these patterns. Therefore, relatively to natives, immigrants are loosing comparative advantage in non-routine manual tasks. Immigrants seem to have moved away from non-routine manual occupations. This pattern of mobility is consistent with the decreasing wage dispersion estimated for immigrants in Table 3 (column 10).

Figure 13 displays changes in the probability to choose an occupation depending on its intensity in routine tasks. Natives' comparative advantage in routine tasks has clearly declined over time: the probability for a native to choose an occupation located at the first decile of the routine index has increased by a factor of three relatively to an occupation located in the upper decile. Natives seem therefore to be moving away from routine task-intensive occupations. This is also the case for immigrants but to a much lower extent. Therefore, immigrants seem to be gaining comparative advantage relatively to natives in these more routine occupations. The pattern and the difference across nativity groups are though explained by changes and differences in the composition of the populations. At constant and identical population composition, we find instead that relatively to immigrants, natives are more likely to choose routine occupations. Therefore, at similar charac-

[39]Note that we control for the effect of the minimum way by introducing the term Year $\times$ Sharew$_j^{min}$ which captures the change relatively to the base period in the probability of choosing an occupation with a relatively larger share of minimum wage earners.

[40]For instance, the fact that more educated workers may have comparative advantage in less routine occupations.

Figure 12: Change in the probability of choosing an occupation depending on the intensity of non-routine manual tasks



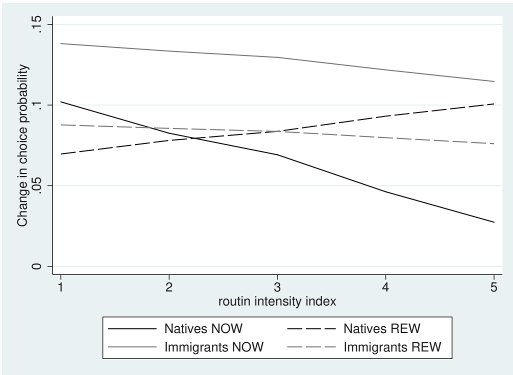
Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine manual task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index.

teristics, natives have gained comparative advantage in these occupations. Combined with Figure 12, this suggests that, despite their departure from non-routine manual task-intensive occupations, immigrants do not seem to be flowing towards routine task-intensive occupations. This is consistent with estimations in Figure 11. Over the past decades immigrants have increasingly allocated towards occupations experiencing high average wage growth. Recent technological changes have promoted a relative decrease in the price of routine intensive goods (see Autor, Levy, and Murnane (2003), Autor, Levy, and Kearney (2006), Goos and Manning (2007), Spitz-Oener (2006) or Maurin and Thesmar (2004)) implying a reduced average wage growth in occupations intensive in routine tasks. Immigrants have thus flied out from this type of occupations.

Figure 14 displays the predicted change in the probability of choosing an occupation depending on its relative intensity in non-routine analytical-interactive tasks. Occupations which are more intensive in non-routine analytical-interactive tasks are increasingly likely to be chosen by both immigrants and natives. Though, this greater specialization of natives in non-routine occupations is entirely due to their skill upgrading in terms of age and education. When removing composition effects, we find that the probability of natives to choose occupations more intensive in non-routine tasks has only slightly increased. In contrast, at similar and constant population composition, we still observe a greater specialization of immigrants in non-routine analytical-interactive task-intensive occupations. Therefore, relatively to natives, immigrants seem to have gained comparative advantage in non-routine analytical-interactive task-intensive occupations.

