Are immigrants' skills priced differently? Evidence from France

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Abstract

We investigate to what extent changes in the returns to occupational tasks have contributed to different wage dynamics between immigrants and natives along the wage distribution in France. Using Labor Force Surveys from 1994 to 2012 and the task content of occupations from the O*NET database, we estimate that while immigrants and natives have experienced a similar employment dynamics, wage dynamics differs across the two nativity groups. Immigrants' wage growth outpaced that of natives along the wage distribution. We show that this different wage growth mainly comes from a divergent between-occupation wage variation, whereas within-occupation wage changes remain fairly close among natives and immigrants. We find that the contribution of returns to tasks to between-occupation wage changes does not significantly differ among both nativity groups. Estimations from a conditional logit model suggest that the divergence in between-occupation wage changes across natives and immigrants results rather from different occupation choices.

JEL Codes: D12, J15, J21, J31, J61, O33
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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 policy debate along various dimensions. One central and often contentious issue is how immigrants fare in societies of host countries. Understanding immigrants' success in host country 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' relative employment and wage performance. This paper will focus on the relative wage performance of immigrants in France over the last two decades. Despite a long history of hosting immigrants from various origins and various motives[1], the country is viewed nowadays as less welcomed to new immigrants. Beyond this major shift in immigration policy, France is an interesting case study given its institutional peculiarities and especially its rigid labor market institutions.

There is a very large literature analyzing the sources of wage inequality and divergent wage dynamics between natives and immigrants. Traditional analysis attributes this wage inequality essentially to three different factors. The first one is human capital in the broad sense, *i.e.* including schooling, experience and skills (see Katz and Murphy (1992), Algan et al. (2010), Kee (1995), Card (2005)). 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 (2005a) for Australia, Friedberg and Hunt (1995) for Israel or Lam and Liu (2002) for Hong Kong).

A second factor underlined by the migration literature as responsible for wage inequality between natives and immigrants refers to reservation wages. Whatever the labor market considered, immigrants are new comers. As a consequence, 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 the empirical works of 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), Chassamboulli and Palivos (2014) and Chas-

[1] During the 20th century, and before WWII, French immigrants were mostly refugees from eastern neighborhood countries (Russia, Poland, Armenia). Soon after WWII, France welcomed immigrants fleeing dictatorial regimes in southern Europe (Spain and Portugal). In the 1960s, with the end of colonies in Africa, over a million of "pieds noirs", mostly from Northern Africa, were repatriated. Starting from 1970s, most of subsequent flows were from these former colonies. Over the last two decades, refugees constitute a growing share of immigrants, although family reunification remains the main gate door for immigrants in France. Except for very special qualifications, doors to economic migration are officially closed since 1977.

samboulli and Peri (2014)).

The third factor is discrimination. Once differences in schooling, experience and reservation wages have been controlled for, it remains an unexplained part of wage differential between natives and immigrants. This "migrant" effect is often attributed to discrimination (see Algan et al. (2010), Card (2005) or Kee (1995)).

Since the seminal papers of 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, occupations and their task content are placed at the heart of the literature on employment and wage dynamics.[2] The inclusion of occupations and their task content in the migration literature is though relatively recent. According to Roy (1951)'s argument, specialization is due to self-selection into jobs based on comparative advantages. Consistently with this argument, Peri and Sparber (2011b), Peri and Sparber (2011a), Peri and Sparber (2009) or D'Amuri and Peri (2014) underline that relative skill endowments differ between natives and immigrants. Whereas natives have a comparative advantage in communication and language-intensive tasks, immigrants have a comparative advantage in manual tasks. Following an immigration induced labor supply shock, natives reallocate towards communication and language task-intensive occupations while immigrants become specialized in manual task-intensive occupations.[3] If immigrants and natives specialize in different occupations, we should observe a different pattern of wage changes between the two nativity groups, due to differences in task intensity across occupations and different returns to tasks. Indeed, similar skills are applied to perform different sets of tasks, whose importance and combinations differ across occupations (Acemoglu and Autor (2011)). Therefore, the same skills may be differently rewarded depending on the nature of the tasks performed in occupations. For instance, manual skills are likely to be better rewarded in manual task-intensive occupations than in cognitive task-intensive occupations.

We seek to assess whether identical skills are priced differently between natives and immigrants because of different tasks performed. This could explain potentially different wage dynamics between immigrants and natives. We characterize the nature of tasks performed by immigrants and natives in their occupations and quantify how this task specialization affects changes in the wage distribution. With the notable exception of Butcher and DiNardo (2002), there are few analysis on the immigrants' performance along the wage distribution. Methodologically, our paper is closely related to Firpo, Fortin, and Lemieux (2011), which stands for the most systematic analysis

[2] According to these studies, 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.

[3] The specialization of immigrants in low paid jobs and its consequences on native population is also analyzed by Cortés and Tessada (2011) or Farre, Gonzalez, and Ortega (2011). On the basis of US data, Cortés and Tessada (2011) find that the reduction in the price of services (being close substitutes for household production) fostered by recent waves of low-skilled immigration has led high-skilled women (earning above the median of the wage distribution) to substitute their own time invested in the production of household goods with hours of work. A similar study but using Spanish data is proposed in Farre, Gonzalez, and Ortega (2011). They find that over the last decade immigration led to an important expansion in the size of the household services sector and to an increase in the labor supply of women in high-earning occupations.

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 linked to the task content of occupations.[4]

In contrast with previous papers, our work focuses on wage dynamics within and across nativity groups. Immigrants represent a particularly interesting group of study to investigate. Downgrading upon arrival at the host country, social networks and relative skill endowments may explain that immigrants perform different tasks and specialize in different occupations than natives. Even if the returns to tasks are the same for both immigrants and natives, we may observe different returns to identical skills between immigrants and natives, since identical skills are applied to different tasks due to the fact that both nativity groups do not allocate in the same occupations.

Using French data over the last 20 years (1994-2012)[5], we find that immigrants and natives have different wage dynamics over this period. These different wage dynamics seem to be mainly explained by different wage changes across occupations. We find that the contribution of returns to tasks to between-occupation wage changes is not significantly different between natives and immigrants. Using a conditional logit, we conclude that differences in between-occupation wage changes between natives and immigrants are mainly due to different occupational choices.

In the next section, we present the data we use. We provide some evidence on the French economy in Section 3. We show that, in spite of similar employment dynamics over the period 1994-2012, wages have evolved differently for natives and immigrants. We propose in Section 4 a simplified theoretical framework providing a rationale to the econometric approach presented in Section 5 and to the econometric estimations presented in Section 6.

2 Data

2.1 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 French 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.

The French LFS provides information on wages and the occupation for each employed individual

[4] 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.

[5] 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.

among a list of 350 possible occupations such as "gardener", "messenger", "clerk in banking activities", or "financial manager". Farmers, civil servants, the military and clergymen are excluded. All jobs related to these categories are dropped from the sample.

Some jobs may have disappeared, while new ones are emerging. The French LFS modified the job classification in 2003 in order to take into account the changes in occupations. We paid 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.

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 a specific occupation classification based on the American Standard Occupational Classification (SOC). We assume that the task content of occupations is identical in the United States and in France, so we can use the O*NET classification to analyze the job content of French occupations.[6] 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, thanks to the EurOccupations database, which covers 1,594 occupational titles within the ISCO-08 classification.[7] 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, a mapping table from the ISCO-08 to the SOC- 2010 classification is used 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.

In order to classify occupations by their task intensity, we follow Autor, Levy, and Murnane (2003)'s strategy (see Appendix A.2 for a summary on the content of the task according to the authors). In this paper 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,

[6] 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.

[7] 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.

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 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.[8] 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 role of occupations in wage differentials between individuals, we first implement a wage variance decomposition analysis in each nativity group. We first consider the wage variance due to observable individual characteristics such as age, education, residence duration and origin country. Specifically, we define 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 residence duration intervals for immigrants (less than 10 years, more than 10 years). These groups are used to define up to 72 different individual cells each year. The French LFS distinguishes among 27 countries or geographical areas of birth, so we introduce a dummy by origin. We estimate:

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

where w_{int} stands for the hourly wage of an individual i from nativity group n (natives, immigrants) in year t, $\text{age}\times\text{educ}\times\text{resid}_{int}$ stands for up to 72 different cells (36 for natives), and country contains a set of dummy variables for geographical origins for immigrants. The estimated residual wage $\widehat{\epsilon}_{int}$

[8] For example if we consider a job classification at the two digit level, liberal professionals (as lawyers, doctors or dentists) have a non-routine manual intensity index equal to 0.0789, a non-routine analytical-interactive intensity index equal to 0.8106 and a routine intensity index equal to 0.1104. In contrast, for non-qualified blue collar workers these indices equal respectively 0.1589, 0.6614 and 0.1795.

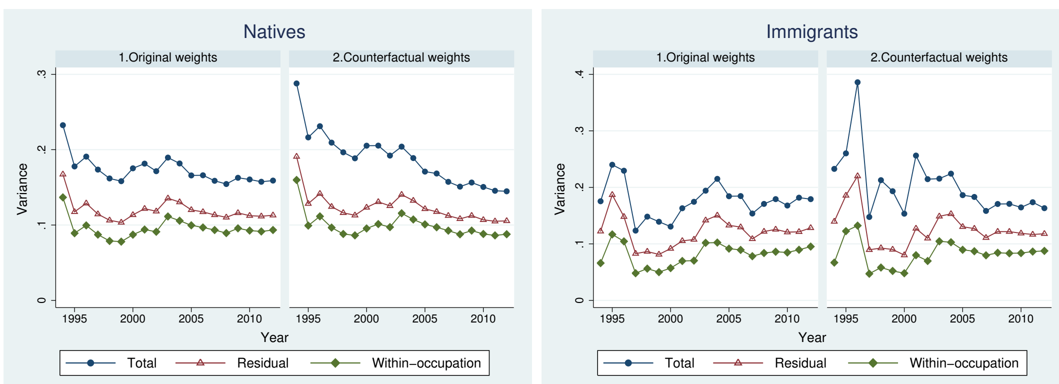
is then regressed on a set of occupational dummies to estimate:

$$\widehat{\epsilon}_{int} = \theta_{njt}\,\text{occupation}_{injt} + \nu_{int}$$

where occupation_{injt} stands for the j-th occupational dummy and ν_{int} is the part of the first stage residual wage that is not explained by differences across occupations.

We implement this variance decomposition analysis under two alternative scenarios. In a first scenario, we apply the original weights provided by LFS. In a second scenario, we reweight each nativity sample so as to get the same composition in terms of age, education and residence duration over all years.[9] This second scenario eliminates the impact of composition changes over time in each nativity group.

Figure 1: Variance decomposition analysis by nativity group. French LFS 1994-2012



We report both scenarios for natives and immigrants in Figure 1. The vertical distance between the total wage variance and the residual wage variance corresponds to the part of the wage variance that is explained by age, education, residence duration and origin country differences. Then, 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. This between-occupation component of the residual wage variance includes wage differentials due to different occupational characteristics (*e.g.* sector, complexity) and task content. Finally, the vertical distance between the X-axis and the within-occupation residual wage variance corresponds to the part of residual wage variance that is explained by differences within occupations. This within-occupation component of the residual wage variance refers to wage differences across individuals working in the same occupation, resulting from differences in the skill composition, returns to skills, unobserved abilities or reservation wages.

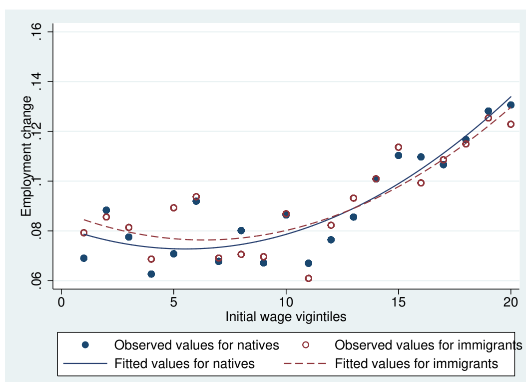
Whatever the nativity group considered and the weights applied, we observe that most of the

[9] 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.

total wage variance is explained by wage differences within and between occupations. Moreover, the importance of occupations has also increased overtime for immigrants and natives.[10] The occupation thus appears as a relevant unit of analysis for examining wage differentials between individuals and their evolution over time.

We then focus on times changes in employment and wages at the occupational level. We characterize in Figure 2 the dynamics of occupational employment for natives and immigrants over the period 1994-2012. We distinguish occupations according to their skills, proxied by the median hourly wage for each job at the beginning of the period (see Goos and Manning (2007)). Occupations are collected into 20 even-sized groups according to their median wage in order to form vigintiles of occupational wages. Figure 2 plots the average employment growth between 1994 and 2012 in these 20 groups. We also present a quadratic fit of average employment growth by vigintile. Figure 2 suggests a mild U or rather a J shape relationship between employment growth and skills.[11] We confirm findings of a previous work showing a polarization of the French labor market (see Moreno-Galbis and Sopraseuth (2014)).

Figure 2: Average employment growth over the 1994 median wage in the occupation. French LFS 1994-2012.



More interestingly for our purpose, employment changes among immigrants and natives along the occupational wage distribution have been relatively similar.[12] This suggests that beyond their potentially important skill differences, immigrants and natives have responded to a common and similar labor demand shift. To what extent this similar pattern of occupational employment dynamics has translated into a similar pattern of wage dynamics?

