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HUMAN RESOURCES AND INNOVATION: TOTAL FACTOR PRODUCTIVITY AND FOREIGN HUMAN CAPITAL

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Human resources and innovation:
Total Factor Productivity and foreign human capital[1]

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Abstract

The objective of this paper is to analyse the role of migrants in innovation in Europe. We use Total Factor Productivity as a measure of innovation and focus on the three largest European countries – France, Germany and the United Kingdom – in the years 1994-2007. Unlike previous research, which mainly employs a regional approach, we analyse the link between migration and innovation at the sectoral level. This allows us to measure the direct contribution of migrants in the sector in which they are actually employed. Moreover, it allows a distinction between the real contribution of migrants to innovation from possible inter-sectoral complementarities, which might as well foster innovation. We control for the different components of human-capital, such as age, education and diversity of origin. To address the possible endogeneity of migration we draw on an instrumental variable strategy originally devised by Card (2001) and adapt it at the sector level The results show that overall migrants are relevant in all sectors, but some important differences emerge across sectors: highly-educated migrants show a larger positive effect in the high-tech sectors, while middle- and low-educated ones are more relevant in manufacturing. The diversity of countries of origin contributes to innovation only in the services sectors, confirming that in empirical analyses at the regional or national level the diversity measure might capture the complementarity between sectors rather than the contribution of different national skills.

Keywords: Migration, innovation, highly skilled migrants, low skilled migrants

JEL Codes: F22, F66, O31, O32

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1. Introduction

The contribution of migrant workers to the economic and innovative performances of European countries has recently gained a lot of academic and policy attention. The global competition challenge stemming especially from the rise of new emerging economies, able to quickly upgrade their level of technological development, is forcing European countries to increase their competitiveness and their overall innovative capacity. It is often argued that migrants can have an important role in this process.

Migrants might, for one, improve the level of innovativeness of European economies through the supply of specific skills and competences. A recent body of literature, mainly focused on the US economy, has shown that the inflow of foreign graduates, especially in science and technology discipline, greatly fostered the production of innovations in US firms, as proxied by the number of patent applications (Kerr and Lincoln, 2010; Hunt Gauthier-Loiselle, 2010). This evidence has suggested the importance of Europe attracting skilled professionals from abroad, in what has often been labeled as the "global race for talent" (Breschi et al, 2014; Münz, 2014). Recent empirical evidence has, indeed, found a positive effect for skilled migration on innovative outcomes in some European countries (Gagliardi, 2011; Bosetti, Cattaneo and Verdolini, 2015).

Studies that adopt a macro perspective also show that, regardless of the level of education and the skills of the inflow of foreign workers, migration *per se* can have positive effects on the productivity growth of destination countries (Ortega and Peri, 2014). This is likely to be the case for some countries in Europe (Germany, for example) in which the progressive aging of the society and of the labor force leads to an undersupply of labor in many sectors of the economy. In this case the inflow of young middle or low skilled migrants could be beneficial for the future growth of these economies.

Finally another recent stream of literature has investigated the effect of the ethnic diversity of the labor force on the innovative performances of firms, regions and countries, finding in most cases a positive effect of diversity on productivity growth and innovation (Alesina, Harnoss and Rapoport, 2013; Ozgen, Nijkamp and Poot, 2012). Therefore the inflow of new migrants in Europe from different countries, by increasing the overall diversity of the labor force, might also spur innovation.

The objective of this paper is to investigate the contribution of migrants to the growth of productivity in Europe. More precisely, it analyzes the role of the human-capital components of the foreign labor force on the economic performances of three European countries, France, Germany and the UK, 1994-2007. These are the three largest countries in the European Union in population terms and they also have been favoured destinations for European and non-European migrants.

In our analysis we consider the above mentioned possible channels through which migration might spur productivity growth. We, then, measure the impact of the share of migrants, controlling for their education levels, their age and the diversity of their countries of origin, on the growth of Total Factor Productivity. We adopt an aggregate level of analysis, in a similar way to existing studies that measure the effect of the share of migrants and of their diversity on the productivity growth of regions and countries (Ortega and Peri, 2012; Ozgen, Nijkamp and Poot, 2012; Alesina, Harnoss and Rapoport, 2013). However, unlike these studies that adopt a geographical approach and use provinces, regions or countries as their preferred unit of analysis, we measure the link between migration and productivity growth at the sectoral level. This approach allows us to contribute significantly to the existing literature in several ways.

The sectoral perspective is able to account for the fact that innovation dynamics are strongly technology-specific and differ widely across sectors, on the basis of the features of the knowledge used in the productive processes. Using the sector as the unit of analysis leads to a more fine-grained investigation into the link between migration and innovation, because it allows to measure the direct impact of migrants on the productivity growth of the sectors in which they are employed. Moreover, we are able to check for differentiated effects of migrants according to the specific type of sectors in which they are employed, distinguishing between manufacturing and services, and also between high- and low-tech sectors. Previous studies that analyze migration and innovation at the aggregate level using a geographical level of analysis do not control for differences across sectors. More importantly they run the risk of measuring spurious relations, due to the fact that migrants often move to innovative regions, but are not necessarily employed in the sectors that are actually innovative.

Moreover, the sectoral perspective allows improving on the analysis of the link between ethnic diversity and innovation. Existing studies have analysed diversity at the geographical level that is, measuring the diversity of migrants in a specific region or country. In our approach instead diversity is measured at the sectoral level, that is, among the migrants that are active in the same sector of economic activity. We argue that sector of activity might be a relevant, confounding factor in the analyses that adopt a geographical level of analysis. Indeed, the positive effect on innovation of ethnic diversity, measured at the geographical level, might simply capture the increasing returns due to the complementarities between the different sectors in which migrants of different nationalities are employed. In other words a higher ethnic diversity might simply indicate higher diversification of a regional or national economy. It is well known that the complementarities between different sectors, the so-called Jacobian or diversification externalities, represent an important driver of innovation activities.

In the paper we also take into account the age of migrants since this is likely to be another relevant factor explaining the impact of migration on innovation, especially in the three countries analyzed in which the native labor force is progressively ageing. Finally, in the paper we introduce a novel version of the methodology devised by Card (2001) to account for the endogeneity of migrants. Our instrumental variable strategy relies on the hypothesis that migrants not only tend to migrate to cities and regions in which their compatriots have already settled, but also that they often exploit the networks provided by their national community to find jobs, and hence often get hired in the same sectors in which their compatriots are already employed.

The results of our analysis, which take into account the endogeneity of migrant flows, show that migration has, in general, a positive effect on Total Factor Productivity growth: however, the impact of this effect is stronger in manufacturing and much stronger in the high-tech sectors, as compared to services. Tertiary-educated migrants have a positive effect on productivity growth in high-tech sectors and to a lesser extent in services, while middle and low educated migrants display a mild positive effect in manufacturing sectors. Finally, we find that the diversity index is not significant in all sectors but in the services sector, supporting the idea that the positive effect often found in the literature might be due to unmeasured complementarities across sectors.

The paper proceeds as follows: Section 2 presents the related literature; Section 3 highlights the advantages of the sectoral perspective; Section 4 describes the data used; Section 5 illustrates the methodology used; Section 6 presents the results of the empirical analysis; and finally Section 7 concludes and provides implications for policy.

2. Background literature

Since the paper of Dolado, Goria and Ichino (1994), which first introduced migrant workers in a production function framework and analysed the impact of highly- and low-skilled workers on GDP *per capita*, research into the impact of immigrant workers on productivity and innovation has increased exponentially.

Innovation is a multifaceted phenomenon. It is difficult to monitor and difficult to measure: different measures are adopted in the literature. The number of patents is often used to capture the ability of a firm, a country, or a sector[2] to produce new products or new ways to produce output, since a patent typically signals the introduction of a technological novelty. A broader measure of innovation used in the literature is the growth of Total Factor Productivity (TFP): assuming a traditional Cobb-Douglas production function, TFP corresponds to the growth of output that is not explained by the relative contributions of capital and labor and can be considered as “technical progress in its broadest sense” (Solow,1957). Another common source of information are firm-level survey data in which firms are asked whether they introduced specific types of innovations, such as product or process innovations.

Different units of analysis have been adopted to study the impact of migration on innovation and productivity growth. The most common approach is to rely on analyses performed at the geographical level (country, regions or provinces). The impact of migrants on different proxies of innovation, such as patent applications, productivity growth (labor productivity or TFP) or number of innovative companies, is then measured. In many of these studies a positive effect of migration (especially highly-skilled migration) is found. Ortega and Peri (2012; 2014) measure the impact of migration on TFP at the country level for a very large set of countries and find a generalized positive effect for the share of migrants over the total population, regardless of their skill level. Also Alesina, Harnoss and Rapoport, (2013) adopt a country level perspective and find a positive effect for the share of immigrants on GDP and TFP *per capita*. Bosetti, Cattaneo and Verdolini (2015) restrict their analysis to European countries and show that the share of migrants employed in highly-skilled occupations is positively related with the number of patent applications. Other studies find a positive effect for highly-skilled migration at the provincial or city level: Kerr and Lincoln (2010) report a positive effect for the number of immigrants on the number of patent applications in US cities. However, they focus their analysis on highly-skilled migrants active in the fields of Science and Technology. Gagliardi (2011) finds that highly-skilled migrants positively impact the innovative performances of British firms using provinces as the unit of analysis.