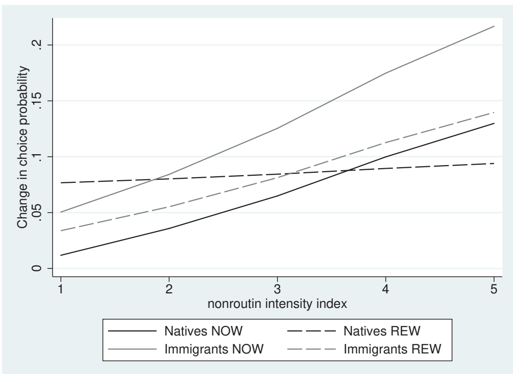
This later result may be somewhat surprising with respect to usual findings in the literature (see Peri and Sparber (2011b), Peri and Sparber (2011a), Peri and Sparber (2009) or D'Amuri and Peri (2014)). To gain further insight, we distinguish in Figure 15 between non-routine analytical tasks and non-routine interactive tasks. Occupations more intensive in analytical tasks are increasingly

Figure 13: Change in the probability of choosing an occupation depending on the intensity of routine tasks



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine manual task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index.

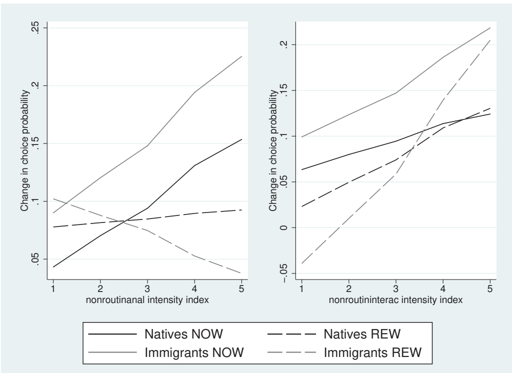
Figure 14: Change in the probability of choosing an occupation depending on the intensity of non-routine tasks



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine analytical-interactive task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index.

likely to be chosen, essentially owing to skill upgrading related to age, education and residence duration. At constant and similar population composition, we estimate a clear improvement in the comparative advantage of natives relatively to immigrants in analytical task-intensive occupations. Actually, immigrants' concentration in occupations intensive in non-routine analytical tasks has slightly decreased over time. Instead, immigrants are increasingly concentrated in non-routine interactive tasks, and their comparative advantage relatively to natives has improved in these tasks. This improvement in immigrants' comparative advantage in non-routine interactive tasks still holds at constant and similar population composition.
Combined with Figures 11, 12 and 13, Figure 15 thus portrays an immigrant population that has experienced an upward occupational mobility relatively to natives and has allocated towards occupations whose average wage has increased the most. Between 1994-96 and 2010-12, immigrants are upgrading from the bottom (manual tasks) to the upper part of the wage distribution (non-routine interactive tasks).

Figure 15: Change in the probability of choosing an occupation depending on the intensity of non-routine analytical and interactive tasks



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the non-routine analytical (LHS panel) and interactive (RHS panel) task intensity index distribution. The task percentiles have been computed over the natives occupational employment distribution in the baseline (1994-1996). In the Y-axis, using coefficient estimates from the conditional logit, we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile of the task intensity index.

6 Robustness checks: minimum wage effects

Unlike many developed countries, the minimum wage in France has increased at a higher pace than the average wage. Moreover, around 11% of workers are minimum wage earners, which is one of the highest shares in OECD countries. Therefore, minimum wage changes in France are expected to have an impact on wage levels, wage distribution, and employment. Minimum wage can impact both the "price effect", by increasing returns to skills which are traditionally employed at the bottom of the wage distribution, and the "quantity effect", by promoting sorting towards

Table 4: Immigrant effect net of the minimum wage in the between- and within-occupation wage changes, from 1994-96 to 2010-12. Pooled sample.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change				Within-occupation wage change			
Scenarios	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	0.0482*	0.0314	0.241***	0.130***	0.253***	0.250***	0.519***	0.166***
	(0.0250)	(0.0241)	(0.0234)	(0.0205)	(0.0654)	(0.0757)	(0.0427)	(0.0422)
Population composition constant								
within group	YES	YES	YES	YES	YES	YES	YES	YES
within and across group	NO	YES	NO	YES	NO	YES	NO	YES
Control for residence duration	NO	NO	YES	YES	NO	NO	YES	YES
Observations	158	154	154	134	158	154	154	134
R-squared	0.018	0.008	0.335	0.161	0.085	0.079	0.427	0.081

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

occupations with a high share of minimum wage earners. We report below the estimates when taking into account the impact of minimum wage changes on these two effects.

