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Immigration and Occupations in Europe

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Abstract

In this paper we analyze the effect of immigrants on natives' job specialization in Western Europe. We test whether the inflow of immigrants changes employment rates or the chosen occupation of natives with similar education and age. We find no evidence of the first and strong evidence of the second: immigrants take more manual-routine type of occupations and push natives towards more abstract-complex jobs, for a given set of observable skills. We also find some evidence that this occupation reallocation is larger in countries with more flexible labor laws. As abstract-complex tasks pay a premium over manual-routine ones, we can evaluate the positive effect of such reallocation on the wages of native workers. Accounting for the total change in Complex/Non Complex task supply from natives and immigrants we find that immigration does not change much the relative compensation of the two types of tasks but it promotes the specialization of natives into the first type.

JEL Classification Codes: J24, J31, J61.

Keywords: immigration, task specialization, European labor markets.

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1 Introduction

In the labor markets of most developed countries two tendencies have become apparent during the last decade and a half: there has been an increase in demand for jobs requiring complex and abstract skills coupled with a decrease in the demand for manual-routine jobs. These tendencies have been documented for the US (Acemoglu and Autor, 2010) as well as for many European Countries (Goos et al., 2009) spanning a large range of different institutions and labor market structures. Economists have looked for common global tendencies that can explain such phenomenon. Most of the economic research (as summarized in Acemoglu and Autor (2010)) has focused on two factors: the effect of technology, namely the fact that information and communication technologies have increased the productivity of complex-abstract jobs, while substituting for routine and manual tasks, and the effects of off-shoring and trade, that allows the relocation abroad of simple and manual phases of production, but not the relocation of complex managerial tasks.

Those factors have certainly been main contributors to changing the aggregate *demand* for specific jobs in rich countries. In this paper we explore another dimension that may have produced a shift in the *supply* of tasks in rich countries: the increase in the immigrant labor force, especially from less developed countries. We consider 14 different European countries over the period 1996-2007. These countries have substantial differences in their institutions and labor market dynamics, a feature which helps to identify whether the response of native specialization to immigrants exhibits a common behavior or whether it depends on local institutions. Our hypothesis is that the inflow of immigrants of a certain skill reduces the cost of their labor and increases the use of their services in production, just as lower costs of IT-capital and off-shoring increase the use of computer and off-shored workers. Whether this phenomenon increases or decreases the use of labor services from native workers and how it affects the demand for specific tasks depends on what services immigrant workers supply and how substitutable or complementary those services are relative to those provided by natives.

To inquire into this question we consider within each skill cell (represented by the combination of education and age of a worker) a partition of productive tasks into abstract-complex tasks and routine-manual tasks, mirroring in large part the literature on "tradability" or "off-shorability" of tasks (e.g. Crino' (2009) and Blinder (2006)). In particular, jobs that can be easily codified, being in large part manual and repetitive in nature, are not only easy to off-shore but can also be undertaken by foreign-born workers who may have poor native language skills or who may not know the intricacy of the culture, social norms and institutions of the host country. Also, as shown in Peri and Sparber (2009), immigrants who do not speak the language of the host country are concentrated in more manual and less interactive tasks (especially among less educated groups) and tend to be paid lower salaries than natives. This increases the supply of manual-routine occupations relative to the supply of abstract-complex ones.

The goal of this paper is to identify whether immigration has also been a force that promoted the specialization of native workers in Europe towards abstract-complex occupations and away from manual-routine ones. We divide immigrants by cells of observable characteristics and we test whether their presence (across countries and years in each cell) is associated with higher specialization of natives in abstract-complex tasks for the same cell. In an effort to establish whether this increased specialization of natives is actually caused by the inflow of immigrants we use an instrumental variable approach. This instrument, inspired to Card (2001), is based on the fact that the initial share of immigrants in each European country is correlated with their subsequent inflow but should not be correlated with subsequent economic shocks. Hence, the predicted inflow of immigrants, based on their initial shares, is a valid instrument for their actual inflow. At the same time we control for proxies of the other processes that are moving natives towards complex-abstract tasks, and may be country or skill-specific, namely technological change and trade.

We also show that for a given education and age level, employment in relatively abstract-complex tasks pays higher wage than employment in routine-manual tasks and hence we identify the increase in the wage for the average skill cell associated with immigration-driven shift in the specialization of natives.

Aggregate European data contain patterns consistent with the idea that immigrants and natives specialize in different production tasks and such specialization increased over time. Figure 1 shows the evolution over time of the relative intensity of Complex versus Non Complex tasks[1] for the average European Worker (1996-2007) either native or foreign-born. While the average native worker increasingly specialized in Complex production tasks (as revealed by their occupational distribution) the average immigrant worker experienced, if anything, the opposite trend. Immigrants' specialization remained almost unchanged, slightly moving towards more manual-routine jobs. Such a pattern cannot be explained by a common demand shock for relative tasks but requires differences in skills' supply (relative efficiency) between the two groups. It also implies that recent immigrants have been taking much more manual-intensive jobs than natives. Figure 2 shows the correlation between the relative Complex/Non Complex task specialization of native workers across E.U. countries and the share of immigrants in the 1996-2007 interval. The picture, in which each point corresponds to a country-year average shows a positive and significant correlation between the share of immigrants and specialization of natives in Complex tasks. According to an OLS regression, an increase in 10 percentage points in the share of migrants on total population is associated with an increase of 4 points in relative Complex/Non Complex task intensity, a coefficient significant at the 10% level with a standard error of 0.219. To give an idea of the magnitude, such an increase in migrants share would entail a change in Complex/Non Complex task intensity slightly bigger than the difference between United Kingdom (54.6) and Italy (50.9) in 2007.

Our idea is that, as immigrants take manual-routine jobs, native move towards Complex-Abstract tasks for which they have comparative advantages. In our empirical analysis we will establish whether such phenomenon: (a) is accompanied to a systematic

[1] Relative intensity of Complex versus Non Complex tasks is the ratio of the two intensities, where the former is equal to the average intensity in Complex, Mental and Communication tasks, while the latter is the average intensity in Manual and Routine tasks. See section 3 for details.

changes in natives' employment rates, implying crowding out of some workers; (b) is causal running from increased supply of immigrants to native specialization; (c) survives the inclusions of several controls and specifically those that proxy for technological change and openness to trade and off-shoring. We will also analyze if such increased specialization of natives in abstract-complex tasks in response to immigration is affected by the labor market institutional setting of each country, e.g. does a more flexible labor market help the specialization process? We will then project the predicted evolution of the relative supply of Complex and non Complex skills in Europe with and without immigration. Finally we will estimate the potential effect of the change in task specialization due to migration on the wage of the average native worker.

The rest of the paper is organized as follows: section 2 defines a theoretical model of immigration and natives' specialization while section 3 describes the datasets at use and the task variables. Results of the empirical analysis on immigration and natives' employment rates and occupations are reported in section 4, while section 5 investigates how labor market institutions affect the extent of the occupational adjustment. Section 6 simulates the wage impact of the occupational reallocation of natives and section 7 concludes.

2 The Model

Suppose each labor market (country in the empirical analysis) is divided into cells of workers with differing observable skills, namely by experience and education. Similarly to Katz and Murphy (1992) and Peri and Sparber (2009) we use a categorization that distinguishes between two education groups, those with secondary education or less and those with more than secondary education. Within each group we consider five age sub-groups. As in Borjas (2003) and Ottaviano and Peri (2006), each of these skill groups provides labor services that are somewhat differentiated. Hence the structure of competition-substitutability within a group is different from that across groups. We capture this production structure by combining different skill cells in a multi-stage nested

Constant Elasticity of Substitution (CES) production function. In particular, output is produced using capital and labor; labor is a CES aggregate of labor services from workers in different education groups and, in turn, each of those groups is a CES composite of labor services of workers with different ages. While such a structure imposes specific restrictions on the cross-cell elasticities, Ottaviano and Peri (2010) show that it is robust to the inversion of the nesting and the split into two schooling groups is the one preferred by the data. For each country c in year t we can represent the production function as follows:

$$Y_{ct} = A_{ct} N_{ct}^{\alpha} K_{ct}^{1-\alpha} \tag{1}$$

$$N_{ct} = \left[\sum_{edu} \theta_{edu,c,t} N_{edu,c,t}^{\frac{\sigma_{EDU}-1}{\sigma_{EDU}}} \right]^{\frac{\sigma_{EDU}}{\sigma_{EDU}-1}} \tag{2}$$

$$N_{edu,c,t} = \left[\sum_{age} \theta_{age,edu,c} N_{age,edu,c,t}^{\frac{\sigma_{AGE}-1}{\sigma_{AGE}}} \right]^{\frac{\sigma_{AGE}}{\sigma_{AGE}-1}} \quad \text{for each } edu \tag{3}$$

Y_{ct}, A_{ct}, K_{ct} and N_{ct} are respectively output, total factor productivity, services of physical capital and the aggregate labor services in country c and year t. $N_{edu,c,t}$ is the composite labor input from workers with the same level of education "edu" and $N_{age,edu,c,t}$ is the composite input from workers of education"edu" and age "age". The parameters $\theta' s$ capture the relative productivity of each skill group within the labor composite. Notice that the relative productivity of education groups $\theta_{edu,c,t}$ is allowed to vary by country and time and the relative productivity of age groups also varies by education and country. The elasticity σ_{EDU} and σ_{AGE} regulate substitutability between labor services of workers with different education and age level.

