Immigration, Jobs and Employment Protection: Evidence from Europe before and during the Great Recession

Francesco D'Amuri (Italian Central Bank, ISER - University of Essex and IZA)
Giovanni Peri (University of California, Davis and NBER)*

October, 2012

Abstract

In this paper we analyze the impact of immigrants on the type and quantity of native jobs. We use data on fifteen Western European countries during the 1996-2010 period. We find that immigrants, by taking manual-routine type of occupations pushed natives towards more "complex" (abstract and communication) jobs. Such positive reallocation occurred while the total number of jobs held by natives was unaffected. This job upgrade was associated in the short run to a 0.7% increase in native wages for a doubling of the immigrants' share. These results are robust to the use of two alternative IV strategies based on past settlement of immigrants across European countries measured alternatively with Census or Labor Force data. The job upgrade slowed, but did not come to a halt, during the Great Recession. We also document the labor market flows behind it: the complexity of jobs offered to new native hires was higher relative to the complexity of lost jobs. Finally, we find evidence that such reallocation was larger in countries with more flexible labor laws and that this tendency was particularly strong for less educated workers.

JEL Classification Codes: J24, J31, J61.

Keywords: Immigration, Jobs, Task specialization, Employment Protection Laws, Europe.

---

*email: francesco.damuri@gmail.com, gperi@ucdavis.edu. We are grateful to four anonymous referees for very useful comments. We thank Anna Salomons for providing to us data and guidance necessary to construct the task variables. We thank Paul Gaggl for excellent assistance in research and editing. William Ambrosini, Michele Giuranno, Antonella Nocco, Chad Sparber and seminar participants at the Bank of Italy, UC Berkeley, Bocconi and Lecce Universities provided helpful comments.

1 Introduction

The net flow of immigrants into Western Europe during the period 1996-2010 was very large. Considering the eleven countries for which we have a consistent time series[1] the percentage of foreign-born[2] nearly doubled from less than 8% of the population in 1996 to almost 14% in 2010. By comparison, in the US, the presence of foreign-born increased by a smaller percentage, going from 10.6% of the population in 1998 to 12.9% in 2010.

Extensive literature has analyzed the labor market effect of immigrants in the US and in other countries with large immigration flows, such as Canada and Australia.[3] With some disagreement, researchers have emphasized two facts. First, immigration is relatively large among workers with high education levels (college or higher).[4] These types of immigrants may compete with highly educated natives but have also positive productivity effects on the economy, 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-intensive and routine-type occupations (e.g. in construction, agriculture and personal-household 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 (2012)) and the fact that they tend to upgrade their job 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 significant wage effect of immigrants (e.g. Card (2009), Ottaviano and Peri (2012)).

Considering European labor markets, economists have analyzed the impact of immigrants in specific countries (see for instance Dustmann et al. (2012) for the UK, Glitz (2012)

[1] Namely Austria, Belgium, Denmark, Finland, France, Greece, Netherlands, Norway, Portugal, Spain and Sweden. In the rest of the paper we also include: Ireland, Italy, Luxembourg and United Kingdom.

[2] This is shown in Figure A1 of the online Appendix.

[3] See for instance Longhi et al. (2005) for a summary and meta-analysis of the literature on the wage effect of immigrants. Okkerse (2008) provides a survey of recent empirical evidence on the effect of immigration.

[4] 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.

for Germany and González and Ortega (2011) 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 local 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 job specialization of natives and how these effects vary across EU countries. Besides a large variation in the inflow of immigrants across countries, the European case also provides significant 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? Do they vary with the conditions of the labor market? Did the recent deep recession affect how immigrants were absorbed in labor markets?

The paper introduces two additional contributions to the literature on migration. First, we analyze some of the channels through which the impact of immigrants on hosts' labor markets operates. In particular, exploiting the recall questions present in our data, we recover labor market transitions of workers at yearly intervals and we inquire whether an increase in the number of migrants stimulates or depresses hiring and separations for natives, and the way it changes the skill content of such transitions. Second, we check whether the labor market adjustment to immigration changed significantly during the Great Recession (GR) years. A number of studies analyzed the impact of the GR on European and US labor markets (Immervoll et al. (2011) and Elsby et al. (2010) among others); there is instead little research on distinguishing the impact of immigration on the labor market of the host country along the business cycle. Exploiting the fact that the number of foreign born continued to rise during the recession years, although at a slower rate, we fill this gap in the literature and study whether there was a differential impact of immigration on native outcomes before and during the recent crisis.

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 the number of jobs requiring the use of complex and abstract skills, and a decrease in the number of manual-routine type of 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 considers 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) and Ottaviano and Peri (2012), 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 do not know the intricacy of the culture, social norms and institutions of the host country. If this is the case, 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 together with a variation of natives' employment rates, due to some crowding-out.

To establish whether the correlation between the inflow of immigrants in a labor-market cell and the increased specialization of natives captures a causal relationship between the first and the second variable we use two alternative instrumental variables, inspired to the approach of Altonji and Card (1991) and Card (2001). The presence of cell-specific demand shocks for complex tasks correlated with the inflow of immigrants and the measurement error in the inflow of immigrants could generate a biased estimate of the effect of immigration, using OLS. We use instruments based on the fact that the initial shares of foreign-born across country-skill cells in a year are good predictors of their subsequent flows. Assuming that the relative demand for manual and complex tasks taking place in Europe between 1996 and 2010 does not vary systematically with foreigners' initial settlements, the instruments are correlated with relative task supply only through their effect on the supply of immigrants. The difference between the two instruments is that in one case we use census data in 1991 and in the other Labor force survey data in 1996 to construct initial immigrant settlements[5]. We also control for factors that proxy shifts in the relative demand for complex-abstract tasks including country or skill-specific effects.

Our main empirical findings are four. First, according to results obtained using our preferred specification, higher immigration pushes natives to occupations with a stronger content of complex abilities. A doubling of the immigrants' share in a skill-country cell increases natives' relative specialization in complex skills by 5-6%. This labour market adjustment takes place with no significant impact on natives' employment rates. Moreover it implies that, in the short run, a doubling of foreign' share in the total population is associated with a 0.7% increase in native monthly wages. Second, we find mild evidence that such a

[5] In the case of Census data we distinguish immigrants by nationality. This is not possible in the Labor force data where we do not know the country of origin of immigrants.

positive reallocation takes place mainly through an increase in the average complexity of jobs offered to new hires. Hiring rates increase but not significantly. The separation margin is not much affected by immigration in the cell. Third, when we split countries in two groups, those with strong Employment Protection Legislation (EPL) and those with weak employment protection, we find that the natives' positive reallocation towards complex jobs, caused by immigration, is more intense in less protected markets. Moreover, in countries with low employment protection, the reallocation is stronger for workers with low levels of education. This is consistent with the hypothesis 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 low EPL countries occupational upgrading moves less educated workers away from immigrants' wage competition. Finally, we test whether the positive job reallocation triggered by migration continued during the economic downturn taking place in 2007-2010. Testing for the differential labor market impact of immigration along the business cycle is not only interesting "per se", but it also provides an additional verification that our instrumental variable strategy works even in period of negative labor demand shocks. We find that the positive reallocation process described above slowed, but remained significant, during those years.

The rest of the paper is organized as follows: Sections 2 and 3.2 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 of the effects of immigration on natives' specialization and employment rates are reported in Section 5. Section 6 analyzes the impact of immigrants separately on natives' hiring and separations, while Section 7 investigates how labor market institutions affect the extent of the occupational adjustment. Section 8 checks whether the impact of migration on the labor market changed in correspondence of the deep recession that affected Europe in the late part of the last decade. We then offer some simple calculations to quantify the effects of immigrants on native wages, through the occupational reallocation channel illustrated above, in Section 9. Section 10 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. Consistently with Katz and Murphy (1992), Ottaviano and Peri (2012) 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 sub-groups. As in Borjas (2003) and Ottaviano and Peri (2012), 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 (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:

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

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

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

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 $\theta_{age,edu,t}$ also varies by education 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.

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

$S_{j,c,t}$ 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 $c_k = (1 - l_k)_D^{\delta} \kappa_k$ of complex service (with $\delta < 1$), compensated respectively at rate w_S and w_C per unit.[6] 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:

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

[6] 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).