6.1 Minimum wage changes and the price effect

To gauge how minimum wage changes may impact our estimates of the "price effect", we propose to concentrate on a set of workers that are less likely to be affected by minimum wage changes, which we take to be those earning above 1.2 times the minimum wage. We proceed as follows. First, we identify the characteristics of this set of workers in the baseline period 1994-1996. Second, we fix the population-composition of each occupation in period 2010-2012 to be the same as that of the sub-sample of workers in that occupation earning above 1.2 times the minimum wage in the baseline period 1994-1996. That is, for every occupation and both periods, we focus on a constant population-composition which is representative of workers for which we think minimum wage changes are less likely to bind.

Results for this particular sample are summarized in Tables 4 and 5.[41] As revealed by Table 4, considering workers outside the reach of minimum wage decreases by more than a half the estimated immigrants' occupational wage growth premium. Minimum wage changes therefore have significantly contributed to immigrants' better relative wage performance. Interestingly, wage growth among this sub-sample of better paid workers is explained by their more favorable skill returns (see column 8 of Table 4), *i.e.* by wage changes within occupations. In Table 5, we control for the task content of occupations, while allowing for heterogenous returns between immigrants and natives. Consistently with estimates in Table 3, we find that there are immigrant-specific positive returns

[41] We do not present here results of the Baseline scenario since they would be identical to columns (1) and (6) from Table 1. Indeed the Baseline scenario does not use counterfactual weights.

Table 5: Task contribution net of the minimum wage to between- and within-occupation wage changes, from 1994-96 to 2010-12. Natives vs. Immigrants.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change				Within-occupation wage change			
Scenarios	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	0.0482	0.0317	0.278***	0.123*	0.169	-0.0237	0.641***	0.231
	(0.0713)	(0.0592)	(0.0736)	(0.0646)	(0.196)	(0.245)	(0.147)	(0.154)
Non-routine analytical-interactive	0.199***	0.204***	0.168**	0.126**	0.485***	0.496***	0.419***	0.324***
	(0.0667)	(0.0674)	(0.0682)	(0.0635)	(0.137)	(0.138)	(0.115)	(0.121)
Routine manual-cognitive	-0.332***	-0.337***	-0.293***	-0.315***	-0.624***	-0.557***	-0.478***	-0.466***
	(0.0839)	(0.0854)	(0.0853)	(0.0890)	(0.144)	(0.149)	(0.133)	(0.143)
Non-routine manual	0.360***	0.359***	0.331***	0.379***	0.340***	0.293**	0.279***	0.351***
	(0.0729)	(0.0714)	(0.0754)	(0.0776)	(0.126)	(0.124)	(0.101)	(0.0986)
Img*Non-routine analytical-interactive	-0.0867	-0.0275	0.113	0.0222	0.595	0.759	-0.318	-0.132
	(0.181)	(0.193)	(0.190)	(0.0943)	(0.514)	(0.592)	(0.278)	(0.274)
Img*Routine manual-cognitive	0.144	0.199	0.197	0.141	1.039**	1.355**	0.922***	0.705**
	(0.158)	(0.147)	(0.175)	(0.125)	(0.404)	(0.644)	(0.255)	(0.323)
Img*Non-routine manual	-0.0657	-0.164	-0.324*	-0.139	-1.313**	-1.411**	-0.887***	-0.727**
	(0.186)	(0.180)	(0.186)	(0.115)	(0.560)	(0.619)	(0.301)	(0.343)
Population composition constant								
within group	YES	YES	YES	YES	YES	YES	YES	YES
within and across group	NO	YES	NO	YES	NO	YES	NO	YES
Control for residence duration	NO	NO	YES	YES	NO	NO	YES	YES
Observations	156	152	152	132	156	152	152	132
R-squared	0.301	0.309	0.513	0.452	0.304	0.282	0.546	0.216

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

to skills associated with routine tasks and negative returns to skills associated with non-routine manual tasks. Overall, these changes in returns to skills are rather consistent with a change in skill endowment promoting immigrants' upward occupational mobility. As estimated in Table 3, returns to skills have not contributed statistically differently to changes in occupational average wage (*i.e.* between-occupation wage change) for natives and immigrants.