The observable characteristics are education and age of a worker. We use the index j (=edu, age) to identify each education-age cell. We consider these characteristics as given at a point in time. In each skill-cell j we separate the labor services supplied as Complex tasks (C) and those supplied as Non Complex (Manual-Routine) tasks (NC) and consider those inputs as imperfect substitutes, also combined in a CES.

$$N_{j,c,t} = \left[\beta_j NC_{j,c,t}^{\frac{\sigma_{NC,C}-1}{\sigma_{NC,C}}} + (1-\beta_j) C_{j,c,t}^{\frac{\sigma_{NC,C}-1}{\sigma_{NC,C}}} \right]^{\frac{\sigma_{NC,C}}{\sigma_{NC,C}-1}} \quad \text{for each } j, c, t$$

$NC_{j,c,t}$ and $C_{j,c,t}$ are the amount of "Non Complex" (manual, routine) and "Complex" (abstract, communication) services supplied by the skill group j in country c and year t. The coefficient β_j determines the relative productivity of Non-Complex tasks in the cell and the elasticity $\sigma_{NC,C}$ determines the substitutability between the two types of tasks. Within this structure we can easily derive the relative demand for Complex and Non Complex tasks in skill group j by taking the ratio of their marginal productivity. As in Peri and Sparber (2009), we assume that native workers have greater relative efficiency in providing the C tasks, which may vary with j. At the individual level, the relative supply of these tasks by natives of a certain skill j depends on their relative efficiency and on the relative compensation of the tasks. An increase in the relative supply of NC/C in skill group j increases the compensation (marginal productivity) of C. Each worker will adjust, supplying more C relative to NC. We assume that immigrants in each skill group supply a larger amount of NC relative to C vis-a-vis native workers, as they are relatively more efficient in manual tasks or have a relatively lower "dislike" for them. Then immigrants in a cell would be associated with an increase in the marginal compensation to Complex tasks and, in response to this, with an increase in the supply of Complex tasks by native in each skill group. Taking a log-linear approximation of the relative task supply of natives for each skill group j (and country-time) we can write the following expression, relating such relative supply to the presence of immigrants in the cell and to a series of fixed effects:

$$\ln\left(\frac{C_D}{NC_D}\right)_{j,c,t} = \gamma \cdot \ln(f_{j,c,t}) + d_j + d_{edu,t} + d_{c,t} + \varepsilon_{j,c,t} \tag{4}$$

where $\frac{C_D}{NC_D}$ is the measure of relative Complex versus Non Complex tasks provided by home-born (D as in Domestic) workers in the specific cell. This relative supply is responsive to the relative compensation of tasks, which in turn depends on the share of immigrants, hence the term $\ln(f_{j,c,t})$ where $f_{j,c,t}$ is the share of foreign-born in the cell. Our main interest is in estimating γ as we assume that a larger share of immigrants would increase returns for complex tasks relative to non-complex ones and pushes natives to supply more of those. Hence our model predicts a positive value of γ. At the same time we want to control for relative skill productivity (due to technological factors) which potentially vary across education groups and years and hence we include a set of education-time effects, $d_{edu,t}$. These fixed effects will capture technological progress that increases demand of complex tasks by more educated workers, driven for instance by information technology. Moreover, as argued in the introduction, trade and off-shoring also affect the domestic demand for tasks, probably decreasing the demand for Non Complex tasks (e.g. Blinder (2007)). As openness varies across country and years we also include a set of country-year effects $d_{c,t}$ to capture their influence. Finally, in order to allow heterogeneous relative productivity of natives and immigrants in Complex-Non Complex tasks depending on their skills (age and education) we also control for a set of age by education (d_j) fixed effects. The term $\varepsilon_{j,c,t}$ is a idiosyncratic random shock (or measurement error) with average 0 and uncorrelated with the explanatory variables.

Our empirical analysis is split in three parts. First, section 4 focuses on estimating the effects of immigration on the task performance of natives and on their employment. Empirically, we analyze the effect on relative Complex/Non Complex supply and we can also separate the effect of immigration on each native-supplied task-group by estimating an equation similar to 4 with $\ln\left(C_D\right)_{j,c,t}$ or $\ln\left(NC_D\right)_{j,c,t}$ alternatively, as dependent variable. We also check whether the shift in relative supply for native workers happens with net crowding-out or with no change in the number of native jobs (i.e. by looking at the effect on natives' employment rates in the cell). Second, section 5 investigates how the adjustment of native occupations triggered by immigration depends on the flexibility of the labor market. We suspect specialization resulting from comparative advantages of immigrants and natives works faster and to a greater extent in countries with more flexible markets. Finally, section 6 estimates the premium paid to performing relatively Complex tasks for a given combination of education and age. We quantify the wage gain for natives due to their shift from Non-Complex to Complex tasks triggered by immigrants.

3 Data and descriptive statistics

The main dataset we use is the harmonized European Labour Force Survey (ELFS), grouping together country specific surveys at the European level (see EUROSTAT (2009)). We restrict our analysis to the period 1996-2007 since before 1996 data on the place of birth are absent in most countries. Moreover, we focus on Western Europe only[2], keeping only observations related to individuals in working age (15-64). The data include information on the occupation, working status and demographic characteristics of the individuals but no information on their wages. We had to drop observations with missing data on education, age or country of birth. In 16 out of 168 (14 countries*12 years) cases one of these variables, fundamental for our analysis, was completely missing in a country/year.[3]

We classify as immigrants those individuals in ELFS data that are identified as foreign born. We do not use the first year of data (1995) since in that year the country of birth variable was missing in 4 out of 14 countries. In figure A1 we show the evolution of the share of foreign born on the aggregate population of the sample countries during the 1996-2007 period analyzed here. In this figure, we pool countries, with the exception of Ireland, Italy, Luxembourg and United Kingdom, for which data are missing for one or more years. The share of foreign born on total population increased 4.5 percentage points from below 8% in 1996 to 12.3% in 2007. This increase was, on average, evenly distributed across educational levels (figure A2).

In the empirical analysis, for each year between 1996 and 2007, we collapse data in cells stratified by country, two educational levels (Upper secondary education or less and strictly more than upper secondary education) and five ten-year age classes covering

[2]We include Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, United Kingdom. We could not include Germany since main variables, including place of birth, were missing for most years.

[3]See table A1 of the appendix for the full list of missing country/years.

ages between 15 and 64 years. Our analysis focuses on men, whose more continuous working life and higher participation rates imply lower measurement error and more representative samples. As a robustness check, however, we run the analysis pooling men and women.

3.1 Tasks variables

In order to test the predictions of the model introduced in section 2, we need indicators of the intensity of skills supplied in each cell over time.

Following Peri and Sparber (2009), we use the US Department of Labor O*NET abilities survey (version 11, available at http://www.onetcenter.org/). This survey, initiated in 2000, assigns values summarizing the importance of different abilities for each of the 339 SOC (Standard Occupation Classification) occupations. We use in particular 78 of such tasks to construct our skill measures. In order to circumvent the fact that the scale of measurement for the task variables is arbitrary, we convert the values into percentiles. We create five abilities' measures: Communication, Complex, Mental, Manual and Routine. For example, skills used to construct the "Communication" category include "Oral Communication" and "Speech clarity"; "Manual Dexterity" and "Reaction Time" are skills used for the "Manual" category and so on (see table A2 of the appendix for the full list of the skills/tasks measures employed to construct the indicators). Communication, Complex and Mental skills constitute the "Complex" group, while Manual and Routine form the "Non Complex" one. As a robustness check, we will also use the alternative "Abstract" and "Routine" classifications employed by Goos et al. (2009). For each indicator, we merge occupation-specific values to individuals in the 2000 Census using the SOC codes. Then, using the Goos et al. (2009) crosswalk, we collapse the more detailed SOC codes into 21 2-digit occupations classified according to the International Standard Classification of Occupations (ISCO) which is the classification used by ELFS. Again, we calculate percentiles for each of the task intensity measures as a weighted average were the weights are the number of workers in each occupation according to the 2000 US Census. To give an idea of the indicators, a score of 0.02 for "communication skills" in a certain occupation indicates that 2% of workers in the US in 2000 were using that skill less intensively than workers in the considered occupation. For the 21 occupations provided in the ELFS dataset we show the score for each of the ability indexes in table A3 of the appendix. For example, "Drivers and mobile plant operators" is the occupation with the highest "manual ability" intensity, while it is the second to last occupation when considering "complex abilities". On the other hand, "Corporate managers" are highly ranked among Complex, Mental and Communication skills while being relatively less intensive in Manual and Routine abilities. In table A4 we report correlations between each of the ability measures and education and age levels that we use to construct our cells in the empirical analysis. Two patterns reveal themselves in the correlations between observable skills and Complex/Non Complex tasks. First there is a strong negative (positive) correlation between high education and non complex (complex) abilities. The schooling level affects the relative productivity in the two tasks and hence it is very important to control for it. Second, Manual and Routine abilities are positively correlated with low age levels while the opposite is true for more sophisticated skills such as Complex, Mental and Communication skills. Those skills exhibit a negative correlation with the lowest age level (15-24), turning positive and then reaching a maximum with age 35-44 to decrease afterward. These patterns are not surprising and they emerge even when considering alternative skill definitions taken from Goos et al. (2009).