Many of the studies which adopt the geographical unit of analysis find that innovation is often fostered by the diversity of the country of origin of migrants, and not only by their quantity, partly adopting the perspective of research on multicultural teams in business studies (Stahl et al., 2010). Alesina, Harnoss and Rapoport (2013) in their country-level analyses find that the diversity of migrants in terms of country of birth is positively associated with TFP and the effect is more prominent for the diversity of highly-skilled migrants. Using data at the regional level for European countries Ozgen, Nijkamp and Poot (2012) find that patent applications are positively associated with the diversity of the immigrant community in the region measured by the fractionalization index; an increase from 0.1 to 0.5 increases the number of patent applications per million inhabitants by 0.2 %. A similar positive effect of migrant diversity on patent production in European regions is found by Dohse and Gold (2014), while Niebuhr (2010) finds a positive effect of diversity among German provinces. Summing up the studies that adopt a geographical approach to study the relationship between migration and innovation some find a positive effect for (skilled) migration on productivity and innovation, while some others find a positive effect for the diversity of migrants’ countries of origin. The majority of these studies hence point to a positive effect of migration and immigrant diversity on innovative performances. There are a few exceptions. For example, the study by Bratti and Conti (2014), instead, finds that among Italian provinces the share of highly-skilled migrants, as well as the diversity of migrants, has no impact on the number of patent applications, while the share of low-skilled migrants has a negative effect.

The studies that, instead, analyse the effect of immigration on innovation at the firm level report much more mixed results. Trax, Brunow and Suedekum (2015) using data on German firms detailed at the plant level do not find any effect for the share of migrants and the diversity of country of origin. Also Østergaard*et al.* (2011), using data at the plant level for Danish firms, do not find clear positive effects for migrants diversity on the probability to introduce innovations. On the contrary, Parrotta *et al.* (2014) find a positive effect for diversity on the production of patents in Danish firms. Ozgen,

[2] See Fassio, Montobbio and Venturini (2015).

Nijkamp and Poot (2013) using firm level data from Dutch firms find a negative effect for the share of migrants, but a positive effect for their diversity on the innovativeness of firms. However, Ozgen *et al.* (2014) also find that when firms from two countries are analysed (Germany and the Netherlands) the effect of diversity on innovation at the firm level varies considerably according to the specific country and according to the econometric specification chosen. McGuirk and Jordan (2012), using data from Irish firms, find a positive effect for the diversity of immigrants on the probability of introducing product innovations. However, the diversity index is not measured at the firm level among the employees of each firm, but at the regional level.

Overall the results from firm-level analyses provide a quite different picture about the effect of migration both in terms of size and of diversity of countries of origin, especially with respect to the studies that measure immigration at the geographical level and find a generalized positive effect. At the firm level the results seem, instead, to be very sensitive to the country analysed, but also to the measure of innovation chosen. In the next section we will show how adopting a sectoral perspective can offer a useful improvement with respect to the existing literature.

3. The advantages of a sectoral analysis of migration and innovation

As shown in the previous section, the literature that has analysed the effects of migration on innovation and productivity from an aggregate perspective has mainly relied on a geographical approach. Therefore, the unit of analysis is the province/region/country in which immigrants are resident and the effect of migration is tested on the innovation performances of that specific geographical unit. Despite the great use made of this approach it has some important limitations, mainly due to the fact that it overlooks the role of the sectors of economic activity in which immigrant workers are employed. The literature on Technological Regimes (Breschi *et al.,* 2000) has shown how the specific technologies used in different sectors also influence the pace of productivity growth: the aggregate productivity growth of a country or a region might be the result of very heterogeneous rates of growth in different sectors (which may or may not employ immigrant workers). Moreover innovative activities can be very different across sectors and often require heterogeneous skills, since they are strictly related to the type of technologies being used for production activities. In this section we will show how adopting a sectoral perspective can help to improve the analysis of the effect of migration on innovation in several respects.

The direct effect of migrants

Studies that adopt a geographical approach may overestimate the effect of migrants on innovation and productivity growth because they do not account for the heterogeneous innovative performances of different sectors in a region or country. A region might experience very high rates of productivity growth because of the positive performances of a limited set of high-tech innovative sectors. Fast growing innovative regions typically attract foreign labor, but it is hard to say if these workers will be employed in those specific sectors and directly contribute to innovation: they might, instead, work in other low-tech or services sectors that display little or no innovation at all. In this context analyses performed at the geographical level tend to overestimate the contribution of immigrants to regional productivity growth. When the unit of analysis is, rather, the sector the effect of immigrant workers can be tested on the performances of each specific industry, therefore considering only their direct contribution to innovation. On the basis of these considerations it seems important to check if the estimated effects of immigration on innovation found in analyses that adopt a geographical approach still hold when a sectoral analysis is implemented.

The effect of migrants' education

Literature on migration and innovation has mainly focused on the role of highly-skilled immigrants. However, different economic activities require different skills for the implementation of innovative strategies. In high-tech sectors innovations can only be implemented through formal R&D activities, based on the use of highly codified knowledge that can only be possessed by highly-educated workers. In middle and low tech sectors, meanwhile, innovation is often implemented through other channels, such as the purchasing of new machinery (Santamaria *et al.,* 2009) or the improvement of existing ones (Von Hippel, 1976). These activities, that can greatly affect the innovativeness of firms in low and medium tech sectors, do not necessarily require highly-educated personnel, but rather experienced employees with an in-depth knowledge of the productive processes of the firm. Therefore, while for high-technology sectors it seems legitimate to focus only on the contribution of highly-skilled migrants, in the case of low tech or services sectors the contribution of low or middle educated foreign workers should also be considered. This is even more relevant as unskilled immigrants represent, by far, the largest share of all immigrants in destination countries.

The effect of migrants' diversity

In most studies at the aggregate level that adopt a geographical approach an increase in diversity is found to increase productivity and TFP. These results would suggest the implementation of a migration policy based on a quota system, which selects migrants by countries of origin and not on the basis of their education and experience (point system). However, also in this case a sectoral perspective allows to highlight the possible limitations of the geographical approach, which might overestimate the real impact of diversity on innovation.

Indeed, in the European framework immigration is a phenomenon that occurs through successive "waves" of immigrants from specific countries of origin. For instance, Germany, after the Second World War, experienced, first, a wave of migrants from Italy, which, was followed by a second wave from Spain, then from Yugoslavia, followed by Turkish, then by Polish migrants. In France, too, migration waves were relevant, though with a different ordering of national groups[3].

This implies that the diversity of migrants' country of origin at the national level increases over time because migrants from different countries progressively penetrate the economy. But when migrants of a given nationality enter the country of destination they will be typically attracted by the sectors that are then booming. When a subsequent wave from a different country of origin arrives, other sectors will be in short supply, therefore gradually migrants from different countries of origin penetrate different sectors of the economy.

The outcome of this process is that different sectors will employ migrants from different countries of origin: hence the higher the number of sectors in a region the higher the diversity of migrants. Now it is well known that the diversification of economic activities in a region can benefit innovation (Jacobs, 1969; Feldman and Audretsch, 1999). According to Jacobs (1969) knowledge spills over among complementary industries, because ideas that are developed in one industry can also be fruitfully applied elsewhere. Complementary knowledge circulate across firms in different sectors of economic activity leading to increasing returns due to the so-called Jacobian or diversification externalities.

If that is the case the positive effect of the diversity of migrants on innovation and productivity found at the regional level might simply capture the positive effect of the (unmeasured) diversification of economic activities in a region.
The sectoral approach is able to disentangle these two different effects, since it only considers the diversity of countries of origin within each sector. In our analyses to measure the diversity among

[3] See on this issues Tapinos (1999) and Venturini (2004).

migrants, we build a diversity index (excluding the natives) following the Herfindahl methodology[4], both at the sector and at the national level.

Table (1) shows that while, at national level, there is always an increase in the index, at sector level we find both increasing, decreasing and stable values in the case of the three countries considered.

The role of age

A final point is related to the age of immigrants. One of the main features of immigrant workers is their relative low average age with respect to the native labor force. The literature is not unanimous on the effect of age on innovation, while there is a general consensus that the cognitive abilities of workers tend to deteriorate over time, as well as their creativity and their ability to innovate (Oberg, 1960; Jones, 2010), it is still not clear when workers are more innovative, either after the education period or at a later stage of their career (Schubert and Andersson, 2013). The different average age of native and immigrant workers should then be taken into account in any analysis of the effect of migration on innovation; otherwise age might result in a confounding factor possibly affecting the results of the analysis.

[Insert Table 1 here]

4. Data

4.1. Source

In this study to assess the impact of migration on innovative performance of sectors we rely on two sets of information. The first one serves to measure the level of innovation in sectors in terms of Total Factor Productivity and comes from the EU KLEMS Growth and Productivity Accounts database[5]. It contains industry-level measures of output, inputs and productivity for 25 European countries, Japan and the US from 1970 onwards. O'Mahony and Timmer (2009) describe, in detail, the advantages of the database and emphasize the cross country comparability of industry specific productivity trends. The second set of information is an original dataset that derives from national microdata. To build sector level datasets of labor force composition for the three countries under examination here, we aggregated at the sector level the data on individuals provided by the Labour Force Surveys for France and the UK and by the Micro-Census for Germany. The datasets allow for the construction of human capital variables at sector level.

