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Abstract

In this paper we analyze the effect of immigrants on native jobs in fourteen Western European countries. We test whether the inflow of immigrants in the period 1996-2007 decreased employment rates and/or if it altered the occupational distribution of natives with similar education and age. We find no evidence of the first but significant evidence of the second: immigrants took "simple" (manual-routine) type of occupations and natives moved, in response, toward more "complex" (abstract-communication) jobs. The results are robust to the use of an IV strategy based on past settlement of different nationalities of immigrants across European countries. We also document the labor market flows through which such a positive reallocation took place: immigration stimulated job creation, and the complexity of jobs offered to new native hires was higher relative to the complexity of destructed native jobs. Finally, we find evidence that the occupation reallocation of natives was significantly larger in countries with more flexible labor laws. This tendency was particularly strong for less educated workers.

JEL Classification Codes: J24, J31, J61.

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1 Introduction

The net flow of immigrants into Western Europe during the decade preceding the great recession (1996-2007) was very large. Considering 14 countries[1] the percentage of foreign-born, shown in Figure 1, increased by more than 4 percentage points from less than 8% of the population in 1996 to more than 12 % in 2007. By comparison, in the US, the presence of foreign-born increased by a smaller percentage of the population (3%), going from 10.6% of the total in 1998 to 13.6% in 2007.

Extensive literature has analyzed the labor market effect of immigrants in US and in other countries with large immigration flows, such as Canada and Australia.[2] With some disagreement, researchers have emphasized two facts. First, immigration is relatively common among workers with very high education levels (college or higher).[3] These types of immigrants may compete with highly educated natives but may also have positive productivity effects, so their overall wage impact on native workers is likely to be positive. Second, among workers in the intermediate to low range of education, immigrants tend to be concentrated among those with very low schooling levels. They also tend to take manual and routine occupations (e.g. in construction and in the personal-household services sectors), which usually require manual and physical skills rather than communication and interactive abilities. This may generate strong competition for the least educated natives (e.g. Borjas (2003), Borjas and Katz (2007)). However, the fact that natives are employed in larger numbers in occupations that are different from those taken by immigrants (Ottaviano and Peri (2011)) and the fact that they tend to upgrade their jobs, in response to immigration (Peri and Sparber (2009)), taking on more complex and communication-intensive tasks and leaving manual tasks to immigrants, protects them from such competition. Hence, even for the group of less educated native workers, several economists do not find any significant wage effects of immigrants (e.g. Card and Shleifer (2009), Ottaviano and Peri (2011)).

As far as European labor markets are concerned, economists have analyzed the impact of immigrants in specific countries (see for instance Dustmann et al. (2008) for the UK, Glitz

[1] Namely Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, United Kingdom.

[2] See for instance Longhi et al. (2005) for a summary and meta-analysis of the literature on the wage effect of immigrants.

[3] This is not only true for US immigrants but also for immigrants to European countries. See for instance Docquier et al.'s (2010) data and empirical analysis that emphasize this fact.

(2011) for Germany and González and Ortega (2008) for Spain) using frameworks similar to those applied to the United States. Often those types of analyses are forced to use variation (of immigrants and labor market outcomes) across regions within a country. Hence, they are subject to the concern, put forward in several studies (e.g. Borjas et al. (1996)), of identifying an attenuated wage effect relative to the possible national effect. With the notable exception of Angrist and Kugler (2003), we are not aware of any study that analyzes the impact of immigration on European Labor markets considering evidence from all (or most) Western European economies. In this paper, we fill this gap by analyzing how immigration affects net employment and job specialization of natives and how these effects vary across EU countries.

We use the European Labor Force survey to analyze the labor market effects of immigrants, exploiting the variation of immigration rates across 14 EU countries over the recent decade. Besides a large panel variation in the inflow of immigrants, European countries also provide large variation in the institutional characteristics of their labor markets. These rich sources of additional variation allow us to address a host of novel questions: Are some countries better equipped to absorb immigrants? Is the response of native workers to immigrants, in terms of occupational mobility, stronger in countries with more flexible labor markets? Are these differences particularly relevant for some groups of workers?

In the broader picture, this paper also contributes to the understanding of the determinants of a shift in demand and supply of productive tasks in Europe. In the recent decades, an increase in employment within jobs requiring the use of complex and abstract skills, and a decrease in employment within manual-routine type jobs has been documented for many developed countries. In particular, these phenomena have been observed in the US (Acemoglu and Autor, 2010) as well as in Europe (Goos et al., 2009). In a search for common global tendencies, that offer explanations for the aforementioned trends, most of the economic research (as summarized in Acemoglu and Autor (2010)) has focused on two factors: the effect of technology and the effect of off-shoring. On one hand, information and communication technologies have increased the productivity of complex-abstract jobs, while substituting for routine manual (and routine non-manual) tasks. On the other, the internationalization of production has allowed the relocation of simple and manual phases of production abroad, but not (yet) the relocation of complex tasks. These two factors affected the demand for these tasks in developed 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. Our hypothesis is that the inflow of these immigrants has increased the supply of manual-physical skills in rich economies, but also shifted native workers to more complex tasks. Hence, immigration has been an additional cause for the increase in employment in cognitive and complex tasks by native workers.

Our empirical strategy consists of considering different skill cells (represented by combinations of education and age in each country) across European countries. Each of them, in the tradition of Borjas (2003), is a differentiated labor market (mobility of natives across countries is small in Europe). Within each of them we consider a partition of productive tasks into "complex" tasks (abstract and cognitive) and "simple" tasks (routine and manual based). Such a partition follows the literature on the effect of information technology on the demand for productive tasks (e.g. Autor et al. (2003)) and the literature on "off-shorability" of tasks (e.g. Crinò (2009) and Blinder (2006)). We consider this partition as relevant also in determining the relative specialization of native and immigrant workers. Jobs that can be easily codified, that are manual and repetitive in nature, are considered "simple" and may be easily taken by foreign-born workers who may have more limited native language skills and not know the intricacy of the culture, social norms and institutions of the host country. If this is the case then an inflow of immigrants in a cell (labor market) increases the supply of "simple" productive tasks in that cell. As we will show in a model of occupational choice, natives, who have a comparative advantage in communication-abstract tasks, would in response specialize in more "complex" tasks.

Using this structure we can then identify whether immigration has been a force promoting the specialization of native workers in Europe toward abstract-complex occupations and away from manual-routine ones. At the same time we can check whether such a shift in the occupational distribution of natives took place with a net increase, decrease or no change in employment for natives. To establish whether the increased specialization of natives, which correlates with the inflow of immigrants, was actually caused by them we use an instrumental variable approach. Our instrument, inspired by Altonji and Card (1991) and Card (2001), is based on the fact that the share of foreign-born in 1990 within each European country, by country of origin, is a predictor of their subsequent flows into EU countries. Assuming that shift in demand for foreign labor taking place between 1996 and 2007 does not vary systematically with foreigners' settlements in 1990, the instrument is correlated with relative task supply only through its effect on the supply of immigrants. We also control for factors that proxy shifts in the relative demand for complex-abstract tasks which may be country or skill-specific.

Our main empirical findings are three. First, according to results obtained using our preferred specification (2SLS estimates with country by education and education by year fixed effects), immigrants flows do not cause a decrease in natives employment rates, but rather increase them; moreover, higher immigration pushes natives to occupations with higher skill contents: a doubling of the immigrants' share in a labor market (defined by skill-country cells) increases natives' specialization in complex skills by 6%. Second, we document that such a positive reallocation takes place through an increase in the average complexity of jobs offered to new hires relative to separations. Third, we split countries in two groups, those with strong employment protection laws (EPL) and those with weak employment protection. We then allow the response of net employment and specialization of natives to differ across groups. We find that the natives' positive reallocation towards complex jobs triggered by migration is more intense in less protected markets, in particular for workers with low education. This implies that in countries with high EPL, less educated workers tend to remain in simple-manual occupations that suffer much more the wage competition of immigrants, while in countries with low EPL the mechanisms of upgrading natives' occupations moves less educated workers away from immigrants' wage competition.

The rest of the paper is organized as follows: Sections 2 and 3 respectively define a theoretical model of immigration and natives' specialization and discuss the identification strategy. Section 4 describes the datasets and the task variables. Results of the empirical analysis on immigration and natives' employment rates and occupations are reported in Section 5, Section 6 analyzes the impact of immigrants separately on new hiring and separations of natives, while Section 7 investigates how labor market institutions affect the extent of the occupational adjustment. Section 8 concludes the paper.

2 The Model

2.1 Relative Demand of Tasks

We consider that each labor market (country) is divided into cells of workers with differing observable skills, experience and education. Similarly to Katz and Murphy (1992), Ottaviano and Peri (2011) and Peri and Sparber (2009), we use a categorization that distinguishes between two education groups, those with secondary education or less and those with some tertiary education and more. These two groups are clearly differentiated for the type of jobs/production tasks that they perform. Within each group we consider five age subgroups. As in Borjas (2003) and Ottaviano and Peri (2011), each of these skill groups provides labor services that are somewhat differentiated because they use different vintages of technology and have had different labor market experiences. Hence the structure of competition-substitutability within a schooling 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. Such a structure imposes specific restrictions on the cross-cell elasticities. We follow the well established practice of grouping skills that are harder to substitute into the outer groups, increasing substitutability as we progress into the inner nests. Card and Shleifer (2009) and Goldin and Katz (2007) argue that the split into two schooling groups is the one preferred by the data and most of the literature organizes the experience groups into bins of five or ten years. Our choice of nesting structure follows their lead. Furthermore, the particular order of nesting does not matter for our results as long as education-age cells are imperfectly substitutable groups of workers. For each country c in year t we represent the production function as follows:

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

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

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

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*". $N_{age,edu,c,t}$ is the composite input from workers of education "*edu*" and age "*age*". The parameters θ 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 across countries and over time and the relative productivity of age groups $\theta_{age,edu,c,t}$ also varies by education, country and time. The elasticities 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 simple tasks (S) and consider those inputs as imperfect substitutes, also combined in a CES.

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

$S_{j,c,t}$ and $C_{j,c,t}$ are the amount of "simple" (manual, routine) and "complex" (abstract, communication, mental) services supplied by the skill group j in country c and year t. The coefficient β_j determines the relative productivity of simple tasks in the cell and the elasticity σ determines the substitutability between the two types of tasks in the cell. We call w_C the compensation for one unit of service of complex work, and w_S the compensation for one unit of service of simple work. This allows us to derive the relative demand for complex and simple services in skill group j by equating the ratio of their marginal productivity to the ratio of their compensations:

$$\frac{C_{j,c,t}}{S_{j,c,t}} = \left(\frac{1-\beta_{j,c,t}}{\beta_{j,c,t}}\right)^{\sigma} \left(\frac{w_C}{w_S}\right)_{jct}^{-\sigma} \tag{4}$$

The relative supply, the relative compensation and potentially the relative productivity of simple and complex services vary with skill, country and year, hence the subscripts. Throughout the remainder of the theory section we omit the $_{j,c,t}$ subscripts and we will re-introduce them when describing the empirical specification.