4 Main Empirical results

4.1 Immigrants and Employment rates of Natives

Before estimating equation 4, we estimate a similar specification to see whether immigrants have a net effect on the employment rates of natives across skill groups. Considering different countries in Europe as separate labor markets and the education-age skill cells as defining specific markets, with highest substitutability for workers within the same cell, we estimate the following:

$$ln(\frac{empl_{j,c,t}}{pop_{j,c,t}}) = \delta \ln(f_{j,c,t}) + d_j + d_{c,t} + d_{edu,t} + e_{j,c,t} \quad (5)$$

where $(empl_{j,c,t}/pop_{j,c,t})$ is the employment-population ratio *for natives* in the education-age group j, living in country c in year t and d_j, $d_{c,t}$, $d_{edu,t}$ are sets of skill, country-year and education-year effects and $e_{j,c,t}$ is an idiosyncratic random shock. Even in this specification we allow education-year productivity changes and factors specific to country-year to affect the employment rate differentially. Table 1 reports the estimates of coefficient δ for different specifications of 5, each cell of the table is from a different regression specification. We use as explanatory variable either the share of foreign-born in the education-age-country cell (first and third row) or, alternatively, the share of immigrants in the same age group irrespective of their schooling (rows 2 and 4). This is to account for competition of immigrants with higher formal schooling who have downgraded their skills in the occupational choice, which several studies (e.g. Dustman et al. (2008)) find to be a relevant phenomenon in Europe. The first two rows show the results when only men are included in the sample, while rows three and four show the results for all workers. Finally, while specification 1 is estimated using Least Squares, specifications 2 and 3 use an instrumental variable method that adapts the one proposed by Card and DiNardo (2000) and Card (2001) and used in several studies since. In particular, we calculate immigrants' distribution across countries and cells for the first available year (1996). This initial distribution of immigrants provides stronger network effects for some country and groups which should affect the subsequent inflows. The instrument is then obtained multiplying this initial distribution by the growth rate of foreign-born adult individuals due to immigration to the country. The stock of immigrants imputed with this method depends on the initial distribution of immigrants across countries and skill groups, but not on the subsequent cell- and country-specific economic shocks affecting employment. The underlying assumption is that, while immigrants tend to settle where foreign-born individuals are already in high numbers in order to exploit networks and common cultural traits, past immigrants' concentrations are unrelated to current economic conditions as long as cell-specific demand factors are not too persistent over time.

The instrument turns out to be strong (first stage statistics are reported in table A5 of the appendix) which we interpret as a sign that network of previous immigrants reduce costs of settling and finding a job for new immigrants, especially those similar to them. To provide a check for the robustness of this assumption, we re-run all the regressions dropping observations relative to the first 2 years (1996 and 1997), while keeping constant the year for which we calculate initial immigrants' concentrations. This should further reduce the correlation between pre-existing demand conditions (potentially affecting the initial migrant stock) and the following demand fluctuations. We address the residual endogeneity issues controlling for country by year and education by year fixed effects in all the specifications.

Each cell of Table 1 shows the estimate of the parameter δ in equation 5 from a different sample/specification. Below the estimated coefficients, the table reports the robust standard error clustered for education-age-country cell in order to allow for autocorrelation of the error over time.

The estimates of Table 1 are consistently close to 0 and insignificant across all specifications. They range between -0.062 and +0.053, never statistically different from zero. No significant differences in the estimated coefficient arise when considering male versus the whole sample or when using 2SLS method versus OLS. In general, the estimated coefficients imply that the inflow of immigrants as measured by changes in their share of population in a cell has no significant correlation with the change in native employment rates in that cell. Immigrants may have an effect on the specialization of natives (as we will see in the next section) and there may be some occupations experiencing an increase in demand and other experiencing a decrease but this does not come at the expenses of the total number of jobs available to natives. To be very clear: there may be some jobs that gain and other that lose within a cell in terms of numbers but the net employment effect in the average cell is null.

4.2 Immigrants and native specialization

To inquire into the effects of immigration on task specialization of natives, Table 2 reports the estimates of the coefficient γ_C from the following regression:

$$\ln\left(C_D\right)_{j,c,t} = \gamma_C \cdot \ln(f_{j,c,t}) + d_j^C + d_{c,t}^C + d_{edu,t}^C + \varepsilon_{j,c,t}^C \qquad (6)$$

The coefficient γ_C, once we control for skill, country-year and education-year fixed effects (d_j^C, $d_{c,t}^C$ and $d_{edu,t}^C$) identifies the estimated impact of immigration on the intensity of complex tasks performed by native (Domestic) workers. A positive and significant value of γ_C implies that an increase in immigrants in the cell pushes natives to specialize in more complex-cognitive tasks relative to cells with smaller inflows of immigrants and hence it would be evidence that the mechanism described in section 2 is at work. We use different definitions for "Complex" tasks variables, including the Goos et al. (2009) definition of abstract tasks, and our own measures of Complex, Abstract and Communication tasks defined in section 3. In Table 2 we report 2SLS results only (OLS results are not too different and available upon request), based on the shift-share IV strategy described above.[4] Robust standard errors, clustered by education-age-country, are reported under the estimates. As a robustness check, we run all the regressions both on the whole period and also dropping the first two years from the sample to avoid potential endogeneity (columns 3, 6, 9 and 12). As in Table 1, the first and third rows are estimated using as explanatory variables the share of immigrants in the education-age cell, while in the second and fourth row we only stratify by age group merging workers of different schooling, as immigrant may compete with natives of different education level (due to the potential downgrading of their skills). Finally, the first two rows are estimated using only male workers and the second two using the whole sample.

The estimates of Table 2 are very consistent across specifications, samples and task definition. First, for almost all the estimates the change in share of immigrants in a cell is associated with an increase in the intensity of Complex tasks performed by

[4] For the first-stage statistics see Table A5 of the Table appendix.

native workers. Using our task measures, the estimated elasticity is between 0.035 and 0.074 implying that a doubling of the share of immigrants in a cell (say from 2 to 4% of employment) is associated with an increase in the supply of complex tasks by natives between 3.5 and 7.4%. We will come back to the magnitude of this effect later. The second important result emerging from Table 2 is that the different definition of "complex" tasks does not affect much the estimated effects. Immigrants push natives in a skill cell to perform more of the non-routine cognitive and communication tasks. On the other hand, comparing the effects estimated using the supply of immigrants in the same education-age cell (first and third row) and those estimated using the immigrants in the same age group (irrespective of education) shows somewhat stronger coefficients in the second case. This implies that even immigrants with different schooling degrees may put pressure on natives in the same age cohort to move towards more tasks to best exploit their comparative advantages and complementarity. When using Goos et al. (2009) definition of abstract tasks, we again see positive estimates for γ_C, but weaker when using the sample pooling male and female workers.

Table 3 is similar to Table 2 and shows the estimated effect of immigrants on the intensity of "Non Complex" tasks performed by natives. The basic estimated specification is as follows:

$$\ln \left(NC_D\right)_{j,c,t} = \gamma_{NC} \cdot \ln(f_{j,c,t}) + d_j^{NC} + d_{c,t}^{NC} + d_{edu,t}^{NC} + \varepsilon_{j,c,t}^{C} \tag{7}$$

Similar to regression (6) the coefficient γ_{NC}, once we control for the usual skill, country-year and education-year fixed effects identifies the estimated impact of immigration on the intensity of manual-routine tasks performed by native (Domestic) workers. A negative and significant value of γ_{NC} implies that an increase in immigrants in the cell pushes natives away from non complex, manual tasks. And similar to the previous regressions, the definitions of Manual and Routine tasks varies. Therefore we alternatively use in Table 3 the Goos et al. (2009) definition for Routine (specifications 1 to 3) and our own "Routine" and "Manual" indexes (specifications 4 to 6), defined in section 3. Also in this case we re-run all the 2SLS regressions on a sample not including the first two years of the interval (for the first-stage statistics see Table A5 of the Table appendix). The estimated coefficients of table 3 are either negative or indistinguishable from 0. The estimates are rather precise (standard error around 0.03) and relatively similar across specifications. The only variable that generates a clearly negative coefficient, denoting a reduction in the intensity of routine tasks for natives when more immigrants are in the cell, is the definition of "Routine" tasks defined by Goos et al. (2009). The other definitions produce small and non significant coefficients. Native workers, while moving actively into complex tasks decrease a bit (or maintain) their intensity of routine and manual tasks. As, in our definition, the sum of intensity of manual-routine and complex tasks is not constant across occupations a worker may increase the intensity of one task without decreasing the intensity of the other.

Hence the results imply that natives move on average to occupations with larger content of complex tasks and about the same or a bit smaller content of manual-routine tasks. A larger supply of manual-routine tasks from immigrants produces higher demand for complex tasks from natives and, on average, they increase their supply of those.

Finally, table 4 reports the estimates of the coefficient γ from regression 4. This coefficient shows the impact of immigrants on the *relative* task supply, defined as the ratio between the average of complex skills (abstract, complex and communication) and the average of non-complex skills (manual and routine). The table reports estimates from OLS (column 1) and 2SLS (columns 2 and 3) methods. As in Tables 2 and 3, we run all the regressions both on the whole sample (lower panel) and on men only (upper panel). We also check the robustness of the results collapsing the main explanatory variable in age cells irrespective of education and limiting the time interval for estimation. Results on relative skill levels are in line with those on complex and non-complex skills, showing that rising immigration forces natives to move toward occupations with a relatively more complex skill content. Coefficient estimates are quite precise and range between 0.057 and 0.079, always being statistically significant at the 1% level.