6.2 Minimum wage changes and the quantity effect

Minimum wage changes also affect workers' sorting across occupations, that is, what we have called, the "quantity effect". When estimating the random utility choice model of equation (11) we have controlled for the share of minimum wage earners in the occupation. Linking the occupational choice of the individual to the share of minimum wage earners in the occupation allows us to assess whether immigrants and natives make different occupational choices when facing an identical change in returns to tasks/skills driven by minimum wage changes. Immigrants and natives may differ in their likelihood to be paid at the minimum wage.

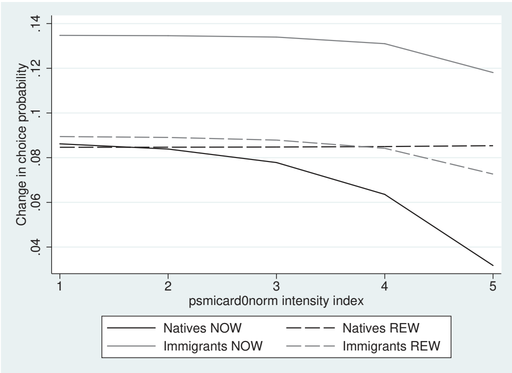
In Figure 16, we display a graph which is similar to ones in section 5.2 but which considers the occupations' share of minimum wage earners. Therefore, Figure 16 shows the pattern of sorting across occupations that are increasingly likely to be affected by minimum wage changes over the period. The figure reveals that the probability of choosing occupations more exposed to minimum wage changes has decreased over time for both immigrants and natives. However, when removing composition effects, we find that this decline is only effective among immigrants at the top of the distribution (*i.e.* for occupations very exposed to minimum wage changes) while the choice probability has remained essentially constant among natives. Therefore, relatively to natives, immigrants are decreasingly concentrated in occupations the most exposed to minimum wage changes. We conclude that selective sorting of immigrants towards occupations highly exposed to minimum wage changes is unlikely to have had an important impact on the overall relative good wage performance of immigrants.[42] Instead, this performance seems to be better explained by changes in comparative advantages leading to upward occupational wage mobility towards occupation which have actually benefitted from the highest average wage growth.

Combining the results in Tables 4, 5 with those in Figure 16 and those in section 5.2, we conclude that immigrants' favorable wage dynamics is, at least, explained by two important factors. On the one hand, we find that immigrants have moved upward across the occupational wage ladder between 1994-1996 and 2010-2012. On the other hand, we find that part of immigrants' more favorable wage growth has been driven by minimum wage increases over the period.[43] This result also suggests that wage growth premium of less and more skilled immigrants are explained by different factors. For the least skilled, changes in skill prices brought about by minimum wage changes are probably the dominant factor. In contrast, changes in relative skill endowments and occupational sorting (induced by changes in returns to skills and average wage growth) are the main factor among more

[42] This does not mean that the minimum wage has had no impact.

[43] One issue we do not deal with is the effect of minimum wage on mobility into non-employment.

Figure 16: Change in the probability of choosing an occupation depending on the share of minimum wage earners in the baseline (1994-1996)



Notes: The X-axis stands for the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of the share of minimum wage earners across occupations. The minimum wage share have been computed over the wage distribution of natives within each occupations in the baseline. The value of the percentiles across occupations have been computed over the natives occupational employment in the baseline. In the Y-axis, using the conditional logit estimates we report the predicted change from period 1 to period 2 in the probability of choosing an occupation located at the corresponding percentile in the distribution of the share of minimum wage earners across occupation

skilled immigrants.