2.2 Relative Supply of tasks

As in Peri and Sparber (2009), we assume that native and immigrant workers divide their labor endowment ($l = 1$) between simple and complex tasks in order to maximize their utility. Here, differently from Peri and Sparber (2009), we allow utility to depend positively on labor wage and negatively on a stigma associated with simple working tasks. Hence, individuals of similar skill j, if natives or immigrants, may have different productivity in simple and complex tasks as well as different degrees of "dislike" (stigma) for earning as simple manual-routine workers. The utility U_k for individuals of type k, with $k = D$ indicating domestic and $k = F$ denoting foreign-born workers, is given by the following expression:

$$U_k = \underbrace{(l_k)^{\delta} \varkappa_k w_S + (1 - l_k)^{\delta} \kappa_k w_C}_{\text{Wage Income}} - \underbrace{d_k (l_k)^{\delta} \varkappa_k w_S}_{\text{Stigma}}. \tag{5}$$

The first part is the wage income. Each individual of type k has some task-specific ability $\varkappa_k$ and κ_k and, by allocating l_k units of labor to simple tasks and $1 - l_k$ units to complex tasks, produces $s_k = (l_k)^{\delta} \varkappa_k$ units of simple service and $c_k = (1 - l_k)^{\delta}_D \kappa_k$ of complex service (with $\delta < 1$), compensated respectively at rate w_S and w_C per unit.[4] However, the part of income earned doing simple tasks does not convey the full utility of income as it may have some stigma, disutility or penalty attached, represented by the second term in U_k. People may dislike doing manual jobs, or the status in society of these jobs may be low, or there may be some dislike of circumstances connected with the manual part of the job (being outside, uncomfortable, etc.). We model this stigma-disutility as an "iceberg" cost on the part of the income that is earned doing the simple tasks, with d_k, between 0 and 1, as the parameter that captures the intensity of such psychological cost/dislike. The second part of the utility is essentially the equivalent amount of income that a person would give up in order to be able to do a "complex" rather than a "simple" job.

Maximizing (5) with respect to l_k we obtain the individual relative supply of tasks for type k:

$$\frac{c_k}{s_k} = \left(\frac{w_C}{w_S}\right)^{\frac{\delta}{1-\delta}} \left(\frac{1}{1 - d_k}\right)^{\frac{\delta}{1-\delta}} \left(\frac{\kappa_k}{\varkappa_k}\right)^{\frac{1}{1-\delta}} \tag{6}$$

In this simplified model each native supplies (c_D, s_D) task units and each immigrant supplies (c_F, s_F) so that members from each group will choose a common combination of tasks (empirically an occupation). Each group will choose a new combination of tasks if their relative compensation changes. The relative supply of complex tasks increases with the relative compensation w_C/w_S and it increases with the relative ability in complex tasks of the group, $\frac{\kappa_k}{\varkappa_k}$, as well as with its dislike for manual-routine services $\frac{1}{1-d_k}$. The aggregate task

[4] The assumption of $\delta < 1$ implies an internal solution: all individuals do at least some of each tasks. This means that when a person spends almost the whole day doing only complex tasks (e.g. writing a complex paper) it is efficient to spend a little time doing simple tasks (such as cleaning up the desk).

supply for native and foreign workers in skill j, country c and year t, will equal the product of individual task supply and total labor supply. This implies $\frac{c_{j,c,t}}{s_{j,c,t}} = \frac{C_{j,c,t}}{S_{j,c,t}}$ (by multiplying numerator and denominator by employment in the cell).

Finally aggregating immigrants and natives we obtain the aggregate relative supply of tasks in cell j, c, t.

$$\frac{C}{S} = \frac{C_F + C_D}{S_F + S_D} = \phi\left(f\right) \cdot \frac{C_F}{S_F} + \left(1 - \phi\left(f\right)\right) \cdot \frac{C_D}{S_D} \tag{7}$$

The term $\phi\left(f\right) = S_F/(S_F + S_D) \in (0, 1)$ is the share of simple tasks supplied by foreign-born workers, and is a simple monotonically increasing transformation of the foreign-born share of less educated workers, $f = L_F/(L_F + L_D)$.[5] Hence, the aggregate relative supply of tasks in the economy is a weighted average of each group's relative supply, and the weights are closely related to the share of each group in employment.

2.3 Equilibrium Results

Substituting (6) for natives and immigrants in (7) and equating relative supply with relative demand (expressed by (4)) one can solve for the equilibrium relative compensation of tasks:

$$\frac{w_C^*}{w_S^*} = \left(\frac{1-\beta}{\beta}\right)^{\frac{(1-\delta)\sigma}{(1-\delta)\sigma+\delta}} \left[\frac{\kappa}{\varkappa}\left(\underset{-}{f}, \underset{+}{\frac{\kappa_F}{\varkappa_F}}, \underset{+}{d_F}\right)\right]^{-\frac{1}{(1-\delta)\sigma+\delta}} \tag{8}$$

The function $\frac{\kappa}{\varkappa}\left(f, \frac{\kappa_F}{\varkappa_F}, d_F\right)$ is a weighted average of the relative task abilities and of simple job aversion among natives and immigrants. More specifically, $\frac{\kappa}{\varkappa}\left(f, \frac{\kappa_F}{\varkappa_F}, d_F\right) = \left[\phi\left(f\right) \cdot \left(\frac{\kappa_F}{\varkappa_F}\right)^{\frac{1}{1-\delta}} \left(\frac{1}{1-d_F}\right)^{\frac{\delta}{1-\delta}} + \right.$
The term $\frac{\kappa}{\varkappa}\left(f, \frac{\kappa_F}{\varkappa_F}, d_F\right)$ depends negatively on f and positively on $\frac{\kappa_F}{\varkappa_F}$ and d_F, as indicated by the signs in equation (8).

By substituting the equilibrium wage into the aggregate relative supply for domestic workers, we find their equilibrium relative provision of tasks (Equation (9)).

$$\frac{C_D^*}{S_D^*} = \left(\frac{1-\beta}{\beta}\right)^{\frac{\delta\sigma}{(1-\delta)\sigma+\delta}} \left(\frac{\kappa_D}{\varkappa_D}\right)^{\frac{1}{1-\delta}} \left(\frac{1}{1-d_D}\right)^{\frac{\delta}{1-\delta}} \left[\frac{\kappa}{\varkappa}\left(\underset{-}{f}, \underset{+}{\frac{\kappa_F}{\varkappa_F}}, \underset{+}{d_F}\right)\right]^{-\frac{1}{(1-\delta)\sigma+\delta}\frac{\delta}{1-\delta}} \tag{9}$$

The equilibrium expression (9) is the basis for the empirical analysis. In particular, based on its logarithmic derivative of (9), the model predicts a positive impact of the share of foreign-born, f, on the relative supply of complex tasks of natives, $\frac{C_D^*}{S_D^*}$.

[5] Specifically: $\phi'(f) > 0$, $\phi(0) = 0$ and $\phi(1) = 1$.

3 Empirical implications and identifying assumptions

Expression (9) holds for each skill-country-year cell; taking the logarithm of both sides of the equation and explicitly writing the subscripts in the variables for each skill-country-time group we approximate the equilibrium condition to the following empirically implementable condition:

$$\ln\left(\frac{C_D}{S_D}\right)_{j,c,t} = \gamma \cdot \ln(f_{j,c,t}) + d_{edu,c} + d_{edu,t} + \varepsilon_{j,c,t} \tag{10}$$

The term $\frac{C_D}{S_D}$ is the measure of relative complex versus simple tasks provided by home-born 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 ($\ln(f_{j,c,t})$, in logarithm) in the cell and $\gamma \equiv -\frac{1}{(1-\delta)\sigma+\delta}\frac{\delta}{1-\delta}\left(\frac{\partial \ln \frac{\kappa}{\varkappa}}{\partial \ln f}\right) > 0$. The country by education effect $d_{edu,c}$ captures the unobservable relative productivity and simple-job aversion for natives, $\frac{1}{1-\delta}\ln\left(\frac{\kappa_D}{\varkappa_D}\right)$ and $\frac{\delta}{1-\delta}\ln\left(\frac{1}{1-d_D}\right)$ and for immigrants $-\frac{1}{(1-\delta)\sigma+\delta}\frac{\delta}{1-\delta}\left(\frac{\partial \ln \frac{\kappa}{\varkappa}}{\partial d_F}\right)$ and $-\frac{1}{(1-\delta)\sigma+\delta}\frac{\delta}{1-\delta}\left(\frac{\partial \ln \frac{\kappa}{\varkappa}}{\partial \frac{\kappa_F}{\varkappa_F}}\right)$. These features of the native and immigrants population depend on the skill group and on the country, but not on the year. A certain country, due to its laws and institutions selects immigrants with certain productivity and preference characteristics (by skill group) relative to natives. This, however, changes only slowly with time and we assume that it is constant over the considered period. The education by time effects $d_{edu,t}$ absorb the variation of the relative productivity and efficiency term $\frac{\delta\sigma}{(1-\delta)\sigma+\delta}\ln\left(\frac{1-\beta}{\beta}\right)$. The relative productivity of simple and complex tasks may evolve over time. For instance, a common complex-biased technological progress that affects college educated workers more than less educated ones over the considered years would be captured by these effects. The term $\varepsilon_{j,c,t}$ is an idiosyncratic random shock (or measurement error) with average 0 and uncorrelated with the explanatory variables. Our main interest is in estimating γ. Our model predicts a positive value of γ, as a larger share of immigrants would increase returns for complex tasks relative to simple tasks and hence push natives to specialize further into those tasks with potential productivity and wage gains. The magnitude of that effect is an empirical question.

3.1 Discussion of Endogeneity

Once we control for the cell-specific selection and for the technological factors, we are assuming that the remaining variation over time in the share of immigrants across cells within country-year is driven by the exogenous variation of immigrant supply. In particular, in the OLS estimates we are assuming that, after controlling for the fixed effects, the whole variation of $f_{j,c,t}$ is exogenous. Residual correlation could still be present if, for example, skill upgrading is taking place among native workers of a particular country, irrespective of immigration. This would determine the excess demand for unskilled workers and, thus, attract immigrants. We deal with this potential bias emerging from reverse causality in two ways.

First, in all specifications we define $f_{j,c,t}$ as the share of foreign born individuals on total population (rather than employment) within each cell. Immigrant population is by and large determined by factors in the sending countries, the costs of migration, as well as immigration laws. Of course, employment opportunities (driven by labor demand conditions) affect immigration choices and hence the whole population in a cell may still depend on unobserved labor demand shocks. Hence we also include country by education and education by year fixed effects, capturing systematic differentials across cells in relative Complex/Simple task demand driven by technology (education by year) and country-specificity (country by education).