5 Differences across Labor Market Institutions

The reallocation of natives toward more complex skills could be slowed by rigid labor markets (Angrist and Kugler, 2003). In fact, in order for native specialization to respond timely to immigration, native workers need to change job easily: a task that is made harder by rigid labor market institutions and laws that may increase the cost of hiring, switching jobs or laying-off. In order to check this possibility we re-estimate equation 4 interacting the main independent variable $ln(f)$, the logarithm of the share of immigrants on total population, with several indicators of Employment Protection Legislation (EPL) at the country level. In particular, we adopt five different ranking based on EPL measures. The first two of them are based respectively on two ad hoc employer surveys conducted by the European Commission in 1989 and 1994 (European-Commission, 1991, 1995). These indicators are based on the share of employers claiming that restrictions on hiring and firing were very important, hence they are based on polls that reflect the perception of employers. We also adopt two OECD indicators summarizing EPL based on averages of specific scores that classify countries according to the strictness of employment protection for regular employment, to norms concerning temporary employment and rules on collective dismissals. The two indicators differ for the reference period and for the weighting procedure used to calculate the overall indexes.[5] The use of four different indicators provides a robustness check of the results to the type of EPL index used and also to the countries included in the comparative analysis, since such indexes are not available for some of the countries included this study.[6] We define a country as a high EPL one when its strictness in labor laws is higher than the weighted average of the surveyed countries. As in section 4, we run both OLS and 2SLS regressions (Table 5). For simplicity we report main results for men only (whole sample results are available upon request). Coefficient estimates show only moderate support to our idea. We find that

[5] OECD1 refers to the late 80s and use a simple average of three indicators, while OECD2 refers to the late 90s and uses a weighted average, see OECD (1999), pp.64-68, for details.

[6] European Commission indicators are not available for Austria, Denmark and Finland; Luxembourg is absent in OECD indexes as well.

the extent of labor reallocation towards occupations requiring a higher content of complex skills in response to increased immigration is stronger in countries with relatively lower EPL. In this case, in fact, the coefficient estimates for $ln(f_s)$ are always positive and strongly significant, ranging between 0.06 and 0.07. For countries with higher EPL, on the other hand, the coefficient estimates are still positive, albeit with lower point estimates (0.04 to 0.06), and are non-significant at standard significance levels. However, a formal test of equality between the EPL interactions would not reject the null of equal effects. We believe that these results, which hold across a number of specifications and indicators, confirm, albeit only mildly, the analysis of Angrist and Kugler (2003) who find that low labor market flexibility can reduce gains from immigration. Our model and explanation provides a reason for this. Countries in which native workers respond to a lesser extent to immigrants without specializing their skill to task allocation, forgo some of the efficiency gains as well as the positive complementarity effect of immigration.

6 Migration, skill intensities and wages 2008-2020

According to the results of section 4, natives tend to move to occupations requiring relatively more complex skills when the share of foreign-born workers increases. In order to quantify the effect that such a reallocation has on wages, we estimate wage/skill elasticities using EU-SILC data. These data report net monthly wages earned in 2007 for most of the countries analyzed here[7]. We estimate the following wage regression:

$$ln(wage_i) = \alpha + d_i + d_j + d_k + \beta ln\left(\frac{C}{NC}\right) + \varepsilon_{ijkt} \tag{8}$$

where the dummies d_i, d_j, d_k are respectively country, education and age fixed effects and $ln\left(\frac{C}{NC}\right)$ is the logarithm of the Complex relative to Non Complex skill intensity. When considering men only, we estimate a wage/skill elasticity equal to 0.1, significant at the 5 per cent level. This implies that an increase of 10 per cent in the relative complex/non

[7] Denmark, Finland, the Netherlands, Norway and United Kingdom are not included since this information is not available.

complex skill mix is associated with a 1% increase in net hourly wages. This result is robust to the inclusion of women in the sample (main coefficient increasing to 0.17).

In order to gauge the overall impact of immigration on wages through labor reallocation, we also need to check whether, and how, migration changes the relative skills level for the whole labor market. This is non trivial as the increase of immigrants in a skill cell has two effects. On the one hand as immigrants supply more Non Complex tasks, they will lower the C/NC ratio. And on the other hand, as we have seen above, they push natives towards complex task, which will increase the C/NC ratio. To evaluate the magnitude of each effect, we project the impact of migration on the evolution of skill intensities using the parameters estimated in equation 4 using the population and employment rates projections provided respectively in European-Commission (2005) and Carone (2005). These projections give the age and gender specific evolution of population and employment in each of the European Countries considered in this study.[8] Demographic projections do not include the evolution of educational levels among the overall population as well as the workers' subgroup. To circumvent this problem, we impute the future evolution of native individuals' educational attainments using a cell-specific AR1 multi-step ahead forecast with an in-sample interval 1996-2007 and an out of sample interval 2008-2020. The dependent variable is the share of individuals with low education in each age-year-country cell. Once we have projected natives' educational attainments on the 2008-2020 interval, we need to attribute the country specific total influx of immigrants estimated in European-Commission (2005) to each education-age-year cell. We do so using a similar AR1 multi-step ahead forecast for the share of foreigners in each cell. Intuitively we project forward the trends of immigratio by skill cell observed in each country during the period 1998-2007. Combining the demographic and labor market projections with estimates of the migration/relative skills elasticities we are now able to gauge the impact of immigration on the evolution of relative skills supply, both for the whole economy, and for natives only (figure 3).

[8] For the country-specific evolution of immigration assumed in European-Commission (2005) see figure A3 of the appendix.

The first fact to note is that, according to the projections, migration balances the whole economy's complex/non complex relative skill level. According to the projection assuming the number of immigrants remains constant at the 2007 level (green line), the level of complex relative to non-complex skills will increase by 3.4 per cent for natives in the time interval under consideration. For given relative demand of skills, this would entail a reduction in the estimated wage premium for occupations having a relatively higher intensity of complex skills. Since natives are specialized in those occupations relative to immigrants, this would produce a reduction in wages paid to home relative to foreign born workers. In the projection assuming an increase in migration based on European-Commission (2005), relative skills levels are more balanced, with the ratio between complex and non complex skills remaining almost stable (decrease by 0.35 per cent). This is due to the fact that, while immigrants cluster in occupations requiring higher intensity of manual/routine skills, natives tend to move to occupations requiring relatively more complex skills when the number of foreign born workers increases (green and red lines in figure 3) hence the balanced outcome. The slight decline in the level of complex relative to non-complex skills assures that, if anything, the skill premium for relatively complex jobs should not decrease due to migration.

Combining results from equation 8 with projections on immigrants flows and their impact on the relative skill mix (equation 4), we can finally simulate the impact of migration on wages in the 2008-2020 interval. We estimate that due to the reallocation of labor towards more complex tasks, immigration will raise native workers wages by 0.6% on average (figure 4). Higher gains from immigration could be obtained by countries with relatively flexible labor markets. Based on results of section 5, we estimate that the positive impact could be definitely lower in countries with strict labor laws (+0.4%) compared to countries with a more flexible institutional system (+0.8%).

7 Conclusions

In the last fifteen years, the labor markets of most developed countries have experienced a secular increase in the number of jobs requiring more abstract and complex skills relative to manual and routine skills. Most of the economics literature has focused on demand side factors explaining this phenomenon: technological change and the effects of off-shoring and trade (Acemoglu and Autor, 2010). In this paper we analyze an interesting supply factor, namely the role played by immigration in determining such a change in the occupational structure. Our idea, summarized in a simple analytical framework, is that immigrants tend to be specialized in occupations requiring mainly non-complex and routine skills. Immigrants inflows thus tend to reduce the supply of complex relative to non complex skills at the economy level and increase the return to the first type of skills. This creates an incentive for native workers to move to occupations requiring relatively more abstract/complex skills. This intuition is confirmed by the empirical analysis conducted on European Labour Force Survey data, a result surviving a number of robustness checks carried out using different skill indicators, estimation methods and sample definitions. This positive reallocation process seems to be mildly stronger in relatively flexible labor markets, while it does not change the overall skill intensity of the economy, since the non-complex specialization of immigrants is balanced by natives' reallocation towards complex skills. This implies that, on aggregate, immigration does not affect much the relative price of manual versus complex tasks. According to our simulations combining results of the empirical analysis with long term demographic projections, natives' skill upgrading due to immigration could account for a small 0.6% increase in average wages of natives in the 2008-2020 period.

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Tables

Table 1: Immigrants and Native Employment

Units of Observation: 8 education-age cells in 14 EU countries in years 1996-2007

Dependent variable: Logarithm of Employment/Population ratio in the Cell			
Column	**1**	**2**	**3**
Method	**OLS**	**2SLS**	**2SLS**
Men Only			
Ln(Share of Immigrants) in Education-Age cell	-0.049	-0.044	-0.046
	[0.073]	[0.092]	[0.093]
Ln(Share of Immigrants) in Age cell	-0.062	-0.013	-0.013
	[0.100]	[0.134]	[0.135]
All workers			
Ln(Share of Immigrants) in Education-Age cell	0.02	0.048	0.048
	[0.079]	[0.102]	[0.103]
Ln(Share of Immigrants) in Age cell	0.012	0.053	0.053
	[0.100]	[0.140]	[0.142]
Observations	1517	1407	1169
Education by year fixed effects	Yes	Yes	Yes
Country by year fixed effects	Yes	Yes	Yes
Education by age fixed effects	Yes	Yes	Yes
1996 and 1997 excluded	No	No	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of Employment/Population for the native population in the cell. The main explanatory variable is described in the first cell of the row. In parenthesis we report the heteroskedasticity robust standard errors clustered by education-age-country group. First-stage statistics for the shift share instrument are reported in table A5 of the appendix.*