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 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, $f = L_F/(L_F + L_D)$.[7] 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, $\frac{\kappa}{\varkappa}\left(f, \frac{\kappa_F}{\varkappa_F}, d_F\right) = \left[\phi\left(f\right) \cdot \left(\frac{\kappa_F}{\varkappa_F}\right)^{\frac{1}{1-\delta}} \left(\frac{1}{1-d_F}\right)^{\frac{\delta}{1-\delta}} + \left(1-\phi\left(f\right)\right) \cdot \left(\frac{\kappa_D}{\varkappa_D}\right)^{\frac{1}{1-\delta}} \left(\frac{1}{1-d_D}\right)^{\frac{\delta}{1-\delta}}\right]^{(1-\delta)}$. 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).

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

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, $\frac{C_D^*}{S_D^*}$.

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:

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

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 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 year effect $d_{c,t}$ 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 may vary across countries and year and hence we absorb them in a country by year effect. A certain country, due to its laws and institutions selects immigrants with certain productivity and preference characteristics relative to natives. The skill by time effects $d_{j,t}$ 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, while α is a constant. 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 and Instruments

Once we control for the technological factors affecting skill demand (with the skill by year coefficients) and for country specific time varying shocks, 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 skill cell and this increases the demand for unskilled workers attracting immigrants. We deal with this potential issue of reverse causality/omitted variable bias in three ways.

First, and less important, 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 determined in large part 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. Still, population shares are less sensitive to labor demand shocks than employment shares.

Second, we address the potential omitted variable bias with two alternative instruments, both based on the strategy first developed by Altonji and Card (1991) and largely used in this literature. The underlying assumption is that, while new immigrants tend to settle where existing immigrant communities already exist, in order to exploit ethnic networks and amenities, their historical presence is unrelated to current cell-specific changes in labor demand. Once we control for the fixed effects described above, current changes in labor demand have no correlation with the past presence of immigrants, which only affects the supply of labor and skills in that cell.

A first instrument (that we name IV1 throughout the paper) is developed using only information contained in the EU Labor Force Survey (EULFS) dataset. This is the main data source used in this study and it includes current data on native and immigrant workers.[8] In this case, we calculate immigrants' distribution across countries of destination and education-age cells for the first available year[9]. The instrument is then obtained by multiplying in each year the initial distribution (as shares of the total) by the total number of foreign-born present in the 15 EU countries analyzed in this study. As a consequence, the stock of immigrants imputed with this method depends on the *initial* distribution of immigrants across countries and skill groups, and on the evolution of the *total* number of foreign born in Europe. The cell- and country-specific evolution of the number of migrants, that might be affected by local economic conditions, do not enter this imputation.

For the second instrument (that we name IV2 throughout the paper), we combine EU-LFS data and external sources. From IPUMS-I (2010) we downloaded micro-data from national Censuses 1990-1991, for seven of the fifteen countries included in the EULFS (Austria, France, Greece, Italy,[10] Portugal, Spain, United Kingdom). For that year, we computed the population of immigrants by area of origin (using nine large geographic groups)[11] in each country-education-age cell. We then use the data on aggregate yearly immigration flows from those nine areas of origin into the 7 considered EU countries, available until 2009 only, and we construct the overall growth rates of each area-of-origin immigrant group.[12] We then multiply the initial (1991) number of immigrants in each country-education-age cell by the overall growth rate of that area-of-origin immigrant group. Finally, we aggregate across areas of origin within each education-age-country cell, in order to calculate the total imputed number of immigrants in the cell. This number is divided by the total (initial natives plus imputed migrants) population in the cell to obtain the imputed cell-specific migrants' share. This method implies that the variation in immigrant shares across cells and years is only driven by the initial cell composition of immigrants by area of origin and the variation in inflows in the aggregate area-of-origin groups over time. Suppose a country had a lot of

[8] See Section 4 for a description of the EULFS data.

[9] For most countries 1996 is the first available year, see Table A1 of the online appendix for a complete list of countries and years included in the analysis.

[10] For Italy we used 2001 data, the first ones providing all necessary information. Nevertheless, for this country EULFS 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.

[11] 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.

[12] Data are described in detail in Ortega and Peri (2011); they were collected from several sources (OECD, UN) and report the total gross inflow of migrants from any country into OECD.

young and highly educated Algerians in 1991, while another had young and less educated Iranians. As Algerians turned out to increase their emigration rates more than Iranians in the considered period (due to push factors in the place of origin), the first country would obtain a larger group of educated young immigrants as of 2009 relative to the second. The advantage of the second instrument is that it uses 1991 as initial year, it employs the larger census sample and exploits the region of origin of immigrants. The disadvantage is that it does not cover all countries of the EULFS.

Both instruments turn out to be fairly strong and their first stage statistics are reported in Table A5. In particular, the first stage coefficients always have the correct sign and the F-test for their exclusion is never below 23 for IV1 and 17 for IV2. Such strong correlation is a sign that the initial distribution across country-age-education cells combined with the subsequent total flows of foreign-born is a strong predictor of the increase in immigrants in a cell, consistently with the idea that the network of previous immigrants reduces costs of settling and finding a job for new immigrants.

Finally, as a check that positive labor demand shocks were not responsible for the positive correlation between immigration and native specialization changes, we test in Section 8 whether our results hold during the years of economic downturn starting with the onset of the Great Recession (2007-2010). In that period, while the foreign born's share in working age population continued to grow, labor demand fell dramatically.[13] If the estimated change in specialization of natives was due to labor demand (rather than to immigrants) we should observe a change in the sign of such estimates during this period.

3.2 Empirical Implementation

We analyze four alternative specifications for our main regressions. In the first two we estimate equation (10) using OLS and IV1, respectively, for all 15 countries included in the analysis. In the third and the fourth specification, we estimate the same equation by OLS and 2SLS restricting the sample to the 7 countries for the years 1996-2009, due to the data limitation in the construction of the IV2 instrument. The main specifications are estimated with two sets of fixed effects (country by year and education by age by year), while standard errors are clustered alternatively at the country-skill (first entry) or at the country-year

[13] Foreign born's share over total working age population averaged 13.0% during the 2007-2010 period, 2.2 points higher than in the preceding four year interval according to EULFS data.

(second entry) level throughout the paper.[14]

Our empirical analysis consists of five parts. After a brief introduction of the data in Section 4, we begin by analyzing the impact of immigration on natives' relative skills based on equation (10) in Section . In the same section we also test whether immigration affects natives' employment rates. In the second part (Section 6), we 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 or separation margin.

In the third part (Section 7), we test whether country-level labor market policies, in particular employment protection laws, affected the native occupational reallocation in response to immigrants. 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. In Section 8 we check whether the impact of migration on the European labor market changed during the Great Recession: the short run effects of migration could be less favorable, or more adverse, during an economic downturn. Finally, we estimate the elasticities of individual wages to changes in the relative skill content of a job using European harmonized household survey data (EU-SILC) and we use them to calculate the impact of immigrants on native wages operating through the described reallocation towards jobs requiring more complex skills.

4 Data and descriptive statistics

The main dataset we use is the harmonized European Union Labour Force Survey (EULFS), which homogenizes country-specific labor force surveys at the European level (see EUROSTAT (2009)). We restrict our analysis to the 1996-2010 period (before 1996 data on the place of birth of individuals are absent for most countries in the survey) and we consider the working age population (age 15-64) of Western European countries only.[15] The data include

[14] We performed estimates including other sets of fixed effects and clustering errors at alternative cell groups (country by age or country by education). The results are very similar to those reported and available upon request. Only when estimating very saturated models with country by education by age and country by time fixed effects (together explaining 97% of the variance of the main dependent variable in equation 10) we find a non significant effect of migration on native jobs relative complexity.

[15] We include Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom. We could not include Germany since main

information on the occupation, working status and demographic characteristics of the individuals. Unluckily the EULFS does not include any information on wage levels. In 16 out of 225 (15 countries × 15 years) country-year cells one or more of the variables fundamental for our analysis[16] was completely missing and we had to drop it.[17]

In line with the previous literature, we classify as immigrants all individuals born in any country outside the considered one. In Figure A1 we show the evolution of the share of foreign born on the aggregate population of the sample countries during the 1996-2010 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 almost doubles from below 8% in 1996 to almost 14% in 2010.

In the empirical analysis, for each year between 1996 and 2010, we aggregate the individual data into cells, that we consider as proxies for labor markets. Cells are the intersection of the 15 countries, 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.

4.1 Task variables

To test the key prediction of the model contained in 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:

variables, including place of birth, were missing for most years.

[16] Education, age or country of birth.

[17] See Table A1 of the Tables and Figures online appendix for the full list of country/years included in the empirical analysis. The table illustrates missing values as well as the subset of cells included in the IV2 specifications.