4.2. Descriptive statistics

Table (2) reports the synthetic description of the dataset presenting the variables of interest for the total pool of observations, manufacturing, services, high-tech and low-tech sectors due to the technological heterogeneity of economic sectors. This allows for the detection of variation in the

[4] The diversity index is based on the Simpson index which is equal to the probability that two entities taken randomly from the dataset of interest (with replacement) represent the same type. Its transformation (1- Simpson index) is the probability that the two entities represent different types and is called the Gini-Simpson index. In the context of our study it implies the probability that two persons randomly taken in the sector have different origin (country of birth or citizenship). $Diversity\ Index_{jc} = 1 - \sum_{i=1}^{N} Share_{ijc}^2$

[5] http://www.euklems.net/

variables of interests, which is crucial for our identification strategy. The information presented in the table indicates that the sectors with the highest average annual TFP growth are the high-tech ones (2.80 %), closely followed by and manufacturing ones (2.79 %). Instead, the slowest growth of TFP is observed in services (0.68 %). The sectors differ not only in terms of innovation dynamics, but also in terms of human capital composition. The sectors are relatively homogenous in their age composition; the percentage of young workers (younger than 35) is around 37-38%. On average, migrants are only slightly younger than natives. Not surprisingly the highest share of tertiary-educated individuals is in high-tech, which is usually characterized by its position on the margin of technological frontiers and, hence, demands a highly-qualified labor force. The lowest percentage is observed in manufacturing where there is a higher intensity of manual work, which often needs no special qualifications. The non-weighted mean percentage of migrants across sectors groups is 7-8. In some sectors migrants constitute more than one quarter of the labor force. Though the percentage of migrants is quite homogenous across sector groups considered (7-8%) the level of instruction of migrants varies significantly. 28% of migrants in high-tech are tertiary-educated which is well above the average of the whole pool of sectors considered (23%). Migrants are least educated in manufacturing where the percentage of the tertiary-educated is only 19%. High-tech sectors have the youngest and most educated employees; whereas manufacturing is characterised by the combination of the oldest and least educated labor force. Summing up, there is significant heterogeneity across sectors both in the terms of labor force composition and innovation dynamics.

[Insert Table 2 here]

[Insert Table 3 here]

5. Model and methodology

5.1. The empirical strategy

We want to test the impact of migration on the innovative performances of different sectors, controlling for specific characteristics such as ethnicity, education and age, since we believe that these will have differentiated effects according to the sector types considered. We adopt a simple model in which innovation is proxied by Total Factor Productivity. As is well known, in the classic Solow formulation (Solow, 1957) Total Factor Productivity is computed as a residual. It indicates the share of output that is not accounted for by the relative contribution of each of the inputs (labor and capital) in a standard Cobb-Douglas production function. It can, therefore, be considered as a rough proxy of technological change and efficiency growth. There are important limitations to keep in mind when using TFP growth as a proxy for technological change and innovation, since TFP is computed as a residual and hence simply indicates the share of output growth that we are not able to explain: other factors might, also, influence its dynamics, such as the changes in the competitive structure of the markets, as well as the lack of proper measurement in the quality of productive inputs.[6] Despite these limitations the use of TFP has important advantages since it directly captures the economic impact of technological change and it can be computed for all sectors in the economy, regardless of the specific type of innovation that they implement.

[6] Other shortcomings, from the use of the growth of total factor productivity, depend on underlying assumptions about the presence of constant returns to scale in the economy and from the adoption of the Euler Theorem according to which the overall compensation of labour equals its marginal productivity. Notwithstanding all these simplifying assumptions TFP growth still remains a good proxy of the share of growth of a firm, country or region which does not depend on the increase of standard productive inputs, and hence is typically associated with innovation.

Our hypothesis is that the composition of labor inputs in terms of ethnicity, education and age is able to explain the different levels of TFP across the different sectors and over time. Since the labor inputs are already used in the computation of Total Factor Productivity we cannot adopt a production function approach in which the levels of the labor variables explain the levels of TFP, because this would risk double counting the labor variables.[7] Therefore, we adopt a specification in which the level of TFP is explained by the specific features of the labor force, such as the ethnicity and the education, and not by the quantity of labor inputs. Accordingly we propose a simple framework as follows:

$$TFP_{sct} = H_{sct}^{\beta} X_{sct}^{\delta} e^{\varepsilon_{sct}} \tag{1}$$

TFP is the level of Total Factor Productivity, *H* is a set of variables related to the composition of the labor force, which includes the share of migrants, the diversity of country of origin among migrants, the share of tertiary educated and the average age of the labor force. *X* is a set of additional controls and ε_{sct} is an idiosyncratic error term. The indexes *s*, *c* and *t* indicate respectively sector, country, and year. In order to obtain a testable specification of equation (1) that we can estimate econometrically we log-linearize it indicating the logs of the variables with lower cases:

$$tfp_{sct} = \beta' h_{sct} + \delta' x_{sct} + \varepsilon_{sct} \tag{2}$$

Through this general empirical specification we will be able to test if the quantity of migrants (share of migrants over the total employment), the diversity of their countries of origin, the share of tertiary-educated and their age have an effect on the overall levels of total factor productivity within different sectors. A further advantage of our empirical approach is that we will be able to check if these effects change according to the subset of sectors taken into consideration. In particular, we will distinguish between manufacturing sectors, service sectors and between high-tech and low-tech sectors.

Share of migrants and diversity

Our first specification focuses specifically on the impact of migrants on TFP within sectors. Moreover, it also accounts for the other characteristics of the foreign labor force that are likely to have an impact on the economic performances of sectors. These include their education and their average age. We also include the diversity of migrants as an additional factor that is likely to impact their contribution to overall TFP levels. We introduce the following specification:

$$tfp_{sct} = \beta_{1'} sm_{sct} + \beta_{2'} age_{sct} + \beta_3 agesq_{sct} + \beta_{4'} stem_{sct} + \beta_{5'} diversity + \delta' x_{sct} + \eta_t + \varepsilon_{sct} \tag{3}$$

Where *sm* indicates the log of the share of migrants over the total employment of a sector, *age* is the log of the average age of migrant workers in the sector and *agesq* is the log of the square of the average age, to account for any non linear effects of age. According to our hypotheses, the level of human capital is likely to have an important role in explaining sectoral economic performances. We, therefore, further include the (log of the) share of migrants with tertiary education over the total number of migrants in a sector (*stem*), and the diversity of migrants' countries of origin (*diversity*),

[7] Total Factor Productivity is typically computed as: $\ln(Y_t) - \alpha^*\ln(K_t) - \beta^*\ln(L_t)$, where Y_t is value added in time *t*, K_t is the capital stock, L_t is labor and α and β are the output elasticities of, respectively, capital and labor. On the basis of this formula it is clear that an increase of labor units *L* in time *t* will already be accounted for in the computation of TFP in time *t*. Therefore, it would not make sense to include the levels of labor units among the determinants of TFP in equation (1). On the contrary, since TFP is computed using only the quantity of labor units, without considering their intrinsic quality (Abramovitz, 1956), it makes sense to include the composition of the labor force (education, ethnicity, age) among the determinants of TFP, since these factors are not accounted for in the computation of TFP, but they may have an impact on its levels.

calculated as 1 minus a Herfindal index of concentration. In the diversity index we exclude the natives, since the share of migrants is usually highly correlated with the diversity index if the latter also includes the native born. The set of x variables includes sectoral fixed effects, η_t accounts for common trends across observations and ε_{sct} indicates the idiosyncratic shocks of the dependent variable.

The log specification implies that a 1% increase in the share of migrants in a sector will have a smaller effect on TFP the larger the initial share of migrants in that sector. In other terms, the elasticity of the growth of migrants share declines with its size. Indeed what we are measuring is the effect of a percentage increase of a share.[8] We believe that this specification should be more attractive. It is, after all, unlikely that an increase in the share of migrants will have the same effect in a sector in which migrants dominate and in a sector in which they are a minimal fraction of the employment.

Education of migrants

While the first specification in equation (3) only considers the role of migrants and their specific characteristics as the drivers of TFP levels, we now allow for a richer specification in which we distinguish more clearly between migrants with tertiary education and migrants who do not have tertiary education (low-middle education). Also, the characteristics of the native labor force are included. Indeed, we want to include, in our model, all the potential effects of the labor force that might affect TFP and the education and age of the native labor force are important determinants of sectoral economic performances. We follow the same log linear specification of equation (3), but now we specifically distinguish between the log share of migrants, differentiating between those with and without tertiary education, and the log share of natives, always taking into account their education levels. We include the log average age of natives among our independent variables too. Our model is as follows:

$$\begin{aligned} tfp_{sct} &= \beta_{1'}\, smte_{sct} + \beta_{1'}\, smmle_{sct} + \beta_{1'}\, snmle_{sct} + \beta_{2'}\, agem_{sct} + \beta_3\, agesqm_{sct} + \beta_{2'}\, agen_{sct} \\ &+ \beta_3\, agesqn_{sct} + \delta' x_{sct} + \eta_t + \varepsilon_{sct} \end{aligned} \tag{4}$$

In equation (4): *smte* indicates the log share of tertiary educated migrants out of total employment; *smmle* is the log share of medium- and low-educated migrants out of total employment; *snmle* is the log share of medium and low educated natives out of total employment;[9] *agem* is the log average age of migrants; *agesqm* is the square of the log average age of migrants; *agen* is the log average age of natives; and *agesqn* is the square term of the log average age of natives. The model includes fixed effects and time dummies.

5.2. Methodology

In order to estimate equations (3) and (4) we implement a fixed effect estimator, which is able to account for all the time-invariant effects of each observation in our regression. Indeed, as is well known, the innovative performances of sectors (that we proxy with the levels of TFP) depend on sector-specific and country-specific factors. The literature on the Technological Regimes and Sectoral Systems of Innovation (Nelson and Winter, 1982; Malerba and Orsenigo, 1996) has shown that technology-related factors such as opportunity conditions, knowledge appropriability and knowledge cumulativeness shape the evolution of sectors and create specific productivity differentials across

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8 As an example, if in a sector the share of migrants increases from 5% to 6%, this will correspond to a 20% increase of the share of migrants in that sector. Conversely, if in a sector the share of migrants increases from 20% to 21% this will correspond to a 5% increase in the share of migrants.