In Figure 3, we provide a preliminary answer. Considering the same grouping of occupations as in

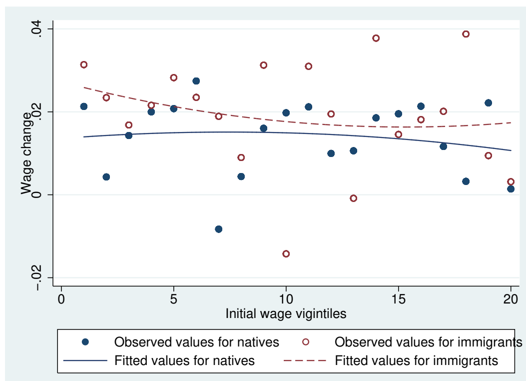
[10]The gap between the residual and total variances is narrowing.

[11]We choose to consider the change in log employment over the 1994-2010 period, as in Goos and Manning (2007). Autor, Levy, and Kearney (2006) examine the change in employment share.

[12]As previously highlighted, due to informational networks, immigrants have a tendency to cluster towards occupations where there is a large share of their country peers. The progressive polarization of the labor market is then likely to have differently affected immigrants depending on their geographical origin (some groups were essentially clustered on routine positions while others were clustered on non-routine positions). Appendix C reports changes in the employment structure for the period 1994-2012, by geographical origin.

Figure 2, we plot the average wage growth between 1994 and 2012. First, we note that the wage growth of immigrants is higher than that of natives along the wage distribution, which may denote a higher rate of human capital investment among immigrants along the line suggested by Chiswick (1978). Relatively to natives, the wage growth of immigrants has been more important at the tails of the wage distribution. Overall changes in the wage distribution among natives have not kept pace with changes in the employment structure. Wage changes among immigrants are more in line with changes in their employment structure. These changes could reflect changes in the composition of workers' skills in expanding and contracting occupations and/or changes in the returns to skills in these occupations. We will investigate this issue in the econometric analysis.

Figure 3: Average wage growth over the 1994 median wage in the occupation. French LFS 1994-2012.



Why do we observe differences in the wage dynamics of immigrants and natives despite similar changes in their employment structure?[13] As suggested by our variance decomposition analysis, these different wage changes between natives and immigrants along the wage distribution may result from a different allocation across occupations and/or from different individual characteristics within occupations. In other words, the different wage dynamics between natives and immigrants may come from differences in the between-occupation component and/or the within-occupation component of wage changes.

Different occupational choices between natives and immigrants would imply differences in the tasks

[13]The divergent wage dynamics by nativity group is confirmed when estimating the quadratic equation:

$$d(\log \text{wage}_i) = \alpha + \beta_1 \log w_{1994} + \beta_2 (\log\ w_{1994})^2$$

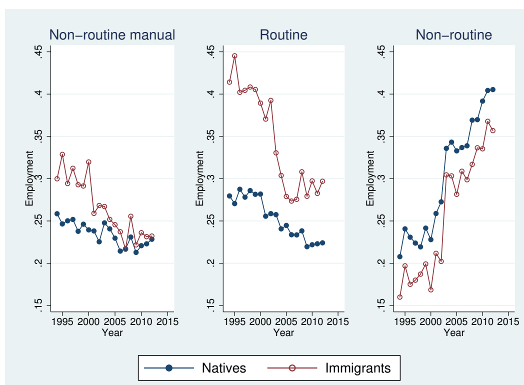
where i stands for natives and immigrants. Implementing a weighted OLS (weights equal native (respectively immigrant) employment in the occupation) estimation we obtain:

$$\begin{aligned} d(\log \text{wage}_{native}) &= -0.3150184^{***} + 0.0818689^{***} \log w_{1994} - 0.0050216^{***} (\log w_{1994})^2 \\ d(\log \text{wage}_{immigrant}) &= 0.1184426^{***} - 0.0206331^{***} \log w_{1994} + 0.0010486^{***} (\log w_{1994})^2 \end{aligned}$$

All coefficients are statistically different from zero. For immigrants the coefficient on the linear term, $log\ w_{1994}$, is negative and significant and the coefficient associated with the quadratic term, $(log\ w_{1994})^2$ is positive and significant, confirming a U-shaped progression of wages. For natives, no quadratic progression seems to arise.

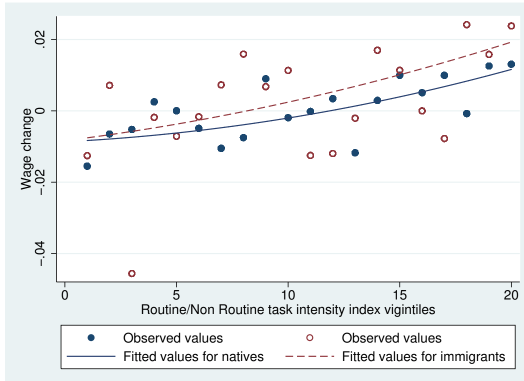
performed. We start first by analyzing how nativity groups' occupational choices are influencing the type of tasks they are performing. We examine in Figure 4 the evolution between 1994 and 2012 in the share of workers employed in the upper quartile of the task intensity index distribution in 1994, as defined for natives. Figure 4 portrays a situation in which contracting and expanding occupations are similar for immigrants and natives. The share of workers employed in non-routine manual task-intensive occupations and routine task-intensive occupations has followed a decreasing path for both natives and immigrants. In contrast, the share of immigrant and natives workers employed in non-routine analytical/interactive task-intensive occupations has followed a continuously increasing path. Figure 4 also suggests that overall changes in the occupational structure have contributed to a convergence in the tasks performed by immigrants and natives. While the share of immigrant workers employed in non-routine manual task-intensive occupations was clearly above that of natives at the beginning of the period, the two shares are almost identical by the end of the period. Similarly, while immigrants remain clearly more specialized than natives in routine task-intensive occupations, the gap has been narrowing throughout the period. This pattern of task specialization should explain the between-occupation wage component of wage dynamics.

Figure 4: Dynamics of the initial top quartile of occupations the most intensive in non-routine and routine tasks (among natives). French LFS 1994-2012, EurOccupations, O*NET.



The within-occupation component of the wage dynamics will result rather from disparities within occupations related to changes over time in skill composition and skill returns. Figure 5 plots wage changes depending on the value of the "Routine /Non Routine" intensity index associated with the occupation. We define the different vigintiles of the routineness index distribution and compute immigrant and native wage changes associated with each vigintile. Native wage changes follow an increasing path along the routineness index. This may be surprising at first sight, but it is consistent with the decreasing trend in the native wage changes estimated along the wage distribution in Figure 3. The pattern of wage growth along the routineness index is more accentuated for immigrants. Immigrant wages have increased relatively more than native wages in similar occupations in the top third of the routineness index. As previously, this could reflect differences in skill endowment or differences in specific skill returns between immigrants and natives, an issue on which we shall

Figure 5: Average wage growth by Routine / Non Routine task intensity. French LFS 1994-2010.



return in the econometric analysis.

To understand the sources of the different wage dynamics between natives and immigrants, we need to identify the determinants of between- and within-occupation wage changes, *i.e.* changes in occupational-level average wage and wage dispersion. These two components of wage changes have been affected by changes in skill endowments and skill returns (or prices). Different wage dynamics between natives and immigrants may result from different changes in skill endowments and skill returns. Natives and immigrants are likely to have experienced different changes in skill returns because of different occupational choices, as suggested in Figure 4, assuming that skills are priced differently depending on the tasks performed. Within the same occupations, the skill endowments of natives and immigrants may have changed differently, justifying different wage changes for identical tasks performed. Before assessing the relative importance of these explanations in the econometric analysis, we propose in the next section a simple theoretical framework to specify the between- and within-occupation components of wage changes.

4 Theoretical setup

This section seeks to provide a simplified framework to guide the econometric approach proposed in Section 5 and help interpreting the results. We consider an economy composed by two sectors, a final good sector and an intermediate good sector. In the final good sector, firms produce a numeraire final good (its price is normalized to unity) using as inputs three types of intermediate goods: non-routine manual, routine and non-routine analytical-interactive intermediate goods. In the intermediate good sector, firms use only labor to produce non-routine manual intensive or non-routine analytical-interactive intensive intermediate goods. To be consistent with the literature on task biased technological change – TBTC hereafter – (see for example Autor, Levy, and Murnane (2003) or Autor and Dorn (2013)), we assume that firms producing routine intensive intermediate goods use labor and computer capital in their production process. We consider a partial equilibrium model (*i.e.* prices are exogenously given) where both the final good sector and the intermediate good sector are assumed to be perfectly competitive.

4.1 The final good sector

For simplicity, we represent the production function of the final good sector as a CES function combining the three considered intermediate goods in the production process:

$$Y_t = A_t \left[\sum_{j=1}^{3} \alpha_j \left(Q_{jt}\right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{1}$$

where A_t stands for Total Factor Productivity, ρ is the elasticity of substitution between intermediate goods, Q_{Mt} corresponds to the quantity of non-routine manual intermediate good, Q_{Rt} the quantity of routine intermediate good and Q_{At} the quantity of non-routine analytical-interactive intermediate good, α_j is the productivity of intermediate good type j in contributing to final output and is supposed to be time-invariant. The cost of each type of intermediate good is exogenously given and equals, respectively, p_{Mt}, p_{Rt} and p_{At}.
Given these prices, the final good firm must choose the quantity of each intermediate good so as to maximize its profits:

$$\max_{Q_{Mt}, Q_{Rt}, Q_{At}} \quad \Pi_t = A_t \left[\sum_{j=1}^{3} \alpha_j \left(Q_{jt}\right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} - p_{Mt}\, Q_{Mt} - p_{Rt}\, Q_{Rt} - p_{At}\, Q_{At} \tag{2}$$

From the FOCs, we can easily define the relative price of routine intermediate goods as:

$$\frac{p_{Rt}}{p_{Mt}} = \frac{\alpha_{Rt}}{\alpha_{Mt}} \left(\frac{Q_{Mt}}{Q_{Rt}} \right)^{1/\rho} \quad \text{and} \quad \frac{p_{Rt}}{p_{At}} = \frac{\alpha_{Rt}}{\alpha_{At}} \left(\frac{Q_{At}}{Q_{Rt}} \right)^{1/\rho} \tag{3}$$

4.2 The intermediate good sector

In the intermediate good sector, firms producing non-routine manual intermediate goods or non-routine analytical/interactive intermediate goods, use labor as a single factor of production. Firms producing routine goods employ two perfectly substitutable production factors: labor and computer capital. Non-routine manual, routine and non-routine analytical-interactive intermediate goods production processes differ in the relative intensity of the tasks used in each process (non-routine manual tasks, routine tasks and non-routine interactive/abstract tasks, respectively).
Labor is then supplied to the intermediate good sector. In each intermediate good sector firms use a linear technology such that

$$Q_{jt} \quad = \quad L_{jt} = \sum_{i=1}^{N_j} s_{ij} \quad \text{for} \quad j = M,\ A \quad \text{and} \quad Q_{jt} = L_{jt} + C = \sum_{i=1}^{N_j} s_{ij} + C \quad \text{for} \quad j = R$$

Labor is measured in efficiency units so that s_{ij} stands for the efficient unit of labor of worker i employed in occupation j. N_j denotes the number of workers employed in occupation j. C stands

for units of computer capital and, as labor, it is assumed to be inelastically supplied. Wages per efficient unit of labor employed in the intermediate good sector are denoted as w_{Mt}, w_{Rt} and w_{At}, and they will determine the price at which intermediate goods are sold to final firms, p_{Mt}, p_{Rt} and p_{At}. Note that because w_{Rt} stands for the wage per efficient unit of labor and since labor and computer capital are perfectly substitutes in the routine good production process, the cost of a unit of efficient labor equals the cost of a unit of computer capital: $w_{Rt} = p_{Ct}$.
The intermediate good sector is assumed to be perfectly competitive. Firms must choose the quantity of labor to hire so as to maximize their profit.

$$\max_{L_{jt}} \ \Pi_{jt} = p_{jt}Q_{jt} - w_{jt}L_{jt} \quad \text{for} \quad j = M,\ A \tag{4}$$

$$\max_{L_{jt},C} \ \Pi_{jt} = p_{jt}Q_{jt} - w_{jt}(L_{jt} + C) \quad \text{for} \quad j = R \tag{5}$$

Profit maximization leads firms to equalize the exogenously determined wage to the value of the marginal productivity of labor (or computer capital when considering the routine good):

$$p_{jt}Q'_{jt}(L_{jt}) = w_{jt} \tag{6}$$

Because we assume a linear technology for the production of intermediate good the marginal productivity of labor and computer capital is equal to one and the wage per efficiency unit of labor is equal to the price of intermediate output. The optimality condition in the intermediate good sector implies: $p_{Mt} = w_{Mt}$, $p_{Rt} = p_{Ct} = w_{Rt}$ and $p_{At} = w_{At}$.
Condition (3) can thus be rewritten as:

$$\frac{w_{Rt}}{w_{Mt}} = \frac{\alpha_{Rt}}{\alpha_{Mt}} \left(\frac{Q_{Mt}}{Q_{Rt}}\right)^{1/\rho} \quad \text{and} \quad \frac{w_{Rt}}{w_{At}} = \frac{\alpha_{Rt}}{\alpha_{At}} \left(\frac{Q_{At}}{Q_{Rt}}\right)^{1/\rho} \tag{7}$$

4.3 The worker's side

4.3.1 The supply of occupation specific skills s_{ij}

The workforce is composed of a continuum of workers with heterogeneous abilities. We assume that workers are heterogeneous with respect to their cognitive abilities but homogeneous with respect to their manual abilities. More precisely, each worker is characterized by a fixed level of cognitive ability and, additionally, each individual is also endowed with one unit of homogenous manual ability. The continuum distribution of cognitive abilities is defined over the support $[\underline{C}, \overline{C}]$.
The quantity of efficient units of labor supplied by a worker in an occupation depends on her ability endowment. The quantity of labor efficient units produced by workers using their ability endowment vary across occupations. In particular, we shall assume that cognitive abilities are more efficiently used in performing analytical-interactive tasks rather than routine and manual tasks. Conversely, manual ability is more useful in performing manual tasks rather than abstract or routine tasks. The number of labor efficient units (*i.e.* quantity of skills) produced in each occupation by the worker is therefore specified according to:

$$s_{ij} = \begin{cases} e^{\beta_M + \gamma_{Mt} C_i} & \text{for } j = M \\ e^{\beta_R + \gamma_{Rt} C_i} & \text{for } j = R \\ e^{\gamma_{At} C_i} & \text{for } j = A \end{cases}$$

where β_j and γ_{jt} are respectively the contributions of manual and cognitive abilities to the production of labor efficient units for task of type j. Parameters β_j and γ_{jt} are proportional to the earning capacity of a worker in a particular occupation and correspond to the differential weight attached to workers' abilities when producing one unit of intermediate good. We will assume that γ_{jt} is time changing. As underlined by Gibbons et al. (2005) these differential weights generate a sorting of workers based on their comparative advantage.