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 online appendix includes the full list of the skills/tasks measures employed to construct each of the indicators. We aggregate these categories into broad groups: *complex* and *non complex*; the average of *communication*, *complex* and *mental* skills constitutes the complex group, while average of *manual* and *routine* forms the non complex one.

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 EULFS. 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, a score of 0.79 in *communication skills* for the ISCO occupation "*corporate managers*" indicates that 79% of all workers in the US in 2000 were using *communication skills* less intensively than corporate managers. Table A3 of the online appendix shows the score for each of the ability indexes in the 21 occupations provided by the EULFS. 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. Of course our way of quantifying the task intensities associated to each occupation has some drawbacks, mainly coming from the fact that i) task intensities are measured for the US and not Europe ii) we collapse 339 Occupations surveyed by O*NET into the 21 ISCO ones provided by EULFS using as weights the distribution of workers of the 2000 US Census, that might be different from the one relevant for the EU countries considered here. These limitations could attenuate the estimated impact, because we can only measure changes in complexity associated to changes in broad occupations. On the other hand their measurement error should not induce a bias in our results since we expect to be uncorrelated with the share of migrants in the relevant cell[18] conditional on the number of controls we employ in our empirical analysis.

In Table A4 of the online appendix we report simple correlations between each of the ability measures and some dummies that capture specific education or age level groups consistent with the cell partition we employ 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. Again controlling for age effects would account for such systematic patterns.

Aggregate European data show patterns consistent with the idea that immigrants and natives specialize in different production tasks and this specialization increased over time. Figure 1, for instance, shows the evolution of the relative intensity of complex versus non-complex tasks for the average European Worker throughout the period 1996-2010, for native and foreign-born workers.[19] While the average native worker (as inferred from their occupational distribution) specialized increasingly in complex production tasks, the average immigrant workers' specialization remained almost unchanged. Such a pattern would be hard to explain as a consequence of a demand shock for tasks. In that case the trend should 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. Figure A2 in the online appendix illustrates additional stylized evidence supporting the main result of the model

[18] The fact that the skill measures for an occupation are taken from the US makes the presence of immigrants in Europe even less likely to contaminate it.

[19] 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.

in Section 2. It shows the correlation between the relative complex/non-complex task specialization of *native workers* across labor markets (cells of age-education groups across EU countries) and the share of immigrants in those cells. 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, an increase in the share of immigrants by 10% of the total population in the same labor market is associated with an increase of 4 percentage points in relative complex/non-complex task intensity. This coefficient is significant at the 1% level with a standard error of 0.137.

5 Immigrants and native specialization

In this section we estimate the empirical implementation of the equilibrium derived in Section 2 (equation 10). The coefficient of interest is γ, capturing the impact of the share of immigrants on natives' *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 of Table 1, we show a set of estimates for the average elasticity (variables are defined in logs), obtained introducing the most demanding specification including country by time and time by age by education fixed effects.[20] We adopt 4 different specifications (Column 1-4): OLS and IV1 on the whole sample, OLS and IV2 on the sub-sample for which IV2 is available. Point estimates range between 0.058 and 0.074; the estimates are strongly significant, both when clustering standard errors at the country-skill level (reported in the top brackets) and at the country-year level (reported in the bottom brackets). Native workers increase their supply of complex skills that are complementary to the manual-routine skills supplied by immigrants. As an additional test of the robustness of our results, we re-estimate (column 5 and 6) equation 10 collapsing data into country-year cells and controlling for country and year fixed effects. This specification assumes that all workers in a country, independently of their education and age, compete within the same labor market and all that matters is the relative content of complex/non-complex skills. We obtain a positive and strongly significant estimate for our parameter of interest, with our preferred 2SLS estimate for γ actually increasing to 0.10. This may imply that there is some actual complementarity across cells and that, accounting for it, further increases the

[20] Results obtained with a less saturated specification including education by year, country by year and country by education controls are reported in Table A6 of the online appendix.

response of natives to immigrants. As a final robustness check, we re-run all the specifications in levels instead of logarithms. Those estimates (not reported) confirm once again a positive and significant value for γ.[21]

In the following rows of Table 1 we move beyond average effects. We interact the main explanatory variable alternatively with age and education dummies. This allows us to estimate a different native response to immigration, depending on age and education levels. Estimates for γ are equal to 0.04 and 0.07 respectively for young and old workers, being non significant for the former in most cases. When considering native workers differing in their educational level, we generally find higher elasticities for workers with low education. Let us emphasize that the task response of natives to immigration was first documented by Peri and Sparber (2009) for US workers. In that case the authors only considered less educated workers and used an IV method. The coefficient they obtained should be compared with the one estimated in *the fourth row, column 2 of Table 1.* Interestingly, while the estimate is positive and significant 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 (in the rage of 0.06 to 0.07). Namely, the coefficient estimated using immigration across US states is 5 to 6 times larger than the one estimated using immigration across European Countries. The reason for such a difference can be the large differential in employment protection laws preventing the same amount of occupational mobility and adjustment in Europe. We will use cross-European differences in labor market institutions to emphasize this point in the Section 7. Overall, the main result of this section is that, employing a number of specifications, differing in the estimating sample, the econometric technique and the controls included we find significant empirical support to the idea that an increase of the immigrants' share on the population pushes native workers to move to occupations requiring a relatively higher level of complexity.

Does this positive reallocation take place at the expense of the total number of jobs available for natives? Namely, do immigrants only encourage specialization of natives or also crowd them out? The employment effects of immigration are relevant in itself, furthermore, an increase in relative skill complexity in equation (10) could be driven by the destruction of "simple" jobs for a given number of "complex" ones. In that case, the set of workers losing their "simple" job (without getting a more "complex" one instead) would certainly suffer

[21] For brevity, we do not report these estimates in Table 1, but they are available upon request.

from immigration. To the contrary, if the increase in relative skill complexity takes place due to a genuine transition of natives from "simple" to "complex" jobs, the group of native workers could be collectively better off through this reallocation.

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

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

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 in the population of the education-age group j, in country c in year t; $e_{j,c,t}$ is an idiosyncratic random shock. Also in this case, we estimate four different OLS and 2SLS specifications including the same sets of fixed effects as in table 1 (age by education by year, country by year)[22]. Table 2 reports the estimates of the coefficient δ for different specifications of equation (11). We find no negative impact of immigration on employment rates. Usually we obtain estimates not significantly different from 0. Sometimes, when clustering standard errors at the country-year level, we find small but positive effects. When we collapse data at the country/year level and control for country and year fixed effects, we find a positive and significant estimate equal to 0.11. Looking at the other rows of Table 2 we find no negative impact of migration on employment rates also when differentiating among young/old workers and low/high educated ones.

What is relevant for our analysis is that the positive job reallocation described before did not take place together with a *decrease* in native workers' employment rates associated to immigration. Consistently with the literature for the US Card (2009) and Peri and Sparber (2009) we find no detrimental impact of immigrants on native employment. Our results point to a null impact of immigration on natives' employment, and seem to rule out the possibility of negative employment effects of immigration.

6 Impact on labor market flows

Our model is static and provides predictions on the task supply and on the employment of a representative agent. In this section we go beyond it. It is interesting and feasible with

[22] Results obtained with less saturated model including only country by education, country by year and education by year effects are reported in Table A7 of the online appendix.

our data to decompose the effect of immigrants on hiring, separations and their complexity in producing the aggregate effect. The current economic literature on migration focusses only on the impact of immigration on the employment levels and/or wages of native workers. In this section, however, we depart somewhat from this literature as well as our model. In particular, we try to unveil the channels through which the labor reallocation found in the previous section takes place. The increase in the relative intensity of "complex" occupations of natives could take place through one or more of the following margins:

i) Immigration could generate more *hiring*, particularly concentrated in occupations requiring relatively complex skills

ii) Immigration could generate more *separations*, particularly in occupations requiring simple 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 each respondent is asked about his/her labor market status and occupation a year before the survey if those have changed during the last year (from employed to non-employed or vice-versa). 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. One caveat to keep in mind is that these flows (and their skill content) are estimated on a relatively small number of individuals (those who change labor market state in a given year). Hence their measurement might be less precise at the country-age-education-year level than the measures of skill intensity used in table 1. Moreover, the measures of job market transitions proposed here are subject to a certain degree of measurement error, being recovered from recall questions (see Poterba and Summers (1986), among others). We estimate the impact of immigration on labor market flows in a set of four equations identical to equation (10), including, respectively, as dependent variables: hiring rates, separation rates, average complexity of hiring and average complexity of separations. As in the previous empirical analysis we estimate these equations both using OLS and IV1 on the 15 countries considered in this study (columns 1 and 2 of Table 3), or on the restricted sample of 7 countries for which the shift-share IV2 instrument is available (column 3 and 4).