****=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 2: Immigrants and Intensity of Complex Task by Natives

Units of Observation: 14 EU countries, 8 education-age cells, years 1996-2007

Dependent variable	**Abstract (Goos et al. 2009)**			**Complex**			**Mental**			**Communication**		
Column	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Method	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**
Men only												
Ln(Share of Immig.) in Educ-Age cell	0.038	0.048	0.052	0.035	0.038	0.035	0.049	0.062	0.061	0.045	0.045	0.042
	[0.017]**	[0.021]**	[0.022]**	[0.012]***	[0.013]***	[0.014]**	[0.012]***	[0.013]***	[0.013]***	[0.014]***	[0.017]**	[0.018]**
Ln(Share of Immig.) in Age cell	0.032	0.052	0.058	0.045	0.045	0.043	0.061	0.07	0.07	0.056	0.052	0.05
	[0.027]	[0.029]*	[0.031]*	[0.014]***	[0.015]***	[0.015]***	[0.013]***	[0.012]***	[0.011]***	[0.017]***	[0.021]**	[0.021]**
All workers												
Ln(Share of Immig.) in Educ-Age cell	0.012	0.032	0.037	0.037	0.04	0.038	0.052	0.065	0.063	0.048	0.053	0.051
	[0.017]	[0.021]	[0.022]*	[0.014]***	[0.016]**	[0.016]**	[0.016]***	[0.019]***	[0.018]***	[0.017]***	[0.020]**	[0.020]**
Ln(Share of Immig.) in Age cell	0.003	0.023	0.027	0.049	0.054	0.053	0.064	0.074	0.074	0.065	0.065	0.065
	[0.023]	[0.028]	[0.030]	[0.015]***	[0.016]***	[0.015]***	[0.016]***	[0.018]***	[0.017]***	[0.017]***	[0.019]***	[0.018]***
Observations	1517	1407	1169	1517	1407	1169	1517	1407	1169	1517	1407	1169
Education by year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education by age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1996 and 1997 excluded	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of Complex task intensity performed by native workers. The main explanatory variable is described in the first cell of the row. In parenthesis we report the heteroskedasticity robust standard errors clustered by education-age-country group. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. ***=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 3: Immigrants and Intensity of Non-Complex Task by Natives

Units of Observation: 14 EU countries, 8 education-age cells, years 1996-2007

Dependent variable	**Routine (Goos et al., 2009)**			**Routine**			**Manual**		
Column	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Method	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**
Men only	-0.052	-0.05	-0.055	0	0.013	0.008	0.002	0.022	0.018
Ln(Share of Immig.) in Educ-Age cell	[0.020]***	[0.028]*	[0.028]*	[0.015]	[0.023]	[0.023]	[0.015]	[0.025]	[0.026]
	-0.06	-0.064	-0.067	0.002	0.005	0.001	0.007	0.013	0.009
Ln(Share of Immig.) in Age cell	[0.028]**	[0.035]*	[0.036]*	[0.019]	[0.031]	[0.031]	[0.019]	[0.028]	[0.028]
All workers	-0.062	-0.076	-0.081	0.001	0.001	-0.003	0.008	0.011	0.006
Ln(Share of Immig.) in Educ-Age cell	[0.021]***	[0.025]***	[0.025]***	[0.019]	[0.026]	[0.026]	[0.018]	[0.026]	[0.026]
	-0.081	-0.079	-0.083	0.005	0.013	0.011	0.016	0.022	0.019
Ln(Share of Immig.) in Age cell	[0.022]***	[0.028]***	[0.028]***	[0.020]	[0.032]	[0.032]	[0.020]	[0.029]	[0.028]
	1517	1407	1169	1517	1407	1169	1517	1407	1169
Observations									
Education by year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education by age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1996 and 1997 excluded	No	No	Yes	No	No	Yes	No	No	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of Non Complex task intensity performed by native workers. The main explanatory variable is described in the first cell of the row. In parenthesis we report the heteroskedasticity robust standard errors clustered by education-age-country group. First-stage statistics for the shift share instrument are reported in table A5 of the appendix.*

****=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 4: Immigrants and Relative Task Performance by Natives

Units of Observation: 14 EU countries, 8 education-age cells, years 1996-2007

Dependent variable: log relative task complexity			
Column	**1**	**2**	**3**
Method	**OLS**	**2SLS**	**2SLS**
Men only			
Ln(Share of Immigrants) in Education-Age cell	0.057	0.06	0.059
	[0.016]***	[0.019]***	[0.020]***
Ln(Share of Immigrants) in Age cell	0.07	0.068	0.067
	[0.018]***	[0.022]***	[0.022]***
	1517	1407	1169
All workers			
Ln(Share of Immigrants) in Education-Age cell	0.06	0.068	0.066
	[0.018]***	[0.021]***	[0.021]***
Ln(Share of Immigrants) in Age cell	0.077	0.079	0.078
	[0.017]***	[0.020]***	[0.019]***
	1517	1407	1169
Education by year fixed effects	Yes	Yes	Yes
Country by year fixed effects	Yes	Yes	Yes
Education by age fixed effects	Yes	Yes	Yes
1996 and 1997 excluded	No	No	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of Complex relative to Non Complex task intensity performed by native workers. The main explanatory variable is described in the first cell of the row. In parenthesis we report the heteroskedasticity robust standard errors clustered by education-age-country group. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. ***=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 5: EPL, Immigrants and Relative Task Performance by natives

Units of Observation: 14 EU countries, 8 education-age cells, years 1996-2007

Dependent variable: log relative task complexity												
EPL measure		**EC89**			**EC94**			**OECD1**			**OECD2**	
Column	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Method	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**	**OLS**	**2SLS**	**2SLS**
Ln(Share of Immig.)*Low EPL	0.069	0.064	0.063	0.062	0.07	0.071	0.07	0.068	0.069	0.064	0.068	0.069
	[0.019]***	[0.024]***	[0.023]***	[0.021]***	[0.024]***	[0.025]***	[0.024]***	[0.031]**	[0.031]**	[0.021]***	[0.026]**	[0.027]**
Ln(Share of Immig.)*High EPL	0.045	0.059	0.053	0.05	0.046	0.04	0.048	0.063	0.061	0.051	0.063	0.058
	[0.024]*	[0.025]**	[0.027]*	[0.017]***	[0.021]**	[0.022]*	[0.020]**	[0.022]***	[0.024]**	[0.021]**	[0.024]***	[0.025]**
Observations	929	929	789	929	929	789	1388	1388	1180	1388	1388	1180
Education by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education by age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1996 and 1997 excluded	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of Complex relative to Non Complex task intensity performed by native workers. The main explanatory variable is described in the first cell of the row. In parenthesis we report the heteroskedasticity robust standard errors clustered by education-age-country group. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. Luxembourg is never included in EPL rankings. EC89 and EC94 indicators do not rank Austria, Denmark and Finland. See text (section 5) and OECD (1999, pp. 64-68) for details on the EPL indexes.*

****=significant at 1%; **=significant at 5%, *=significant at 10%.*

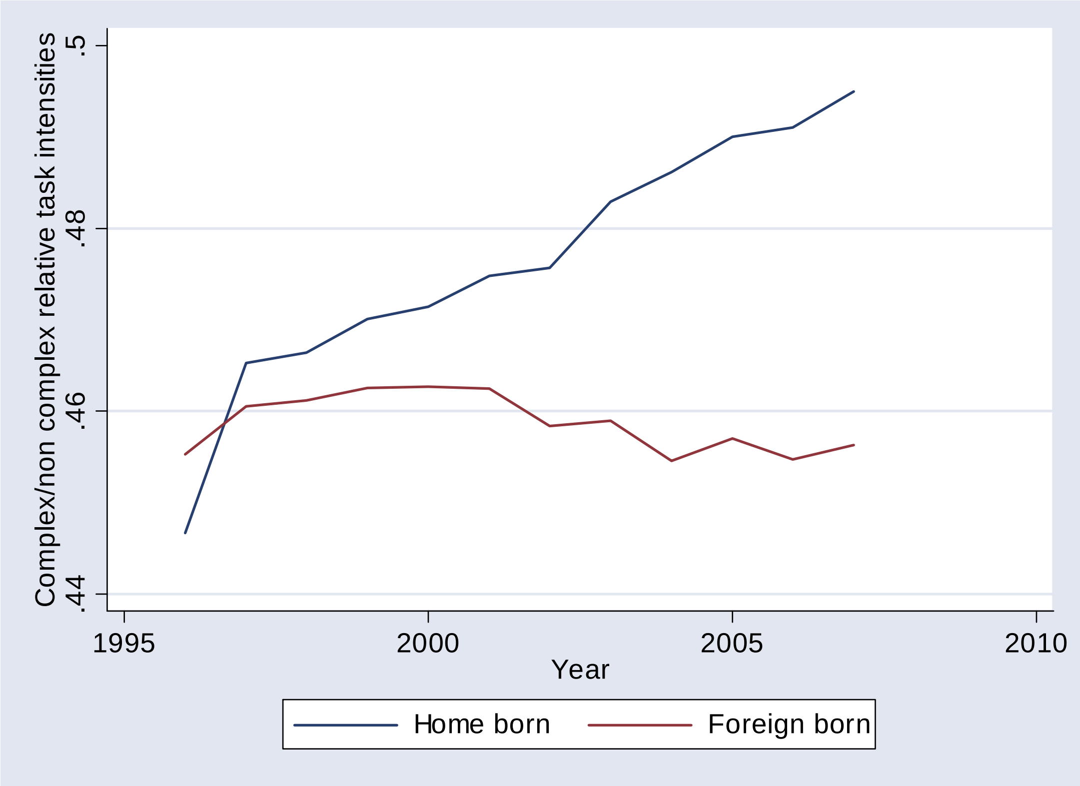
Table 6: Wages and relative Task performance by natives in 2007
Dependent variable: log monthly net wages