7 Conclusion

Based on the French Labor Force Survey, the EurOccupations and O*NET datasets, we analyze in this paper two crucial sources of immigrants' labor market performance: immigrants' skills and how these skills are valued by the labor market. Despite being non-observable, we have been able to assess changes in immigrants' and natives' relative skill endowments along dimensions that have so far been overlooked in the literature focused on immigrants' labor market outcomes: task-specific skills.

We show that in France immigrants' wage growth has outperformed that of natives along the whole wage distribution, over the period 1994-2012. While a substantial part of immigrants' wage growth is due to their specific characteristics, we show that immigrants have also accumulated task-specific skills which are more rewarded along the occupational wage ladder. In particular, their pattern of occupational sorting over the period suggests that they have moved relatively more than natives upward in the occupational wage distribution, towards occupations whose average wage level has risen sharply.

In addition, we identify variations in the sources of the immigrant-native wage growth premium depending on the skill level. While the premium for the most skilled immigrants results from their increasing specialization in more rewarded tasks, the wage growth performance of the least skilled immigrants seems to be mainly related to the sharp increases in the French minimum wage over the period.

Though not unequivocal, our results show that the relative “labor market quality” of immigrants has improved over the last two decades in France. Interestingly, this improvement is not only the consequence of changes in the market reward of skills but potentially also the result of immigrants’ human capital adjustment. Overall, it seems that immigrants have been able to better price their skills by moving across tasks. We hope to confirm these patterns in future research by investigating, using individual panel data, the dynamics of wages and human capital adjustments which have followed the deep changes in skills and tasks driven by globalization and technological changes. In addition, while this paper focuses on male earnings, bringing into the analysis gender differences will be a worthy complement to the present research.

Appendices

A Databases

A.1 The French Labor Force Survey

The French Labor Force Survey (LFS) was launched in 1950 and established as an annual survey in 1982. Redesigned in 2003, it is now a continuous survey providing quarterly data. Participation is compulsory and it covers private households in mainland France. All individuals in the household older than 15 are surveyed.

The quarterly sample is divided into 13 weeks. From a theoretical point of view, the sampling method consists of a stratification of mainland France into 189 strata (21 French regions $\times$ 9 types of urban unit) and a first stage sampling of areas in each stratum (with different probabilities, average sampling rate = 1/600). Areas contain about 20 dwellings and among them only primary residences are surveyed. Each area is surveyed over 6 consecutive quarters. Every quarter, the sample contains 6 sub-samples: 1/6 of the sample is surveyed for the first time, 1/6 is surveyed for the second time, ..., 1/6 is surveyed for the 6th (and last) time. When it was run as an annual survey, every year a third of the sample was renewed meaning that each individual was interviewed only 3 times. The collection method has always been a face-to-face interview.[44]

A.2 Occupational task composition

[44] Since 2003, a telephone interview has been employed for intermediate surveys (2nd to 5th).

Table 6: Occupational tasks.