Second, we also address the potential omitted variable bias with an instrumental variable strategy.[6] In particular, from IPUMS-I (2010) we downloaded micro-data from national Censuses 1990-1991, for seven of the fourteen countries included in the ELFS (Austria, France, Greece, Italy,[7] Portugal, Spain, United Kingdom). For that year, we computed the population of immigrants by area of origin (using nine large geographic groups[8]) in each country-education-age cell and the native population in each of those cells. We have then used the data on yearly immigration flows into OECD countries by country of origin from Ortega and Peri (2011). Those data, described in detail in Ortega and Peri (2011), were collected from several sources (OECD, UN) and report the total gross inflow of migrants from any country into OECD countries. Based on these gross flows, we construct yearly net inflows by attributing a 40% re-migration rate to immigrants. Further, for each year within the

[6] This strategy has evolved as a favorite one in this literature since its first use by Altonji and Card (1991).

[7] For Italy we used 2001 data, the first ones providing all necessary information. Nevertheless, for this country ELFS data are available starting with 2005 and not with 1996, so that the shares are still calculated according to the distribution of immigrants taking place 4 years before the estimation interval starts.

[8] The groups of origin of immigrants are: North Africa, Other Africa, North America, Central and South America, Middle East and Central Asia, South and Eastern Asia, Eastern Europe, Western Europe, Oceania.

period 1996-2007 and the seven EU countries in our sample, we break net immigration rates down by the nine areas of origin mentioned above. Multiplying the resulting origin-specific growth rates by the 1991 stock of immigrants in each education-age-country cell allows us to infer origin-cell-specific stocks of immigrants at an annual frequency. We aggregate across countries of origin, in order to impute the total stock of immigrants at the education-age-country level for each year within the period 1996-2007. Finally, we obtain shares of immigrants on the cell-year level by representing the imputed population of immigrants as a fraction of the total population, assuming that the number of natives remained at its 1991 level. This method implies that the variation in shares obtained across cells and years is only driven by the initial cell composition of immigrants by origin and the variation in inflows across origin groups in Europe over time. If a country had a lot of young and highly educated Algerians in 1991 (rather than, say, young and less educated Filipinos) and Algerians turned out to increase their immigration rates more than Filipinos in the considered period, the first country would obtain a larger group of educated young immigrants as of 2007 relative to the second.

The underlying exclusion assumption is that, while immigrants of certain origins tend to settle where historical communities of similar origin already are, in order to exploit networks and supply of ethnic public goods, the 1991 distribution of immigrants by origin is unrelated to changes in labor demand during the 1996-2007 period. The instrument turns out to be fairly strong (first stage statistics are reported in Table A5 of the appendix). In particular the F-test of the constructed IV for the whole sample is around 69 when considering men and women and 58 when considering men only. Such strong correlation is a sign that the composition of immigrants and the subsequent flows by origin work as strong predictor of the increase in immigrants in a cell. This shows that the network of previous immigrants reduces costs of settling and finding a job for new immigrants of similar origin.

Since we can only calculate the initial 1991 shares of immigrants on a subset of 7 out of 14 countries, we analyze three alternative specifications for our main regressions. First, based on all the 14 countries, we estimate equation (10) using OLS with fixed effects. Second, we restrict the OLS analysis to the sample of 7 countries for which we have the instruments, and finally, we employ the 2SLS strategy outlined above for this subset of countries.

3.2 Empirical Implementation

Our empirical analysis consists of four parts. First, after a brief introduction of our data in Section 4, we begin by analyzing the impact of immigration on natives' employment rates in Section 5.1. While this is of interest in itself, it also complements the subsequent analysis of relative skill effects, based on equation (10). In the second part, we continue by quantifying the adjustment in the distribution of skills across different types of workers, which is potentially triggered by immigrants' flows (Section 5.2). As a preliminary step, we separately investigate the effects of immigration on the total amount of "complex" as well as "simple" tasks performed by native workers. We do so by estimating two models, akin to equation (10), with $\ln (C_D)_{j,c,t}$ and $\ln (S_D)_{j,c,t}$ as the respective dependent variables. The aim is to gauge the impact of immigration on the numerator and the denominator of the left hand side of equation (10) in isolation. This decomposition helps us to understand whether a potential relative reallocation takes place with a net increase or a net decrease in the intensity with which native workers perform the two respective types tasks.

In order to check whether the regularities found for the composite "complex" and "simple" task measures are also present at a more disaggregate level, we run separate regressions for each of the underlying basic task components.[9] As an additional robustness check we further estimate the impact of immigration on alternative measures of "complex" and "simple" task intensity taken from Goos et al. (2009).

We conclude the second part by estimating the impact of immigration on *relative task* levels (our main specification, equation (10)), in order to empirically test the equilibrium conditions (equation (9)) derived from the model outlined in Section 2.

The third part (Section 6) outlines our approach to investigate the labor market flows behind the potential task adjustment in response to immigrant inflows. In particular, we inquire whether native workers' labor reallocation takes place through systematic changes in the hiring (job creation) or separation (job destruction) margin.

Finally, in Section 7, we test whether country-level labor market policies, in particular employment protection laws, are fostering or discouraging a potentially favorable skill reallocation. The process we envision is a dynamic shift of native workers across occupations. Thus, the ease of transition between jobs within a particular country is potentially a crucial component in determining the strength of this channel.

[9] See Section 4.1 for details on the construction of our skill measures.

4 Data and descriptive statistics

The main dataset we use is the harmonized European Labour Force Survey (ELFS), which homogenizes and groups 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 of individuals are absent for most countries in the survey. We restrict our analysis to the working age population (age 15-64) of Western European countries only.[10] The data include information on the occupation, working status and demographic characteristics of the individuals. Unluckily the ELFS does not include any information on their wages. We dropped observations with missing data on education, age or country of birth, which are fundamental for our empirical analysis. Only in 16 out of 168 (14 countries $\times$ 12 years) country-year cells one of these variables, fundamental for our analysis, was completely missing and we had to drop it.[11]

In line with previous literature, we classify as immigrants all individuals born in any country (both EU or non-EU) outside the considered one. 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 1 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 data from all countries except Ireland, Italy, Luxembourg and United Kingdom, for which data are missing for one or more years. The share of foreign born in the total population increased by more than 4 percentage points from below 8% in 1996 to 12.3% in 2007. This increase was, on average, rather evenly distributed across educational levels (as one can see from Figure A1 in the Tables and Figures appendix).

In the empirical analysis, for each year between 1996 and 2007, we aggregate the individual data to the country-level, two educational levels (upper secondary education or less and strictly more than upper secondary education) and five ten-year age-classes covering individuals between 15 and 64 years of age. Our analysis includes both women and men, and as a robustness check we also show the results of the specifications including only men.

[10] 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.

[11] See Table A1 of the Tables and Data appendix for the full list of country/years. The table illustrates missing values as well as the subset of cells included in the 2SLS specifications.

4.1 Task variables

To test the predictions of the model in Section 2, especially the equilibrium condition (10), we need indicators of the intensity of skills supplied in each job over time. Following Peri and Sparber (2009) and considering occupations as capturing the different types of jobs performed, we use the *O*NET* data from the US Department of Labor (version 11, available at http://www.onetcenter.org/). This survey, started in 2000 (when it replaced the Dictionary of Occupational Titles, *DOT*), assigns values summarizing the importance of several different abilities to each of 339 Occupations (according to the Standard Occupation Classification, SOC). We use 78 of these tasks to construct our measures of skill-intensity for each occupation. As the scale of measurement for the task variables is arbitrary, we convert the values into the percentile of the task intensity in the 2000 distribution of occupations. We create five abilities' measures: *communication, complex, mental, manual and routine*. For example, skills used to construct the *communication* category include, among others, *oral comprehension*, *oral communication* and *speech clarity*; *manual dexterity* and *reaction time* are among the skills used to construct the manual category and so on. Table A2 of the appendix includes the full list of the skills/tasks measures employed to construct each of the indicators. When we consider only two broad groups, *complex* and *simple*, the *communication*, *complex* and *mental* skills are included in the complex group, while *manual* and *routine* form the simple one. In some of the empirical specifications, we also use the alternative *abstract* and *routine* classifications employed by Goos et al. (2009) as a robustness check.[12]

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 the ELFS. We aggregate the scores (between 0 and 1) for each of the task intensity measures as a weighted average of the SOC occupations into the ICSCO one. The weights used are the share of workers for each SOC occupation in the total of the ISCO grouping, according to the 2000 US Census. To give an idea of the indicators, the ISCO occupation "*corporate managers*" that gets a score of 0.79 in *communication skills* indicates that 79% of all workers in the US in 2000 were using *communication skills* less intensively than corporate managers. Table A3 of the appendix shows the score for each of the ability indexes in the 21 occupations provided

[12] These measures employ a different set of skills and are normalized with zero mean and unitary variance.

by the ELFS. 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 simple correlations between each of the ability measures and some dummies that capture specific education or age level groups consistent with our cell partition in the empirical analysis. Two patterns emerge clearly in the correlations between observable skills and complex/simple tasks. First, there is a strong positive (negative) correlation between the high education dummy and complex (simple) 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 young age dummies, 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 dummy (15-24), turning positive and then reaching a maximum with the age-dummy 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).

Looking at the aggregate European data shows patterns consistent with the idea that immigrants and natives specialize in different production tasks and this specialization increased over time. Figure 2, for instance, shows the evolution of the relative intensity of complex versus non-complex tasks for the average European Worker throughout the period 1996-2007, split by native and foreign-born workers.[13] While the average native worker (as inferred from their occupational distribution) increasingly specialized in complex production tasks, the average immigrant worker experienced the opposite trend. Immigrants' specialization remained almost unchanged, slightly moving toward more manual-routine jobs. Such a pattern would be hard to explain as consequence of a demand shock for relative tasks. In that case the trend would be common to the two types of workers. The divergent evolution, to the contrary, suggests that there is an increasing specialization, along the lines of comparative advantages, between the two groups. It also implies that recent immigrants have been taking much more manual-intensive jobs than natives, possibly because their schooling is lower or because their countries of origin have not provided them with complex skills. Fig-

[13] 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 4 for details.

ure 3 illustrates additional stylized evidence supporting the model in Section 2. It shows the correlation between the relative complex/non-complex task specialization of native workers across cells (age-education groups across EU countries) and the share of immigrants. The picture shows a positive and significant correlation between the share of immigrants and the specialization of natives in complex tasks. According to an OLS regression, a 10 percentage point increase in the share of immigrants within the total population of similarly skilled individuals is associated with a 4 percentage point increase in relative complex/non-complex task intensity. This coefficient is significant at the 10% level with a standard error of 0.219. To give an idea of the magnitude, this 10 percentage point increase in the share of immigrants would be associated with a change in complex/non-complex task intensity slightly bigger than the difference between United Kingdom (54.6) and Italy (50.9) in 2007.