Column	1	2
	Men only	**Whole sample**
ln(C/NC)	0.105	0.176
	[0.007] ***	[0.006]***
Age 15-24	-0.787	-0.789
	[0.015] ***	[0.013] ***
Age 25-34	-0.199	-0.19
	[0.011] ***	[0.009] ***
Age 45-54	0.057	0.089
	[0.011] ***	[0.009] ***
Age 55-64	-0.12	-0.086
	[0.013] ***	[0.011] ***
High education	0.294	0.336
	[0.010] ***	[0.008] ***
Observations	28761	52522

Note: *Authors' calculations on EUSILC (2008). The table reports results for estimation of equation 8 in main text.*
Includes country fixed effects. Denmark, Finland, the Netherlands, Norway and United Kingdom are not included since the dependent variable is not available.
****=significant at 1%; **=significant at 5%, *=significant at 10%.*

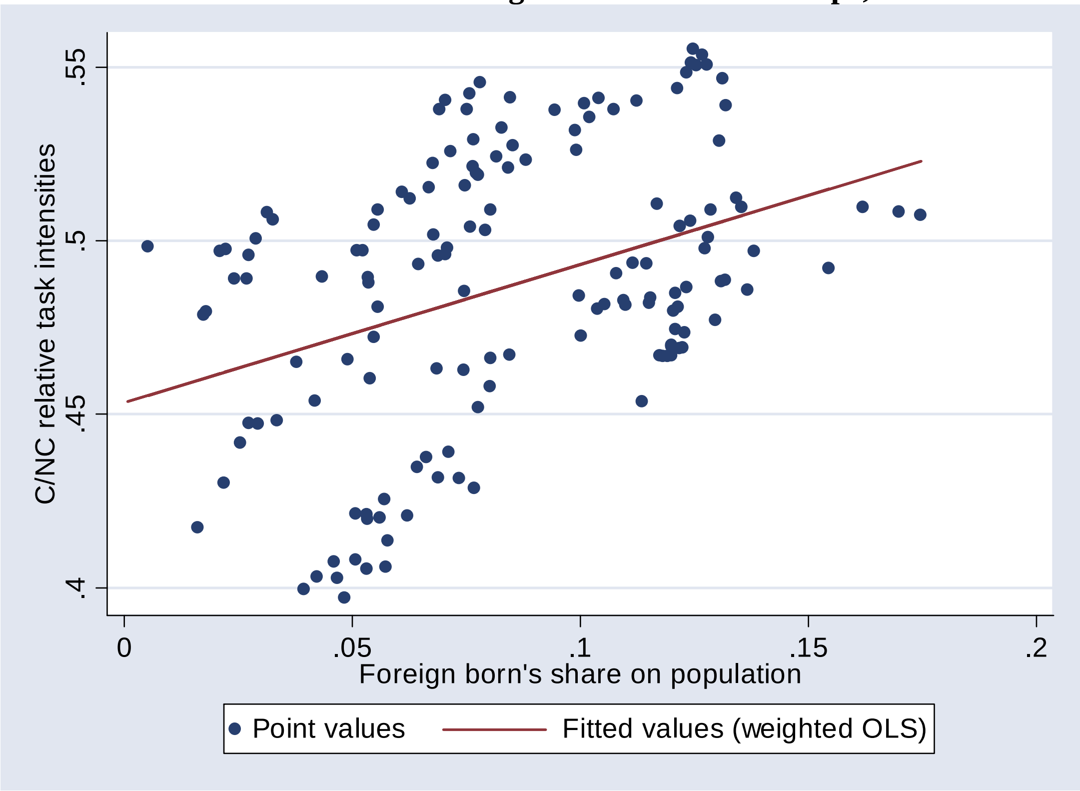
Figures

Figure 1
Relative productive tasks performed by Natives and Foreign-Born in Europe



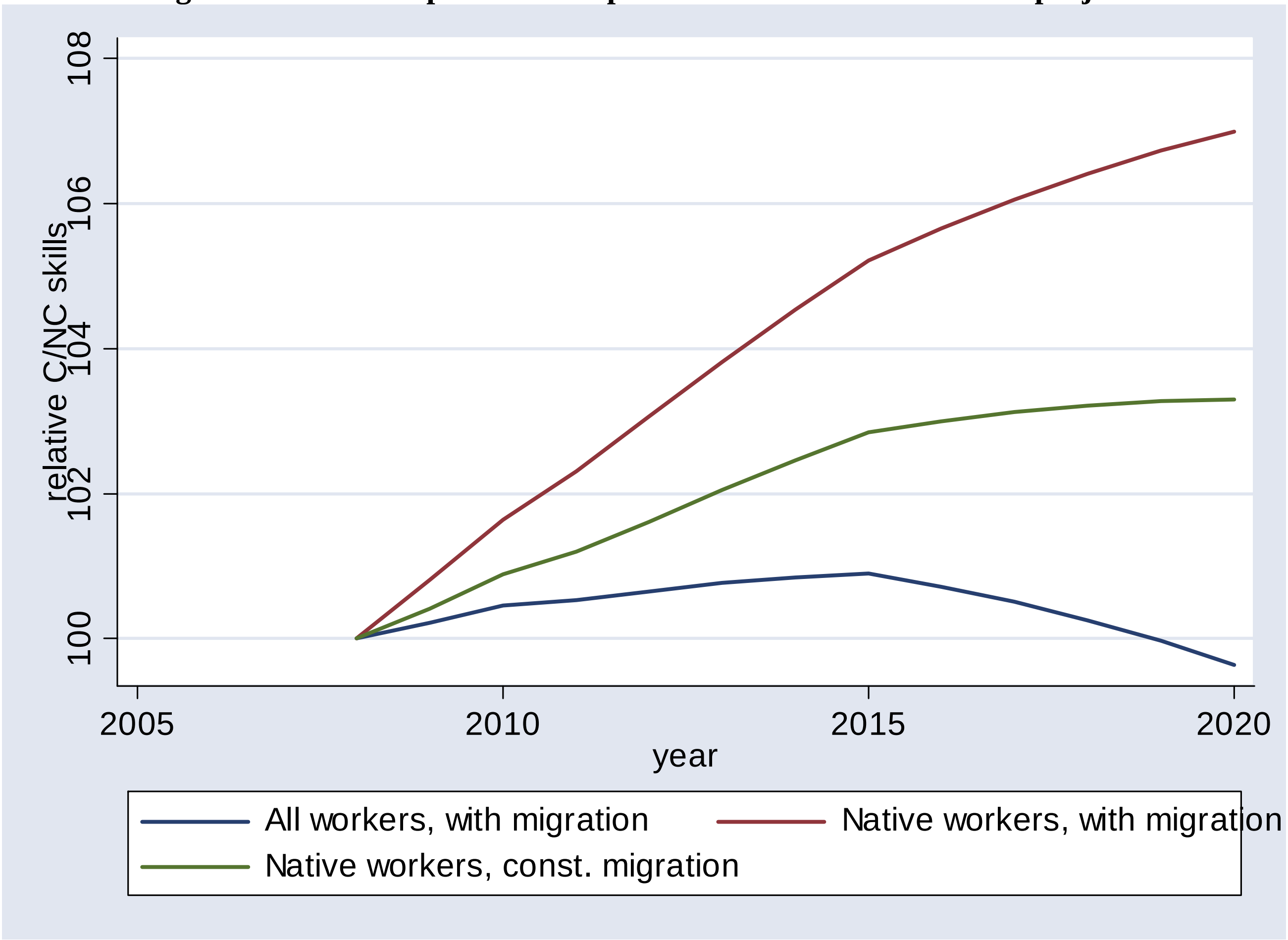
Note: *Authors' calculations on EULFS data. It does not include countries for which one or more years of data are missing (Ireland, Italy, Luxembourg and United Kingdom).*