Non-routine Analytical	Organizing, Planning, and Prioritizing Work ; Getting Information ; Analyzing Data or information; Making Decisions and Solving Problems ; Developing Objectives ; Judging the Qualities of Things, Services, or People ; Updating and Using Relevant Knowledge ; Interacting with Computers ; Thinking Creatively ; Estimating the Quantifiable Characteristics of Products, Events, or Information ; Evaluating Information to Determine Compliance with Standards; Scheduling Work and Activities ; Interpreting the Meaning of Information for Others ; Processing Information and Strategies.
Non-routine interactive	Guiding, Directing, and Motivating Subordinates ; Communicating with Supervisors, Peers, or Subordinates ; Communicating with Persons Outside the Organization ; Developing and Building Teams ; Resolving Conflicts and Negotiating with Others ; Performing for or Working Directly with the Public ; Staffing Organizational Units Providing Consultation and Advice to Others ; Coordinating the Work and Activities of Others ; Selling or Influencing Others ; Training and Teaching Others ; Assisting and Caring for Others ; Coaching and Developing Others ; Establishing and Maintaining Interpersonal Relationships ; Monitoring and Controlling Resources.
Routine Cognitive	Performing Administrative Activities, Documenting/Recording Information.
Routine Manual	Handling and Moving Objects ; Performing General Physical Activities ; Repairing and Maintaining Mechanical Equipment ; Repairing and Maintaining Electronic Equipment.
Non-routine Manual	Operating Vehicles, Mechanized Devices, or Equipment ; Inspecting Equipment, Structures, or Material ; Monitoring Processes, Materials, or Surroundings ; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment.

Source : Constructed using data from O*NET.

B Removing composition effects in wage changes

In order to capture the precise contribution of tasks to the estimated residual wage differentials between 1994-1996 and 2010-2012, we remove the part of the residual wage change that results from changes in the composition of occupations in terms of age, education and residence duration. We propose alternative scenarios where we successively impose occupations to keep the same composition in terms of workers' age-education-residence duration in both periods, for each nativity group separately or taking as reference natives.

B.1 A cell-by-cell approach

We rely on the cell-by-cell approach suggested by Lemieux (2002), which is equivalent to the reweighting method of DiNardo, Fortin, and Lemieux (1996) but has the advantage to be more flexible. This non-parametric procedure consists first of dividing the data into a limited number C of cells, in each occupation j and at each period t, according to a set of dummy variables $x_{ijt} = (x_{i1jt}, \ldots, x_{icjt}, \ldots x_{iCjt})$. This procedure is based on the definition of the same age-education cells for natives and the same age-education-residence duration cells for immigrants within each of the occupations. We keep only cells that are observed in both periods to ensure we have a common support when applying this reweighting method.

For both native and immigrant workers, we use the following dummies to define age-education cells: we consider 9 distinct 5-year interval age groups (from 15 to 60), and within each age group we distinguish 4 education degrees (below baccalaureate, baccalaureate or equivalent, baccalaureate+2 years, higher degree). For immigrant workers, we additionally distinguish within each age-education cells two residence durations: less than 10 years, 10 years and more. Thus, we can define up to 36 age-education cells for natives and up to 72 age-education-residence duration cells for immigrants. Age is often used to proxy actual work experience in the literature. We could also use instead potential work experience, which is, under the standard assumption, equal to the worker's age minus the typical age at which she is expected to have completed her education.[45] A caveat of using such proxies is that actual work experience is measured with error, except for individuals who work full-time and continuously. Indeed, when work experience is acquired without interruption after schooling, potential experience and actual experience coincide. In contrast, potential experience may be a noisy proxy of actual experience for women or immigrants (see, *e.g.* , Barth, Bratsberg, and Raaum (2012)).

For each cell c, in occupation j and at period t, we then estimate a reweighting factor Ψ_{cjt} that will be used to calculate a counterfactual sample weight : $\omega^{a}_{cjt} = \Psi_{cjt}\,\omega_{cjt}$, where ω_{cjt} is the original sample weight of cell c, in occupation j and period t. The reweighting factor of each cell c is built up first from the sample share of workers in the cell (natives or immigrants), in occupation j and period t, denoted η_{cjt}, which is given by the sample average of the dummy variable x_{ict}:

$$\bar{x}_{cjt} = \sum_{i} \omega_{it}\, x_{icjt} = \sum_{x_{icjt}} \omega_{it} = \eta_{cjt}, \tag{12}$$

where ω_{it} is the original LFS sample weight, that we have multiplied by monthly hours of work, following for instance DiNardo, Fortin, and Lemieux (1996), and Lemieux (2002).