5 Main Empirical results

5.1 Immigrants and Employment rates of Natives

Before estimating equation (10), we estimate a similar specification to inquire whether immigration had a net impact on the employment rates of natives across skill groups. As mentioned before, the employment effects of immigration are relevant in itself. Furthermore, an increase in relative skill complexity in equation (10) could either be driven by the destruction of "simple" jobs for a given number of "complex" ones or, alternatively, by a favorable reallocation of native workers toward relatively more "complex" jobs. In the former case, the set of workers losing their "simple" job (without getting a more "complex" one instead) would certainly suffer from immigration. Quite contrarily, in the latter case, the group of native workers who are affected by immigration might very well be equally or even better off, as they transition to an occupation characterized by more "complex" tasks.

Considering different education-age skill cells in European countries as separate labor markets, we estimate the following equation:

$$ln\left(\frac{empl_{j,c,t}}{pop_{j,c,t}}\right) = \delta \ln(f_{j,c,t}) + d_{c,edu} + d_{edu,t} + e_{j,c,t} \tag{11}$$

where $(empl_{j,c,t}/pop_{j,c,t})$ is the employment-population ratio for natives and $\ln(f_{j,c,t})$ is the logarithm of the share of foreign-born workers in the education-age group j, living in country c in year t; $d_{c,edu}$ and $d_{edu,t}$ are sets of country-education and education-year fixed effects, capturing demand changes common to education groups over time and demand differences across countries. Finally, $e_{j,c,t}$ is an idiosyncratic random shock. Table 1 reports the estimates of the coefficient δ for different specifications of equation (11). The first three columns show the results when both women and men are included in the sample, while columns four to six show the results when only men are included. In each case, we estimate the equation in three different ways. In a first specification (columns 1 and 4) we estimate equation (11) using OLS and the whole group of fourteen countries analyzed in this study. In the second set of OLS estimates (columns 2 and 5) we restrict the sample to 7 countries for which national census data allow us to construct the initial shares of immigrants for year 1991, necessary to compute the shift-share instrument introduced in Section 3.1. Finally, in columns 3 and 6, we estimate the equation via 2SLS on the same subset of countries using the imputed shares of immigrants as IV. We also differentiate among rows. In the first row we report the estimates for equation (11), assessing the *average impact* of immigration on natives' employment rates. In the second and third row we estimate the *age specific impact* by interacting the explanatory variable $\ln(f_{j,c,t})$ with a dummy equal to one for cells in the age class 15-40 (young) and another equal to one in the age class 41-64 (old), respectively. Finally in the fourth and fifth row we estimate *education specific effect* by interacting the same explanatory variable with dummies for Low and High education levels. Underneath the estimated coefficients we report robust standard errors clustered by education-age-country cells in order to allow for within-cell correlation over time, as certainly some autocorrelation can be present in yearly data.

The estimated coefficients of Table 1 are consistently positive and significant across all specifications, and they range between +0.243 and +0.463. These estimates imply that a one per cent increase in the foreigners' share of the population within the cell is associated with an increase in the native employment/population ratio around 0.3 per cent of its initial value. The OLS estimates, in spite of the dummies controlling for education-specific demand shifts and for country-specific determinants may still contain some demand-driven spurious correlation. However the 2SLS estimates (e.g., column 3) show that our estimates are consistent with a causal effect of immigration equal to 0.37% on the employment/population ratio of native workers (0.28% on native males). No significant differences emerge between estimated coefficients when considering the whole sample versus the restricted one or when using 2SLS instead of OLS. The impact on the employment rate, however, looks somewhat smaller when considering male workers only. The inflow of immigrants could be complementary in particular to the employment opportunities of women, partly for labor market reasons (specialization as described in this paper), partly for the reasons described in Tessada and Cortes (2011) and due to the fact that some services, provided by immigrants, substitute for the house-work of women and allow them to supply more labor on the market.

Interesting results come when we allow the employment effect of immigrants to differ across groups. Higher elasticities are estimated for young workers and more educated workers (especially when including women in the sample). While the point estimates are suggestive of these tendencies the standard errors are too large to find significant differences among the group-specific coefficients. In general, however, immigration seems to stimulate employment growth in the considered European countries.

5.2 Immigrants' and natives' specialization

To inquire into the effects of immigration on task specialization of natives, the heart of our paper, we implement a series of specifications, following the structure of (10) and, in general, estimate the coefficient γ_{Skill} from the following type of regression:

$$\ln (Skill)_{j,c,t} = \gamma_{Skill} \cdot \ln(f_{j,c,t}) + d_{c,edu} + d_{edu,t} + \varepsilon_{j,c,t} \tag{12}$$

The coefficient γ_{Skill}, once we control for country-education and education-year fixed effects ($d_{c,edu}$ and $d_{edu,t}$), identifies the impact of immigration on the intensity of a certain "Skill" supplied by a native worker. A positive and significant value of γ_{Skill} implies that an increase in immigrants in the cell pushes natives to use a particular "Skill" (perform skill-specific tasks) more intensively relative to cells with smaller inflows of immigrants. We estimate equation (12) for the five different skill measures (introduced in Section 4.1) that we also aggregate to construct average indexes for the "complex" (mental, complex and communication skills) and "simple" (manual and routine) content of each occupation. As a further robustness check we also use the "abstract" and "routine" measures, employed by Goos et al. (2009) which are based directly on the ISCO occupational classification. These last indicators are defined by a different classification of skills and are normalized with zero mean and unitary variance.[14] In Table 2 we report OLS and 2SLS (columns 3 and 6) results,

[14] Given the presence of negative values for these indicators we do not estimate equation (12) in logs but in levels.

based on the shift-share IV strategy described above.[15] Robust standard errors, clustered on education-age-country, are reported underneath the estimates. As in Table 1, the first three columns are estimated on the whole sample, while columns 4 to 6 include men only.

The estimates of Table 2 are very consistent across specifications, samples and task definitions. First, for all the estimates higher shares of immigrants in a cell are associated with higher intensity of complex tasks performed by native workers. Using our task measures, the estimated elasticity is between 0.047 and 0.054 for communication tasks and between 0.045 and 0.056 for complex tasks, while it is slightly higher (0.06 to 0.081) for mental ones. These elasticities imply 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 the relevant tasks by natives between 4.5 and 8.1%. When considering "simple" skill measures, the effects are usually smaller and more imprecisely estimated: for "manual" tasks, the elasticity is not significantly different from zero in the OLS estimates, while it is marginally significant and equal to 0.065 only in the 2SLS ones. A similar picture emerges for "routine" tasks, with an elasticity of 0.036 (smaller than for complex tasks) using the OLS estimates, increasing to 0.067 for the 2SLS specification. When considering the alternative Goos et al. (2009) definitions, we find positive and significant (in most cases) elasticities for abstract tasks, while for routine tasks the coefficient estimates are negative and are not statistically different from zero. While there is no overwhelming evidence of a reduction in the supply of "simple" skills by natives in response to immigration, there is clear evidence of a robust increase in complex skill supply. Our model has implications for the relative supply of those skills.

Table 3 reports the estimates of the coefficient γ from regression (10), the empirical implementation of the equilibrium derived in Section 2. 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). In the first row, we show a set of estimates for the average elasticity across the usual 6 different specifications, all workers versus only men and OLS on the complete sample, OLS and 2SLS on the sub-sample for which the instrument is available. Our point estimates are very precise, strongly significant, and range between 0.052 and 0.061; the only exception is the 2SLS estimate for the sample including men only, which is positive but non significantly different from zero. This confirms that, in relative terms, native workers increase

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

their supply of complex skills that are complementary to those supplied by immigrants, prevalently manual-routine. When checking for possible different elasticities of immigration for individuals of different age, we find no substantial differences between the parameters estimated for young/old workers, ranging between 0.05 and 0.06 in both cases. When restricting the sample to men, we find a slightly greater elasticity for young compared to old workers, but we remain reassured by the stability of parameter estimates. When considering native workers differing in their educational level, we find higher elasticities for workers with low education, but this pattern is evident only when using the full sample including both women and men. Let us emphasize that the task response of natives to immigration estimated here has been convincingly documented by Peri and Sparber (2009) for US workers. In that case the authors only consider less educated workers (of both sexes) and use an IV method. Hence, they obtain a coefficient comparable with the one estimated in the fourth row, column 3 of Table 3. Interestingly, while we estimate a significant effect in both cases, the magnitude of Peri and Sparber's (2009) coefficient (in the range of 0.30-0.35) is much larger than the one estimated in this paper. Namely, the coefficient estimated using immigration across states in the US is 5 to 6 times larger than the one estimated for Europe. Such a quantitative difference can have important implications in evaluating the impact of immigration on native wages. More interestingly, the reason for such a difference can be a large differential in employment protection laws that prevent the same amount of occupational mobility in Europe. Thus, we use cross-European differences to emphasize this point in the Section 7.

Overall, the main result of this section is that, employing 6 specifications, differing for the estimating sample and the econometric technique adopted, we find strong empirical support for the idea that an increase of the immigrants' share on population pushes native workers to move to occupations requiring a relatively higher complexity. The results presented in Section 5.1 also show that this positive reallocation did not take place at the expense of the total number of jobs available for natives. To the contrary, occupational mobility and employment growth seem to take place at the same time. Hence, the results imply that, on average, natives move to occupations with a larger content of "complex" tasks and about the same 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.

In the next two sections we will explore the channels through which positive labor reallocation is taking place, and we will also assess the role of country-level labor market institutions in helping, preventing or accommodating such a reallocation.

6 The role of labor market flows

While our model is static and provides predictions on the task supply and on the employment of a representative agent, it is also interesting (and feasible with our data) to empirically decompose the relevance of hiring and separations in producing the aggregate effect. The current economic literature on migration focusses only on the impact of immigration on the employment levels and wages of native workers. In this section, however, we depart somewhat from this literature as well as our model. In particular, we try to discover the channels through which the empirically significant labor reallocation found in the previous section takes place. The increase in the relative intensity of "complex" skills of jobs held by natives and the increase of their net employment could be obtained because of effects on one or more of the following margins:

i) Immigrants could induce more *hiring*, particularly concentrated in occupations requiring relatively complex skills

ii) Immigrants could induce fewer *separations* particularly in occupations requiring relatively complex skills

iii) Immigrants could induce more *job to job* transitions from less complex to more complex jobs.