4.3.2 The workers' earnings

A worker with a quantity of efficient labor equal to s_{ij} will earn a different wage depending on the type of occupation he has since 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. Wages perceived by the worker in each occupation will then equal $W_{ijt} = s_{ijt} * p_{jt} = s_{ijt} * w_{jt}$, for $j = M, R, A$, or with the log-specification:

$$\begin{aligned} \ln(W_{iMt}) \equiv \omega = \ln(p_{Mt}) + \ln(s_{iMt}) = \ln(p_{Mt}) + \beta_M + \gamma_{Mt} C_i = \ln(w_{Mt}) + \beta_M + \gamma_{Mt} C_i \\ \ln(W_{iRt}) \equiv \omega = \ln(p_{Rt}) + \ln(s_{iRt}) = \ln(p_{Rt}) + \beta_R + \gamma_{Rt} C_i = \ln(w_{Rt}) + \beta_R + \gamma_{Rt} C_i \\ \ln(W_{iAt}) \equiv \omega = \ln(p_{At}) + \ln(s_{iAt}) = \ln(p_{At}) + \gamma_{At} C_i = \ln(w_{At}) + \gamma_{At} C_i \end{aligned} \tag{8}$$

Due to the divergent returns to identical skills across occupations, workers employed in different occupations earn different wages. For example, in manual intensive tasks, manual skills are better rewarded than in routine intensive tasks, and similarly, in abstract intensive occupations, cognitive skills will be better rewarded than in manual or routine intensive occupations. Consequently, the wage gap between two workers will not be the same across different occupations.
Moreover, to ensure that the three intermediate goods are produced[14] we impose at any moment t: $\ln(p_M) + \beta_M > \ln(p_R) + \beta_R > 0$ or $\ln(w_M) + \beta_M > \ln(w_R) + \beta_R > 0$.[15] Therefore, the earning capacity of manual skills must be the highest in manual occupations and the lowest in the routine occupations (manual skills are not used in the abstract occupations). Furthermore, at any t, $\ln(p_A) + \gamma_A > \ln(p_R) + \gamma_R > \ln(p_M) + \gamma_M$, that is, the earning capacity of cognitive skills must be the highest in abstract task-intensive occupations and the lowest on manual task-intensive occupations.

[14] We have assumed that the production function of the final good is CES, which implies that, at the equilibrium, we could have a situation where the firm does not employ the three intermediate goods. For simplicity we assume that the firm uses a positive quantity of each intermediate good to produce.

[15] This can be proved by contradiction, assume that the lowest cognitive ability worker does not find it profitable to work in occupation M ($\ln(p_M) + \beta_M < \ln(p_R) + \beta_R$), then so it is for the all workers. Then return in manual occupation will go to infinity, which contradicts the assumption that $\ln(p_M) + \beta_M < \ln(p_R) + \beta_R$.

4.3.3 The sorting of workers across occupations

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

$$W^*_{ijt} = \underset{j=M,R,A}{\arg\max}\,\{W_{iMt}, W_{iRt}, W_{iAt}\} \tag{9}$$

4.4 From theory to econometrics

Denoting $\omega = \ln(W_j)$ for $j = M, R, A$ the log of wages, the average of ω across individuals within each occupation is given by:

$$\overline{\omega}_{jt} = ln(p_{jt}) + \beta_j + \gamma_{jt} * \overline{C}_{ij} \qquad \text{or} \qquad \overline{\omega}_{jt} = ln(w_{jt}) + \beta_j + \gamma_{jt} * \overline{C}_{ij} \tag{10}$$

implying the following standard deviation of wages across individuals within an occupation $\sigma_{\overline{\omega}_{jt}} = \gamma_{jt} * \sigma_{C_{ij}}$, since the wage by efficient unit of labor, $p_{jt} = w_{jt}$, is the same across individuals employed in the same occupation, so that the variance is nil. The same reasoning applies to the contribution of manual abilities, β_j, to the production of good j which is identical across individuals and it is assumed to be time invariant. In contrast, the contribution of cognitive abilities, γ_{jt}, to the production of intermediate input j is assumed to vary across time. Unlike most of the literature, and especially Acemoglu and Autor (2011), we assume that the contribution of cognitive abilities to the production process is time varying. We do so because we are interested in wage disparities within occupations, while most of the literature focuses on wage disparities between occupations.
While γ_{jt} changes along time, we assume the cognitive skill distribution within occupations is time invariant, that is $\overline{C}_{ij}$ is constant. Changes in the average wage within an occupation are then given by:

$$\Delta\overline{\omega}_{jt} = \Delta\ln(p_{jt}) + \overline{C}_{ij}\Delta\gamma_{jt} \qquad \text{or} \qquad \Delta\overline{\omega}_{jt} = \Delta\ln(w_{jt}) + \overline{C}_{ij}\Delta\gamma_{jt} \tag{11}$$

where both the contribution of cognitive abilities, γ_{jt}, and the selling price of intermediate good j, $p_{jt} = w_{jt}$, are allowed to change over time. Most papers on TBTC manage to econometrically identify p_{jt} by assuming that the contribution of cognitive abilities to the production process, γ_{jt}, has remained constant over time. Here, our identification hypothesis requires the skill distribution within the occupation to be time invariant, so that we can identify $\Delta\gamma_{jt}$ from $\Delta\sigma_{\omega_{ijt}} = \Delta\gamma_{jt} * \sigma_{C_{ij}}$ and then use equation (11) to identify $\Delta\ln(p_{jt}) = \Delta\ln(w_{jt})$.
Because we do not have individual longitudinal data, in order to assess the importance of returns to skills as a determinant of the divergent wage dynamics across nativity groups, we will compare time wage changes along the wage distribution (decile by decile) of each occupation. For this purpose, let F_{jt} denote the distribution of s_{ij} (or C_{ij} since manual skills are homogeneous across workers) within occupation at time t, which in the simple one dimension case depends only on cognitive

skills. Under suitable normalization the q^{th} quintile of the distribution of wages is equal to:

$$\omega_{jt}^{q} = \overline{\omega}_{jt} + \gamma_{jt} F_{j}^{-1}(q), \tag{12}$$

where the wage at quintile q equals the average wage of the distribution (equation (10)) plus the marginal return γ_{jt} corresponding to the cognitive ability level of that quintile.
Taking differences over time $\Delta\omega_{jt}^{q} = \Delta\overline{\omega}_{jt} + F_{j}^{-1}(q)\Delta\gamma_{jt}$, where $F_{j}^{-1}(q)$ is not modified since we are assuming that the distribution of cognitive skills is time invariant and $\Delta\overline{\omega}_{jt}$ is driven by equation (11).
Solving for $F_{j}^{-1}(q)$ in (12) at the base period gives $F_{j}^{-1}(q) = \frac{\omega_{j0}^{q} - \overline{\omega}_{j0}}{\gamma_{j0}}$. Replacing in the difference equation yields:

$$\begin{aligned} \Delta\omega_{jt}^{q} &= \Delta\overline{\omega}_{jt} + \frac{\omega_{j0}^{q} - \overline{\omega}_{j0}}{\gamma_{j0}} \Delta\gamma_{jt} = \quad \Delta\overline{\omega}_{jt} + \frac{\Delta\gamma_{jt}}{\gamma_{j0}}(\omega_{j0}^{q} - \overline{\omega}_{j0}) \\ &= a_j + b_j(\omega_{j0}^{q} - \overline{\omega}_{j0}) \end{aligned} \tag{13}$$

where $(\omega_{j0}^{q} - \overline{\omega}_{j0})$ is simply a normalization (quintiles are written in deviation from their average).
The wage variation within a particular quintile depends on:

- the term $a_j = \Delta\overline{\omega}_{jt} = \Delta \ln(p_{jt}) + \overline{C}_{ij}\Delta\gamma_{jt}$, which corresponds to the between-occupation wage variation. This term depends on the average wage change in the occupation, which depends on changes in the market price of tasks and changes in the return to cognitive skills.
- the term $b_j = \frac{\Delta\gamma_{jt}}{\gamma_{j0}}$, which captures the within-occupation component of wage changes due to changes in the return to cognitive skills. Specifically, it measures how the growth rate in the contribution of cognitive skills has widen wages between workers employed in the same occupation but having different levels of skills, as measured by the occupation specific quintile.

Under the assumption that the distribution of cognitive skills within occupations does not change over time, we find a positive correlation between average wage changes across occupations and wage dispersion changes within occupations, *i.e.* $Cov(a_j, b_j) > 0$, since they both depend on returns to cognitive skills.
Finally, we seek to relate time changes in wages along the distribution with tasks carried out by workers. From equation (8), we can relate wages by efficient unity of labor with the effective wage earned by an employee, since $\ln(W_{iIt}) \equiv \omega = \ln(w_{It}) + \beta_I + \gamma_{It}C_i$, for $I = R, M, A$. Then, using equations (11) and (12) we can easily justify the relationship between the task indices and the between- and within-occupation components of wage changes:

$$a_j = \pi_0 + \pi_{Rj}R_j + \pi_{Mj}M_j + \pi_{Aj}A_j + \varsigma \quad \text{or} \quad b_j = \delta_0 + \delta_{Rj}R_j + \delta_{Mj}M_j + \delta_{Aj}A_j + \epsilon \tag{14}$$

where again M_j, R_j and A_j are the intensity indices of non-routine manual, routine and non-routine analytical-interactive tasks in occupation j, and π_{kj} and δ_{kj} for $k = M, R, A$ are the linear projections of the between- and within-occupation components of wage changes on these task indices. As an attempt to assess whether immigrants' skills are priced differently, we will estimate whether coefficients π_{kj} and δ_{kj} are the same for immigrants and natives.

4.4.1 The limits of our identification strategy

Our interpretation of sources of wage changes and our identification strategy strongly rely on the hypothesis of time-invariant skill distribution within occupations.[16] This assumption is clearly inconsistent with the sorting behavior of workers along time, based on their comparative advantages in terms of skills. This sorting behavior will be driven by both price changes and changes in the relative contribution of cognitive and manual abilities to efficient units of labor (resulting from technological changes).

At the equilibrium, the mapping of abilities into skills and the optimal decision rule (9) define two thresholds: (i) $C_{lt} = \frac{\ln(p_M/p_R)+\beta_M-\beta_R}{\gamma_{Rt}-\gamma_{Mt}}$, which corresponds to the cognitive skill level such that $W_{iMt} = W_{iRt}$, and (ii) $C_{ht} = \frac{\ln(p_R/p_A)+\beta_R}{\gamma_{At}-\gamma_{Rt}}$ which stands for the skill level such that $W_{iAt} = W_{iRt}$. As shown by Figure 6:

$$
\begin{aligned}
\text{all } i \text{ with } C_i &< C_{lt} \text{ choose the Manual (non routine) occupation,}\\
\text{all } i \text{ with } C_{lt} < C_i &< C_{ht} \text{ choose the Routine occupation,}\\
\text{all } i \text{ with } C_i &> C_{ht} \text{ choose the Analytical-Interactive (non routine) occupation.}
\end{aligned}
$$

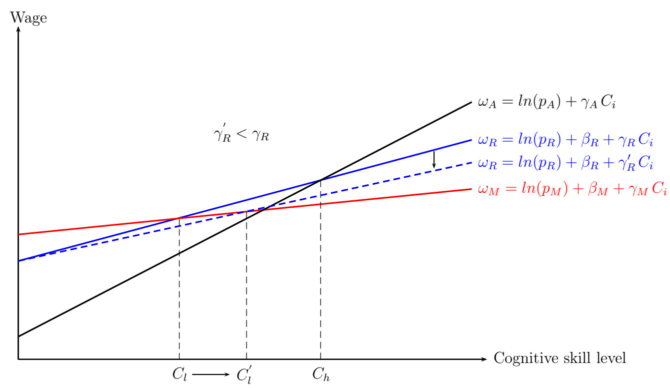
Several conclusions can be drawn from this simple setup. First, within a given type of occupation, there is a continuum of individuals with heterogenous skills. Second, wages differ across individuals within an occupation depending on their cognitive ability level. Third, wages differ from one occupation to another, with a discontinuity point arising in the wage distribution at the threshold values C_{lt} and C_{ht}.