To insure that the age-education-years of residence composition is the same for each occupation in periods 0 and 1, we assign to each cell c the same average weight of the cell at period 0. This implies including the sample share of cell c in period 0 in the calculation of the corresponding reweighting factors. Thus, the reweighting factor of cell c in occupation j and period t is defined as:

$$\Psi_{cjt} = \frac{\eta_{c0}}{\eta_{cjt}}, \tag{13}$$

where η_{cjt} corresponds to the observed share of cell c (defined by a particular age-education-residence duration) in occupation j in period t, and η_{c0} is the same share in period 0. That is, the numerator stands for the counterfactual sample share of cell c in occupation j that we want to impose to be identical for both periods.

[45] Borjas (2003) assumes that the age of entry in the labor force is 16 for high school dropouts with no vocational education, 19 for high school dropouts with vocational education or high school graduates without vocational education, 21 for high school graduates with vocational education, 24 for those who completed non-university higher education and 25 for workers who hold a university degree. Ottaviano and Peri (2012) calculate years of potential experience under the assumption that people without a high school degree enter the labor force at age 17, people with a high school degree enter at 19, people with some college enter at 21, and people with a college degree enter at 23.

The resulting counterfactual sample weights $\omega^a_{cjt} = \Psi_{cjt}\,\omega_{cjt}$ allow to estimate the individual wage distribution that would have arisen if the age-education composition for natives and age-education-residence duration composition for immigrants in each occupations had been constant over time.

B.2 The alternative scenarios

We propose to measure the contribution of tasks' returns to between- and within-occupation wage changes under five alternative scenarios differing on (i) the explanatory variables considered to estimate residual wages with the Mincer equation, and (ii) the sampling weights employed to estimate occupation-specific residual wage deciles used in the regression and to compute the between and within components. The 5 scenarios are:

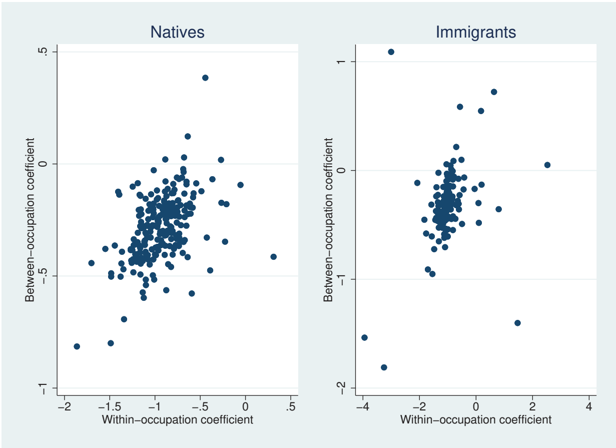
- The "Baseline" scenario corresponds to the case where residual wages result from regressing the log wage over standard variables in a Mincer equation: age × educ. Then, occupation-specific residual wage deciles are estimated using the LFS sampling weights.
- In the "Composition 1 (Weight 1 type)" scenario, estimated residual wage deciles are obtained as in the Baseline scenario, and they are reweighted to insure a constant age-education composition by nativity group within occupations.
- The "Composition 2 (Weight 2 type)" scenario differs from the previous one in that the reweighting factor imposes the age-education composition of natives in period 0, for both natives and immigrants in periods 0 and 1. This scenario is useful for interpreting differences between immigrants and natives.
- In the "Residence 1 (Weight 1 type) " scenario, residual wages for immigrants are obtained by regressing the log wage over age × educ × resid[46] and the origin country. Residual wage deciles are then obtained using counterfactual weights insuring a constant composition of worker characteristics (age × educ × resid) by nativity group within occupations.
- In the "Residence 2 (Weight 2 type)" scenario, residual wage deciles are obtained using counterfactual weights insuring a constant composition of worker characteristics (age × educ × resid) across nativity groups within occupations: the age-education composition of natives in period 0 is taken as reference.