With the dataset at hand, we are able to analyze the impact of immigration on the first two types of flows. This is because, in the survey, each respondent is asked about his/her labor market state and occupation a year before the survey, in case this status has changed during the last year. This information allows us to define two binary variables, "hiring" and "separations". The "hiring" ("separations") variable is equal to one if the individual was not employed (was employed) in year $t-1$ and is employed (is not employed) in year t and zero otherwise. We then compute the hiring (separation) rate for each country-age-education-year cell as the ratio between the total number of hires (separations) and the population within the cell in each year. Moreover, as we know the occupation currently held by the individual (and the one previously held if the worker does not have a current job) we can also compute the average relative complexities of hiring and separations. Unfortunately, since respondents are asked about their occupation last year only if they do not have a current one, job to job transitions cannot be analyzed. We estimate the impact of immigration on labor market flows estimating a set of four equations identical to equation (10) and (11), but having, respectively, as dependent variables: hiring and separation rates (rather than employment rates), and average complexity of hiring and separations (rather than of total employment). As in the previous empirical analysis we estimate these equations both on the whole sample (column 1 to 3) and on men only (column 4 to 6); moreover, we run the regressions using OLS on all the 14 countries (column 1 and 4), or on the restricted sample of 7 countries for which we are able to calculate the shift-share instrument (column 2 and 5) or using 2SLS as the estimation method on the restricted sample (column 3 and 6).

An interesting pattern emerges across specifications and it is particularly clear when considering our preferred specification, namely the 2SLS estimation with all workers, reported in column 3 of Table 4. One way to summarize the pattern is as follows: an increase in immigration alters the *quantity* and the *quality* of the transitions into and out of employment. In our 2SLS specification, we find a marginally significant impact of foreign-born inflows in stimulating hiring and no impact at all on separation rates, as previously defined. In particular, an increase of immigrants by 1% of their share has a positive impact of 0.42% on the hiring rate of native workers while it has no impact at all on the separation rates for natives. Hence, in net terms, immigration encourages new hires of natives and this may be one channel for the positive employment effect found in Table 1. At the same time, for a given size of the flows (into and out of employment) an increase in the number of immigrants within a cell is associated with an increase in the average relative complexity of jobs offered to new hires. The estimate for this elasticity is between to 0.081 (significant at the 1% level) based on the OLS estimates and 0.119, still significant at the 1% level, when considering the 2SLS estimates. Estimates are similar, but lower in magnitude, when employing the sample including men only. When considering the separation margin, the effect of immigrants on the relative complexity of separations also has a positive sign. However, for the sample pooling women and men together, the elasticities' estimates are 30 to 40% smaller compared to hiring (with an effect between 0.05 and 0.07) while, when using the male-only sample, coefficient estimates are very close to zero, ranging from 0.007 to 0.01, and are not statistically significant. These results are thus coherent with the overall labor reallocation process described in the previous section, also providing additional details on the channels through which this process operates. The magnitude of labor market flows into and out of employment is mainly affected by immigrants via an increase in hiring, and a substantial skill upgrading is obtained because the relative complexity of the new hires increases with immigration while the relative complexity of separations is less affected by immigration. Unfortunately, due to data limitations we cannot look at job to job transitions, another important margin of labor reallocation.

7 Differences across Labor Market Institutions

The positive reallocation of natives toward more complex skills could be slowed by rigid labor markets. Labor markets with strong employment protection may reduce mobility in and out of employment, they may also keep workers within the boundaries of narrowly defined occupations as workers' protection (via collective contracts) is defined in terms of a specific occupation. Hence, labor market institutions can affect both the job creation margin and the occupational mobility margin of natives in response to immigrants. More flexible labor markets could facilitate immigrants' absorption, facilitating the job upgrading and job creation, and thereby easing productive specialization of natives (Angrist and Kugler, 2003).

To check for this possibility, we re-estimate equations (10) and (11) interacting the main explanatory variable $ln(f)$, the logarithm of the share of immigrants in the total population, with several country-level indicators of employment protection legislation (EPL). In particular, we adopt six different rankings based on EPL measures and we construct a dummy (that we interact with $ln(f)$) capturing whether the country has a high or low level of EPL. The first two measures of EPL are based on two ad hoc employer surveys conducted by the European Commission in 1989 and 1994, respectively (European-Commission, 1991, 1995). These indicators are based on the share of employers claiming that restrictions on hiring and firing were very important in the relevant year. We also use an aggregate OECD indicator summarizing EPL in the 1990s based on averages of specific scores that classify countries along the following dimensions: (i) strictness of employment protection for regular employment, (ii) norms concerning temporary employment, and (iii) rules on collective dismissals.[16] Finally, we use each of these last three elementary measures. The six different indicators provide a robustness check for the results to the type of EPL index used and also to the

[16] OECD (1999), for details see pp. 64-68.

countries included in the comparative analysis, since such indexes are not available for some of the countries included this study.[17] For each indicator, we define a country as a "high EPL" one when its strictness in the labor laws is higher than the weighted average of the surveyed countries. Similarly, "Low EPL" corresponds to a value of the strictness index below the weighted average. As in the previous sections, we run both OLS and 2SLS regressions estimated both on the whole sample and including men only. For simplicity, we report main results for two indicators only: the EC89 and the OECD aggregate index. Evidence emerging when using the other indicators (which is available upon request) is very similar[18]. First of all, we assess the impact of immigration on employment rates (equation (11), Table 5). Irrespective of the specification adopted and of the sample used for estimation, the estimates for δ (the elasticity of natives' employment rates with respect to immigrants' share in the population) for countries with below-average EPL are always greater than the ones for countries with above-average EPL. However, due to the size of the standard errors, such differences in the parameter estimates are often not statistically significant. This result is particularly strong when we consider the OECD measure of EPL and the preferred 2SLS estimation. In that case, the positive employment effect of immigration is much stronger when estimated for countries with low EPL relative to those with high EPL. The difference is significant at standard confidence levels. As for the differential impact of immigration on employment rates of specific groups, there seems to be a similar effect for both the more and less educated natives, who are much more responsive to immigration in countries with low EPL.

Even more interesting is the extent of labor reallocation toward complex occupations in response to increased immigration (equation (10)). As illustrated in Table 6, we find two very clear patterns. First, across specifications, the positive reallocation of natives toward "complex" tasks is stronger in countries with low levels of EPL. The preferred 2SLS estimates, using alternatively the EC89 index and the OECD aggregate one, we find that low EPL countries show coefficient estimates in a range between 0.123 and 0.129 (always significant at the 1% confidence level). The estimated coefficients are considerably smaller (ranging between 0.032 and 0.056) for high EPL countries, with the difference between the

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

[18] Using the EC89 index the countries with high EPL are: Spain, Greece, Italy and Portugal. Luxembourg is missing and the other countries are classified as low EPL.

coefficients being statistically significant at 1% when considering results obtained using the EC89 indicator. Results are even stronger when looking at the same estimates obtained on the sample including only men (not reported and available upon request).

Another particularly interesting exercise is the assessment of differential interactions between EPL and the extent of specialization among subgroups of workers, defined alternatively by age or education. When interacting $ln(f_s)$ with two age-specific dummies, we find patterns similar to the ones found at the aggregate level: estimated elasticities are greater for low EPL countries than for high EPL ones, both when considering young and old workers, with differences between coefficient estimates being statistically significant at least at 5% in most specifications. According to our preferred 2SLS estimates, in countries with low EPL young and old workers alike respond to the inflow of immigrants with an elasticity of relocation to "complex" jobs ranging between 0.12 and 0.16. To the contrary, in countries with high EPL that elasticity is never larger than 0.059. Considering workers of different schooling levels it is interesting to notice that the change in specialization in response to immigrants is particularly strong for less educated workers in countries with low EPL. The response of less educated workers in flexible labor markets is 0.12% for each 1% increase in the share of immigrants, while in more rigid markets this value is equal to 0.06% at most. Differently, for highly educated workers the point estimates do not show a clear pattern between high and low EPL countries. In particular when considering the sample including both women and men, the estimated elasticities for highly educated workers are never different from zero at standard confidence levels both for high and low EPL countries. When looking at estimates obtained on the men only sample, parameter elasticities are positive and significant only for low EPL countries, but the difference between low and high EPL countries is never statistically significant.

These patterns support an interesting regularity. Namely, we find that more "protected" workers in more rigid labor markets, when confronted with shocks such as the inflow of immigrants, are less able to respond and adjust. This may result in a less favorable impact of migration. This idea has been previously proposed in order to explain the high and persistent unemployment in Europe (vis-a-vis America) following the oil shocks of the seventies (e.g. ?). We argue that in a fast changing labor market, also due to the inflow of immigrants, strong EPL's limit the response of natives.

Moreover, these results, which hold across a number of specifications and indicators, confirm the analysis of Angrist and Kugler (2003), who find that low labor market flexibility can reduce gains from immigration and worsen its employment effects. Our model and explanation provides a reason for this. Countries in which native workers respond to a lesser extent to immigration forgo some of the efficiency gains as well as the positive complementarity effect of immigration. Moreover, less educated workers, who are more vulnerable to foreigners, being specialized in manual-routine tasks, are those who can potentially gain the most from the positive job reallocation brought about by migration. Stricter EPL, preventing such a reallocation, is thus particularly harmful for them.

8 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. At the same time, Europe has been experiencing an unprecedented increase in its immigrant population during the same period. Most of the economics literature has focused on demand side factors explaining shifts in task demand: technological change and the effects of off-shoring and trade (Acemoglu and Autor, 2010). In this paper we combine evidence on task changes and on immigration to analyze a supply factor, namely the role of immigration, in determining such a change in the occupational structure of natives. Our idea, summarized in a simple analytical framework, is that immigrants tend to be specialized in occupations requiring mainly non-complex and routine skills. Immigrant 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. This result withstands a number of robustness checks, carried out using different skill indicators, estimation methods, sample definitions, and, most significantly, it is robust to the use of credible instrumental variables. We also document the labor market flows through which such a positive reallocation took place: immigration stimulated hiring, and a substantial skill upgrading was obtained because the complexity of jobs offered to new hires was higher relative to the one of separations. Finally, this positive reallocation process is stronger in relatively flexible labor markets, and in those markets is particularly prominent for less educated workers. By moving to complex jobs, natives protect their wages from immigrant competition and take advantage of the creation of those jobs that complement the manual tasks provided by immigrants. Letting this mechanism work may benefit less educated natives, in particular through more job-creation (new hires) in those occupations. Strong protection of labor hurts this mechanism and reduces labor markets' ability to absorb immigrants through occupational upgrading of natives.