Any exogenous variation in the price of intermediate goods (or tasks), or any technological change modifying the relative contribution of manual and cognitive skills to efficient units of labor, will foster a change in these threshold values and thus workers' reallocation across occupations since their skill price will be modified. A decrease in p_R or γ_{Rt} increases C_{lt} and decreases C_{ht}. A decrease in the relative price of routine tasks triggers a reallocation of workers away from routine occupations towards occupations relying on non-routine manual tasks and on non-routine analytical-interactive tasks. In routine occupations, the lowest skilled workers reallocate towards non-routine manual occupations while the highest skilled workers reallocate towards non-routine analytical-interactive occupations (see Figure 6). As a result, the labor share of occupations at the upper and lower ends of the skill distribution expands while that in the middle is contracted. This corresponds well to the well-known job polarization process.

Note that the selective mobility of workers from routine occupations towards non-routine manual and analytical-interactive occupations implies that, during the TBTC, the skill distribution within occupations did not actually remain fixed over time, as we have assumed in the model in order

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

Figure 6: Wages and skill returns



to be able to identify $\Delta\gamma_{jt}$ and Δp_{jt}. Therefore, we cannot simply compare average wage and wage dispersion changes to infer changes in skill prices, since workers' sorting is going to affect both average wages and wage dispersion within occupations. Moreover, the direction of the bias is unclear. Depending on the exact distribution of cognitive skills, stayers in routine occupations can be on average less or more skilled than movers. Since movers comprise the most and the lowest skilled workers in routine occupations, we will overestimate the price effect in manual occupations, and underestimate it in analytical-interactive occupations.

To deal with this issue, we would need ideally to follow the same workers over time as in the recent contribution of Cortes (2016). 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. We will compare wage changes for workers having the same skill distribution (as measured by their age and education) within occupations and, when working with immigrants, we will also control for the residence duration. 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).[17] This is important for instance if some occupations attract more educated workers over time and the return to education rises, since we will be measuring this effect instead of occupation-specific skill returns.

5 Econometric approach

To identify the source of the different wage dynamics between natives and immigrants, we first characterize changes in the wage distribution across and within occupations in each nativity group taking into account workers' sorting on observables. To do so, we will apply the Roy-type model proposed by Firpo, Fortin, and Lemieux (2011) in a quantile regression analysis in order to estimate

[17]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.

for each occupation the between- and within-occupation components of wage changes (see equation (13)). We consider residual wage changes of males[18] between the periods 1994-96 and 2010-12.[19] Using residual wages allows us to control for the wage variation across individuals that results from differences in age, education or residence duration in the host country when referring to immigrants. Analyzing long difference wage changes helps to limit the influence of short-term variations and thus to identify long-term variations. In addition, using long differences instead of year-to-year changes avoids to get a serial correlation problem, which would lead the estimated standard errors to be understated (see Bertrand, Duflo, and Mullainathan (2004)). Moreover, in our case, the two periods for which we are computing long differences include themselves three years in order to increase the number of observations per occupation, since we are using a very detailed definition of occupations (four digit).[20]

Second, we will assess the contribution of the different types of tasks to these estimated between- and within-occupation residual wage changes. Third, we will repeat the whole estimating procedure while controlling for composition effects that may affect changes in the structure of residual wages between periods 1994-96 and 2010-12. We will use the reweighting strategy suggested by Lemieux (2002), to remove from occupational wage changes the part that results from changes in the composition in terms of age, education and residence duration within occupations.[21] Finally, we implement some additional robustness checks.

5.1 Between- and within-occupation wage changes

Ideally, we would like to estimate directly the determinants of skill pricing γ_{jt} in equation (10) using repeated cross sections on the same set of individuals from a sufficiently large data set containing detailed information on wages, skills, and occupations as for instance in Cortes (2016). This will allow us in particular to track and control for workers' job mobility across occupations characterized by different tasks. Unfortunately, no such data set exists with detailed information on workers' skills beyond their level of education. As in Acemoglu and Autor (2011) and Firpo, Fortin, and Lemieux (2011), we have to rely on repeated cross-sectional data. As a result, we derive some indirect predictions with respect to changes in overall wage dispersion between and within occupations that we relate to the task content of occupations (instead of workers' skills).

As noted by Firpo, Fortin, and Lemieux (2011) and as shown on Figure 6, a first general prediction

[18] Excluding females allows to simplify the analysis because this avoids dealing with labor supply choices related with maternity and family matters.

[19] 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.

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

[21] Therefore, we will not measure residual wage changes that are due to the fact that the share of the group with the greater residual wage may have increased over time in some occupations. This is important since education and experience levels may have increased in some occupations, and more educated and experienced workers have larger residual wage variance.

of the model above is that if γ_{jt} changes differently in different occupations, this should have an impact on both the between- and within-occupation components of wage changes. [22] A second prediction is that changes in both the level and dispersion of wages in occupations should be tightly related to the task content of occupations, which is itself closely related to workers' skills. Although wages depend solely on skills and occupation-specific returns to skills, returns to the task content of occupations should be a useful predictor for changes in both the level and dispersion of wages within occupations.

We propose a basic Mincer type equation and regress the log wage over age, education and country of origin in order to recover the residual wage $\tilde{w}_{int}$:

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

where $\ln w_{int}$ stands for the log hourly wage of an individual i from nativity group n (natives, immigrants) in period $t = 0, 1$, age $\times$ educ_{int} correspond to the different cells defined in each nativity group (4 education levels and 9 age groups), country_c corresponds to the origin country dummy variable. Within each considered period, *i.e.* period 0 from 1994 to 1996 and period 1 from 2010 to 2012, we introduce the yearly dummies year_{yt}. By construction, $\tilde{w}_{int}$ stands for the part of log-wage that is orthogonal to other observable worker characteristics (age, education, origin country). For immigrants, we will enrich the previous wage equation by adding the duration of residence in the host country (above or below 10 years) as a measure of host country specific human capital to remove all wage differences that may stem from these observable characteristics:[23](we then regress the log wage over age $\times$ educ $\times$ resid_{int}).

Then we summarize changes in the residual wage distribution between and within occupations by estimating the parameters a_j and b_j in equation (13). We do so by estimating first a linear regression model that links for each occupation the residual wage change at the different quantiles q of the wage distribution, $\Delta\tilde{w}_j^q$, to the corresponding level of the wage quantile measured at the base period ($t = 0$), $\tilde{w}_{j0}^q$[24]:

$$\Delta\tilde{w}_j^q = a_j + b_j\, \tilde{w}_{j0}^q + \lambda^q + \upsilon_j^q, \qquad (15)$$

where λ^q is a percentile-specific error component, which represents a generic change in the return to unobservable job characteristics or tasks, υ_j^q is an idiosyncratic error term. The gap between wage quantiles is interpreted here as a skill gap. The parameters a_j and b_j stand, respectively, for the between and within occupation wage changes. Both summary statistics are directly linked to changes in skill returns in the occupation, $\Delta\gamma_{jt}$. In addition, the intercept a_j depends on changes

[22] The simple intuition for this prediction is that if the return to a skill heavily used in one occupation goes up (*e.g.* quantitative analytical skills among economists), the wage gap between that occupation (*e.g.* economist) and others will increase (between-occupation component), and so will the wage dispersion within the occupation (*e.g.* between an economist highly endowed with quantitative analytical skills and a mediocre one).

[23] The duration of residence may also capture the cohort effect, so we should be cautious about its interpretation as a measure of specific human capital.

[24] We use here different quantiles of the wage distribution because we have no panel data on workers.

in occupational wage differentials that are not directly related to skills, Δp_j.
From the first step of the analysis, we recover as many a_j and b_j as we have occupations. This allows us to link, in a second step, the estimated intercepts and slopes ($\widehat{a_j}$ and $\widehat{b_j}$) to task content measures within each occupation (see equation (14)). Define these task summary measures as TC_{jk}, for k = (1) non-routine analytical or interactive, (2) routine cognitive or manual, and (3) non-routine manual. The second step regressions are:

$$\widehat{a_j} \;=\; \gamma_0 + \sum_{k=1}^{3} \pi_{jk} TC_{jk} + \mu_j \quad \text{and} \quad \widehat{b_j} = \delta_0 + \sum_{k=1}^{3} \delta_{jk} TC_{jk} + \nu_j \tag{16}$$

6 Results

6.1 Between-occupation vs. within-occupation wage changes

We estimate equation (15) with $q = 10$, that is, we consider 10 even-sized groups (deciles) in each occupation. We keep wage deciles within an occupation for which there is a change compared to the preceding and following deciles. Moreover, in order to be able to compute the long differences between identical wage deciles within an occupation (*e.g.* between the 4th decile of medical secretaries in period 1 and the 4th decile of medical secretaries in period 0), we require both the occupation and the wage decile to exist in period 0 and period 1. By the end, the sample of male natives contains 229 occupations and the sample of male immigrants 146 occupations.

Figure 7: Between- and within-occupation coefficients with constant labor force composition.

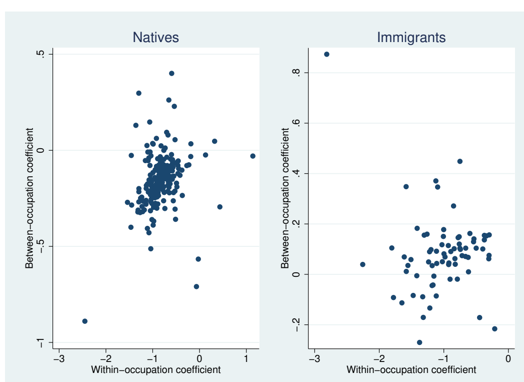
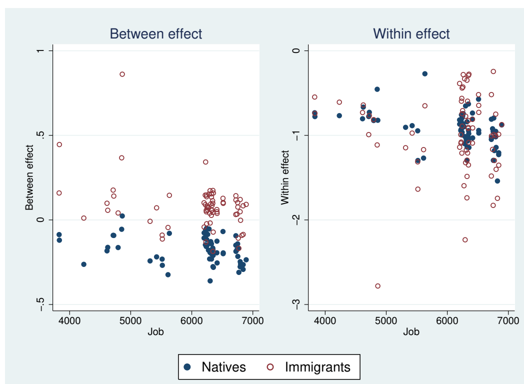


Figure 7 displays the relationship between the between- and within-occupation components of residual wage changes when using the counterfactual weights, so that the composition of the nativity group within each occupation remains constant in terms age, education and residence duration between the two periods. These counterfactual weights are computed using as reference composition for both nativity groups the age-education composition of natives in period 0 for each occupation separately. For immigrants the residence duration composition is the same as in period 0 (see appendix B for a detailed explanation).[25]

Whatever the nativity group considered (and the weights[26]) used, we observe a positive correlation between the two components of the residual wage changes, meaning that occupations characterized by higher growth on average wages (the between-occupation component), are also characterized by higher growth of wage inequality within the occupation (the within-occupation component). This is perfectly consistent with the definition of the between- and within-occupation components of wage changes provided in equation (13), where we observed that $Cov(a_j, b_j) > 0$.[27]

Moreover, as shown in Figure 8, (as well as in Figures 15 and 16 in Appendix C), the difference between natives and immigrants is more important on the between-occupation component than on the within-occupation component. Whatever the occupation, the between-occupation component (*i.e.* the intercept) is systematically larger for immigrants.

Figure 8: Between- and within-occupation wage changes. Comparing Natives vs. Immigrants. Counterfactual weights Residence 2



Another test to identify the source of the different wage dynamics between natives and immigrants consists in comparing the estimated wage changes of immigrants with respect to immigrant wage changes that would have arisen if the immigrant between- and within-occupation wage changes had been equal to that of natives. Using estimates of the between- and within-occupation components, *i.e.* $\widehat{a_j}$ and $\widehat{b_j}$, we can predict immigrant residual wage changes along the distribution:

$$\widehat{\Delta\tilde{w}^q_{Ij}} = \widehat{a_{Ij}} + \widehat{b_{Ij}}\,\tilde{w}^q_{j0}$$

How immigrant residual wages would have evolved if we had observed for immigrants the same within-occupation residual wage change as for natives? Estimating $\widehat{\Delta\tilde{w}_{Ij}} = \widehat{a_{Ij}} + \widehat{b_{Nj}}\,\tilde{w}_{j0}$ is inter-

[25] 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.

[26] See Figure 12 in Appendix C.

[27] Removing occupations having more than 25% of minimum wage earners in period 0 does not alter this result (see Figures 13 and 14 in Appendix C). This is reassuring since a minimum wage increase, which was important in France over the period, together with the reduction in official weekly working hours from 39 to 35, is supposed to affect both dimensions of wage inequality.