C Figures

C.1 Between and within wage changes

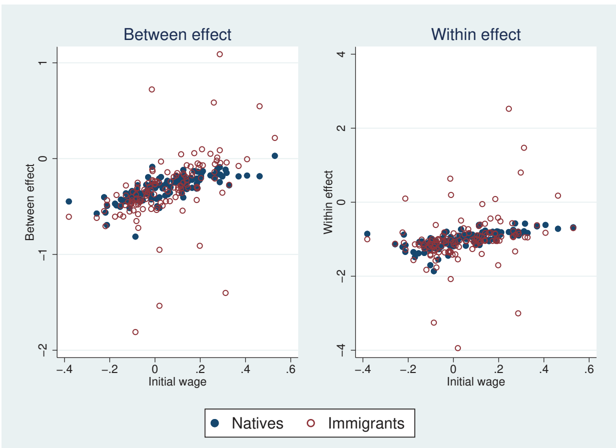
[46] The resid variable is defined for more than ten years of residence or less than ten years of residence.

Figure 17: Between- and within-occupation coefficients using LFS weights.



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 10 deciles. Composition effects are not controlled for.

Figure 18: Between- and within-occupation wage changes. Comparing Natives vs. Immigrants. Weights from the LFS



Notes: Natives' residual wages have been computed by including in the wage equation a full set of age*education dummies while immigrants' residual wages have been computed by including in the wage equation a full set of age*education*residence duration dummies and 27 origin country dummies. The between and within occupation coefficients have been computed considering 10 deciles. The X-axis stands for the occupational residual wage in period 1994-96 (common support for natives and immigrants). Composition effects are not controlled for.

Table 7: Task contribution to the estimated differential in between- and within-occupation wage changes for natives and immigrants, from 1994-96 to 2010-12.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change					Within-occupation wage change				
Scenarios	Baseline	Weight 1	Weight 2	Weight 1	Weight 2	Baseline	Weight 1	Weight 2	Weight 1	Weight 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Non-routine analytical-interactive	0.135**	0.104	0.200**	0.133	0.0919	-0.119	-0.204	-0.115	-0.321	0.0996
	(0.0671)	(0.123)	(0.0776)	(0.172)	(0.0611)	(0.178)	(0.216)	(0.243)	(0.265)	(0.292)
Routine manual-cognitive	-0.0909	-0.0414	0.0584	0.123	0.0209	0.337*	0.679**	0.451*	0.692**	0.202
	(0.0896)	(0.138)	(0.125)	(0.162)	(0.0886)	(0.202)	(0.271)	(0.247)	(0.309)	(0.319)
Non-routine manual	0.0661	0.0314	-0.200*	-0.193	-0.0821	-0.277	-0.862***	-0.591**	-1.015***	-0.613*
	(0.0817)	(0.147)	(0.108)	(0.201)	(0.0730)	(0.186)	(0.288)	(0.238)	(0.334)	(0.323)
Population composition constant										
within group	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
within and across group	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Control for residence duration	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Observations	124	92	89	81	72	124	92	89	81	72
R-squared	0.032	0.023	0.123	0.038	0.034	0.018	0.119	0.081	0.142	0.107

Notes: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. In all regressions we control for an occupation specific labor demand shift index (see text for details). Regressions are weighted using the initial period employment level. In all columns, natives' wage residuals have been computed by including in the wage equation a full set of age*education dummies. In columns (1)-(3) and (6)-(8) immigrants' wage residuals have been computed by including in the wage equation a full set of age*education dummies and 27 country of birth dummies. In columns (4), (5), (9) and (10) wage residuals for immigrants have been computed by including a full set of dummies for age*educ*(residence duration) categories. In the weighting scenario Weight 1, population composition within occupations is kept constant as in the baseline for each nativity group. In the weighting scenario Weight 2, population composition within occupations is kept constant as that of natives in the baseline for both immigrants and natives. In columns (4), (5), (9) and (10) control for population composition effects includes immigrants' residence duration.

D Estimations

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