9 Only three components of total employment can be included in the regression, since the sum of all four components adds up to 1 and cannot be included because of multicollinearity. In this case the share of native highly educated was excluded.

sectors. Moreover, the National Systems of Innovation literature (Lundvall, 1993) has stressed as additional factors, the role of country-level institutional factors such as: the strength of university-industry relationships; the quality of public funded research; public support to entrepreneurship and start-up activities. These are likely to introduce important differentials in the level of economic performances of firms between countries. Therefore, the introduction of fixed effects at the country-sector level is a necessary first step in avoiding potential omitted variables that might be positively correlated with the quality of the labor force and with the evolution of TFP.

Sectors are also tightly interconnected, because of the economic interactions that occur between them: a typical by-product of this fact is the transmission of TFP shocks from one sector to another, for example, through user-supplier interactions. In order to account for the presence of common shocks in TFP we also introduce time dummies.

The use of fixed effects allows us to make sure that the coefficients of our variables of interest, specifically the variables that measure the employment share of migrant workers (share on total employment), are not affected by time-invariant omitted variables at the sector-country level. However, it does not allow us to avoid the possibility that unobserved factors occurring during the period of observation of our analysis affect both the level of attractiveness of a sector for foreign workers and the level of TFP, resulting in a risk of biased results.[10] Moreover, the fixed effects estimator is only consistent under the strict exogeneity assumption, according to which past shocks of the dependent variable (TFP) do not influence the current levels of the independent variables. This is very unlikely for migrant mobile workers who tend to locate in sectors that have experienced recent expansion. Therefore, in this case too, we might expect some bias in our fixed effects results. Finally the difficulty of national statistical institutes to measure the number of the foreign workers in a country precisely might induce measurement errors in our variables, which, in turn, might result in attenuation bias in our estimates.

The instrumental variable strategy

In order to account for these problems we follow the well-known identification strategy based on instrumental variables that was first implemented by Card (2001) to account for the potential endogeneity of migrants with respect to the economic conditions of the geographical areas to which they would migrate. The methodology proposed by Card takes advantage of the fact that migrants of a certain nationality tend to move to locations where other people of their same nationality have already settled. Therefore, using the initial distribution of nationalities across geographical areas and the exogenous migration flows from each country of origin, it is possible to create a fictional flow, built as if the new entrants would settle only where their compatriots had already settled. This fictional flow is a valid instrument since it is correlated with the endogenous shares of migrants, but uncorrelated with the shocks of the dependent variable. For the sake of our empirical design we adapt this instrumental variables methodology substituting geographical areas with sectors.

Our choice is based on the following hypothesis: yes, migrants tend to move to areas where people of their same nationality are already settled, but in most cases they also start to work in the same economic activities in which their compatriots are already active. The existing literature (Danzer and Yaman, 2013; Strom et al. 2013; Tapinos; 1996, Dustmann et al. 2003; Constant, 2005) suggests that

[10] If, for example, in time *t* a high-tech multinational company decides to start up a new venture in, say, Germany, investing a large amount of resources in Research and Development activities this will typically have two effects. On the one hand, the presence of a technologically-advanced large firm in a sector might boost the overall level of TFP in that specific sector, since R&D expenditures are the main determinant of productivity growth; on the other, the large investments activities of the company might attract new workers coming also from outside the country where the new venture will be located. In this case, we expect that the unobserved shock due to the establishment of the new company will also be positively correlated with the share of migrants in that specific national sector, leading to an endogeneity problem in our estimates.

this is mostly due to the fact that the main channels to find a job for the newly arrived migrants are their compatriots. In this sector-specific allocation cultural ability matters, of course, but not necessarily or primarily: often migrants are not employed in the same sector where they worked in the country of origin. Therefore, according to our hypothesis, new migrants from a specific nationality are likely to work in the same sectors in which their fellow countrymen are already working.

To test the validity of our hypothesis we compare the distribution of migrants by country of origin across sectors in all three countries of interest. More specifically, we compute the share of immigrants from a specific country of origin in a sector over the total number of migrants in that sector. We call this measure the *ethnic sector share*, computed as follows:

$$\text{Ethnic sector share} = \frac{\text{migrants}_{\text{isc}}}{\text{migrants}_{\text{sc}}}$$

The index measures the share of migrants from country of origin *i* that are employed in sector *s* in the destination country *c* over the total number of migrant workers employed in sector *s* in country *c*. This measure tells us how much a community of migrants is relevant among the total number of immigrants in a specific sector in each of the three European countries of our database. In the Tables (A1a), (A1b) and (A1c) of the Appendix (Section 1) we report the value of the ethnic sector share for the most important countries of origin for each country of destination. The Tables indeed show that there is a tendency of migrants from specific countries to concentrate in some sectors: for instance in the UK Western Asian and Indian workers are concentrated in Textiles, while Polish workers are to be found in the Rubber and Wood sector; in France Turkish workers are mainly in Textile and Construction, Tunisians in Food and Wood, while Moroccan workers are in Agriculture; finally in Germany Turkish workers are concentrated in Mining.

Moreover, we find that these concentration patterns are quite stable over time, meaning that over years migrants, from specific countries of origin, continue to go and work where their compatriots are already working. In Table (4) we show the correlation of the ethnic sector share between the first and the last year available for each country of destination.[11] The high levels of correlation of the ethnic sectoral share over time plainly indicate that the initial distribution of migrants across sectors explains much of their distribution in later periods.

In Figure (1) we provide, instead, a graphical representation of this correlation, with the ethnic sectoral share, in the first year of observation in our sample, plotted on the x-axis and the ethnic sectoral share in the last year of observation plotted on the y-axis. Again this corroborates our hypothesis that the initial distribution of migrants across sectors is a good predictor of the future distribution of newcomers.

[Insert Table 4 here]

[Insert Figure 1 here]

[11] The correlation is computed between each combination of country of origin and sector in 1994 (in Germany 1996) and 2007, excluding the values when the ethnic sector share is equal to zero.

The sector-based instrument

On the basis of the evidence provided in Section 5.2 and sticking to the original notation of Card (2001), for each of our migration-related variables we implement the following strategy, in which geographical areas are substituted by sectors, to create fictional shares of migrants workers in each sector. For each of the three countries of destination under analysis (France, Germany and the UK) we computed the flow M_{ot} of new migrants from a specific country of origin *o* that entered the country of destination in year *t*. [12]

$$M_{ot} = \Delta Mig_{ot}$$

Then, we computed the distribution of migrant workers from a specific country of origin in the different sectors of the economy of the country of destination at the beginning of our period of observation (1994 for France and UK, 1996 for Germany). In other words for each sector and each country of origin we calculated the share λ_{oj}, where *s* indicates the sector in which they are active:

$$\lambda_{os} = \frac{Mig_{os94}}{Mig_{o94}}$$

Finally, in order to distinguish between skilled and unskilled migrants we calculated for each year *t* the fraction τ_{ogt} of all new immigrants from a specific country of origin *o* that have a specific type *g* of education (either tertiary education or below tertiary education).

$$\tau_{ogt} = \frac{\Delta Mig_{ogt}}{\Delta Mig_{ot}}$$

Following our hypotheses concerning the choice of the economic activity by new entrants from a specific country, we expect that the fictional flow of new migrants from a specific country of origin and with education *g*, which that will work in sector*s* of a specific country of destination, will be equal to:

$$\Delta Mig\_instr_{osgt} = M_{ot} * \lambda_{os} * \tau_{ogt}$$

These fictional flows of new migrants (differentiated by the two types of education) have been, then, aggregated over countries of origin in order to obtain the new fictional flow of total migrants of a specific type of education in sector *j* at time *t*. These new flows were, then, used to build the fictional shares of migrants. For the sake of our analysis we created a fictional share of highly-educated migrants, one of middle-low educated and, finally, a fictional share of migrants (regardless of education) by summing up the two previous shares. These measures can be used as suitable instruments for the real shares of migrants in equation (3) and for the real shares of high and middle-low educated migrants in equation (4) in an IV setting with a two-stage least squares estimator. According to our hypotheses these fictional flows should be highly correlated with the actual shares of migrants in each sector, but at the same time they should not be correlated with the unobserved shocks of TFP.

[12] To do so we computed the difference between the total number of immigrants from a specific country *o* in the country of destination in time *t* minus their value in time *t-1*.

6. Results

In this section we discuss the results of the empirical estimation. Table (5) reports the results of estimation of the empirical model described by equation (3) and includes only the components of foreign human capital. It allows for accounting for its **quantity,** proxied by the share of foreign workers out of total employment, its **quality**, proxied by the share of tertiary-educated foreign workers out of total migrants employed, and its diversity in terms of the countries of origin. Moreover, by including the average age of migrant workers as an additional regressor, we control for possible effects from the heterogeneity of age composition of employees across sectors. All models include time dummies in order to account for common shocks of TFP in sectors in a given year.

The results of the fixed effects estimation show that the effect of migrant workers on the level of total factor productivity is, in general, positive, with some differences across different sector groups. At the aggregate economy level (column 1a) migrants have a positive impact on the total factor productivity, with a coefficient of 0.054. However, when we distinguish between the manufacturing (column 2a) and the service sectors (column 3a) we find that in manufacturing the coefficient is slightly lower and not significant, while the impact estimated for services is stronger and statistically significant. In columns (4a) and (5a) we distinguish between high-tech sectors[13] and low-tech sectors[14]: we find that the coefficients of the share of migrant workers stand at around 0.050, though significant only in low-tech sectors.