Figure 9: Estimated and counterfactual residual wage changes of immigrants

Note: Counterfactual weights have been used so as to ensure that the age-education-residence duration of each nativity group in each occupation is constant between period 0 and period 1.

esting since the parameter b_j is related to changes in skill returns within occupation j, and should be, in principle, similar for immigrants and natives. In the same way, it is interesting to analyze how immigrant residual wages would have evolved if we had observed for immigrants the same between-occupation residual wage change as for natives: $\widehat{\Delta \tilde{w}_{Ij}} = \widehat{a_{Nj}} + \widehat{b_{Ij}}\, \tilde{w}_{j0}$

Figure 9 represents in the X-axis the first-period residual wage and in the Y-axis the corresponding estimated wage change between 1994-96 and 2010-12.[28] Overall, this figure suggests important differences in between-occupation residual wage changes across nativity groups and minor differences in within-occupation residual wage changes across nativity groups. The left-hand side panel suggests that the within-occupation residual wage dispersion of natives and immigrants has been very similar along the distribution, with minor differences at the extremes. Given that the within-occupation component is driven by returns to cognitive skills (see equation (13)), we conclude that within occupations, returns to skills do not seem to significantly differ among nativity groups.

The right-hand side panel of Figure 9 compares the estimated residual wage changes of immigrants with the counterfactual estimate of these wage changes when imposing the same between-occupation change as for natives. The counterfactual estimated locus is situated at a much lower level than the estimate locus of immigrants' wage changes. As suggested by equation (13), the between-occupation wage component is explained by both returns to skills and a demand effect. The left-hand side panel of Figure 9 suggests that returns to skills do not significantly differ between immigrants and natives. Therefore, differences in the between-occupation component must be explained by a demand effect (or price effect). Immigrants may be flowing towards expanding occupations whose wages are increasing.

[28]Since residual (log) wages capture the part of (log) wages that cannot be explained by differences in age, education and residence duration, they may adopt a positive or a negative value.

6.2 The contribution of tasks to between- and within-occupation wage changes

We turn to the estimation of equations in (16) using as weights the size of the nativity group in the occupation. We work with normalized task indices across occupations.[29] Beside technological changes, labor demand may evolve due to changes in the output mix, which may affect occupations differently. Moreover, immigrants and natives within occupations may be employed in different sectors and therefore may be impacted differently by changes in the output mix. To mitigate this effect, we add to our regressions an occupation-specific labor demand shift index, which is constructed from the distribution of occupations across sectors in period 0 and interiorizes changes in the industrial composition between periods 0 and 1 (see Bartik (1991)).[30]

Equations in (16) become then:

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

Results from estimating these equations are provided in Tables 1 and 2. In both tables, we present results obtained for the six scenarios described in Appendix B: Baseline, Origin, Composition 1, Composition 2, Residence 1 and Residence 2. This allows to understand to what extent differences in wage dynamics observed for natives and immigrants come from changes in observable characteristics. To understand the econometric estimations provided below, we need to keep in mind the theoretical foundations of our estimating equation, which are provided by equation (13). The between-occupation component of wage changes may come from a price effect, or from changes in returns to skills. In contrast, within-occupation wage changes are only explained by changes in returns to skills[31]

To comment results reported in Tables 1 and 2, we will proceed first in an "horizontal way" and then in a "vertical way". The former implies comparing the sign and the significance of the task

[29] Let us consider again the summary task measure TC_{jk} for each occupation j and task category k = (1) non-routine analytical-interactive, (2) routine cognitive-manual, and (3) non-routine manual. We define the "normalized" task intensity index by occupation as:

$$TC_{jk}^{norm} = \frac{TC_{jk} - \min[TC_k]}{\max[TC_k] - \min[TC_k]} \tag{17}$$

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] We define as follows the labor demand shift indicator for occupation j and origin i: $\text{DemandShift}_{ji} = \sum_k \left[\frac{N_{kji0}}{N_{ji0}} \cdot \Delta N_{ki}\right]$, where N_{kji0} stands for the number of employees in sector k, occupation j from origin i in period 0. N_{ji0} represents the total number of employees in occupation j from origin i in period 0. ΔN_{ki} is the variation in the number of employees from origin i in sector k. In order to obtain the labor demand shift associated with an occupation, we must sum shifts over all sectors k composing the occupation j.

[31] Therefore, if for a given nativity group, the coefficients associated with tasks arise as significant only for between-occupation wage changes, we will conclude that the between-occupation wage change is driven by a demand (or price) effect. In contrast, if for a given nativity group, coefficients associated with tasks arise as significant for both within- and between-occupation wage changes, returns to tasks would be playing a major role in wage dynamics, particularly if both coefficients are not statistically different.

coefficients depending on the reweighting factor employed in the estimation. This horizontal analysis allows us to measure the importance of composition effects as a determinant of wage dynamics. Then, the vertical analysis consists in comparing for a given nativity group the significance and the size of the task coefficients obtained in Tables 1 and 2. This analysis will allow us to determine whether wage dynamics are driven by a price effect or by changes in returns to skills.

Table 1: Task contribution to between-occupation wage changes, from 1994-96 to 2010-12. Natives vs. Immigrants.

Dependent variables: Between-occupation wage changes

Scenarios	Baseline		Origin		Composition 1		Composition 2		Residence 1		Residence 2	
	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.118***	0.225	0.125***	0.227	0.128***	0.129	0.130***	0.322*	0.127***	0.207	0.129***	0.141**
	(0.0324)	(0.147)	(0.0326)	(0.194)	(0.0344)	(0.119)	(0.0344)	(0.164)	(0.0340)	(0.174)	(0.0343)	(0.0684)
Routine manual-cognitive	-0.143***	-0.154	-0.150***	-0.131	-0.122**	-0.0711	-0.122**	-0.164*	-0.119**	-0.0558	-0.121**	-0.126*
	(0.0484)	(0.0996)	(0.0486)	(0.164)	(0.0484)	(0.156)	(0.0483)	(0.0846)	(0.0478)	(0.157)	(0.0480)	(0.0640)
Non-routine manual	0.203***	0.244*	0.205***	0.107	0.161***	0.170	0.161***	0.105	0.159***	0.0669	0.160***	0.194**
	(0.0410)	(0.138)	(0.0414)	(0.196)	(0.0421)	(0.144)	(0.0420)	(0.134)	(0.0417)	(0.182)	(0.0418)	(0.0733)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	213	89	213	84	215	80	215	75	215	81	215	69
R-squared	0.235	0.099	0.242	0.053	0.209	0.072	0.211	0.151	0.207	0.059	0.209	0.119

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 2: Task contribution to within-occupation wage changes, from 1994-96 to 2010-12. Natives vs. Immigrants.

Dependent variables: Within-occupation wage changes

Scenarios	Baseline		Origin		Composition 1		Composition 2		Residence 1		Residence 2	
	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.352***	0.146	0.349***	-0.447	0.416***	0.0356	0.409***	0.333	0.409***	0.192	0.407***	0.225
	(0.0821)	(0.301)	(0.0812)	(0.726)	(0.0866)	(0.292)	(0.0861)	(0.325)	(0.0863)	(0.268)	(0.0861)	(0.273)
Routine manual-cognitive	-0.487***	-0.0967	-0.486***	-0.208	-0.424***	0.411	-0.416***	-0.206	-0.414***	0.471**	-0.410***	0.0162
	(0.134)	(0.228)	(0.132)	(0.335)	(0.136)	(0.249)	(0.135)	(0.242)	(0.135)	(0.214)	(0.135)	(0.289)
Non-routine manual	0.221**	-0.0977	0.215**	0.0423	0.181*	-0.469	0.177*	-0.104	0.176*	-0.741**	0.173*	-0.233
	(0.0968)	(0.327)	(0.0957)	(0.456)	(0.0990)	(0.308)	(0.0985)	(0.323)	(0.0985)	(0.299)	(0.0982)	(0.288)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	213	89	213	84	215	80	215	75	215	81	215	69
R-squared	0.241	0.017	0.243	0.028	0.234	0.041	0.229	0.035	0.229	0.070	0.227	0.017

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

We start with the horizontal analysis for natives. Estimates from the between- and within-occupation (residual) wage changes provided respectively by Tables 1 and 2 reveal that, among natives, the significance, the sign and the size of the task coefficients are barely altered when removing age-education composition effects. This suggests that sorting on observable worker characteristics has not been a relevant driver of observed between-occupation wage changes for natives. Non-routine tasks (both analytical-interactive and manual) have positively affected wage changes both across and within occupations, while routine tasks have negatively affected wage changes across and within occupations.

The vertical analysis of task returns for natives reveals that, for a given reweighting factor, task coefficients estimated for between-occupation wage changes are smaller than those estimated for within-occupation wage changes. Theoretical foundations provided by equation (13) show that within-occupation wage changes are explained by changes in returns to skills, while between-occupation wage changes may also come from demand changes (price effect) along with changes in returns to skills. Given that task coefficients are larger for within-occupation wage changes, returns to skills seem to be the main driver behind natives' wage dynamics.

We now turn to the analysis of estimates for immigrants. We start with estimates provided in Table 1. The horizontal analysis reveals that composition effects play a major role in immigrants' between-occupation wage changes – see columns (2), (4), (6), (8), (10) and (12). When imposing a constant age-education composition, equivalent to that of natives in the occupation in period 0 (see column (8)), we find that non-routine analytical-interactive tasks have positively contributed to between-occupation wage changes. The contribution of non-routine manual tasks is also positive, but is significant only once we additionally impose the residence duration composition of immigrants within occupations to be constant between period 0 and period 1. The larger wage increase in non-routine manual task-intensive occupations obtained when removing composition effects suggests that the proportion of newly arrived immigrants (with residence duration < 10 years) in these occupations has increased between the two periods. Assuming that newly arrived immigrants are younger and less paid, we underestimate the average wage increase of immigrants in these occupations when failing to control for their increasing proportion between the two periods. In contrast, as for natives, we find that routine tasks have negatively contributed to between-occupation wage changes.

The wage dynamics within occupations draws a different picture. Even when removing composition effects, most of the task coefficients remain non-significant. The contribution of routine tasks (positive) and non-routine manual tasks (negative) becomes significant only once we remove composition effects in terms of age, education and residence duration, using as reference the composition of the nativity group in the occupation in period 0 (Residence 1 scenario). Based on the theoretical foundations provided in equation (13), the vertical analysis of immigrants' task returns allows us to conclude that, in contrast to natives, their wage dynamics is essentially driven by occupation-specific demand effects.[32] This would explain why task coefficients are significant only

[32] When we drop from the sample occupations where more than 25% of their employees are minimum wage earners

for between-occupation wage changes.
Owing to smaller sample size, we lack precision for immigrants. This can be explained by several potential factors. First, our analysis of wage dynamics is based on around 69 to 89 occupations for immigrants against 215 occupations for natives. Second, task indices are also more likely to be strongly correlated in regressions conducted for immigrants given the small number of occupations analyzed. Third, up to now, we have ignored worker sorting on unobservables, which is likely to affect our estimates.[33] Following recent literature, we may expect that this sorting will differ between natives and immigrants if they actually have different skill endowments (Cortes (2008), Ottaviano and Peri (2012), Peri and Sparber (2009)) or lower mobility costs (Chiswick, Lee, and Miller (2005b)). Section 6.4 tests the relevance of these factors as determinants for the lack precision for immigrants' estimations.

6.3 Are there divergent task returns for natives and immigrants?

The previous section analyzes the contribution of different task returns to between- and within-occupation residual wage changes for each nativity group. However, this approach does not allow us to compare whether returns to identical tasks have a divergent influence on between- and within-occupation residual wage changes across nativity groups, since we are working separately on each group.
In this section, we combine the two sets of estimates of between- and within-occupation residual wage changes, obtained from separate regressions for natives and immigrants.[34] We focus now on the sample of occupations where there are both natives and immigrants. Other occupations are ignored, so that we use a common support of occupations for both nativity groups. The sample size varies depending on the reweighting factor employed (from 84 to 71 occupations), *i.e.* on the nature of the composition effects considered. For each occupation, we gather the estimated between- and within-occupation components for natives and immigrants. Thus, we have two observations per occupation, that implies a total going from 178 observations when applying LFS weights to 142 observations when reweighting occupations so that the composition of each nativity group remains constant over time in terms of age, education and residence duration.
Equations in (16) become then:

$$\begin{aligned}
\widehat{a_j} &= \gamma_0 + \gamma_1 \text{Immigrant} + \sum_{k=1}^{3} \gamma_{jk} TC_{jk}^{norm} + \sum_{h=1}^{3} \gamma_{jk} \text{Immigrant} \times TC_{jk}^{norm} + \mu_j, \\
\widehat{b_j} &= \delta_0 + \delta_1 \text{Immigrant} + \sum_{k=1}^{5} \delta_{jk} TC_{jk}^{norm} + \sum_{h=1}^{5} \delta_{jh} \text{Immigrant} \times TC_{jk}^{norm} + \nu_j,
\end{aligned}$$

where the variable "Immigrant" is a dummy variable taking the value 1 if the parameter has

in period 0, the sign of the coefficients remains essentially unaffected, but the coefficients are estimated with less precision. See Appendix D.

[33] As explained in section 4, sorting represents one of the limits of our econometric estimations.

[34] Note that, while task indexes are identical for natives and immigrants within an occupation, the between- and within-occupation wage changes differ between the two nativity groups.

been estimated on the sample of immigrants, 0 otherwise. Each task intensity index measures the contribution of the task component to natives' wage changes across occupations ($\widehat{a_j}$) and within occupations ($\widehat{b_j}$), while each interaction term captures the immigrant-native differential in the contribution of the task component considered.