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Tables

Table 1: The effect of Immigrants on Native Employment

Units of Observations are eight education-by-age cells in 14 EU countries in each year, 1996-2007

Dependent variable: log(employment rate of natives)

Specification	**1**	**2**	**3**	**4**	**5**	**6**
Sample	**Women and men**			**Men only**		
Method of Estimation	**OLS, Full Sample**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**	**OLS, Full Sample**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**
$\ln(f_{j,c,t})$	0.371	0.367	0.373	0.287	0.276	0.28
	[0.077]***	[0.088]***	[0.084]***	[0.081]***	[0.092]***	[0.078]***
$\ln(f_{j,c,t})$**Young***	0.429	0.426	0.463	0.347	0.339	0.382
	[0.080]***	[0.090]***	[0.072]***	[0.084]***	[0.095]***	[0.064]***
$\ln(f_{j,c,t})$**Old***	0.353	0.341	0.379	0.259	0.243	0.285
	[0.064]***	[0.072]***	[0.074]***	[0.066]***	[0.073]***	[0.063]***
$\ln(f_{j,c,t})$**Low Edu***	0.379	0.371	0.365	0.284	0.269	0.263
	[0.086]***	[0.098]***	[0.093]***	[0.092]***	[0.103]**	[0.086]***
$\ln(f_{j,c,t})$**High Edu***	0.305	0.335	0.44	0.305	0.332	0.421
	[0.088]***	[0.102]***	[0.097]***	[0.084]***	[0.096]***	[0.102]***
Sample	Full	Restricted	Restricted	Full	Restricted	Restricted
Obs	1517	740	740	1506	738	738
Fixed effects						
Country by education	Yes	Yes	Yes	Yes	Yes	Yes
Education by year	Yes	Yes	Yes	Yes	Yes	Yes

Note: *The dependent variable is the logarithm of Employment/Population for the native population in the cell (equation 11 of section 5.1). The main explanatory variable (row 1) is the log of the share of immigrants in the cell. In rows 2 and 3 it is interacted with Young/Old dummies, in rows 4 and 5 it is interacted with High/Low education dummies. In parenthesis we report the heteroskedasticity robust standard errors clustered at the country-education-age level. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. The restricted sample is the one including only countries for which it is possible to construct the instrument.*

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

Table 2: The Effect of Immigrants on Task Performance of Natives

Units of Observations are eight education-by-age cells in 14 EU countries in each year, 1996-2007

Specification		**1**	**2**	**3**	**4**	**5**	**6**
Sample		**Women and Men**			**Men only**		
Method of Estimation		**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**	**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**
Complex tasks	**Communication Tasks**						
		0.047	0.05	0.054	0.047	0.045	0.018
		[0.011]***	[0.013]***	[0.018]***	[0.016]***	[0.018]**	[0.017]
	Mental Tasks						
		0.06	0.063	0.081	0.056	0.055	0.054
		[0.012]***	[0.014]***	[0.019]***	[0.011]***	[0.012]***	[0.013]***
	Complex Tasks						
		0.045	0.047	0.056	0.045	0.044	0.036
		[0.010]***	[0.011]***	[0.015]***	[0.010]***	[0.010]***	[0.012]***
	Abstract Tasks (Goos et al 2009)						
		0.998	0.926	1.177	1.438	1.35	1.504
		[0.434]**	[0.479]*	[0.827]	[0.529]***	[0.580]**	[1.104]
Non complex tasks	**Manual Tasks**						
		0.027	0.028	0.065	0.018	0.018	0.063
		[0.023]	[0.027]	[0.029]**	[0.024]	[0.027]	[0.028]**
	Routine Tasks						
		0.036	0.037	0.067	0.028	0.027	0.061
		[0.016]**	[0.018]**	[0.023]***	[0.017]*	[0.018]	[0.022]***
	Routine Tasks (Goos et al. 2009)						
		-0.46	-0.469	-0.158	-0.584	-0.573	0.446
		[0.350]	[0.394]	[0.546]	[0.447]	[0.497]	[0.870]
Sample		Full	Restricted	Restricted	Full	Restricted	Restricted
Obs		1517	740	740	1506	738	738
Fixed effects							
Country by education		Yes	Yes	Yes	Yes	Yes	Yes
Education by year		Yes	Yes	Yes	Yes	Yes	Yes

Note: *Each coefficient in the table is estimated in a separate regression (equation 12, see section 5.2 for details). The dependent variable is the* logarithm *of task intensity performed by native workers in all the equations but those using the Goos et al. (2009) measures, estimated in levels since the corresponding values can be negative. The main explanatory variable is described in the first cell of the row. In parenthesis we report the heteroskedasticity robust standard errors clustered at the country-education-age level. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. The restricted sample is the one including only countries for which it is possible to construct the instrument. ***=significant at 1%; **=significant at 5%, **=significant at 1%.*

Table 3: The Effects of Immigrants on Relative Task Performance of Natives

Units of Observations are eight education-by-age cells in 14 EU countries in each year, 1996-2007

Dependent variable: log(*Relative complex/simple task intensity*)						
Column	**1**	**2**	**3**	**4**	**5**	**6**
Sample	**Women and men**			**Men only**		
Method of Estimation	**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**	**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**
$\ln(f_{j,c,t})$	0.054	0.057	0.061	0.054	0.052	0.024
	[0.013]***	[0.015]***	[0.018]***	[0.020]***	[0.023]**	[0.020]
$\ln(f_{j,c,t})$*Young	0.055	0.056	0.061	0.074	0.07	0.054
	[0.013]***	[0.015]***	[0.017]***	[0.015]***	[0.016]***	[0.019]***
$\ln(f_{j,c,t})$*Old	0.053	0.057	0.061	0.044	0.042	0.026
	[0.013]***	[0.015]***	[0.018]***	[0.013]***	[0.014]***	[0.017]
$\ln(f_{j,c,t})$*Low edu	0.06	0.063	0.062	0.052	0.049	0.013
	[0.015]***	[0.016]***	[0.020]***	[0.023]**	[0.025]*	[0.021]
$\ln(f_{j,c,t})$*High edu	0.01	0.006	0.052	0.065	0.07	0.113
	[0.018]	[0.022]	[0.035]	[0.019]***	[0.022]***	[0.038]***
Sample	Full	Restricted	Restricted	Full	Restricted	Restricted
Obs	1508	740	740	1497	738	738
Fixed effects						
Country by education	Yes	Yes	Yes	Yes	Yes	Yes
Education by year	Yes	Yes	Yes	Yes	Yes	Yes

Note: *The dependent variable is the logarithm of the relative task intensity (equation 10 of section 3). The main explanatory variable (row 1) is the log of the share of immigrants in the cell. In rows 2 and 3 it is interacted with Young/Old dummies, in rows 4 and 5 it is interacted with High/Low education dummies. In parenthesis we report the heteroskedasticity robust standard errors clustered at the country-education-age level. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. The restricted sample is the one including only countries for which it is possible to construct the instrument.*
****=significant at 1%; **=significant at 5%, **=significant at 1%.*

Table 4: The Effect of Immigrants on employment flows and their task intensity

Units of Observations are eight education-by-age cells in 14 EU countries in each year, 1996-2007

Dependent variable: log of the variable specified in the header						
Column	**1**	**2**	**3**	**4**	**5**	**6**
Sample	**Women and men**			**Men only**		
	OLS	**OLS, Restricted Sample**	**2SLS, Restricted Sample**	**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**
Dep. Variable	**Hirings rate**					
ln($f_{j,c,t}$)	0.174	0.196	0.419	-0.094	-0.048	0.131
	[0.191]	[0.216]	[0.244]*	[0.183]	[0.202]	[0.246]
Dep. Variable	**Hirings' relative complex/non complex skill intensity**					
ln($f_{j,c,t}$)	0.081	0.085	0.119	0.054	0.051	0.072
	[0.018]***	[0.020]***	[0.026]***	[0.019]***	[0.021]**	[0.031]**
Dep. Variable	**Separations rate**					
ln($f_{j,c,t}$)	0.042	0.064	-0.008	-0.108	-0.093	-0.173
	[0.065]	[0.072]	[0.080]	[0.076]	[0.084]	[0.082]**
Dep. Variable	**Separations' relative complex/non complex skill intensity**					
ln($f_{j,c,t}$)	0.051	0.058	0.074	0.007	0.002	0.01
	[0.015]***	[0.017]***	[0.023]***	[0.016]	[0.018]	[0.030]
Sample	Full	Restricted	Restricted	Full	Restricted	Restricted
Obs	1508	740	740	1497	738	738
Fixed effects						
Country by education	Yes	Yes	Yes	Yes	Yes	Yes
Education by year	Yes	Yes	Yes	Yes	Yes	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of the variable specified in the header (see section 6 for details). In parenthesis we report the heteroskedasticity robust standard errors clustered at the country-education-age level. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. The restricted sample is the one including only countries for which it is possible to construct the instrument. ***=significant at 1%; **=significant at 5%, **=significant at 1%.*

Table 5: The Effect of Immigrants on native employment, by EPL levels

Dependent variable: log(employment rate) in the edu-age cell; all workers

Column		**1**	**2**	**3**	**4**	**5**	**6**
EPL MEASURE			**EC89**			**OECD**	
Method		**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**	**OLS**	**OLS, Restricted Sample**	**2SLS, Restricted Sample**
ln(fj,c,t)	*Low EPL	0.449	0.413	0.451	0.517	0.573	1.584
		[0.173]**	[0.189]**	[0.223]**	[0.170]***	[0.237]**	[0.393]***
	*High EPL	0.335	0.323	0.289	0.292	0.294	0.269
		[0.046]***	[0.047]***	[0.050]***	[0.044]***	[0.046]***	[0.081]***
ln(fj,c,t)* ***Young***	*Low EPL	0.453	0.423	0.53	0.52	0.573	1.954
		[0.148]***	[0.161]**	[0.165]***	[0.151]***	[0.207]***	[0.592]***
	*High EPL	0.425	0.446	0.386	0.47	0.478	0.471
		[0.049]***	[0.054]***	[0.058]***	[0.051]***	[0.053]***	[0.092]***
ln(fj,c,t)* ***Old***	*Low EPL	0.382	0.347	0.464	0.492	0.561	2.14
		[0.125]***	[0.134]**	[0.178]**	[0.134]***	[0.200]***	[0.714]***
	*High EPL	0.341	0.335	0.279	0.337	0.343	0.335
		[0.057]***	[0.064]***	[0.063]***	[0.053]***	[0.055]***	[0.080]***
ln(fj,c,t)* ***Low edu***	*Low EPL	0.469	0.427	0.411	0.571	0.631	1.67
		[0.196]**	[0.215]*	[0.238]*	[0.196]***	[0.275]**	[0.457]***
	*High EPL	0.335	0.321	0.282	0.289	0.291	0.255
		[0.050]***	[0.051]***	[0.054]***	[0.048]***	[0.050]***	[0.091]***
ln(fj,c,t)* ***High edu***	*Low EPL	0.322	0.322	1.094	0.271	0.32	1.068
		[0.159]**	[0.173]*	[0.574]*	[0.137]**	[0.182]*	[0.589]*
	*High EPL	0.343	0.354	0.353	0.347	0.35	0.374
		[0.096]***	[0.101]***	[0.118]***	[0.092]***	[0.094]***	[0.115]***
Obs		930	620	620	1407	740	740
Fixed effects							
Country by education		Yes	Yes	Yes	Yes	Yes	Yes
Education by year		Yes	Yes	Yes	Yes	Yes	Yes