[Insert Table 5 here]

[Insert Table 6 here]

As already anticipated in Section 5.2 the results of the fixed effects estimations are undermined by the possible endogeneity of immigrants to TFP dynamics in a given sector. On the one hand, growing sectors most probably demonstrate higher TFP growth and attract more migrants due to a higher demand for labor. If so, this would lead to an upward bias in fixed effects estimates. On the other hand, declining sectors most probably demonstrate lower TFP; however, they might have a relatively higher presence of foreign labor force, as migrants might be more willing to accept relatively low salaries in these sectors than natives. In this case, the fixed effects estimates would be biased downwards. To verify the validity of the obtained results we instrument the potentially endogenous share of migrants with the fictional share computed following our sector-based version of Card's (2001) methodology, as described in Section 5.2. The coefficients of the log share of migrants increase quite substantially. Now, in all specifications, the share of migrants is positive and significant, with a coefficient that varies between 0.08 and 0.32. These results, therefore, suggest the existence of a downward bias in the fixed effects estimates with respect to the true parameters represented by the IV estimator. The estimates indicate that the overall effect of foreign human capital on TFP is on average positive. The credibility of these results relies on the validity of the instrumental variable used. The results of the First-stage statistics in the IV estimation (the First-stage results are reported in Table 7) indicate that the Card-like instrument used to account for the endogeneity of the log share of migrants

[13] We classify as High Tech the following sectors: Chemicals and chemical products, Electrical and optical equipment, Financialintermediation, Machinery, Renting of machinery and equipment, Transport equipment.

[14] We classify as Low tech sectors the following sectors: Agriculture, hunting, forestry and fishing, Mining and quarrying, Food, beverages and tobacco, Textile, leather and footwear, Wood and products of wood and cork, Pulp, paper, printing and publishing, Coke, refined petroleum and nuclear fuel, Rubber and plastic products, Other non-metallic mineral product, Basic metals and fabricated metals, Manufacturing nec; recycling, Electricity, gas and water supply, Construction, Sale, maintenance and repair of motor vehicles, Wholesale trade and commission trade, Retail trade, except of motor vehicles; etc., Hotels and restaurants, Transport and storage, Post and telecommunications, Real estate activities, Public admin and Education,Health and social work, Other community, social services, Private households with employed persons.

is a strong and reliable predictor of the real shares of migrants; the first-stage F-statistics are well beyond the critical values indicated in the literature (Stock and Yogo, 2005).

In terms of magnitudes, our estimate implies that a 1 percent increase in the share of migrants in the sector leads to a 0.23 percent increase in TFP. On average, the share of migrants across sectors is 8 percent. An increase in migrants from 8 to 9 percent would lead to an increase in TFP by 2.74 percent. However, the effect is not linear and it varies depending on the share of migrants distribution. For example, in France in Basic Metals and Fabricated Metals, where the share of migrants for the considered period was around 5 percent, an increase from 5 to 6 would lead to approximately 3.65 percent increase in TFP. Instead, in the same sector in Germany, where migrants constitute around 13 percent of employees, an increase of 1 percent (that is from 13 to 14 percent) would lean to only 1.5 percent increase in TFP.

In the fixed effects specification the education level of migrants, proxied by the share of the highly-skilled in all migrants employed, is never significantly different from zero. These results are confirmed by the IV estimation. The only exception is in high-tech sectors where the positive coefficient becomes statistically significant. For the time being we do not instrument the education of migrants (the share of tertiary-educated migrants), since we will properly account for its possible endogeneity in equation (4).

The diversity of migrants, which is often found to be positive and significant in studies at the regional or plant level, seems less relevant at the sector level. The fixed effects estimate of the diversity index is positive across all specifications, but it is significant only in services and in high-tech sectors.[15] However, the IV estimation confirms the positive and the statistically significant effect only in services. These results suggest that the effect of ethnic diversity on productivity varies according to the specific type of economic activity and to the type of tasks that workers need to perform. While in the services sectors the type of tasks performed allow for a positive effect of diversity, in the manufacturing sectors diversity does not have any effect on productivity.

Lastly, the average age of migrants and its squared term are significant and respectively negative and positive in the manufacturing and high-tech sectors. This points to a positive effect of young age on innovation (both with fixed effects and with IV). On the contrary, we find that in the total economy and in the low-tech sectors the coefficients are never significant. In the services sectors the opposite is true: the average age of migrants is positive and significant, while its square term is negative, suggesting that in services sectors experience on the job is more important and thus older migrants contribute more to TFP growth.

Further, we investigate more specifically into the role of highly–skilled/low-skilled foreign labor force, which is at the center of the migration policy debate[16]. Table (6) reports the results of an estimation based on the model described in equation (4). We consider the effect of the migrants by skill level, while taking into account the effects of native workers as well. By adding variables related to the native labor force, in addition to the fixed effects and the time dummies, we are able to control the idiosyncratic sector-country specific dynamics better. Here as well, we first present the fixed effects estimation results and then the results of the two-stage least squares estimation. In the latter ones the share of highly-educated migrants and the share of middle-low educated migrants are instrumented respectively by the fictional shares built following the methodology described in Section 5.2.

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[15] To better understand the role of diversity we tried a non-linear specification of the diversity index and following Ceren, Nijkamp, Boot (2011) we introduced a squared term: however, the square term was never significant.

[16] We also built two measures of diversity, one for highly-educated migrants and another one for low and medium educated ones. However, the two variables were never significant in our estimates, probably because the age and sector specification capture a large part of its effect, thus we present only the specifications without them.

The fixed effects estimation results suggest that highly-skilled migrants play a positive role on TFP growth; the corresponding coefficient is positive in all five specifications. However, it is statistically significant only in high-tech sectors. This result is partially in line with what we find for the previously discussed specification (Table 5). When controlling for potential endogeneity we find that the effect is, indeed, positive and significant in almost all specifications (High tech, Services, Low tech). The first stage F-statistics, reported at the bottom of Table (6) (see also the First-stage results in Tables 8a and 8b), are always beyond the critical levels indicated in the literature (Stock and Yogo, 2005).

The only exception is manufacturing, where the coefficient of the log share of highly-skilled migrants is neither positive nor statistically significant. However, as shown by the F-statistics at the bottom of Table (6) among manufacturing sectors the Card-like instrument for highly-educated migrants does not have sufficient explicative power. Therefore, the reliability of the results of the second stage for highly-educated migrants is not very high. The failure of the instrument to predict the stock of highly-skilled in manufacturing can be imputed to the low presence of the highly-skilled migrants. The moderate presence of the highly-skilled in manufacturing (less than 1%) does not allow the Card-like instrument to capture the sector penetration pattern by country of origin and, hence, to predict the future flows of migrants into sectors.[17] Hence, the weakness of the instrument in manufacturing is not,so much due to the different behaviour of highly-skilled migrants in manufacturing, as it is due to the limited number of high-skilled migrants in low-tech manufacturing sectors.

The fixed effects estimates suggest that middle-low educated migrants have a positive and statistically significant effect in the total economy, in services and in low tech sectors. However, when we account for the possible endogeneity of migrants we find that the positive effect suggested by fixed effects estimation disappears in most of the specifications. Instead, the estimate for manufacturing increases in magnitude and becomes statistically significant. This result once more demonstrates the important role played by low-skilled migrants in manufacturing.

The share of low and medium educated natives is always positive and significant in most specifications. This shows that the role of native workers must be taken into account in order to properly understand the contribution of foreign human capital. Looking at the age results we find that in high-tech sectors the age effect is negative for migrants (young educated migrants contribute more to the increase of TFP), while it is positive for natives, pointing to job-experience's different role among the two types of workers.

Our analysis shows that when one adopts a sectoral perspective the effect of the migrant labor force comes out different for different sectors of the economy. Therefore analyses that consider the results only at the economy-aggregate level might mix up different effects and components. Considering that, on average, the share of migrants out of total employment is not higher than 10% in the three countries considered, our results tell us that an increase from 10% to 11% (which amounts to a 10% increase of the share of migrants) would lead to a 3% increase in TFP in high-tech sectors (where the effect is stronger), but of only 0.8% in services. Our results are lower than Ortega and Peri (2014)'s elasticity of 6%, which sound slightly too optimistic[18], because we are able to control for sectors, but still strongly positive

Our results also point to the important role of highly-skilled migrants, especially in high tech sectors, where their impact is the strongest. Low skilled migrants, instead, have a much less fundamental role, but they are still important in manufacturing as a whole. These results confirm part of the existing

[17] To test this hypothesis we split the whole pool of manufacturing sectors into two subgroups: high-tech manufacturing and low-tech manufacturing. We repeat the IV estimation for both subgroups. The results indicate that the instrument for highly-skilled migrant is not valid for low-tech subgroup of manufacturing, while in high-tech manufacturing the F-statistics is well above the conventional threshold (Stock and Yogo, 2005).

[18] Ortega and Peri (2014) results probably differ from ours because their analysis adopts a cross-country approach which cannot account for the panel/time dimension of the innovation process, which is instead an important element of our analysis.

literature that stresses the important role of highly skilled migrants for innovation performances, but it provides a more complete perspective highlighting how in the manufacturing sectors middle and low-educated migrants also contribute to innovation and productivity growth.[19]

Another outcome of our analysis is that the sector perspective shows that, unlike Alesina, Harnoss and Rapoport (2013), diversity does not always playing a positive role for innovation performances: it has a strong and positive effect in the services sectors, but it has no effect in the other sectors of the economy. A possible explanation for the difference in our results for the limited role of diversity might be related to our sectoral specification choice. Indeed, it is likely that the positive results of the diversity index found in previous empirical works at the regional and national level might be driven more by some form of complementarity among sectors, rather than by the real existence of a positive effect due to a diversified migrant population.