Results reported in Table 3 confirm for natives that non-routine tasks, either analytical-interactive or manual, have positively contributed to residual wage changes across and within occupations, while routine tasks have contributed in the opposite direction. Moreover, sorting on observable characteristics (age and education) does not play an important role on wage dynamics apart the case when we control for residence duration for immigrants. In this case, returns to non-routine analytical-interactive tasks are no longer significantly different from zero when considering between-occupation wage changes.[35]

None of the coefficients on the interaction terms arises as statistically significant when considering the between-occupation component. In contrast, for the within-occupation component, the interaction term "Img × Non-routine manual" arises as negative and significant when controlling for composition effects. This implies that, in non-routine manual task-intensive occupations, the wage dispersion has less increased among immigrants than among natives.

The coefficient on the dummy variable "Immigrant" arises as positive and strongly significant when considering between-occupation wage changes (while for the within-occupation effect significance is lost when using the weighting factor Residence 2). As shown in Figures 8 and 9, native-immigrant differences in wage dynamics are mostly explained by different between-occupation wage changes. Estimates from Table 3 suggest that differences in between-occupation wage changes are not coming from different returns to tasks between natives and immigrants, but rather from the fact of belonging to the immigrant group. This suggests that immigrants might have allocated towards occupations whose demand is expanding and where internal wage dispersion has increased.

[35] To test the robustness of these (non) differences in task returns between natives and immigrants, 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} stand again for the task content measures within each occupation k = (1) non-routine analytical or interactive, (2) routine cognitive or manual, and (3) non-routine manual. Results in Table 12 in Appendix D reveal that none of the task coefficients arises as significant. This is consistent with conclusions drawn from Table 3: task returns do not differ between natives and immigrants.

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	Origin	Composition 1	Composition 2	Residence 1	Residence 2	Baseline	Origin	Composition 1	Composition 2	Residence 1	Residence 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Immigrant (Img)	0.228***	0.501***	0.380***	0.493***	0.438***	0.242***	0.230	0.377*	0.414**	0.301*	0.432***	0.0642
	(0.0678)	(0.0706)	(0.0468)	(0.0574)	(0.0614)	(0.0506)	(0.159)	(0.224)	(0.168)	(0.175)	(0.158)	(0.196)
Non-routine analytical-interactive	0.0705	0.0808*	0.108**	0.102**	0.124**	0.0636	0.266**	0.278**	0.397**	0.346**	0.419***	0.296*
	(0.0448)	(0.0465)	(0.0487)	(0.0476)	(0.0478)	(0.0454)	(0.128)	(0.129)	(0.154)	(0.145)	(0.149)	(0.156)
Routine manual-cognitive	-0.199***	-0.206***	-0.159***	-0.190***	-0.159***	-0.180***	-0.547***	-0.547***	-0.400**	-0.464***	-0.396**	-0.459***
	(0.0560)	(0.0571)	(0.0594)	(0.0567)	(0.0588)	(0.0587)	(0.158)	(0.157)	(0.179)	(0.172)	(0.178)	(0.173)
Non-routine manual	0.278***	0.285***	0.217***	0.239***	0.205***	0.270***	0.347***	0.342***	0.249**	0.319***	0.230*	0.364***
	(0.0513)	(0.0522)	(0.0529)	(0.0527)	(0.0509)	(0.0530)	(0.105)	(0.104)	(0.123)	(0.108)	(0.119)	(0.111)
Img × Non-routine analytical-interactive	0.146	0.136	0.00908	0.220	0.0598	0.0756	-0.146	-0.727	-0.436	-0.0113	-0.262	-0.0541
	(0.150)	(0.198)	(0.135)	(0.168)	(0.182)	(0.0780)	(0.325)	(0.703)	(0.322)	(0.348)	(0.304)	(0.309)
Img × Routine manual-cognitive	0.0311	0.0556	0.0740	0.0255	0.0667	0.0521	0.404	0.336	0.722**	0.260	0.812***	0.446
	(0.113)	(0.161)	(0.151)	(0.101)	(0.156)	(0.0881)	(0.265)	(0.328)	(0.301)	(0.294)	(0.276)	(0.326)
Img × Non-routine manual	-0.0237	-0.164	-0.0349	-0.134	-0.110	-0.0689	-0.412	-0.297	-0.638**	-0.425	-0.928***	-0.563*
	(0.143)	(0.195)	(0.142)	(0.142)	(0.181)	(0.0890)	(0.339)	(0.433)	(0.315)	(0.328)	(0.317)	(0.287)
Observations	178	168	160	150	162	144	178	168	160	150	162	144
R-squared	0.618	0.788	0.784	0.860	0.767	0.689	0.182	0.130	0.260	0.220	0.266	0.123

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

6.4 Robustness tests

6.4.1 Natives in the same occupations that immigrants

Immigrants are present in fewer occupations than natives. We want to test whether this subset of occupations is at the origin of the lack of significance observed in immigrant parameter estimates. For this purpose, we propose to conduct for natives the same regressions as previously but considering only the subset of occupations where immigrants are present. Estimates from these new regressions are reported in Table 4.

As observed, restricting the native sample to this reduced set of occupations does not alter neither the sign nor the significance of task returns to between- or within occupation wage changes as reported in Table 1. Only the size of the coefficients is modified.[36] The greater explanatory power of tasks in this sub-sample of occupations is reflected in the value of the R-squared, which is larger than that of natives in Tables 1 and 2. Restricting the sample to these occupations employing immigrants seems to induce an increase in the wage variance of natives, probably due to an over-representation of immigrants in occupations at the extremes of the wage distribution. Note that, the R-squared reported in Table 4 is also larger than that of immigrants reported in Tables 1 and 2, suggesting that immigrants' wages are explained by other factors. Therefore, it is unlikely that the lack of precision in immigrant estimates comes from this sample restriction.

[36] One exception arises once we control for age-education-residence duration. The set of occupations is so reduced that we loose precision in the between-occupation estimation of returns to non-routine analytical-interactive tasks.

Table 4: Task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12. Natives in the same occupations as immigrants.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change						Within-occupation wage change					
Scenarios	Baseline	Origin	Composition 1	Composition 2	Residence 1	Residence 2	Baseline	Origin	Composition 1	Composition 2	Residence 1	Residence 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.0801*	0.0900*	0.125**	0.116**	0.140***	0.0834	0.290**	0.297**	0.433***	0.383***	0.450***	0.349**
	(0.0459)	(0.0477)	(0.0522)	(0.0516)	(0.0495)	(0.0522)	(0.119)	(0.121)	(0.145)	(0.134)	(0.139)	(0.147)
Routine manual-cognitive	-0.190***	-0.196***	-0.147**	-0.178***	-0.144**	-0.171***	-0.525***	-0.527***	-0.376**	-0.433**	-0.367**	-0.428**
	(0.0549)	(0.0557)	(0.0588)	(0.0562)	(0.0576)	(0.0596)	(0.153)	(0.153)	(0.174)	(0.166)	(0.171)	(0.171)
Non-routine manual	0.265***	0.271***	0.197***	0.220***	0.184***	0.251***	0.315***	0.312***	0.209	0.267**	0.189	0.307**
	(0.0536)	(0.0548)	(0.0583)	(0.0594)	(0.0548)	(0.0605)	(0.112)	(0.111)	(0.133)	(0.124)	(0.124)	(0.129)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	89	84	80	75	81	69	89	84	80	75	81	69
R-squared	0.336	0.363	0.313	0.341	0.326	0.372	0.254	0.260	0.229	0.242	0.250	0.211

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**\ p < 0.05$, $*p < 0.1$

Table 5: Task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12. Immigrants. Sequential introduction of task indices.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation wage change						Within-occupation wage change					
Scenarios	Residence 1	Residence 1	Residence 1	Residence 2	Residence 2	Residence 2	Residence 1	Residence 1	Residence 1	Residence 2	Residence 2	Residence 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.212			0.175**			0.102			0.130		
	(0.145)			(0.0756)			(0.252)			(0.274)		
Routine manual-cognitive		0.0221			0.0650			-0.0813			-0.110	
		(0.126)			(0.0521)			(0.186)			(0.216)	
Non-routine manual			0.0581			0.138**			-0.359*			-0.162
			(0.136)			(0.0533)			(0.210)			(0.207)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	81	81	81	69	69	69	81	81	81	69	69	69
R-squared	0.057	0.015	0.019	0.064	0.015	0.067	0.005	0.005	0.039	0.004	0.004	0.008

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**\ p < 0.05$, $*p < 0.1$

6.4.2 Sequential introduction of task indices

As immigrants are present in a small number of occupations, analyzing simultaneously the effect of the three task indices on wage changes in these occupations may result in abnormally high standard errors, due to collinearity between the task indices. To assess whether the lack of precision in immigrant estimates (particularly when considering within-occupation wage changes) is due to multicollinearity, we propose to conduct again regressions for immigrants but now introducing task indices one by one. These additional estimates for immigrants are reported in Table 5. As observed, the sequential introduction of task indices does not improve the precision of estimates for immigrants.

6.4.3 Worker sorting across occupations

As explained in the theoretical setup (Section 4), a change in the skill returns in a particular job will foster mobility of utility maximizing workers. Mobility will be evidently more important for individuals bearing lower mobility costs, most likely immigrants.

Figure 6 reveals that a decrease in the returns to routine tasks (or equivalently, an increase in the returns to non-routine analytical-interactive or manual tasks) will promote a double reallocation: the most skilled workers initially employed in routine task-intensive occupations will reallocate towards non-routine analytical-interactive task-intensive occupations while the lowest skilled workers initially employed in routine task-intensive occupations will move downwards towards non-routine manual task-intensive occupations. In an effort to mitigate and assess the importance of workers' sorting, we propose the following methodology.

First, we normalize, as previously, task indices across occupations. Second, we classify as routine task-intensive occupations those whose routine task index is located above the median of the distribution and whose value is above the non-routine manual index and the non-routine analytical-interactive index. We apply the equivalent procedure to define non-routine manual task-intensive occupations and non-routine analytical-interactive task-intensive occupations. Third, for occupations classified as non-routine manual task-intensive, we compute the between- and within-occupation components by focusing exclusively on wage changes below the median. For routine task-intensive occupations, we focus on residual wage changes in the 3rd, 4th, 5th, 6th and 7th decile to compute the between- and within-occupation components. For non-routine analytical-interactive task-intensive occupations, we consider residual wage changes in wages above the median. With this methodology, we are computing the between- and within-occupation residual wage changes over the part of wage distribution which is less likely to have been affected by workers' selective mobility.

Coefficients reported in Table 6 are estimated when controlling for composition effects in terms of age, education and residence duration. Estimated coefficients are not statistically different from those estimated in Tables 1 and 2 (in some cases, there is though a loss of precision). When focusing on immigrants, coefficient estimates for the within-occupation component are not statistically different from those estimated in Table 2. Concerning coefficient estimates for the between-occupation

Table 6: Task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12 controlling for sorting. Natives vs. Immigrants.

Dependent variable: Between- and within-occupation wage changes

	Between-occupation wage change				Within-occupation wage change			
Scenarios	Residence 1		Residence 2		Residence 1		Residence 2	
	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-routine analytical-interactive	0.119***	0.517	0.129***	0.308	0.404***	0.428	0.411***	0.407
	(0.0334)	(0.409)	(0.0352)	(0.205)	(0.101)	(1.863)	(0.101)	(0.784)
Routine manual-cognitive	-0.127***	-0.301**	-0.148***	0.256	-0.400***	0.576	-0.443***	1.742
	(0.0459)	(0.125)	(0.0486)	(0.444)	(0.152)	(0.434)	(0.151)	(1.880)
Non-routine manual	0.177***	0.391**	0.196***	-0.170	0.114	-0.343	0.139	-1.600
	(0.0402)	(0.161)	(0.0422)	(0.399)	(0.123)	(0.723)	(0.120)	(1.718)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES
Observations	211	79	213	66	211	79	213	66
R-squared	0.199	0.038	0.225	0.024	0.161	0.003	0.176	0.020

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**\ p < 0.05$, $*p < 0.1$

component, there is a loss of precision with respect to those reported in Table 2. To summarize, sorting does not seem to have significantly influenced wage dynamics of natives or immigrants. This result is confirmed when considering the pool sample of immigrants (see Table 13 in Appendix D).

6.5 Occupational Choices

According to Figure 8 the divergence in wage dynamics between natives and immigrants is mostly coming from a difference in between-occupation wage changes. Estimates reported in Table 3 reveal that differences in between-occupation wage changes across nativity groups are not driven by different returns to tasks but rather from the fact of belonging to the immigrant group. This suggests that immigrants may be allocating towards occupations that are in expanding sectors, or where the base payment (not linked to skills) is increasing relatively more.

To test this hypothesis, we propose a random utility model of occupational choice in which individuals choose from a variety of occupations. Individuals are here aggregated into age-education cells within occupations[37] using the same age and education categories as previously. In the following, we use the term individuals to designate these different cells. The utility that a worker i derives from choosing an occupation j depends on her individual characteristics X_i and the characteristics of the occupation Z_j: $U_{ij} = U(X_i, Z_j)$. Assuming a linear functional form and adding a disturbance term yields:

$$U_{ij} = \beta X_i + \gamma Z_j + \varepsilon_{ij} \tag{18}$$

An individual will choose among J occupations the one that yields the highest utility. An individual

[37]For tractability reasons, we regroup our 4-digit jobs into 2-digit jobs, taking into account the employment contribution of the 4-digit job to the 2-digit job when computing the weighted task indices.