Note: *Each coefficient in the table is estimated from equation 11 (see section 7 for details). The dependent variable is the logarithm of Employment/Population for the native population in the cell. The main explanatory variable (row 1) is the log of the share of immigrants in the cell, by EPL level. In rows 2 and 3 it is further interacted with Young/Old dummies, in rows 4 and 5 it is interacted with High/Low education dummies. In parenthesis we report the heteroskedasticity robust standard errors clustered at the country-education-age level. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. Luxembourg is never included in EPL rankings. EC89 does not rank Austria, Denmark and Finland. See text (section 7) and OECD (1999, pp. 64-68) for details on the EPL indexes.*

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

Table 6: The Effect of Immigrants on Task Performance of natives, by EPL levels

Dependent variable: relative complex/non complex skill intensity (all workers)

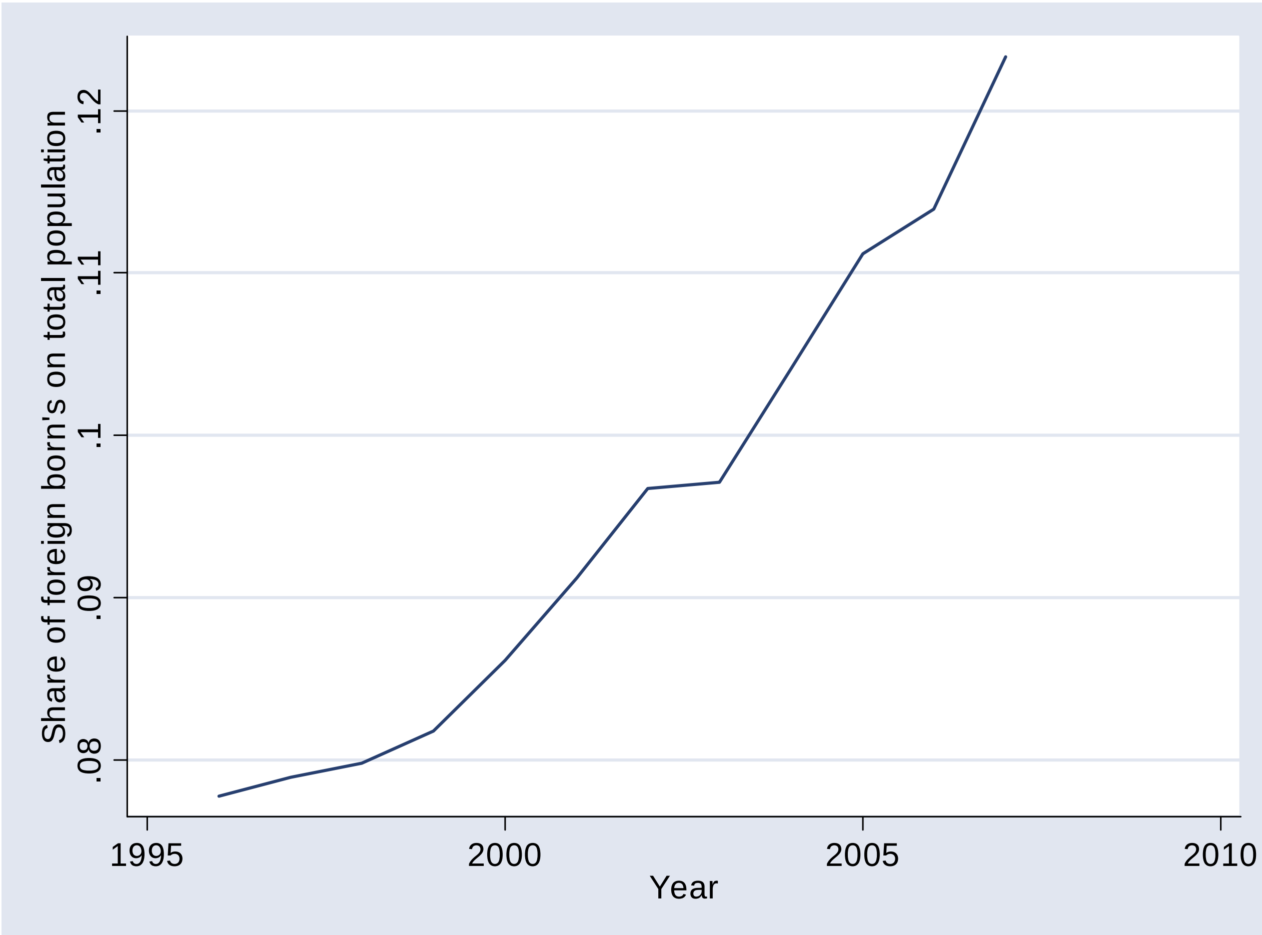
Column		**1**	**2**	**3**	**4**	**5**	**6**
EPL MEASURE			**EC89**			**OECD**	
Estimates		**OLS**	**OLS**	**IV**	**OLS**	**OLS**	**IV**
ln(fj,c,t)	*Low EPL	0.095	0.097	0.129	0.057	0.069	0.123
		[0.023]***	[0.025]***	[0.038]***	[0.020]***	[0.025]***	[0.043]***
	*High EPL	0.032	0.029	0.032	0.052	0.052	0.056
		[0.008]***	[0.008]***	[0.010]***	[0.016]***	[0.017]***	[0.018]***
P value ftest Low EPL=high EPL		*0.0118*	*0.0098*	*0.0112*	*0.8614*	*0.5789*	*0.1254*
ln(fj,c,t)* *Young*	*Low EPL	0.096	0.097	0.12	0.055	0.073	0.148
		[0.023]***	[0.024]***	[0.034]***	[0.018]***	[0.027]***	[0.046]***
	*High EPL	0.042	0.034	0.036	0.05	0.051	0.059
		[0.012]***	[0.011]***	[0.012]***	[0.015]***	[0.015]***	[0.017]***
P value ftest Low EPL=high EPL		*0.0376*	*0.0209*	*0.0141*	*0.8359*	*0.4557*	*0.0558*
ln(fj,c,t)* *Old*	*Low EPL	0.102	0.105	0.129	0.051	0.078	0.162
		[0.026]***	[0.027]***	[0.037]***	[0.017]***	[0.029]**	[0.055]***
	*High EPL	0.033	0.029	0.03	0.052	0.052	0.057
		[0.008]***	[0.008]***	[0.010]***	[0.015]***	[0.016]***	[0.018]***
P value ftest Low EPL=high EPL		*0.0128*	*0.0097*	*0.009*	*0.9683*	*0.4389*	*0.0615*
ln(fj,c,t)* *Low edu*	*Low EPL	0.111	0.113	0.124	0.069	0.087	0.112
		[0.024]***	[0.025]***	[0.040]***	[0.021]***	[0.024]***	[0.042]***
	*High EPL	0.034	0.03	0.032	0.055	0.056	0.058
		[0.009]***	[0.008]***	[0.010]***	[0.018]***	[0.018]***	[0.020]***
P value ftest Low EPL=high EPL		*0.0033*	*0.0029*	*0.0224*	*0.614*	*0.2914*	*0.2221*
ln(fj,c,t)* *High edu*	*Low EPL	-0.004	-0.008	0.205	0.001	-0.009	0.188
		[0.034]	[0.036]	[0.226]	[0.028]	[0.038]	[0.217]
	*High EPL	0.023	0.02	0.028	0.02	0.02	0.037
		[0.013]*	[0.013]	[0.030]	[0.012]*	[0.013]	[0.032]
P value ftest Low EPL=high EPL		*0.4188*	*0.435*	*0.4012*	*0.4848*	*0.4306*	*0.4493*
Obs		929	619	619	1397	738	738
Fixed effects							
Country by education		Yes	Yes	Yes	Yes	Yes	Yes
Education by year		Yes	Yes	Yes	Yes	Yes	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The dependent variable is the logarithm of Complex relative to Simple task intensity performed by native workers. The main explanatory variable (row 1) is the log of the share of immigrants in the cell, by EPL level. In rows 2 and 3 it is further interacted with Young/Old dummies, in rows 4 and 5 it is interacted with High/Low education dummies. In parenthesis we report the heteroskedasticity robust standard errors clustered at the country-education-age level. First-stage statistics for the shift share instrument are reported in table A5 of the appendix. Luxembourg is never included in EPL rankings. EC89 does not rank Austria, Denmark and Finland. See text (section 7) and OECD (1999, pp. 64-68) for details on the EPL indexes.*