7. Conclusions

The role of innovation at the European level is becoming increasingly important given the rapid and increasing role played by emerging economies, like India and China. The migration policy could represent a way to help improve the competitiveness of European countries by opening the domestic labour market to highly-skilled workers able to spur innovation and growth.

In this paper we have analysed whether and to what extent migrants contribute to the productivity growth of three large European countries namely France, Germany and the UK. Our level of analysis is the sector of activity of migrant workers. This approach provides a relevant contribution to the existing literature for several reasons.

With respect to the literature that measures the impact of migration at the aggregate regional or country level we are able to measure the direct impact of migrants in the sector in which they are actually employed, avoiding spurious relations due to the fact that migrants often move through growing and innovative regions, but are not necessarily employed in innovative sectors. Moreover by measuring ethnic diversity at the sectoral level, we are able to disentangle the actual effect of diversity from the effect of the so-called Jacobian externalities, that is complementarities between sectors. Since migration typically occurs through successive waves of migrants from distinct countries of origin, in each period the flow of migrants will be absorbed by the sectors that are booming in those specific years. Therefore, over the years migrants from different nationalities will be employed in different sectors according to when they arrive. As a consequence a high level of ethnic diversity in a region might simply indicate a high level of diversification of regional economic activities and the existence of substantial diversification externalities that are likely to generate increasing returns and spur innovation and growth. By measuring ethnic diversity at the sectoral level (and not at the geographical level) we are able to account for this important confounding factor. Finally, with respect to firm-level micro studies our sectoral aggregate approach seems better suited to derive policy implications, since the external validity of results based on specific samples of firms in a specific country is necessarily lower than studies implemented at the country level.

Our analysis is performed using the total number of sectors of the economies of France, Germany and the UK for the years 1994-2007. Our outcome measure is the growth of Total Factor Productivity,

[19] In our analysis we paid a great deal of attention to the possible existence of a larger brain drain among migrants than among natives. To our surprise, though, when we built a variable indicating the share of migrants in highly-skilled occupations we found that the correlation with the share of highly-educated migrants was very high, around 98%. This result suggested that brain waste should not be a big issue among migrants in these three countries and, therefore, we did not investigate the role of brain waste in the innovation process. We replaced the education variable with the occupation one and the result, given the strong correlation of the two variables, remained the same or, in some cases, they were less significant than the education one.

which we consider a rough proxy of technological change. The advantage of using TFP with respect to other indicators of innovative activity (such as patents) is that it can be easily computed for all sectors in the economy, regardless of the specific type of innovation that they implement. In our specification we measure the impact of the migrant share, their level of education, their average age, and the level of ethnic diversity measured at the sectoral level.

In order to account for the possible endogeneity of migrants we adapt the well-known procedure first implemented by Card (2001) to our sectoral specification: we hence put forward the hypothesis that migrants not only tend to migrate to cities and regions in which their compatriots have already settled, but also that they often exploit the networks provided by their national community to find jobs, and hence often get hired in the same sectors in which their compatriots are already employed.

The results of the econometric analysis show that our instrumental variable strategy works well and that the share of migrants has in general a positive effect on Total Factor Productivity growth. However, the impact of this kind of effect varies considerably across sectors: it is much stronger in manufacturing and especially in high-tech sectors, when compared to services. Moreover, we find that tertiary-educated migrants have a positive effect on productivity growth mainly in high-tech sectors and to a lesser extent in services. These results might be driven by the fact that highly-qualified migrants in low skill jobs (in low-tech sectors) give reduced contributions, making the overall effect of their human capital negligible. In manufacturing, instead, we find that middle and low educated migrants display a positive effect on TFP growth. Finally, we find that the diversity index is never significant in all sectors but in the services sector, supporting the idea that the positive effect often found in the literature might be due to unmeasured complementarities across sectors.

Our analysis shows that the impact of migrants on productivity growth varies considerably according to the sectors in which they are employed. Moreover, the positive effect of tertiary-educated migrants is confined to the high-tech sectors and to a lesser extent to services. These findings suggest that a migration policy intended to foster the innovative performances of European countries should be strongly demand-driven, that is, it should take into account the specific needs of firms active in different sectors. While tertiary-educated migrants are important for specific sectors with high knowledge content, countries in which manufacturing still has an important role in the overall economy should also consider facilitating the inflow of young non tertiary educated foreign workers. Our results also suggest that in order to foster innovation European member states should promote the European Blue Card or specific national programmes (i.e. the Dutch or the UK highly-skilled visa regime) which facilitate the entrance of highly-skilled migrants. However, they should also introduce a more diversified policy mix strongly connected with the actual demand of firms (and sectors), in order to facilitate the entrance of the workers most in need. The non-significance of the diversity index, meanwhile, for most of the sectors analysed suggests that migration policy should rather focus on the skill-specific needs of the productive system, rather than on the specific country of origin of new migrants.

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Table 1. Diversity Index (within migrants)

	1994-1996			2005-2007		
Sector	**UK**	**France**	**Germany**	**UK**	**France**	**Germany**
Agriculture, hunting, forestry and fishing	0.91	0.77	0.88	0.89	0.79	0.91
Mining and quarrying	0.86	0.59	0.56	0.88	0.64	0.70
Food, beverages and tobacco	0.89	0.77	0.84	0.88	0.84	0.87
Textile, leather and footwear	0.80	0.89	0.79	0.79	0.86	0.87
Wood and products of wood and cork	0.86	0.69	0.85	0.78	0.77	0.88
Pulp, paper, printing and publishing	0.91	0.84	0.88	0.90	0.87	0.91
Coke, refined petroleum and nuclear fuel	0.77	0.67	0.78	0.87	-	0.68
Chemicals and chemical products	0.89	0.89	0.87	0.91	0.88	0.91
Rubber and plastic products	0.88	0.84	0.72	0.88	0.88	0.86
Other non-metallic mineral product	0.85	0.75	0.76	0.89	0.75	0.81
Basic metals and fabricated metals	0.85	0.85	0.79	0.89	0.82	0.85
Machinery, nec	0.90	0.83	0.85	0.90	0.85	0.90
Electrical and optical equipment	0.90	0.88	0.89	0.92	0.93	0.91
Transport equipment	0.87	0.84	0.77	0.89	0.88	0.86
Manufacturing nec; recycling	0.89	0.74	0.88	0.91	0.85	0.89
Electricity, gas and water supply	0.88	0.58	0.82	0.87	0.78	0.90
Construction	0.78	0.79	0.83	0.91	0.77	0.87
Sale, maintenance and repair of motor vehicles	0.87	0.80	0.84	0.89	0.80	0.89
Wholesale trade and commission trade	0.91	0.91	0.90	0.93	0.92	0.92
Retail trade, except of motor vehicles; etc.	0.89	0.89	0.88	0.90	0.92	0.91
Hotels and restaurants	0.92	0.89	0.89	0.92	0.92	0.91
Transport and storage	0.89	0.88	0.89	0.90	0.88	0.90
Post and telecommunications	0.86	0.53	0.89	0.89	0.81	0.89
Financial intermediation	0.92	0.87	0.92	0.92	0.91	0.92
Real estate activities	0.88	0.73	0.93	0.92	0.61	0.90
Renting of machinery and equipment	0.91	0.90	0.90	0.92	0.88	0.92
Public admin and	0.89	0.87	0.91	0.89	0.87	0.91
Education	0.92	0.91	0.94	0.93	0.92	0.94
Health and social work	0.88	0.87	0.91	0.89	0.89	0.91
Other community, social services	0.92	0.91	0.92	0.93	0.92	0.93
Private households with employed persons	0.93	0.80	0.90	0.93	0.73	0.91
Average	**0.88**	**0.80**	**0.85**	**0.89**	**0.81**	**0.89**
National	**0.91**	**0.88**	**0.88**	**0.92**	**0.89**	**0.91**

Note: The diversity estimates here are based on the Simpson index, which is equal to the probability that two entities taken randomly from the dataset of interest (with replacement) represent the same type. Its transformation (1- Simpson index) represents the probability that the two entities represent different types and are called the Gini-Simpson index. In the context of our study it implies the probability that two persons randomly taken in the sector have different origins

Table 2. Aggregate sector specific descriptive statistics

	Total	Manufacturing	Services	Hightech	Lowtech
TFP index growth (%)	1.58	2.79	0.68	2.80	1.35
Share of young	0.38	0.38	0.37	0.39	0.37
Tertiary educated	0.07	0.06	0.07	0.10	0.06
Non-tertiary educated	0.31	0.32	0.30	0.29	0.31
Share of tertiary educated	0.16	0.13	0.18	0.20	0.15
Share of immigrants	0.08	0.08	0.07	0.07	0.08
Tertiary educated	0.23	0.19	0.25	0.28	0.22
Non-tertiary educated	0.77	0.80	0.75	0.71	0.78

Note: The population under 35 is considered young. The share of young Tertiary and Non-tertiary is decomposed using as a base the total employed. The share of immigrants is decomposed into Tertiary and Non-tertiary educated using as a base the total number of migrants.