An interesting pattern emerges across specifications and it is particularly clear when considering our preferred specification, namely the 2SLS estimation employing the IV2, reported in column 4. The pattern emerging, while not too strong, 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 positive, but usually not very significant impact of foreign-born inflows in stimulating hiring and no impact at all on separation rates, as previously defined. Specifically, in our preferred estimate, an increase of immigrants by 1% of their share increases the hiring rate of native workers by 0.43%, significant when we cluster at the country/year level, while it has no impact at all on the separation rates for natives. Hence, in net, there is some evidence that immigration encourages new hires of natives. This effect is compatible with the positive, and only sometimes significant effect of immigration on employment, shown in table 2. 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 equal to 0.15 (significant at 1%) in our preferred 2SLS estimate based on IV2. When considering the separation margin, the effect of immigrants on the relative complexity of separations also has a positive sign. However the elasticities' estimates are 30 to 50% smaller compared to hiring (the elasticity is equal to 0.10 in the preferred estimates using IV2). These results, although somewhat sensitive to the specification used, are consistent with the overall labor reallocation process described in the previous section. Labor market flows into and out of employment are not very significantly affected by immigration. Instead 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. Moreover there could be a substantial degree of skill upgrading in job-to-job transition that we cannot observe in our data.

7 Differences across Labor Market Institutions

Could the positive reallocation of natives towards more complex jobs be slowed by rigid labor markets and sluggish transition? 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 (via collective contracts). Hence, labor market institutions can affect the occupational mobility margin of natives in response to immigrants. More flexible labor markets could facilitate immigrants' absorption, facilitating job upgrading and job creation, and thereby easing productive reallocation of natives (Angrist and Kugler, 2003). As in any cross-country comparison, our results could be driven by the presence of confounders (such as the efficiency of the judiciary or the strictness of product market regulation); it is hard to disentangle their effects from the effect of labor market institutions especially with a limited number of countries as in our sample. Nevertheless, after controlling for time-varying country level differences with country by time fixed effects, we expect labor market institutions in each country to be the main determinant of natives' labor dynamics associated with migration.

To check for this possibility, we re-estimate equation (10) interacting the main explanatory variable $ln(f)$, the logarithm of the share of immigrants in the cell population, with two country level indicators of the employment protection legislation (EPL). We construct a dummy (that we interact with $ln(f)$) capturing whether the country has a high or low level of EPL. As a first measure of EPL we 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.[23] We also consider an alternative measure of EPL based on an ad hoc employer survey conducted by the European Commission in 1989, (European-Commission, 1991). This last indicator is based on the share of employers stating that restrictions on hiring and firing were very important when surveyed. The two different indicators provide a robustness check for the results to the type of EPL index used and also to the countries included in the comparative analysis, since such indices are not available for some of the countries included in this study.[24] For each

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

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

indicator, we define a country as a "high EPL" one when its strictness in the labor laws is higher than the weighted median of the countries included in the EPL ranking (see table A1, last two columns, for a list of countries by EPL levels). Similarly, "Low EPL" corresponds to a value of the strictness index below the weighted median. We show the results of OLS and 2SLS estimation based on the IV1 instrument. We do not consider the IV2 instrument, since this would restrict the analysis to 7 countries only, leaving little variability by EPL level.

In Table 4 we report the estimates of EPL-specific γ, finding two patterns. First, the positive reallocation of natives toward "complex" tasks is stronger in countries with low levels of EPL. In the preferred 2SLS estimates, using alternatively the EC89 index and the OECD aggregate one, we find that low EPL countries show coefficient estimates between 0.055 and 0.085 (always significant at the 1% confidence level), with these values increasing when using OLS. Again considering 2SLS estimates, the estimated coefficients are smaller (ranging between 0.019 and 0.047) for high EPL countries.[25] The difference in γ for high and low EPL countries is always significant at 1% when using the EC index, while it is not significant using the OECD one.

We also analyze whether the difference in the response due to the degree of employment protection across countries varies across skill groups 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. 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 0.052 and 0.055. To the contrary, in countries with high EPL that elasticity is never larger than 0.04. Considering workers of different schooling levels it is interesting to note that the change in specialization in response to immigrants is strong in particular for less educated workers in countries with low EPL. In our preferred 2SLS-IV1 estimate, the response of less educated workers in flexible labor markets is 0.076% for each 1% increase in immigrants' shares, while in more rigid markets this value is equal to 0.054%. To the contrary, for highly educated workers the point estimates do not show a clear pattern between high and low EPL countries.

[25] We also tried to distinguish labor market flows between Low and High EPL countries following the analysis presented in Section 6, but the results became noisy and hard to interpret.

The estimated elasticities for highly educated workers tend to be not different from zero at standard confidence levels both for high and low EPL countries. This is very interesting as it implies that strong employment protection laws hinder the ability of less educated workers to change occupations in response to immigration. This deprives them of one of the most effective mechanism to protect their job and wage from immigration.

As an additional check we explore the country-specific pattern of the native occupational response. We use a specification that interacts the log of the share of migrants in each cell with a full set of country specific dummies. This allows to identify a country-specific coefficient and check whether the main results of this section are due to the contribution of some outliers or if they follow a regular pattern across countries. In Figure 2 we show two graphs. On the horizontal axis we report the EPL indices (the OECD index in the left panel, and the EC in the right one) and on the vertical axis we report the country-specific estimates for γ together with 95% confidence intervals for those estimates. We also include two horizontal lines identifying the average values for γ estimated for the low and the high EPL countries. Due to the low number of observations there is not much precision in the country-by-country estimates but, on average, countries with a higher EPL level tend to have lower γ. We also see from the figure that Greece and Ireland (the country with highest and lowest estimated γ) are two outliers.

As a further robustness check, we re-run the previous regressions in which countries were grouped into High and Low EPL levels (Table 4) excluding the countries for which we estimated the highest and the lowest γ (Greece and Ireland, respectively) in the country by country regressions. If anything, main results are reinforced in this case (Table A8 of the Online Appendix), and once again show that the positive job reallocation of natives is stronger in countries with less regulated labor markets.

The idea that labor market rigidities interact with shocks to produce inefficient labor market outcomes 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. Blanchard and Wolfers (2000)). We argue that another type of change to the economy, represented by the inflow of immigrants, has less efficient effects in the presence of strong EPL. Moreover, these results 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 provide a reason for this. Countries in which native workers respond less 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. Peri and Sparber (2009) find an even larger specialization response of natives to the inflow of immigrants that can be due to the very low levels of EPL in the U.S.

8 Immigration during the Great Recession

The results presented above are obtained using the fifteen year interval 1996-2010. It is interesting to check whether the positive impact of immigration on native specialization continued after the onset of the Great Recession (GR) that we can date with the collapse of Lehman Brothers in 2007. There are a number of studies on the impact of the Great Recession on European and US labor markets.[26] There is no research, however[27], analyzing the different impact of new immigrants on the labor markets along the business cycle. In this section we address this issue. We test whether there is evidence that immigrants had different effects on the European labor markets before and during the Great Recession. In principle, the short run effects of migration could be less favorable, or more adverse, during an economic downturn. At the same time, however, the net inflow of immigrants may be reduced during periods of low labor demand and this may attenuate the effects.

Checking whether the job reallocation process outlined above was still at work during the crisis years is not only interesting in itself, but it also provides an additional check for our main results in a period of negative labor demand shocks. During a period of low labor demand, in fact, the other determinants of immigration (ethnic networks, family reunification) are relatively stronger and produce a more clearly "supply-driven" change in immigrants. According to EULFS data, foreign born' share over working age population continued to grow during the economic downturn, averaging 13.0% during the 2007-2010 period and hence 2.2 points higher than in the preceding four year interval.

In our empirical analysis, we modify equation (10), interacting our main explanatory variable with binary variables, the first equal to one during the period before the Great

[26] Among others, see respectively Immervoll et al. (2011) and Elsby et al. (2010).

[27] The policy study (Peri, 2011) is the only attempt we know of, considering this issue.