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 independent and identically distributed with an extreme value distribution[38], we can estimate this random utility model using McFadden (1974)'s conditional logit:

$$\Pr(U_{ij} = 1) = \frac{\exp\{\beta X_i + \gamma Z_j\}}{\sum_{j=1}^{J} \exp\{\beta X_i + \gamma Z_j\}} \tag{19}$$

Terms that do not vary across alternatives and are specific to the individual, i.e. W_i, 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 individual characteristics. We mainly link the occupational choice to the task content of occupations and so include task indices in Z. As the sum of task indices within occupations equals 100, one task indice must be excluded and will serve as a reference. We chose to exclude the routine task index. Then, as we analyze occupational choice in both periods, we also include a dummy $Year$ that takes the unitary value for the period 2010-2012 and interact it with task indices to be able to interpret our coefficient from a dynamic point of view, with respect to period 1994-1996. In other words, coefficients associated with the interaction terms $Year \times Task_j$ allows us to capture the odds of choosing an occupation whose intensity in $Task_j$ has increased with respect to routine tasks between period 0 and 1. We also interact these latter terms with the dummy Img (for immigrants) to capture the odds differential between immigrants and natives.
Estimates from this conditional logit model are reported in Table 7[39]. In column (1), all occupations are considered. In column (2) are removed occupations whose more than 10% of the workforce is paid at the minimum wage[40], to take into account that the minimum wage may be a significant driver of the base payment in some occupations. According to estimates reported in column (1), occupations whose intensity in non-routine manual tasks has marginally increased with respect to routine tasks between period 0 and 1 have 1.52 more chances to be chosen by a native. Occupations whose intensity in non-routine analytical-interactive tasks has marginally increased with respect to routine tasks have 1.32 more chances to be chosen by a native. These values equal, respectively, 0.03 ($0.0225 \times 1.52 = 0.03$) and 0.04 ($0.0339 \times 1.32 = 0.04$) for immigrants. Therefore, following changes in relative intensity of tasks, immigrants and natives follow divergent allocation choices. Both nativity groups are then likely to be occupying different types of jobs. Immigrants seem to be more likely to remain in routine task intensive occupations. Following the polarization literature,

[38] According to this independence of irrelevant alternatives (IAA) assumption, choices are independent from irrelevant alternatives and therefore the omission of a choice does not significantly alter estimates. This assumption should be tested using a specification test *à la* Hausman and McFadden (1984).

[39] We apply the same weights as in the Residence 2 scenario.

[40] In France, 11% of the workforce is paid the minimum wage, so we decide to drop occupations where more than 10 percent of the workforce earns the minimum wage.

wages associated to routine task intensive jobs are those experiencing the lowest increase over the past decades. How can we then explain the higher between-occupation wage change?

Table 7: Natives vs. Immigrants probability of choosing a job.

Dependent variable: probability of choosing a job with respect to others

	All occupations		Occupations with $< 10\%$ w^{min} earners	
	(1)	(2)	(3)	
Year·Non-routine manual	1.514***	0.725***	2.509***	2.368***
	(0.00187)	(0.000865)	(0.00205)	(0.00192)
Year·Non-routine analytical-interactive	1.320***	0.651***	0.806***	0.796***
	(0.00103)	(0.000465)	(0.000100)	(9.80e-05)
Img·year·Non-routine manual	0.0227***	0.0229***	19.61***	19.61***
	(3.45e-05)	(3.48e-05)	(0.0236)	(0.0236)
Img·year·Non-routine analytical-interactive	0.0341***	0.0343***	0.717***	0.717***
	(3.10e-05)	(3.11e-05)	(0.000136)	(0.000136)
Year·network	5.103***		3.947***	
	(0.00387)		(0.00772)	
Job FE	YES	YES	YES	YES
Observations	41,200	41,200	16,688	16,688

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**\ p < 0.05$, $*p < 0.1$

A non-negligible share of employees in routine task intensive jobs, is likely to be rewarded at the minimum wage. The minimum wage is one of the main drivers of the base payment in a job, since its level is not determined by the workers' skill but by an institutional decision. Column (2) in Table 7 replicates the same estimation as in column (1) but removing occupations (defined at the 4-digit level) where the percentage of employees earning the minimum wage is equal or bigger than 10%. The minimum wage in France has increased above the average wage over the past decades. These increases are a major driver of the base payment (part of the wage not associated with the workers' skill) in occupations characterized by a wide presence of minimum wage earners. These estimates reveal that when ignoring occupations where more than 10% of wage earners, previous estimations are strongly modified.

Occupations whose intensity in non-routine manual tasks has marginally increased with respect to routine tasks between period 0 and period 1 have 1.17 more chances to be chosen by a native. Occupations whose intensity in non-routine analytical-interactive tasks has marginally increased with respect to routine tasks have 12% less chances to be chosen by a native ($1 - 0.88 = 0.12$). These values equal, respectively, 4.51 ($3.83 \times 1.178 = 4.51$) and 0.599 ($0.677 \times 0.886 = 0.599$) for immigrants. By eliminating the effect of the minimum wage on the base payment of occupations, we realize that immigrants are more likely to reallocate towards non-routine manual intensive occupations than natives and less likely to reallocate towards non-routine analytical-interactive tasks.

To summarize, minimum wage seems to be a main driver of the divergent wage dynamics between natives and immigrants. A large share of foreign born is rewarded at the minimum wage and, since in France, this minimum wage has increased more than the average wage over the past decades, we find a larger between-occupation wage effect for immigrants. When ignoring occupations where the share of minimum wage earners is above 10%, our results are perfectly consistent with the literature. For an identical change in relative tasks' intensities, immigrants are more likely than natives to reallocate towards non-routine manual task-intensive occupations and natives are relatively more likely than immigrants to reallocate towards non-routine analytical-interactive task-intensive occupations.

7 Conclusion

Based on the French Labor Force Survey, the EurOccupations and O*NET datasets, we analyze in this paper changes in the wage distribution of natives and immigrants over the period 1994-2012. We show that in spite of similar employment dynamics over the period, wages have evolved differently for natives and immigrants. To understand the different wage dynamics of natives and immigrants, we focus our analysis at the occupation level. Indeed, whatever the nativity group considered, we observe that most of the total wage variance is explained by wage differentials between and within occupations.

The different wage dynamics of natives and immigrants may be explained by different occupational choices in the two nativity groups (between-occupation component) as well as by different task returns (or prices) within-occupations (within-occupation component). After showing that natives and immigrants are in fact employed in occupations that differ in their task content, we seek to assess to what extent this drives the divergence in returns to identical skills across both nativity groups. For this purpose, we estimate between- and within-occupation residual wage changes predicted by a simple model and then assess the contribution of the different types of tasks to these components of residual wage changes.

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.[41]

A.2 Occupational task composition

Table 8: 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 are going to 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. As revealed by Table 9 population composition has been modified in terms of age, education, years of residence or countries of origin between period 1994-1996 and period 2010-2012. To remove these composition effects, we will 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.

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

Table 9: Changes in the population composition from 1994-96 to 2010-12.

	1994-1996			2010-2012		
Female in %	115134	42.58	0.49	195586	43.10	0.50
Education	115134	3.49	0.90	195586	3.94	1.12
10 years of residence (in %)	115134	99.22	0.09	195586	97.46	0.16
Age in %						
15-20	115134	1.44	0.12	195586	1.93	0.14
20-25	115134	8.83	0.28	195586	8.29	0.28
25-30	115134	16.32	0.37	195586	11.57	0.32
30-35	115134	16.56	0.37	195586	12.19	0.33
35-40	115134	14.82	0.36	195586	13.03	0.34
40-45	115134	13.01	0.34	195586	14.31	0.35
50-55	115134	8.27	0.28	195586	12.69	0.33
55-60	115134	5.34	0.22	195586	9.68	0.30
60-65	115134	1.14	0.11	195586	2.38	0.15
Origin in %						
North African	115134	0.91	0.09	195586	3.70	0.19
Africa	115134	0.22	0.05	195586	1.89	0.14
South-East Asia	115134	0.07	0.03	195586	0.40	0.06
Southern Europe	115134	1.25	0.11	195586	2.13	0.14
Northern Europe	115134	0.23	0.05	195586	1.00	0.10
Eastern Europe and Rusia	115134	0.13	0.04	195586	0.69	0.08
Tukey	115134	0.13	0.04	195586	0.47	0.07
North America	115134	0.02	0.01	195586	0.09	0.03
South America	115134	0.04	0.02	195586	0.38	0.06

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 2 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.[42] 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)), who have a more discontinuous career than men.

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}:

$$\bar{x}_{cjt} = \sum_i \omega_{it}\, x_{icjt} = \sum_{x_{icjt}} \omega_{it} = \eta_{cjt}, \tag{20}$$

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

[42] 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.

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:

$$\Psi_{cjt} = \frac{\eta_{c0}}{\eta_{cjt}}, \tag{21}$$

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.

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.1 Six different alternative scenarios

We propose to measure the contribution of tasks' returns to between- and within-occupation wage changes under six 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. The six 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 $\times$ educ. Then, occupation-specific residual wage deciles are estimated using the LFS sampling weights.

- In the "Origin" scenario, residuals are obtained by adding to the previous regressions a set of indicators for the origin country of immigrants. LFS sampling weights are used again to estimate occupation-specific residual wage deciles used in the regression.

- In the "Composition 1" scenario, estimated residual wage deciles are obtained as in the Origin scenario, and they are reweighted to insure a constant age-education composition by nativity group within occupations.

- The "Composition 2" 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 " scenario, residual wages for immigrants are obtained by regressing the log wage over age $\times$ educ $\times$ resid[43] and the origin country. Residual wage deciles are then obtained using counterfactual weights insuring a constant composition of worker characteristics (age $\times$ educ $\times$ resid) by nativity group within occupations.

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

- In the “Residence 2 ” scenario, residual wage deciles are obtained using counterfactual weights insuring a constant composition of worker characteristics (age $\times$ educ $\times$ resid) across nativity groups within occupations: the age-education composition of natives in period 0 is taken as reference.

C Figures

C.1 Job polarization by geographical origin

We distinguish 6 nativity groups depending on their origin and their cultural proximity:

- North African: Algerian, Tunisian, Morrocan
- African: Original from other African country.
- South-Asian: Vietnamese, Cambodian, Laotian
- South-European: Italian, Portuguese, Spanish, Greek, Turkey
- Northern countries: German, Belgian, Dutch, Luxembourg, Irish, Danish, British, Swiss, Austrian, Norwegian, Swedish, the United States
- Eastern Europe and USSR: Yugoslavian, Polish, USSR
- South-America

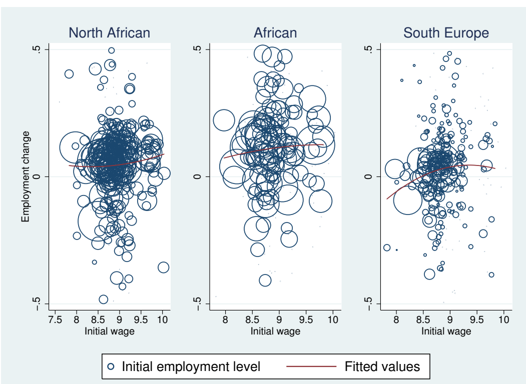
We now relate first period wage in each job to the average subsequent change in log employment by minority group from 1993 through 2012.[44] Figure 10 presents the average change in log employment in the period 1993-2012(Y-axis) for each job quality, proxied by its median wage (X-axis).[45] Panels (*i*), (*ii*) and (*iii*) of Figure 10 suggests that the polarization process has concerned all minority groups considered here. For African and South Asian people, the growth rate of employment at the bottom of the wage distribution has remained though moderated.

[44] Unfortunately, we could not use the LFS prior to 1993 because of a drastic change in industry classification. Thus it was not possible to obtain consistent industry codes over time.

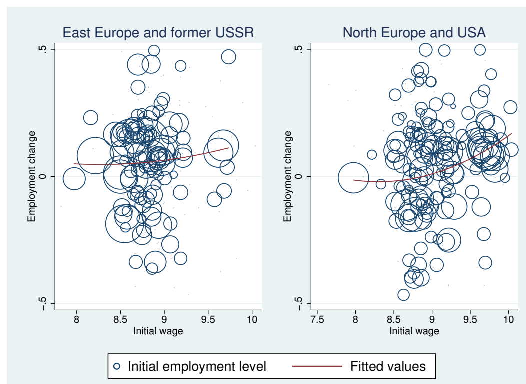
[45] For the sake of clarity, all graphs in this section have been rescaled by removing outliers from the chart.

Figure 10: Average employment growth of minority groups by job median wage at the beginning of the period. French LFS 1993-2010.