Figure 2
Relative tasks and share of immigrants in Western Europe, 1996-2007



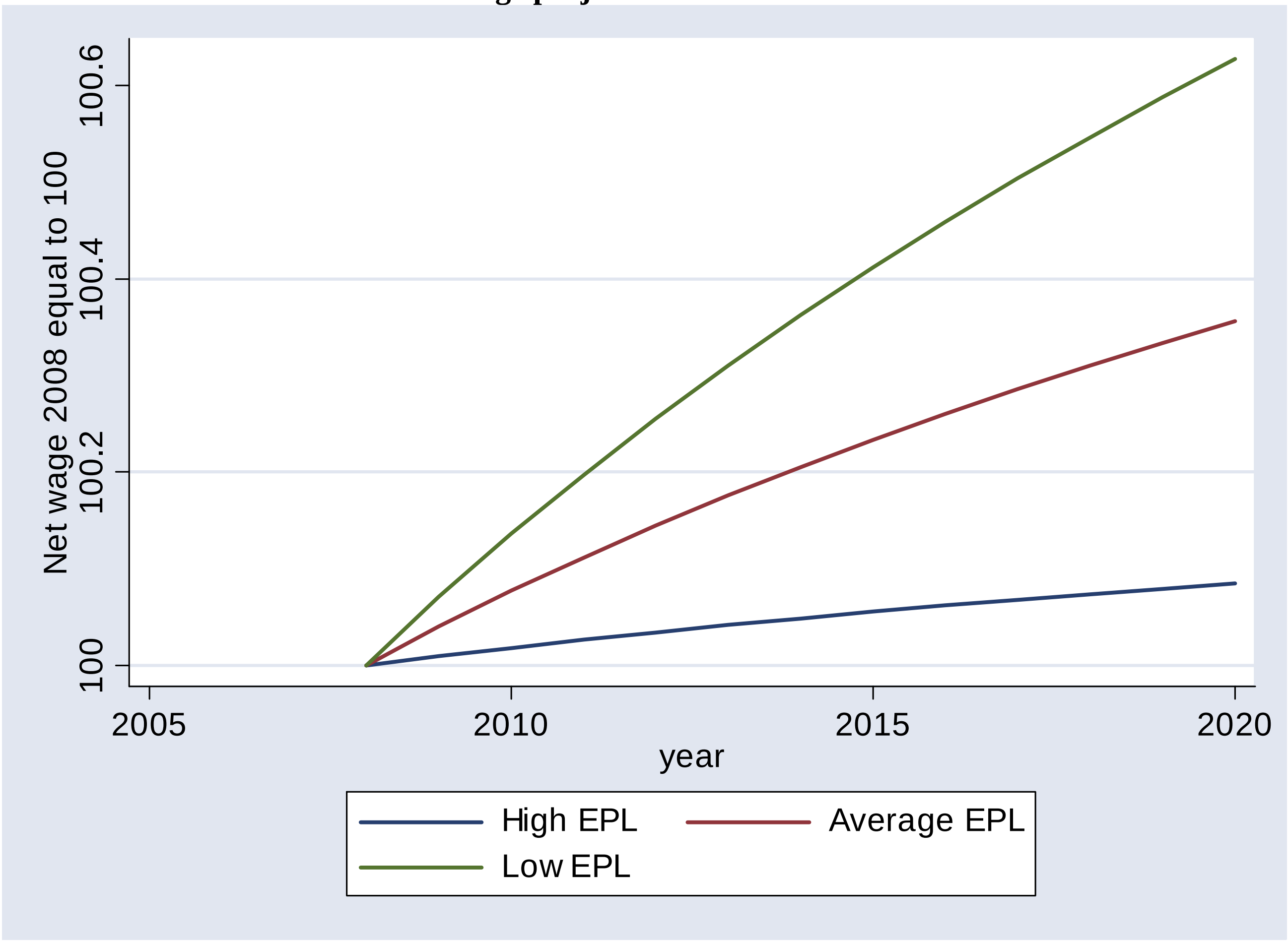
Note: *Authors' calculations on EULFS data. Fitted values estimated from a weighted OLS regression of relative task intensities (Complex/Non Complex) on the share of foreign born population and a constant with standard errors clustered at the country level. The estimated coefficient for immigrants' share is equal to 0.398 significant at the 10 per cent with a standard error of 0.219.*

Figure 3
Changes in relative complex/non complex skill intensities: 2008-2020 projections



Note: *Relative complex/non-complex skill projections are based on 2SLS estimates of equation 4 (table 4) and on the evolution of country-specific demographic structure and level of immigration forecast by the European Commission (Carone, 2005; European Commission, 2005).*

Figure 4
Wage projections: 2008-2020



.

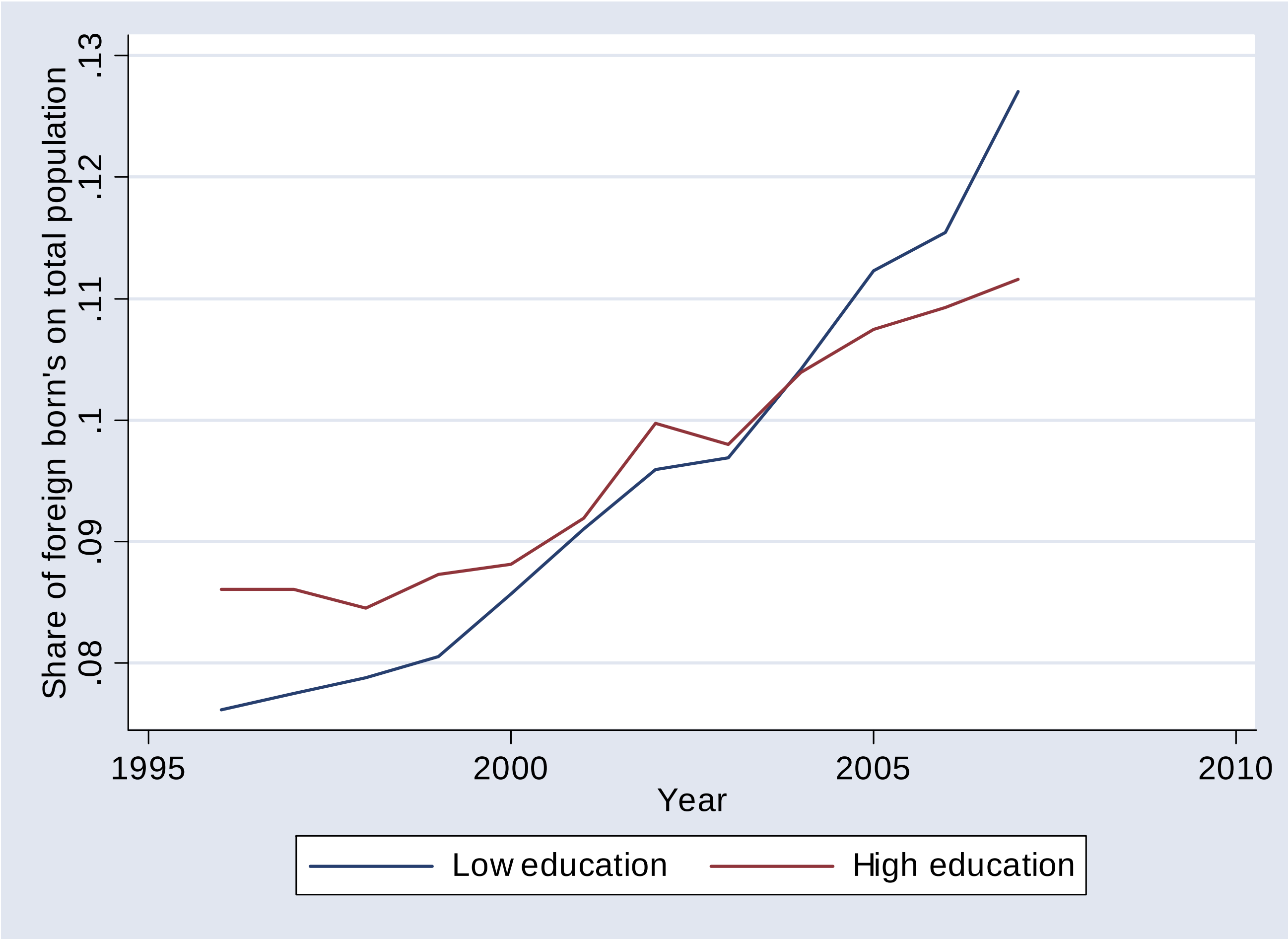
Note: *Wage projections based on Relative complex/non complex skill response to immigration obtained through a 2SLS estimation of equation 4 (table 4), on wage/skill elasticities (equation 8, results in table 5, column 1) and on the evolution of country-specific demographic structure and level of immigration forecast by the European Commission (Carone, 2005; European Commission, 2005).*

Tables and Figures Appendix

Figure A1: Immigrants in the European Population

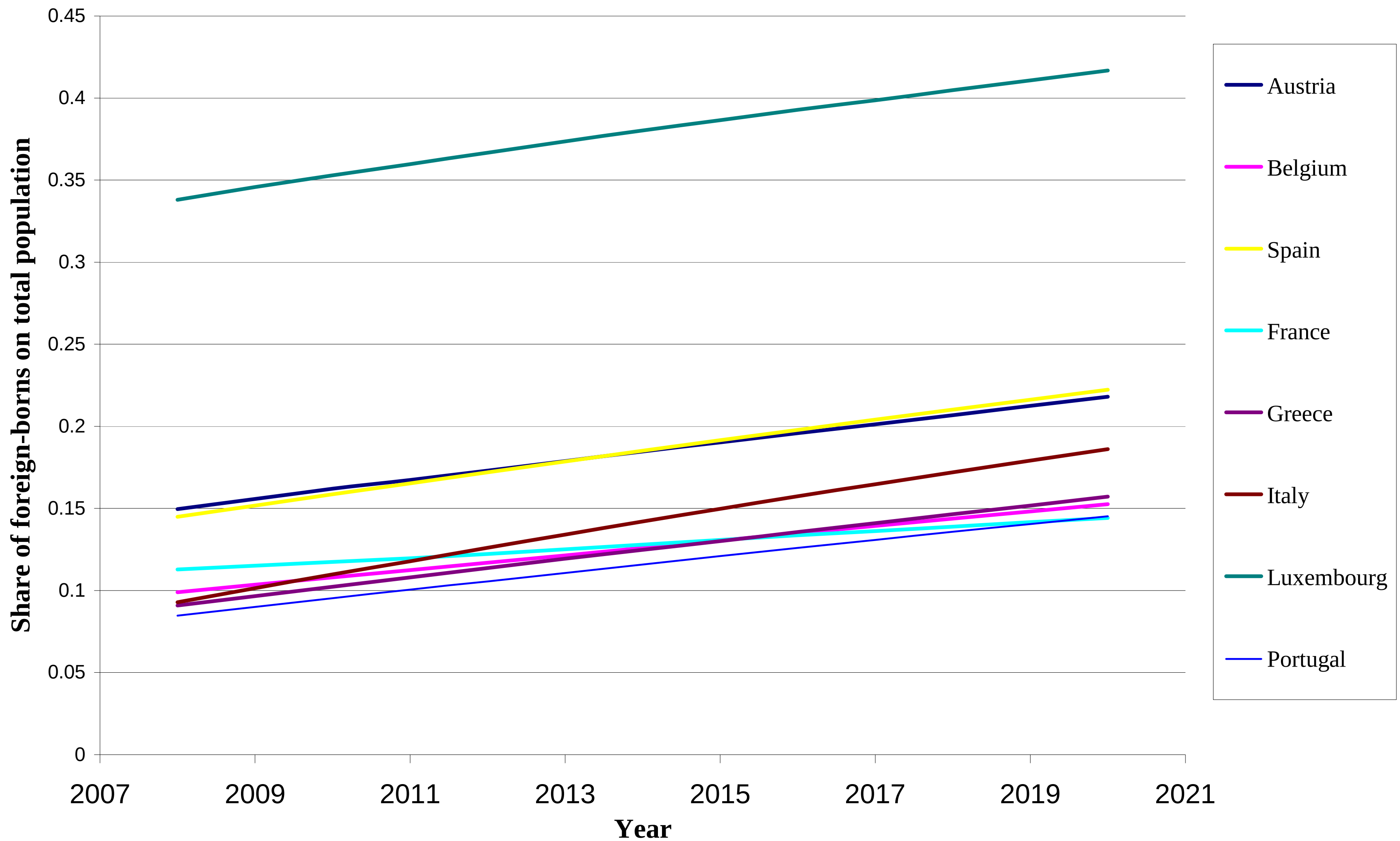
Source: *Authors' calculations on EULFS data. It does not include countries for which one or more years of data are missing (Ireland, Italy, Luxembourg and United Kingdom).*