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

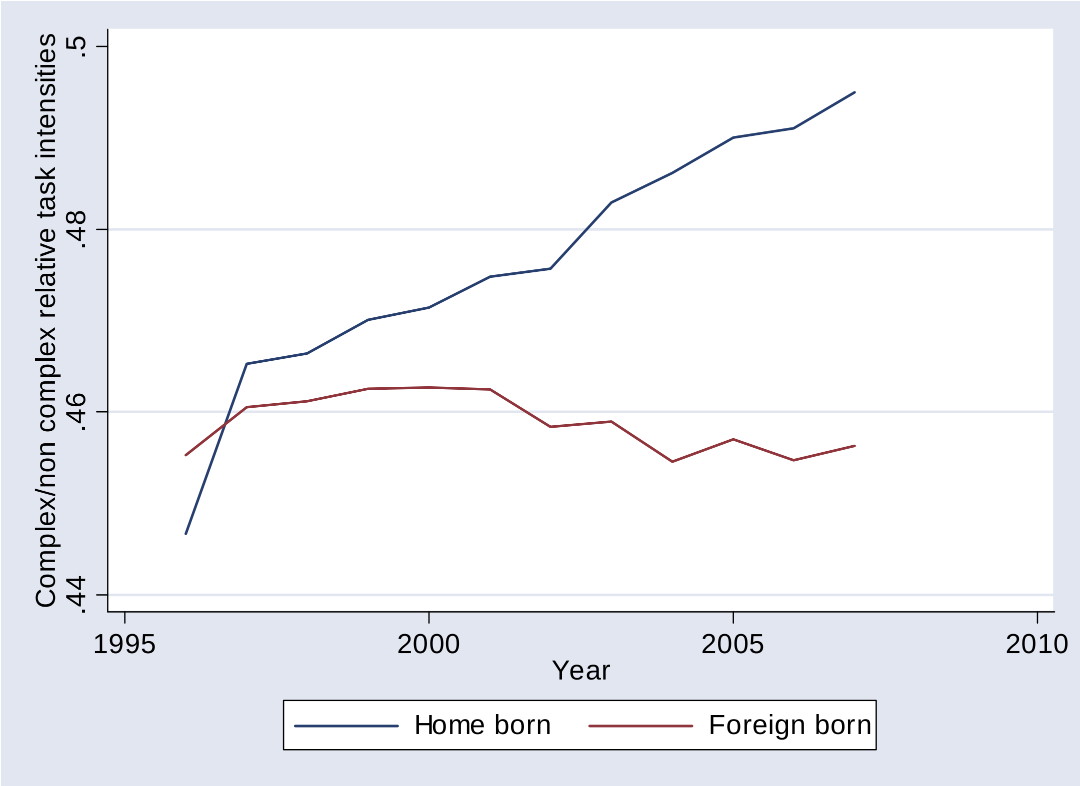
Figures

Figure 1: Immigrants as percentage of the European Population



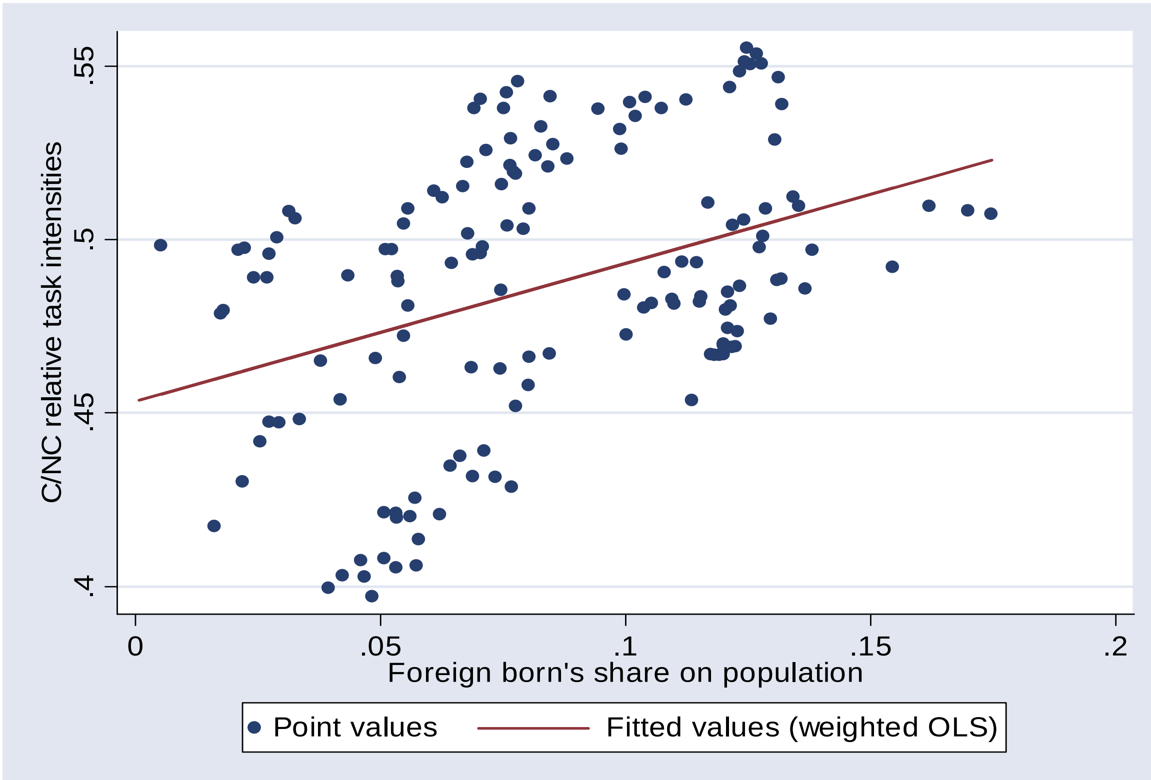
Source: Authors' calculations on EULFS data. It does not include countries for which one or more years of data are missing (Ireland, Italy, Luxembourg and United Kingdom).

Figure 2
Relative productive tasks, Natives and Foreign-Born in Europe



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).

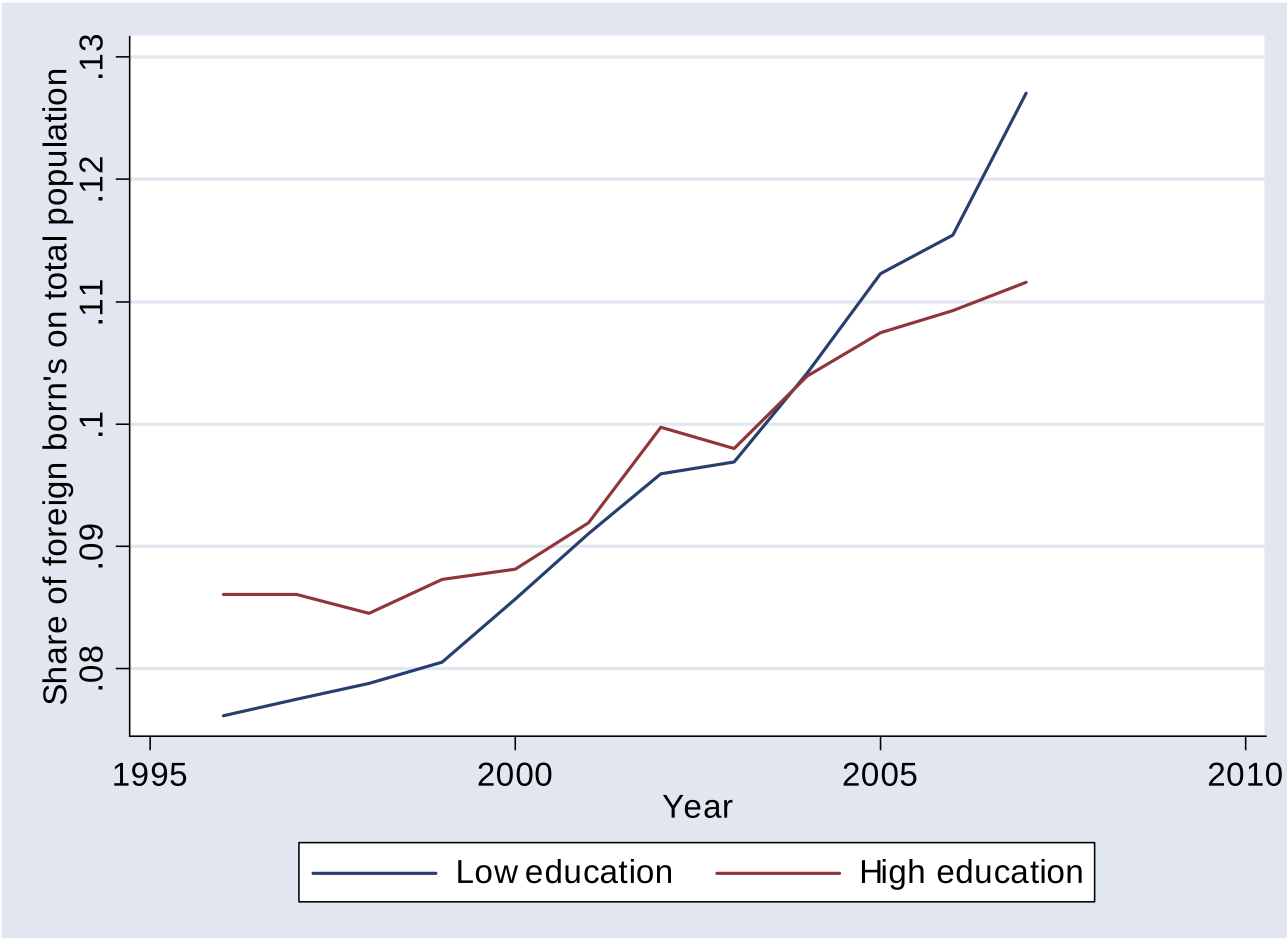
Figure 3
Relative productive tasks and the share of immigrants in Western Europe,
Education-Age-Country cells, 1996-2007



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.

Tables and Figures Appendix

Figure A1: 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).

Table A1: Countries and years included in the analysis, Those in Bold are also included in the 2SLS regressions

Data	EULFS													Shift Share IV
	Year													
Country	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Tot	
Austria	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**12**	**12**
Belgium	1	1	1	1	1	1	1	1	1	1	1	1	12	0
Denmark	1	1	1	1	1	1	1	1	1	1	1	1	12	0
Spain	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**12**	**12**
Finland	1	1	1	1	1	1	1	1	1	1	1	1	12	0
France	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**12**	**12**
Grece	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**12**	**12**
Ireland	0	0	0	1	1	1	1	1	1	1	0	0	7	0
Italy	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**3**	**3**
Luxembourg	1	1	0	1	1	1	1	1	1	1	1	1	11	0
Netherlands	1	1	1	1	1	1	1	1	1	1	1	1	12	0
Norway	1	1	1	1	1	1	1	1	1	1	1	1	12	0
Portugal	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**12**	**12**
United Kingdom	**1**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**11**	**11**
Tot	12	12	10	13	13	13	13	13	13	14	13	13	152	74

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 completely missing.*
For the Shift-share IV, 0 denotes a country not included since Census data were not available.

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

Complex tasks / mental skills (C)	Simple skills (S)
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	

This table reports skill and tasks intensities used to construct each of our broad skill measures.
See text (section 4.1) 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 plant operators	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.
To give an idea of the indicators, a score of 79 in "communication skills" for "corporate managers" indicates that 79% of all workers in US in 2000 were using "communication skills" less intensively than "corporate managers".

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

Source: authors calculations on ELFS data. The table reports simple correlations between skills intensities, age and education.

Table A5
First stage statistics for the instruments

Column		**1**	**2**
		Women and men	**Men only**
ln(f $_{j,c,t}$)	Coeff	0.99	1.050
	Std error	[0.033]***	[0.033]***
	Ftest	69.27	58.08
ln(f $_{j,c,t}$)* *Young*	Coeff	1.035	1.058
	Std error	[0.026]***	[0.027]***
	Ftest	533.80	515.20
ln(f $_{j,c,t}$)* *Old*	Coeff	0.899	0.954
	Std error	[0.022]***	[0.025]***
	Ftest	756.82	590.91
ln(f $_{j,c,t}$)* *Low edu*	Coeff	1.052	1.113
	Std error	[0.029]***	[0.032]***
	Ftest	390.03	319.71
ln(f $_{j,c,t}$)* *High edu*	Coeff	0.688	0.708
	Std error	[0.030]***	[0.036]***
	Ftest	1305.09	986.67

This table reports the first stage statistics for the shift-share instrument. We calculate immigrants' distribution across countries and cells for year 1991. The instrument is then obtained multiplying, for each year and country of origin, this fixed distribution by the total growth in the stock of immigrants from that country of origin (see section 3.1 for details).