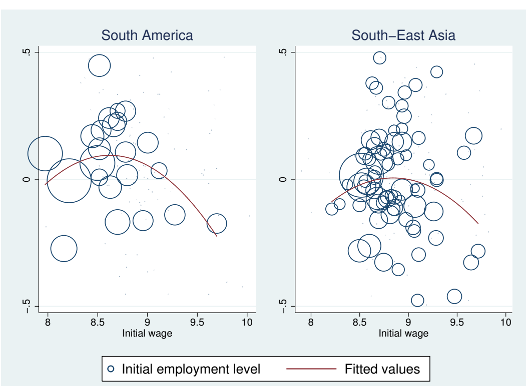
(*i*): North Africa, Africa and South Europe



(*ii*): East EU-USSR and North EU-USA

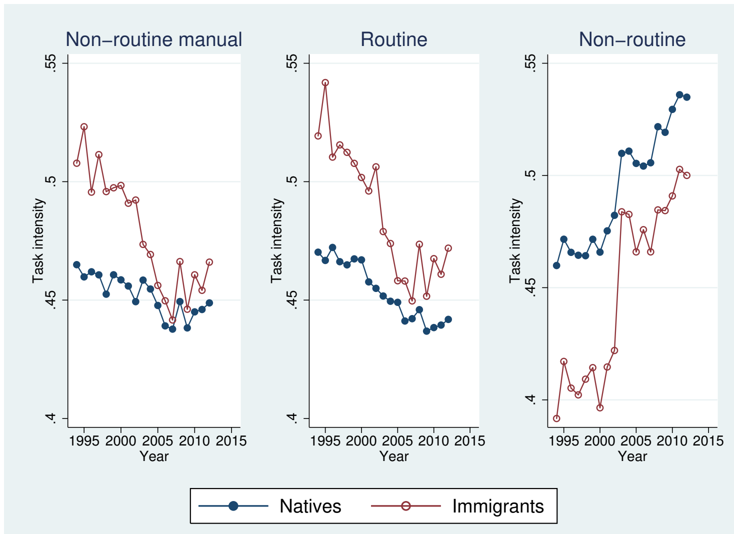


(*iii*): South America and South Asia



C.2 Task specialization by nativity group

Figure 11: Dynamics in non-routine and routine task specialization by nativity group. French LFS 1994-2012, EurOccupations, O*NET.



C.3 Between and within wage changes

Figure 12: Between- and within-occupation coefficients using LFS weights.

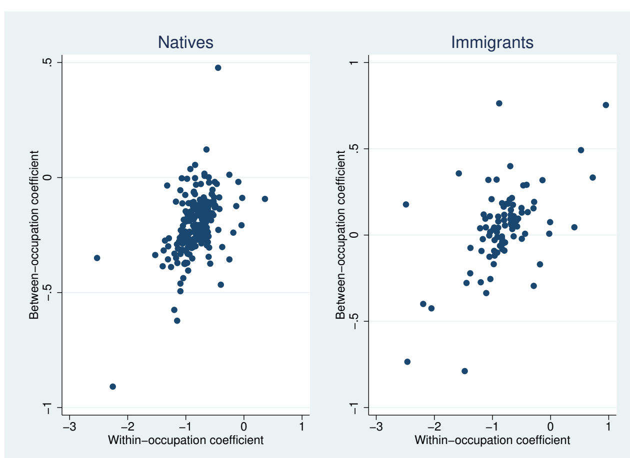


Figure 13: Between- and within-occupation wage changes. Weights from the LFS. Without occupations with 25% of w^{min} earners.

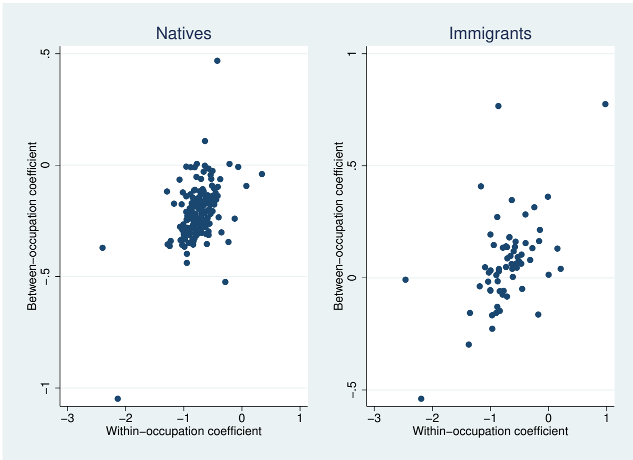


Figure 14: Between- and within-occupation residual wage changes. Counterfactual weights Residence 2. Without occupations with 25% of w^{min} earners.

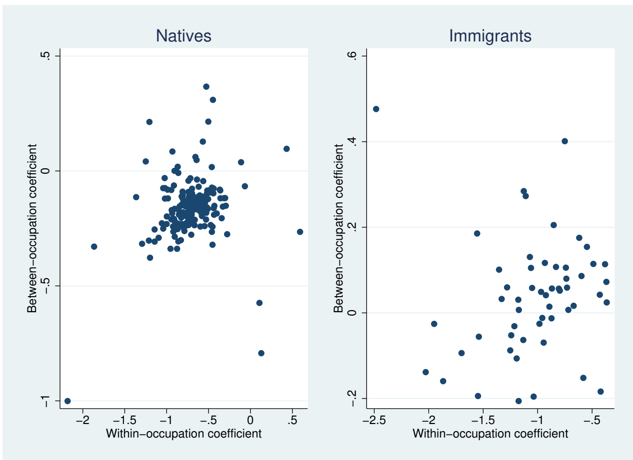


Figure 15: Between- and within-occupation wage changes. Comparing Natives vs. Immigrants. Weights from the LFS

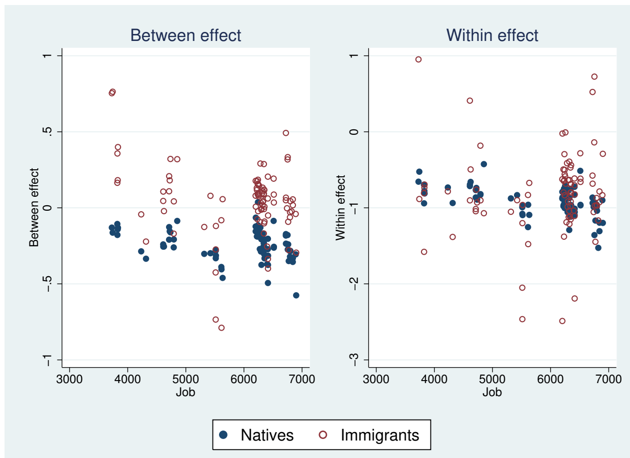
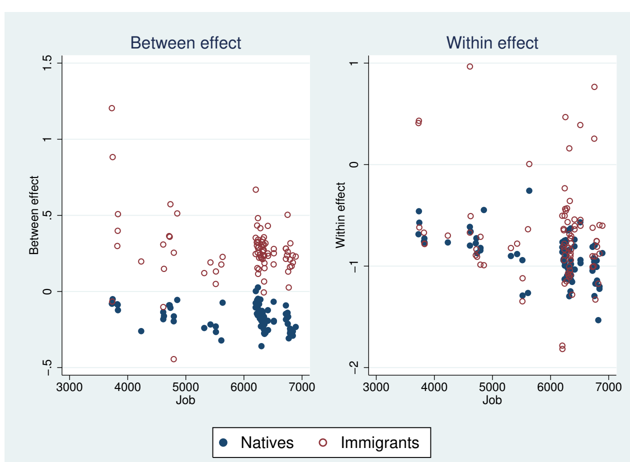


Figure 16: Between- and within-occupation wage changes. Comparing Natives vs. Immigrants. Counterfactual weights Residence 1



D Estimations

Table 10: Task contribution to between-occupation wage changes, from 1994-96 to 2010-12. Without occupations with 25% of w^{min} earners. Natives vs. Immigrants.

Dependent variables: Between-occupation wage changes

Scenarios	Baseline		Origin		Composition 1		Composition 2		Residence 1		Residence 2	
	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.143***	0.261	0.146***	0.344	0.108***	0.153	0.107***	0.536**	0.107***	0.211	0.107***	0.279***
	(0.0346)	(0.178)	(0.0347)	(0.228)	(0.0326)	(0.148)	(0.0322)	(0.212)	(0.0323)	(0.192)	(0.0321)	(0.0924)
Routine manual-cognitive	-0.103**	-0.169	-0.106**	-0.0554	-0.0560	-0.0510	-0.0538	-0.103	-0.0539	-0.0237	-0.0529	-0.123
	(0.0423)	(0.126)	(0.0425)	(0.189)	(0.0376)	(0.195)	(0.0372)	(0.127)	(0.0372)	(0.192)	(0.0370)	(0.0864)
Non-routine manual	0.133***	0.0981	0.133***	-0.118	0.0870**	0.0124	0.0860**	-0.102	0.0854**	-0.0754	0.0852**	0.144
	(0.0409)	(0.178)	(0.0410)	(0.269)	(0.0380)	(0.188)	(0.0376)	(0.206)	(0.0377)	(0.236)	(0.0374)	(0.0933)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	177	66	177	64	179	63	179	58	179	63	179	54
R-squared	0.269	0.135	0.272	0.110	0.190	0.077	0.189	0.286	0.188	0.073	0.188	0.212

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**\,p < 0.05$, $*\,p < 0.1$

Table 11: Task contribution to within-occupation wage changes, from 1994-96 to 2010-12. Without occupations with 25% of w^{min} earners. Natives vs. Immigrants.

Dependent variables: Within-occupation wage changes

Scenarios	Baseline		Origin		Composition 1		Composition 2		Residence 1		Residence 2	
	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.	Nat.	Immig.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.292***	0.137	0.292***	0.377	0.308***	-0.0474	0.303***	0.528	0.303***	0.338	0.300***	0.555**
	(0.0650)	(0.340)	(0.0649)	(0.277)	(0.0747)	(0.334)	(0.0741)	(0.336)	(0.0743)	(0.334)	(0.0739)	(0.259)
Routine manual-cognitive	-0.310***	-0.208	-0.312***	0.107	-0.251**	0.394	-0.242**	-0.0726	-0.245**	0.482	-0.240**	0.156
	(0.0956)	(0.314)	(0.0960)	(0.272)	(0.108)	(0.409)	(0.107)	(0.294)	(0.107)	(0.382)	(0.107)	(0.307)
Non-routine manual	0.0628	-0.174	0.0661	-0.370	0.0622	-0.392	0.0582	-0.283	0.0594	-0.851**	0.0573	-0.309
	(0.0856)	(0.405)	(0.0858)	(0.338)	(0.0946)	(0.372)	(0.0936)	(0.371)	(0.0942)	(0.389)	(0.0934)	(0.283)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	177	66	177	64	179	63	179	58	179	63	179	54
R-squared	0.268	0.044	0.269	0.087	0.212	0.052	0.208	0.095	0.209	0.115	0.206	0.058

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**\,p < 0.05$, $*\,p < 0.1$

Table 12: 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	Origin	Composition 1	Composition 2	Residence 1	Residence 2	Baseline	Origin	Composition 1	Composition 2	Residence 1	Residence 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Non-routine analytical-interactive	0.186	0.196	0.0239	0.238	0.133	0.0944	-0.202	-0.772	-0.518*	0.0135	-0.321	0.0831
	(0.136)	(0.182)	(0.114)	(0.154)	(0.172)	(0.0595)	(0.319)	(0.707)	(0.279)	(0.319)	(0.265)	(0.297)
Routine manual-cognitive	0.00854	0.0838	0.0909	0.0484	0.123	0.0246	0.247	0.00770	0.615*	0.0321	0.692**	0.254
	(0.0876)	(0.166)	(0.165)	(0.102)	(0.162)	(0.0831)	(0.310)	(0.465)	(0.350)	(0.289)	(0.309)	(0.322)
Non-routine manual	-0.108	-0.249	-0.0620	-0.170	-0.193	-0.0848	-0.531	-0.236	-0.710**	-0.449	-1.015***	-0.616*
	(0.128)	(0.204)	(0.159)	(0.139)	(0.201)	(0.0687)	(0.382)	(0.520)	(0.353)	(0.357)	(0.334)	(0.323)
Labor demand shift	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	89	84	80	75	81	70	89	84	80	75	81	70
R-squared	0.079	0.070	0.007	0.108	0.038	0.036	0.041	0.068	0.152	0.073	0.142	0.110

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table 13: Task contribution to between- and within-occupation wage changes, from 1994-96 to 2010-12 controlling for sorting. Natives vs. Immigrants.

Dependent variables: Between- and within-occupation wage changes

	Between-occupation		Within-occupation	
Scenarios	Residence 1	Residence 2	Residence 1	Residence 2
	(1)	(2)	(3)	(4)
Immigrant (Img)	0.482***	0.0795	-0.420	-0.0953
	(0.184)	(0.125)	(0.700)	(0.545)
Non-routine analytical-interactive	0.0962**	0.0510	0.392**	0.338
	(0.0452)	(0.0528)	(0.167)	(0.212)
Routine manual-cognitive	-0.192***	-0.180***	-0.460**	-0.464**
	(0.0526)	(0.0611)	(0.189)	(0.209)
Non-routine manual	0.245***	0.288***	0.318**	0.469***
	(0.0473)	(0.0537)	(0.133)	(0.129)
Img × Non-routine analytical-interactive	0.423	0.266	0.0498	0.126
	(0.409)	(0.211)	(1.817)	(0.839)
Img × Routine manual-cognitive	-0.105	0.371	1.062***	1.799
	(0.132)	(0.393)	(0.395)	(1.657)
Img × Non-routine manual	0.142	-0.417	-0.683	-1.807
	(0.163)	(0.365)	(0.627)	(1.557)
Observations	158	132	158	132
R-squared	0.573	0.175	0.020	0.027

Note: Robust standard errors in parentheses. Statistical significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

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