Figure A2: Immigrants by education in Europe



Source: *Authors' calculations on EULFS data. It does not include countries for which one or more years of data are missing (Ireland, Italy, Luxembourg and United Kingdom).*

Figure A3: EC projections on immigration



Source: *authors' calculations on European Commission (2005) and EULFS data.*

Table A1: Countries and years included in the analysis

Data	EULFS													EUSILC
Country	Year												Tot	Year
	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007		2007
at	1	1	1	1	1	1	1	1	1	1	1	1	12	1
be	1	1	1	1	1	1	1	1	1	1	1	1	12	1
dk	1	1	1	1	1	1	1	1	1	1	1	1	12	0
es	1	1	1	1	1	1	1	1	1	1	1	1	12	1
fi	1	1	1	1	1	1	1	1	1	1	1	1	12	0
fr	1	1	1	1	1	1	1	1	1	1	1	1	12	1
gr	1	1	1	1	1	1	1	1	1	1	1	1	12	1
ie	0	0	0	1	1	1	1	1	1	1	0	0	7	1
it	0	0	0	0	0	0	0	0	0	1	1	1	3	1
lu	1	1	0	1	1	1	1	1	1	1	1	1	11	1
nl	1	1	1	1	1	1	1	1	1	1	1	1	12	0
no	1	1	1	1	1	1	1	1	1	1	1	1	12	0
pt	1	1	1	1	1	1	1	1	1	1	1	1	12	1
uk	1	1	0	1	1	1	1	1	1	1	1	1	11	0
Tot	12	12	10	13	13	13	13	13	13	14	13	13	152	9

Note: *0 denotes a country/year not included in the empirical analysis (16 out of 168) since one of the main variables (education, age, country of birth, occupation) is missing.*

Table A2
Skill's composition in terms of abilities/tasks

Complex tasks / mental skills (C)	Non complex tasks/manual skills (NC)
Communication	**Manual**
Oral Comprehension	Arm-Hand Steadiness
Oral Expression	Auditory Attention
Speech Clarity	Control Precision
Speech Recognition	Depth Perception
Written Comprehension	Dynamic Flexibility
Written Expression	Dynamic Strength
	Explosive Strength
Complex	Extent Flexibility
Coaching and Developing Others	Far Vision
Communicating with Persons Outside Organization	Finger Dexterity
Communicating with Supervisors, Peers	Glare Sensitivity
Coordinating the Work and Activities of Others	Gross Body Coordination
Developing and Building Teams	Gross Body Equilibrium
Developing Objectives and Strategies	Hearing Sensitivity
Estimating the Quantifiable Characteristics of Products	Manual Dexterity
Guiding, Directing, and Motivating Subordinates	Multilimb Coordination
Identifying Objects, Actions, and Events	Near Vision
Interpreting the Meaning of Information for Others	Night Vision
Judging the Qualities of Things, Services, or People	Peripheral Vision
Making Decisions and Solving Problems	Rate Control
Performing for or Working Directly with the Public	Reaction Time
Processing Information	Response Orientation
Provide Consultation and Advice to Others	Sound Localization
Resolving Conflicts and Negotiating with Others	Speed of Limb Movement
Selling or Influencing Others	Stamina
Thinking Creatively	Static Strength
Training and Teaching Others	Trunk Strength
Updating and Using Relevant Knowledge	Visual Color Discrimination
	Wrist-Finger Speed
Mental	
Category Flexibility	**Routine**
Deductive Reasoning	Controlling Machines and Processes
Flexibility of Closure	Documenting/Recording Information
Fluency of Ideas	Handling and Moving Objects
Inductive Reasoning	Monitor Processes, Materials, or Surroundings
Information Ordering	Monitoring and Controlling Resources
Mathematical Reasoning	Performing General Physical Activities
Memorization	
Number Facility	
Originality	
Perceptual Speed	
Problem Sensitivity	
Selective Attention	
Spatial Orientation	
Speed of Closure	
Time Sharing	
Visualization	

Note: This table reports skill and tasks intensities used to construct each of our broad skill measures. See text (section 3) for details.

Table A3
The skill content of each occupation

	Manual		Mental		Communic.		Routine		Complex	
	Score	Rk	Score	Rk	Score	Rk	Score	Rk	Score	Rk
Corporate managers	27	18	80	3	79	5	47	13	83	3
Managers of small enterprises	16	20	69	8	92	1	50	12	97	1
Physical,mathematical and engineering professionals	34	15	85	1	56	10	34	17	63	9
Lifescience and health professionals	46	12	82	2	86	2	75	6	89	2
Other professionals	34	14	61	9	67	8	42	14	74	5
Physical,mathematical and engineering associate prof.	36	13	77	5	48	13	39	16	61	10
Life science and health associate professionals	63	8	72	7	81	4	82	4	71	6
Other associate professionals	15	21	72	6	74	7	27	19	67	7
Office clerks	29	17	47	13	59	9	33	18	44	14
Customer service clerks	29	16	77	4	81	3	19	20	46	13
Personal and protective service workers	59	10	50	12	51	12	51	11	54	11
Models,salesperson and demonstrators	18	19	59	10	77	6	15	21	66	8
Extraction and building trades workers	62	9	57	11	55	11	90	1	80	4
Metal,machinery and related tradework	84	3	42	15	19	19	75	7	30	17
Precision,handicraft,craft printing and related trade workers	68	6	35	18	26	15	64	10	35	16
Other craft and related trade workers	74	5	18	21	9	21	83	3	22	21
Stationary plant and related operators	65	7	27	19	23	18	86	2	40	15
Machine operators and assemblers	82	4	36	17	16	20	77	5	30	18
Drivers and mobile plan toperators	88	1	38	16	24	16	69	9	28	20
Sales and service elementary occupations	55	11	25	20	35	14	42	15	28	19
Laborers in mining,construction,manufacturing and transport	87	2	46	14	24	17	73	8	49	12

Source: *authors' calculations on O*NET and 2000 US census. For each occupation, the score is equal to the percentile along the distribution of skill intensities. For example, a score of 2 for "communication skills" in a certain occupation indicates that 2% of workers in the US in 2000 were using that skill less often.*

Table A4
Correlations between skill intensities, age and education

	Goos et al (2009)		Our definition					
			Complex (C)			Non Complex (NC)		(C/NC)
	Abstract	Routine	Mental	Communication	Complex	Manual	Routine	Relative
Aged 15-24	-0.470	0.296	-0.310	-0.344	-0.333	0.313	0.174	-0.343
Aged 25-34	0.028	-0.025	0.136	0.056	0.062	0.023	0.000	0.087
Aged 35-44	0.145	-0.073	0.142	0.135	0.156	-0.047	0.010	0.125
Aged 45-54	0.168	-0.088	0.082	0.107	0.103	-0.101	-0.040	0.095
Aged 55-64	0.122	-0.109	-0.076	0.032	-0.005	-0.197	-0.155	0.021
High edu	0.869	-0.891	0.740	0.715	0.613	-0.837	-0.796	0.793

Note: *authors calculations on ELFS data. The table reports simple correlations between skills intensities and dummies for age and education.*

Table A5
First stage statistics for the instruments

Interval	1996-2007		1998-2007	
Main indep variable	Immigrants by edu/age	Immigrants by age	Immigrants by edu/age	Immigrants by age
Male only				
Coeff	0.778	0.828	0.751	0.812
	[0.016]***	[0.0166]***	[0.0188]***	[0.018]***
F test	76.75	122.06	59.13	93.6
Obs	1407	1407	1169	1169
All workers				
Coeff	0.814	0.831	0.791	0.82
	[0.017]***	[0.015]***	[0.02]***	[0.0183]***
F test	88.46	123.92	68.56	95.24
Obs	1407	1407	1169	1169

Note: *This table reports the first stage statistics for the shift-share instrument .We calculate immigrants' distribution across countries and cells for the first available year (1996 in most countries). The instrument is then obtained multiplying this fixed distribution by the total influx of immigrants in a country in a certain year. The instrument addresses potential endogeneity due the correlation between cell-specific economic shocks and immigrants' flows.*