Recession (1996-2006) and zero otherwise and the other one equal to one in the 2007-2010 period and 0 otherwise. Results reported in Panel A of Table 5 show that the positive reallocation process described in the previous sections is at work even during the years of the Great Recession. The parameter estimates for γ, the impact of immigration on skill complexity of native jobs is positive, significant and ranging between 0.038 and 0.05. Nevertheless, the values estimated for the pre-GR period are 50 to 70% higher, ranging between 0.059 and 0.08. In both cases the estimates are precise and statistically significant at the one percent level irrespective of the level adopted for standard errors' clustering. These patterns also emerge when we differentiate further between high and low EPL countries in PANEL B of Table 5. The estimated values for γ are higher in countries where labor laws are more flexible, in particular during the Great Recession.

In Panels C and D of Table 5, we also test for differential effects of the recession on the different margins of labor market flows. We find evidence that changes in migrants' shares have only a mild and barely significant positive effect on hiring and no effects on separation rates (before and during the great recession). In specification 3 we find a slightly larger and barely significant effect of immigration on separation rates during the recession, but not before. However this result seems weak and not confirmed in other specifications in which immigrants do not have effect on separations before or during the recession. Moreover an exogenous increase in immigration stimulates the creation of jobs with a higher complexity, the larger is the inflow of immigrants, while the complexity of destroyed jobs relative to the created ones is not as high. This difference in complexity between jobs created and jobs destroyed, decreases somewhat during the GR years. Overall we estimate similar effects before and during the recession, confirming that the occupational upgrading of natives continued even during a period of weak labor demand.

9 Wage simulations

In order to quantify the effect that the immigration-induced job reallocation has on wages, we first estimate the elasticity of individual wage to the complex/non complex skill mix of the job using data from the EU-Statistics on Income & Living Conditions (EU-SILC). The EU labor force data, used in the previous sections, do not contain information on wage levels. The EU-SILC data are gathered through household surveys conducted by EU member states and harmonized by EUROSTAT, the official statistical office of the European Union. The dataset is based on individual records, being representative of the whole population of the surveyed countries. It provides information on occupational and migration status, as well as on total and labor income together with the main socio demographic characteristics. The survey is conducted every year since 2005, but we will use only the three waves conducted in 2007, 2008 and 2009 (latest available), since in those years the data provide all the relevant information for each of the 15 countries included in the previous analysis.[28]

To estimate the elasticity of gross individual wages to the relative complexity of the job held we estimate the following wage regression:

$$ln(wage_{i,t}) = \alpha + \beta * ln\left(\frac{C_D}{S_D}\right)_{i,t} + d_{edu,c} + d_{edu,t} + d_{c,t} + \varepsilon_{i,t} \tag{12}$$

where $ln(wage_{i,t})$ is the log of gross monthly average wage earned by native worker i in year t, $ln\left(\frac{C}{NC}\right)$ is the logarithm of the complex relative to non complex skill intensity of her job and $d_{edu,c}$, $d_{edu,t}$ and $d_{c,t}$ are the usual education by country, education by year and country by year fixed effects. Expression (12) can be seen as a Mincerian regression at the individual level in which the return to the complex/simple skills are represented by β. The equilibrium condition in (9) determines the optimal $ln\left(\frac{C_D}{S_D}\right)_{i,t}$ for natives which corresponds to an occupation. Hence β measures how the productivity and wage of the native worker will change as $ln\left(\frac{C_D}{S_D}\right)_{i,t}$ changes in response to immigration.

When estimating (12) we cluster standard errors at the country-age-education level and alternatively at the country-year level. We estimate a wage/skill elasticity equal to 0.117 (Table 6), significant at the 1 per cent level. This implies that an increase of 10 per cent in the relative complex/non complex skill mix of the job is associated with a 1.2% increase in gross monthly wages of natives in the same labor market. As a robustness check, we interact the main explanatory variable with binary dummies for each of the considered years, finding fairly stable estimates ranging between 0.117 (year 2007 and 2009) and 0.12 (year 2009), always significant at the 1% level. This effect on native wages is the one due only to the job upgrading estimated in this paper.[29]

Combining results from equation 12 with our favorite estimate of 0.06 for the migra-

[28] An overview of EU-SILC data, together with national questionnaires, is available at circa.europa.eu/Public/irc/dsis/eusilc/library.

[29] Immigrants will also have an effect on the return to complex and non complex skills. This effect will also benefit natives as they specialize more intensely in complex type of jobs. Quantifying that effect would require the knowledge of wages for natives in each year, that we do not have.

tion/skill reallocation elasticity (Table 1, row 1, column 2), we can finally simulate the short run impact of migration on wages, through job transition. We estimate that due to the reallocation of labor towards more complex tasks, triggered by migration, a doubling of the share of foreign born, as it took place in the period 1996 to 2010, raised native workers wages by 100%*0.06*0.12=0.7%. This effect is not large however (i) it is positive, (ii) it is a lower bound as only changes in broadly defined occupations are captured in the data (iii) it takes place without any negative employment effect (iv) it is realized already in the short-run, as our analysis uses yearly data.

10 Conclusions

In the last fifteen years, the labor markets of most OECD 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 experienced an unprecedented increase in its immigrant population. 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 is simple. Immigrants tend to be specialized in occupations requiring mainly non-complex and routine skills, because their knowledge of local language and norms is lower than natives'. Immigrant inflows, thus, tend to reduce the supply of complex relative to simple skills in a labor market 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 two sets of reasonable instrumental variables. We also document the labor market flows through which such a positive reallocation took place: immigration stimulated hiring, in jobs with relatively high complexity content. To the contrary, separations were not affected much by immigrants in the cell. We find evidence that this process slowed somewhat, but did not stop, during the economic downturn of 2007-2010. This positive reallocation process was stronger in relatively flexible labor markets, and in those markets it is particularly prominent for less educated workers. By moving to complex jobs, natives protected their wages from immigrant competition and took 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 hiring in those occupations. Strong protection of labor hurts this mechanism and reduces labor markets' ability to absorb immigrants through occupational upgrading of natives.

References

Acemoglu, A. and D. Autor (2010). Skills, Tasks and Technologies: Implications for Employment and Earnings. In O. Ashenfelter and D. E. Card (Eds.), *Handbook of Labor Economics*. Elsevier.

Altonji, J. G. and D. Card (1991). The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives. In J. Abowd and R. B. Freeman (Eds.), *Immigration, Trade, and the Labor Market*. The University of Chicago Press.

Angrist, J. D. and A. D. Kugler (2003). Protective or counter-productive? Labour market institutions and the effect of immigration on EU natives. *Economic Journal 113*(488), F302–F331.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The Skill Content Of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Blanchard, O. and J. Wolfers (2000, March). The Role of Shocks and Institutions in the Rise of European Unemployment: The Aggregate Evidence. *Economic Journal 110*(462), C1–33.

Blinder, A. S. (2006). Preparing America's Workforce: Are We Looking in the Rear-View Mirror? *Princeton University WP* (67).

Borjas, G. J. (2003). The Labor Demand Curve Is Downward Sloping: Reexamining The Impact Of Immigration On The Labor Market. *The Quarterly Journal of Economics 118*(4), 1335–1374.

Borjas, G. J., R. B. Freeman, and L. Katz (1996). Searching for the Effect of Immigration on the Labor Market. *American Economic Review 86*(2), 246–51.

Borjas, G. J. and L. F. Katz (2007). The Evolution of the Mexican-Born Workforce in the United States. In *Mexican Immigration to the United States*, NBER Chapters, pp. 13–56. National Bureau of Economic Research, Inc.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Market Impacts of Higher Immigration. *Journal of Labor Economics* (19(1)), 22–64.

Card, D. (2009). Immigration and Inequality. *American Economic Review 99*(2), 1–21.

Crinò, R. (2009). Service Offshoring and the Skill Composition of Labor Demand. *IAE WP* (802).

Docquier, F., c. Özden, and G. Peri (2010). The Wage Effects of Immigration and Emigration. NBER Working Papers 16646, National Bureau of Economic Research, Inc.

Dustmann, C., T. Frattini, and I. Preston (2012). The effect of immigration along the distribution of wages. *Review of Economic Studies, forthcoming*.

Elsby, M., B. Hobijn, and A. Sahin (2010). The Labor Market in the Great Recession. *Brookings Papers on Economic Activity 41*(1), 1–69.

European-Commission (1991). *European economy, March*.

EUROSTAT (2009). EU Labour Force Survey database. *User guide*.

Glitz, A. (2012). The Labour Market Impact of Immigration: A Quasi-Experiment Exploiting Immigrant Location Rules in Germany. *Journal of Labor Economics, forthcoming*.

Goldin, C. and L. F. Katz (2007). The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005. NBER Working Papers 12984, National Bureau of Economic Research, Inc.