Table 3. Descriptive statistics

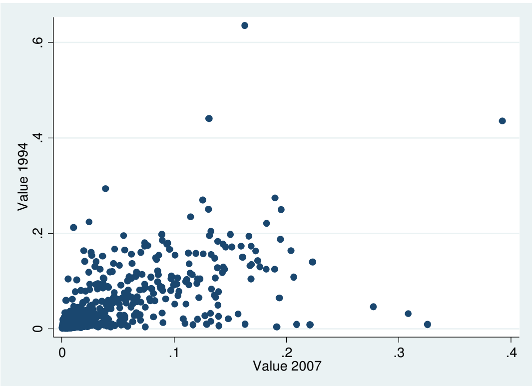
	Mean	Std. Dev.	Min	Max	Definition
TFP	107.82	21.86	26.74	290.87	Total Factor Productivity
Share of migrants	0.073	0.046	0.000	0.29	Share of foreign born in total employed
Education Quality of Migrants	0.228	0.177	0.000	1	Share of high skill foreign born in total foreign born
Share of High Skill Migrants	0.015	0.015	0.000	0.091	Share of high skill foreign born in total employed
Share of Low Skill Migrants	0.058	0.042	0.000	0.274	Share of low skill foreign born in total employed
Share of Low Skill Natives	0.783	0.104	0.318	0.95	Share of low skill native born in total employed
Diversity Index	0.858	0.100	0.000	1	Simpson index
Age of Migrants	39.49	3.114	22	53.361	Average age of foreign born
Age of Natives	39.98	2.038	32.319	46.541	Average age of natives born

Note: Highly skilled are workers with tertiary education.
Source: KLEMS, UK LFS, FR LFS, DE Micro-census

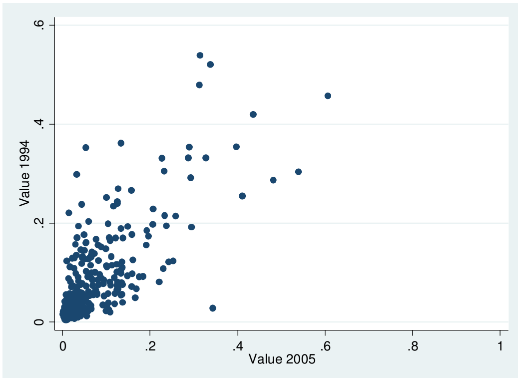
Table 4. Correlation of ethnic sector share over time by countries

Country	Correlation
UK 1994 & 2007	0.92
France 1994 & 2005	0.74
Germany 1996 & 2008	0.97

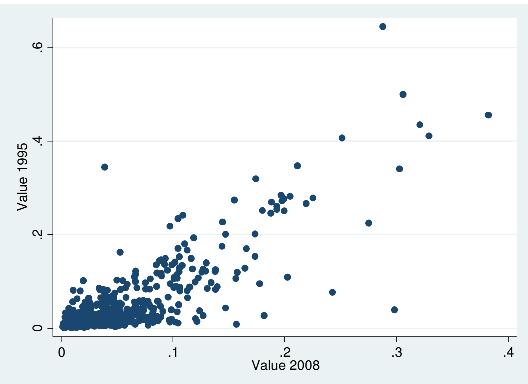
Figure 1.
The relationship between ethnic sector shares (first vs last periods by countries of destination)



Country: UK



Country: France



Country: Germany

Note: Ethnic Sector Share is calculated as the share of a given country of origin in a specific sector by year and country of destination (Ex. share of Moroccans in the texite in France in a given year). Source UK LFS, FR LFS, DE Micro-Census

Table 5 Total Factor Productivity and Foreign Labor Force: Quantity, Quality and Diversity

	(1)		(2)		(3)		(4)		(5)	
	Total Economy		Manufacturing		Services		High-Tech Sectors		Low-Tech Sectors	
VARIABLES	FE	IV	FE	IV	FE	IV	FE	IV	FE	IV
log Share of Migrants	**0.054****	**0.219*****	0.047	**0.229*****	**0.065***	**0.084****	0.046	**0.319*****	**0.055****	**0.184*****
	(0.026)	**(0.036)**	(0.032)	**(0.056)**	**(0.037)**	**(0.036)**	(0.068)	**(0.062)**	**(0.026)**	**(0.042)**
log Education Quality of Migrants	-0.015	0.007	-0.029	-0.003	-0.005	-0.002	0.037	**0.056***	-0.022	-0.004
	(0.014)	(0.011)	(0.022)	(0.018)	(0.015)	(0.013)	(0.033)	**(0.029)**	(0.016)	(0.012)
Diversity Index	0.162	-0.042	0.031	-0.279	**0.286****	**0.265*****	**0.857***	0.712	0.132	-0.035
	(0.109)	(0.091)	(0.156)	(0.180)	**(0.116)**	**(0.087)**	**(0.414)**	(0.463)	(0.111)	(0.096)
log Age of Migrants	-4.306	-5.377	-8.130**	-12.306**	6.760	6.545*	-43.744***	-36.842***	-3.108	-2.592
	(3.381)	(3.496)	(3.740)	(6.246)	(4.391)	(3.567)	(12.250)	(12.824)	(3.615)	(3.666)
log Age of Migrants squared	0.596	0.737	1.145**	1.700**	-0.950	-0.920*	5.960***	5.018***	0.433	0.359
	(0.469)	(0.475)	(0.520)	(0.847)	(0.590)	(0.486)	(1.638)	(1.739)	(0.503)	(0.498)
Constant	12.483**	15.140**	19.267***	27.873**	-7.428	-6.970	84.500***	72.716***	10.274	9.870
	(6.073)	(6.452)	(6.695)	(11.538)	(8.152)	(6.566)	(22.959)	(23.629)	(6.464)	(6.774)
Observations	1,148	1,142	478	472	670	670	228	228	920	914
Number of sectors	92	91	39	38	53	53	18	18	74	73
R-squared	0.140	-	0.252	-	0.132	-	0.477	-	0.107	-
First stage F statistics	-	317.83	-	147.74	-	247.05	-	126.61	-	220.7

Note: The dependent variable is the log of Total Factor Productivity. FE columns report the results of fixed-effect estimator, while IV columns report the results of a two-stage least squares estimator with fixed effects, using the Card-like instruments, as described in Section 5.2. The instrumented variable is the log share of immigrants. All models include time dummies. First-stage F-statistics are reported. See Table (7) for First-Stage coefficients. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 Total Factor Productivity and Foreign Labor Force: Skill Composition Effect.

	(1) Total Economy		(2) Manufacturing		(3) Services		(4) High-Tech Sectors		(5) Low-Tech Sectors	
VARIABLES	FE	IV	FE	IV	FE	IV	FE	IV	FE	IV
log Share of High Skill Migrants	0.009	**0.205*** **	-0.005	-0.314	0.018	**0.122*** **	**0.064** **	**0.308*** **	0.004	**0.241*** **
	(0.010)	**(0.061)**	(0.013)	(0.378)	(0.015)	**(0.035)**	**(0.029)**	**(0.073)**	(0.010)	**(0.071)**
log Share of Low Skill Migrants	**0.058** **	0.083	0.034	**0.393* **	**0.082** **	-0.008	0.016	0.154	**0.076*** **	0.046
	(0.026)	(0.063)	(0.028)	**(0.203)**	**(0.034)**	(0.049)	(0.064)	(0.141)	**(0.028)**	(0.069)
log Share of Low Skill Natives	0.109	0.839***	-0.051	0.628	0.236	0.290*	0.406	1.256***	0.232	1.041***
	(0.225)	(0.213)	(0.385)	(0.888)	(0.268)	(0.160)	(0.413)	(0.433)	(0.299)	(0.310)
log Age of Migrants	-1.921	-9.448**	-4.657	-0.673	5.072	3.220	-43.428***	-62.432***	-1.006	-6.494
	(2.928)	(4.145)	(4.188)	(14.961)	(4.358)	(3.930)	(11.462)	(16.706)	(3.112)	(4.623)
log Age of Migrants squared	0.264	1.300**	0.667	0.058	-0.723	-0.465	5.911***	8.490***	0.136	0.903
	(0.404)	(0.565)	(0.579)	(2.082)	(0.589)	(0.535)	(1.536)	(2.271)	(0.430)	(0.630)
log Age of Natives	7.935	27.735	-126.372**	-160.444**	40.391**	47.865***	15.100	125.893**	-5.127	11.515
	(19.620)	(17.371)	(48.547)	(66.215)	(19.722)	(14.260)	(31.243)	(62.756)	(20.492)	(20.338)
log Age of Natives squared	-0.926	-3.581	17.293**	21.808**	-5.394**	-6.404***	-1.953	-16.904**	0.845	-1.397
	(2.673)	(2.355)	(6.612)	(8.903)	(2.673)	(1.936)	(4.150)	(8.543)	(2.804)	(2.760)
Constant	-8.223	-30.389	243.770**	301.526***	-79.389**	-89.723***	55.708	-112.640	14.243	-5.697
	(37.829)	(31.722)	(91.933)	(113.204)	(36.584)	(26.344)	(67.915)	(119.867)	(39.987)	(37.385)
Observations	1,147	1,140	478	471	669	669	228	228	919	912
R-squared	0.155		0.282		0.143		0.482		0.126	
Number of sectors	92	91	39	38	53	53	18	18	74	73
First stage F-statistics										
log Share of High Skill Migrants		31.07		2.66		58.41		27.81		18.27
log Share of Low Skill Migrants		78.95		33.88		62.88		18.83		61.27

Note: The dependent variable is the log of Total Factor Productivity. FE columns report the results of fixed-effect estimator, while IV columns report the results of a two-stage least squares estimator with fixed effects, using the Card-like instruments, as described in Section 5.2. The instrumented variables are the log share of educated immigrants and the log share of low and middle educated immigrants. All models include time dummies. First-stage F-statistics are reported. See Tables (8a) and (8b) for First-Stage coefficients. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7 First stage of the 2SLS: the dependent variable is the log share of migrants