González, L. and F. Ortega (2011). How Do Very Open Economies Absorb Large Immigration Flows? Recent Evidence from Spanish Regions. *Labour Economics* (18), 57–70.

Goos, M., A. Manning, and A. Salomons (2009). The Polarization of the European Labor Market. *American Economic Review Papers and Proceedings* (99), 58–63.

Immervoll, H., A. Peichl, and K. Tatsiramos (2011). Who Loses in the Downturn? Economic Crisis, Employment and Income Distribution. In *Research in Labor Economics, Vol. 32*. Emerald Publishing.

IPUMS-I (2010). *Integrated Public Use Microdata Series, International: Version 6.0*. Minnesota Population Center, Minneapolis: University of Minnesota.

Katz, L. and K. Murphy (1992). Change in Relative Wages 1963-1987: Supply or Demand Factors. *Quarterly Journal of Economics* (107), 35–78.

Longhi, S., P. Nijkamp, and J. Poot (2005). A meta-analytic assessment of the effect of immigration on wages. *Journal of Economic Surveys 19*(3), 451–477.

OECD (1999). Employment Protection and Labour Market Performance. *Employment Outlook - 1999*.

Okkerse, L. (2008). How to measure labour market effects of immigration: A review. *Journal of Economic Surveys 22*(1), 1–30.

Ortega, F. and G. Peri (2011). The Aggregate Effects of Trade and Migration: Evidence from OECD Countries. Technical Report 5604, IZA.

Ottaviano, G. and G. Peri (2012). Rethinking the Effects of Immigration on Wages. *Journal of the European Economic Association* (10(1)), 152–197.

Peri, G. (2011). The Impact of Immigrants in Recession and Economic Expansion. *Migration Policy Institute WP*.

Peri, G. and C. Sparber (2009). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics* (1(3)), 135–169.

Poterba, J. M. and L. H. Summers (1986). Reporting Errors and Labor Market Dynamics. *Econometrica 54*(6), 1319–1338.

Tables

Table 1: The Effects of Immigrants on Relative Task Performance of Natives

Dependent variable: log of relative skill intensity in the education-age cell							
Column		**1**	**2**	**3**	**4**	**5**	**6**
Estimates		**OLS**	**IV1**	**OLS2**	**IV2**	**IV1**	**IV2**
PANEL A	**$\ln(f_{j,c,t})$**	0.058	0.06	0.069	0.074	0.104	0.076
		[0.018]***	[0.021]***	[0.022]***	[0.036]**	[0.011]***	[0.005]***
		[0.008]***	[0.007]***	[0.010]***	[0.016]***		
PANEL B	**$\ln(f_{j,c,t})$*Young**	0.033	0.024	0.041	0.045		
		[0.022]	[0.056]	[0.028]	[0.096]		
		[0.012]***	[0.020]	[0.018]**	[0.054]		
	$\ln(f_{j,c,t})$*Old	0.062	0.06	0.074	0.074		
		[0.018]***	[0.022]***	[0.022]***	[0.035]**		
		[0.008]***	[0.008]***	[0.010]***	[0.015]***		
PANEL C	**$\ln(f_{j,c,t})$*Low edu**	0.065	0.065	0.071	0.064		
		[0.017]***	[0.020]***	[0.022]***	[0.037]*		
		[0.008]***	[0.007]***	[0.010]***	[0.017]***		
	$\ln(f_{j,c,t})$*High edu	-0.002	-0.022	0.03	-0.012		
		[0.024]	[0.039]	[0.043]	[0.065]		
		[0.012]	[0.021]	[0.021]	[0.042]		
Observations		2106	2094	840	840	205	84
Controls							
Year by Country		Yes	Yes	Yes	Yes		
Year by age by education		Yes	Yes	Yes	Yes		
Country and year						Yes	Yes

Note: *Units of Observations are eight education-by-age cells in 15 EU countries in each year 1996-2010 (columns 1-4) and country/year cells (columns 5 and 6). 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 squared bracket we report the heteroskedasticity robust standard errors clustered respectively at the country-education-age level (first entry) or at the country-year level (second entry). Standard errors are not clustered in columns 5 and 6. OLS2 estimates are OLS estimates on the sample for which it was possible to compute the IV2 estimates. See section 3.1 for details on the shift share instruments IV1 and IV2, first-stage statistics are reported in table A5 of the appendix. ***=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 2: The effect of Immigrants on Native Employment

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

Column		1	2	3	4	5	6
Estimates		OLS	IV1	OLS2	IV2	IV1	IV2
		0.015	0.044	0.028	0.096	0.11	0.134
PANEL A	$\ln(f_{j,c,t})$	[0.078]	[0.099]	[0.095]	[0.156]	[0.018]***	[0.017]***
		[0.013]	[0.018]**	[0.015]*	[0.031]***		
		0.134	0.341	0.153	0.181		
	$\ln(f_{j,c,t})$*Young	[0.080]*	[0.208]	[0.089]*	[0.347]		
PANEL B		[0.026]***	[0.071]***	[0.033]***	[0.102]*		
		0.001	0.045	0.007	0.095		
	$\ln(f_{j,c,t})$*Old	[0.078]	[0.098]	[0.097]	[0.154]		
		[0.015]	[0.023]*	[0.018]	[0.031]***		
		0.017	0.047	0.031	0.081		
	$\ln(f_{j,c,t})$*Low edu	[0.080]	[0.100]	[0.097]	[0.157]		
PANEL C		[0.013]	[0.018]***	[0.016]*	[0.032]**		
		0.003	0.001	-0.025	-0.039		
	$\ln(f_{j,c,t})$*High edu	[0.073]	[0.110]	[0.105]	[0.219]		
		[0.015]	[0.031]	[0.024]	[0.065]		
Observations		2106	2094	840	840	205	84
Controls							
Year by Country		Yes	Yes	Yes	Yes		
Year by age by education		Yes	Yes	Yes	Yes		
Country and year						Yes	Yes

Note: *Units of Observations are eight education-by-age cells in 15 EU countries in each year (columns 1-4) and country/year cells (columns 5 and 6).*
The dependent variable is the logarithm of Employment/Population for the native population in the cell (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 squared bracket we report the heteroskedasticity robust standard errors clustered respectively at the country-education-age level (first entry) or at the country-year level (second entry). Standard errors are not clustered in columns 5 and 6. OLS2 estimates are OLS estimates on the sample for which it was possible to compute the IV2 2SLS estimates. See section 3.1 for details on the shift share instruments IV1 and IV2, first-stage statistics are reported in table A5 of the appendix.
****=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 3: The Effect of Immigrants on the task intensity of employment flows

Units of Observations are eight education-by-age cells in 15 EU countries in each year, 1996-2010

Column	**1**	**2**	**3**	**4**
Estimates	**OLS**	**IV1**	**OLS2**	**IV2**
	Hirings rate			
	0.242	0.432	0.196	0.587
	[0.266]	[0.272]	[0.325]	[0.402]
	[0.121]**	[0.124]***	[0.158]	[0.147]***
Hirings	**Hirings' relative complex/non-complex skill intensity**			
	0.085	0.108	0.088	0.152
	[0.020]***	[0.021]***	[0.025]***	[0.040]***
	[0.009]***	[0.009]***	[0.011]***	[0.018]***
	Separations rate			
	0.028	0.031	0.066	-0.046
	[0.085]	[0.097]	[0.091]	[0.127]
	[0.025]	[0.031]	[0.028]**	[0.038]
Separations	**Separations' relative complex/non-complex skill intensity**			
	0.064	0.068	0.069	0.102
	[0.017]***	[0.020]***	[0.020]***	[0.029]***
	[0.008]***	[0.010]***	[0.009]***	[0.017]***
Observations	1986	1974	840	840
Controls				
Country by education	Yes	Yes	Yes	Yes
Education by year	Yes	Yes	Yes	Yes
Country by year	Yes	Yes	Yes	Yes

Note: *Each coefficient in the table is estimated in a separate regression. The main explanatory variable is the log of the share of immigrants in the cell. In squared brackets we report the heteroskedasticity robust standard errors clustered respectively at the country-education-age level (first entry) or at the country-year level (second entry). OLS2 estimates are OLS estimates on the sample for which it was possible to compute the IV2 2SLS estimates. See section 3.1 for details on the shift share instruments IV1 and IV2, first-stage statistics are reported in table A5 of the appendix.*
****=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 4: The Effects of Immigrants on Relative Task Performance of Natives, by EPL levels

Units of Observations are eight education-by-age cells in 15 EU countries in each year, 1996-2010

Dependent variable: log of relative complex/non complex skill intensity

Column			**1**	**2**	**3**	**4**
EPL indicator			**OECD**	**OECD**	**EC89**	**EC89**
Estimates			**OLS**	**IV1**	**OLS**	**IV1**
PANEL A	$\ln(f_{j,c,t})$	*Low EPL	0.066	0.055	0.096	0.085
			[0.020]***	[0.021]***	[0.022]***	[0.024]***
			[0.005]***	[0.005]***	[0.007]***	[0.008]***
		*High EPL	0.053	0.047	0.028	0.019
			[0.021]**	[0.022]**	[0.010]***	[0.009]**
			[0.009]***	[0.010]***	[0.005]***	[0.005]***
PANEL B	$\ln(f_{j,c,t})$* Young	*Low EPL	0.065	0.055	0.096	0.084
			[0.018]***	[0.020]***	[0.022]***	[0.024]***
			[0.004]***	[0.004]***	[0.007]***	[0.008]***
		*High EPL	0.049	0.043	0.04	0.034
			[0.024]**	[0.027]	[0.018]**	[0.019]*
			[0.010]***	[0.010]***	[0.007]***	[0.007]***
	$\ln(f_{j,c,t})$* Old	*Low EPL	0.062	0.052	0.102	0.09
			[0.017]***	[0.019]***	[0.024]***	[0.026]***
			[0.004]***	[0.005]***	[0.008]***	[0.009]***
		*High EPL	0.051	0.044	0.032	0.027
			[0.022]**	[0.023]*	[0.011]***	[0.012]**
			[0.009]***	[0.010]***	[0.006]***	[0.005]***
PANEL C	$\ln(f_{j,c,t})$* Low edu	*Low EPL	0.076	0.06	0.109	0.096
			[0.019]***	[0.022]***	[0.022]***	[0.024]***
			[0.008]***	[0.008]***	[0.009]***	[0.010]***
		*High EPL	0.054	0.047	0.029	0.019
			[0.021]**	[0.022]**	[0.010]***	[0.009]**
			[0.009]***	[0.010]***	[0.005]***	[0.004]***
	$\ln(f_{j,c,t})$* High edu	*Low EPL	0.022	0.033	0.016	0.021
			[0.031]	[0.038]	[0.037]	[0.041]
			[0.014]	[0.016]**	[0.017]	[0.018]
		*High EPL	0.038	0.027	0.02	0.053
			[0.027]	[0.072]	[0.023]	[0.063]
			[0.010]***	[0.020]	[0.010]**	[0.026]**
Observations			1947	1935	1220	1220
Controls						
Country by education			Yes	Yes	Yes	Yes
Education by year			Yes	Yes	Yes	Yes
Country by year			Yes	Yes	Yes	Yes

Note: *Coefficients in each* panel *are estimated in a separate regression. The dependent variable is the logarithm of the relative task intensity (equation 10 of section 3). The main explanatory variable (Panel A) is the log of the share of immigrants in the cell by 2 EPL levels. In Panel B it is further interacted with Young/Old dummies, in Panel C it is further interacted with High/Low education dummies. In squared bracket we report the heteroskedasticity robust standard errors clustered respectively at the country-education-age level (first entry) or at the country-year level (second entry). OLS2 estimates are OLS estimates on the sample for which it was possible to compute the IV2, 2SLS, estimates. See section 3.1 for details on the shift share instruments IV1 and IV2, first-stage statistics are reported in table A5 of the appendix. Luxembourg is never included in EPL rankings. EC89 does not rank Austria, Denmark, Finland, Norway and Sweden. See text (section 7), Table A1 of this online Appendix and OECD (1999, pp. 64-68) for details on the EPL indexes. ***=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 5: Immigrants and jobs, before and during the Great Recession

Units of Observations are eight education-by-age cells in 15 EU countries in each year, 1996-2010

Column		**1**	**2**	**3**	**4**
Estimates		**OLS**	**IV1**	**OLS2**	**IV2**
	Relative skill intensity				
PANEL A	**ln($f_{j,c,t}$)*Before GR**	0.067 [0.017]*** [0.008]***	0.059 [0.019]*** [0.008]***	0.072 [0.020]*** [0.010]***	0.08 [0.026]*** [0.014]***
	ln($f_{j,c,t}$)* GR	0.045 [0.013]*** [0.008]***	0.038 [0.012]*** [0.007]***	0.043 [0.016]** [0.012]***	0.05 [0.025]** [0.020]**
PANEL B	**ln($f_{j,c,t}$)* Before GR* Low EPL**	0.067 [0.021]*** [0.005]***	0.06 [0.022]*** [0.006]***		
	ln($f_{j,c,t}$)* Before GR* High EPL	0.066 [0.027]** [0.015]***	0.057 [0.029]* [0.015]***		
	ln($f_{j,c,t}$)* GR* Low EPL	0.064 [0.019]*** [0.008]***	0.044 [0.019]** [0.005]***		
	ln($f_{j,c,t}$)* GR* High EPL	0.034 [0.014]** [0.009]***	0.034 [0.015]** [0.010]***		
	Hirings rate				
PANEL C	**ln($f_{j,c,t}$)* Before GR**	0.208 [0.279] [0.154]	0.273 [0.302] [0.172]	0.188 [0.326] [0.181]	0.63 [0.392] [0.162]***
	ln($f_{j,c,t}$)* GR	0.298 [0.258] [0.188]	0.668 [0.225]*** [0.144]***	0.218 [0.341] [0.315]	0.445 [0.456] [0.306]
	Hirings' relative complex/non complex skill intensity				
PANEL D	**ln($f_{j,c,t}$)* Before GR**	0.092 [0.023]*** [0.011]***	0.104 [0.025]*** [0.012]***	0.098 [0.027]*** [0.013]***	0.16 [0.039]*** [0.019]***
	ln($f_{j,c,t}$)* GR	0.074 [0.020]*** [0.014]***	0.114 [0.025]*** [0.015]***	0.063 [0.024]*** [0.021]***	0.125 [0.054]** [0.048]**
	Separations' rate				
PANEL E	**ln($f_{j,c,t}$)* Before GR**	0.018 [0.080] [0.025]	0.034 [0.089] [0.032]	0.038 [0.090] [0.027]	-0.049 [0.117] [0.039]
	ln($f_{j,c,t}$)* GR	0.044 [0.111] [0.051]	0.026 [0.127] [0.059]	0.145 [0.105] [0.070]**	-0.037 [0.182] [0.087]
	Separations' relative complex/non complex skill intensity				
PANEL F	**ln($f_{j,c,t}$)* Before GR**	0.066 [0.020]*** [0.011]***	0.074 [0.024]*** [0.015]***	0.083 [0.023]*** [0.013]***	0.107 [0.031]*** [0.021]***
	ln($f_{j,c,t}$)* GR	0.061 [0.020]*** [0.012]***	0.062 [0.022]*** [0.012]***	0.038 [0.016]** [0.009]***	0.088 [0.036]** [0.019]***

Note: *Coefficients in each* panel *are estimated in a separate regression. The dependent variable is specified in the header. The main explanatory variable is the log of the share of immigrants in the cell interacted with GR/ Before GR dummies. The GR (before GR) dummy is equal to one from year 2007 to 2010 (1996 to 2006) and zero otherwise. In Panel B, it is further interacted with High/Low EPL. Heteroskedasticity robust standard errors clustered respectively at the country-education-age level (first entry) or at the country-year level (second entry) are reported in squared brackets. OLS2 estimates are OLS estimates on the sample for which it was possible to compute the IV2 2SLS estimates (see section 3.1 for details on the shift share instruments, first-stage statistics are reported in table A5 of the appendix). Luxembourg is never included in EPL rankings. EC89 does not rank Austria, Denmark, Finland, Norway and Sweden. See text (section 7), Table A1 of the online Appendix and OECD (1999, pp. 64-68) for details on the EPL indexes. ***=significant at 1%; **=significant at 5%, *=significant at 10%.*

Table 6: Relative Complex/Simple intensity and wages, native workers

Elasticity: log of gross wage - log of relative skill complexity: 2007-2009				
Column	**1**	**2**		
	log(C/S)	**log(C/S)* year 2007**	**log(C/S)* year 2008**	**log(C/S)* year 2009**
	0.115	0.117	0.11	0.117
	[0.019]***	[0.019]***	[0.019]***	[0.021]***
	[0.009]***	[0.018]***	[0.012]***	[0.014]***
Observations	275608	275608		
Controls				
Country by education	Yes	Yes		
Education by year	Yes	Yes		
Country by year	Yes	Yes		

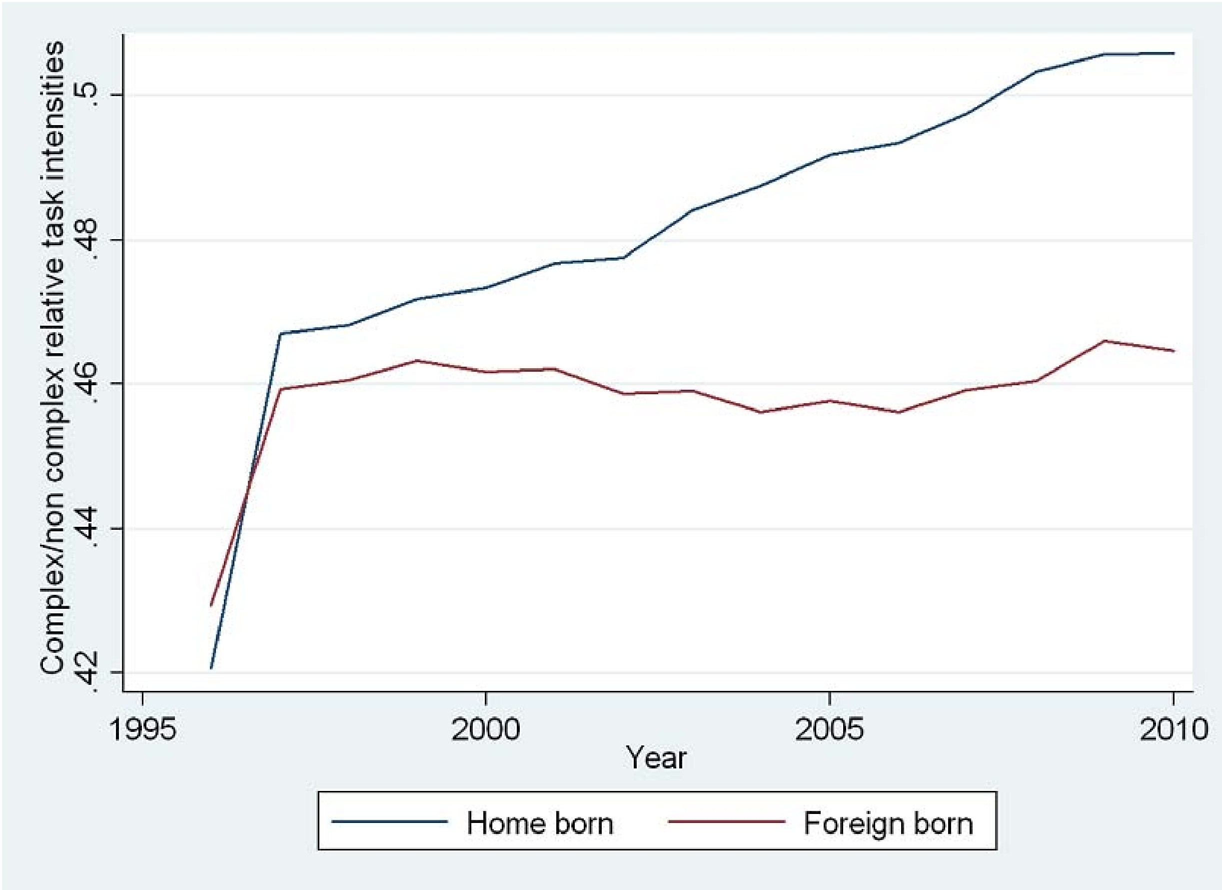
Note: Authors' calculations EU-SILC (2007, 2008 and 2009 waves); includes natives only. *Coefficients in each* column *are estimated in a separate regression. Each regression is weighted with individual cross-sectional weights. The dependent variable is the log of gross monthly wage, the main explanatory variable is the log of the relative skill intensity for the individual (Column 1). In Column 2, the main explanatory variable is interacted by year.*

Heteroskedasticity robust standard errors clustered respectively at the country-education-age level (first entry) or at the country-year level (second entry) are reported in squared brackets.

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

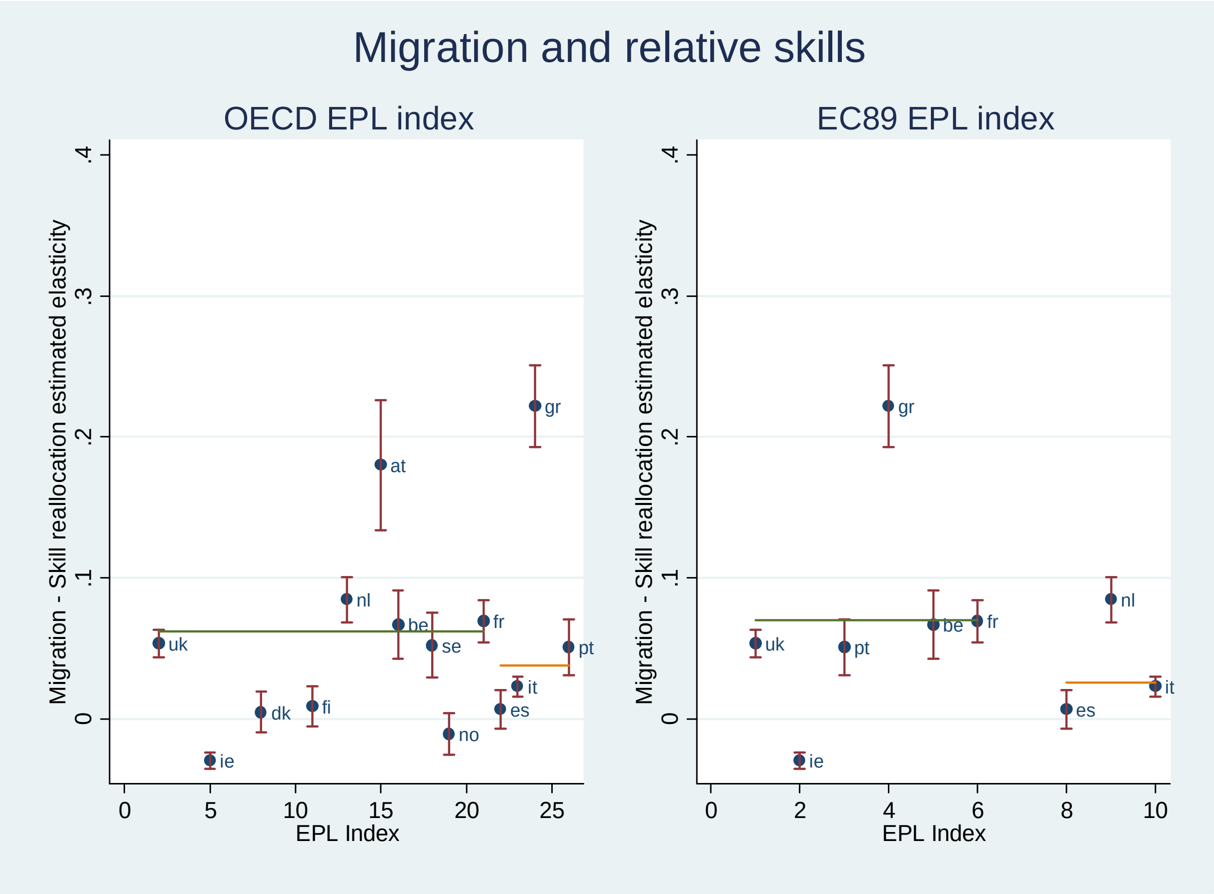
Figures

Figure 1: Relative Complex/Simple 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 2
Job reallocation intensity, and EPL: Country by Country IV1 estimates



Note: *Units of Observations are eight education-by-age cells in each of the 15 EU countries in each year. The figure reports the results of the estimation of country by country regressions where the dependent variable is the logarithm of the log of skill intensity and the main explanatory variable is the log of the share of migrants in the cell. The regression includes education by year, country by education and country by year fixed effects. Each point represents the point value country estimate, while the red vertical bars identify 95% confidence intervals. The green (yellow) horizontal line identifies the weighted average of the estimated γ for low (high) EPL countries. Luxembourg is never included in EPL rankings. EC89 does not rank Austria, Denmark, Finland, Sweden and Norway. The specification adopted to estimate the skill reallocation elasticity on the y-axis is the one reported in column 2 of table 1. See section 3.1 for details on the shift share instrument IV1, first-stage statistics are reported in table A5 of the appendix.*