VARIABLES	(1) Total Economy	(2) Manufacturing	(3) Services	(4) High-Tech Sectors	(5) Low-Tech Sectors
Predicted (log) share of migrants	0.594***	0.683***	0.639***	0.707***	0.572***
	(0.333)	(0.056)	(0.041)	(0.063)	(0.039)
Set of exogenous variables included in the second stage	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,142	472	670	228	914
Number of sectors	91	38	53	18	73
F statistics (I stage)	317.83	147.74	247.05	126.61	220.7

Note: This table reports the first stage statistics for the Card-like instrument in Table (5), where we instrument the (log) share of migrants in each sector. The construction of the instrument is explained in detail in Section 5.2. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8a. First stage of the 2SLS: the dependent variable is the log share of highly educated migrants

VARIABLES	(1) Total Economy	(2) Manufacturing	(3) Services	(4) High-Tech Sectors	(5) Low-Tech Sectors
Predicted (log) share of high skill migrants	0.282***	0.175***	0.522***	0.793***	0.265***
	(0.048)	0.094	(0.058)	(0.157)	(0.052)
Set of exogenous variables included in the second stage	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,140	471	669	228	912
Number of groups	91	38	53	18	73
F statistics (I stage)	31.07	2.66	58.41	27.81	18.27

This table reports the first stage statistics for the Card-like instrument in Table (6), where we instrument the log share of highly educated migrants in each sector. The construction of the instrument is explained in detail in Section 5.2. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8b. First stage of the 2SLS: the dependent variable is the log share of middle-low educated migrants

VARIABLES	(1) Total Economy	(2) Manufacturing	(3) Services	(4) High-Tech Sectors	(5) Low-Tech Sectors
Predicted (log) share of Low Skill migrants	0.509***	0.350***	0.553***	0.620***	0.519***
	(0.049)	(0.095)	(0.055)	(0.118)	(0.054)
Set of exogenous variables included in the second stage	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,140	471	669	228	912
Number of groups	91	38	53	18	73
F statistics (I stage)	78.95	33.88	62.88	18.83	61.27

Note: This table reports the first stage statistics for the Card-like instrument in Table (6), where we instrument the log share of middle-low educated migrants in each sector. The construction of the instrument is explained in detail in Section 5.2. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix Section 1

Table A1.a Specialization of immigrants across sectors: United Kingdom, the largest origin groups

Sector	USA	France	Germany	Ireland	Poland	West Asia	India	Common Wealth	Africa
Agriculture, hunting, forestry and fishing	1.35	1.54	1.05	1.16	3.54	0.00	0.25	1.77	0.24
Mining and quarrying	3.30	0.00	0.93	1.61	0.10	0.64	1.01	1.25	1.44
Food, beverages and tobacco	0.43	0.28	0.56	0.19	3.73	0.81	0.96	0.42	0.49
Textile, leather and footwear	0.00	0.93	0.76	0.35	1.70	2.69	2.83	0.24	0.82
Wood and products of wood and cork	0.00	1.82	0.00	0.72	5.49	0.46	0.15	0.77	0.00
Pulp, paper, printing and publishing	1.42	3.06	1.01	1.50	0.29	0.22	0.82	2.28	1.12
Coke, refined petroleum and nuclear fuel	0.58	2.19	0.30	0.00	0.00	0.88	1.51	1.50	0.44
Chemicals and chemical products	0.00	4.12	0.77	0.49	0.64	0.81	0.86	0.88	1.26
Rubber and plastic products	0.91	0.44	0.81	1.49	3.89	2.10	0.40	0.28	0.92
Other non-metallic mineral product	0.00	1.46	1.02	0.00	3.18	0.58	0.83	1.34	0.34
Basic metals and fabricated metals	0.17	0.00	1.24	0.86	1.87	1.61	1.37	0.52	0.76
Machinery, nec.	0.19	0.80	1.29	0.37	2.53	0.52	0.96	0.78	0.69
Electrical and optical equipment	0.64	1.27	1.29	0.57	1.60	0.72	1.00	0.75	0.57
Transport equipment	0.67	1.20	1.38	0.96	2.40	1.29	1.08	0.47	0.63
Manufacturing nec; recycling	0.18	2.34	0.42	1.31	1.60	0.57	1.21	0.82	0.63
Electricity, gas and water supply	0.00	0.37	1.55	2.93	0.21	1.22	1.25	1.93	1.41
Construction	0.15	0.11	0.68	2.44	2.19	0.41	0.67	0.77	0.46
Sale, maintenance and repair of motor vehicles	0.50	0.00	1.45	0.10	0.97	2.27	1.41	0.78	0.97
Wholesale trade and commission trade	0.54	1.66	0.38	0.98	1.52	1.59	0.96	0.63	0.75
Retail trade, except of motor vehicles; etc.	0.68	1.10	1.20	0.69	0.61	1.55	1.32	0.71	1.25
Hotels and restaurants	0.40	0.84	0.61	0.60	1.26	1.01	1.32	1.06	0.50
Transport and storage	0.13	0.57	1.00	0.68	1.48	3.26	0.91	0.63	1.01
Post and telecommunications	0.98	0.92	1.12	0.69	0.72	1.74	1.61	0.72	0.93
Financial intermediation	2.41	2.12	1.04	1.05	0.23	0.75	1.04	1.54	0.77
Real estate activities	0.89	0.97	0.98	0.88	0.72	2.58	0.68	0.87	1.31
Renting of machinery and equipment	1.45	1.17	0.80	0.80	0.67	0.82	0.99	1.26	1.19
Public admin and defense; compulsory soc. secur.	2.67	0.69	1.97	1.09	0.13	0.38	0.87	1.11	1.45
Education	1.84	1.70	1.28	1.17	0.35	0.73	0.82	1.33	0.91
Health and social work	0.49	0.49	1.02	1.38	0.39	0.41	1.03	0.86	1.52
Other community, social and personal services	2.34	0.93	1.25	1.16	1.04	0.47	0.43	1.50	0.83
Private households with employed persons	0.33	2.43	0.54	0.40	0.81	0.00	0.24	0.79	0.49

Source: LFS, UK.

Table A1.b Specialization of immigrants across sectors: France, the largest origin groups

Sector	Tunis	Turkey	Belgium	Germany	Algeria	Italy	Portugal	Spain	Africa	Maroc.
Agriculture, hunting, forestry and fishing	0.42	1.45	0.97	2.01	0.43	0.00	1.29	0.66	0.06	2.55
Mining and quarrying	0.00	0.00	0.00	4.07	0.00	4.73	2.13	0.00	0.00	0.00
Food, beverages and tobacco	2.89	0.29	4.73	0.53	0.37	0.92	1.24	0.00	1.13	0.73
Textile, leather and footwear	0.00	4.51	0.78	0.00	0.43	0.00	0.81	0.00	0.42	0.19
Wood and products of wood and cork	2.87	0.86	0.00	0.00	1.17	2.27	1.63	4.77	0.69	0.00
Pulp, paper, printing and publishing	1.46	0.00	1.22	0.00	0.37	0.59	1.16	0.00	0.49	0.24
Coke, refined petroleum and nuclear fuel	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.08	0.00
Chemicals and chemical products	0.00	0.00	0.00	2.93	1.17	2.97	0.48	0.00	0.73	1.71
Rubber and plastic products	1.23	3.60	0.00	1.40	0.26	0.46	0.90	2.61	0.68	0.45
Other non-metallic mineral product	1.10	0.00	0.00	0.00	0.58	1.33	1.34	0.00	0.12	3.05
Basic metals and fabricated metals	0.34	0.33	0.00	1.19	2.05	1.84	1.02	1.53	0.30	1.96
Machinery, nec.	0.23	1.35	1.06	4.89	0.71	3.62	1.14	0.00	0.00	0.88
Electrical and optical equipment	0.00	0.75	2.76	0.45	0.78	0.71	0.41	2.24	0.84	0.39
Transport equipment	2.15	0.60	0.00	3.49	0.58	1.61	0.54	2.25	0.62	2.06
Manufacturing nec; recycling	0.00	4.97	0.00	3.96	1.48	2.87	0.53	0.00	0.85	0.53
Electricity, gas and water supply	0.66	0.00	6.48	1.75	2.74	7.44	0.20	1.84	0.00	0.00
Construction	1.38	2.34	0.18	0.34	0.77	0.98	1.72	0.90	0.45	0.59
Sale, maintenance and repair of motor vehicles	0.00	0.44	0.85	0.39	1.21	1.20	1.57	2.86	0.77	0.28
Wholesale trade and commission trade	0.32	1.98	0.28	1.18	0.99	0.40	0.78	2.40	0.49	0.47
Retail trade, except of motor vehicles; etc.	1.07	0.77	1.36	0.68	1.39	0.82	0.49	1.67	0.98	1.10
Hotels and restaurants	1.75	1.48	0.85	0.11	0.88	1.27	0.53	0.24	1.25	0.84
Transport and storage	1.84	0.87	1.52	0.26	1.30	0.86	0.82	1.79	0.95	1.43
Post and telecommunications	2.51	0.00	1.26	7.06	1.72	0.00	0.22	0.00	2.67	0.29
Financial intermediation	1.50	0.00	5.28	4.19	0.14	2.10	0.46	1.03	0.46	1.18
Real estate activities	0.00	0.00	0.72	0.00	0.37	0.54	2.40	1.25	0.42	0.88
Renting of machinery and equipment	0.97	0.14	0.82	1.43	1.04	0.76	0.53	0.00	2.20	1.42
Public adm. and defense; compulsory soc. sec.	0.00	0.00	2.10	0.58	0.59	2.80	0.62	1.43	2.29	0.74
Education	0.83	0.22	1.93	1.55	1.68	1.32	0.49	1.29	0.56	0.88
Health and social work	1.11	0.57	2.48	1.61	2.08	0.93	0.49	0.73	1.24	0.90
Other community, social and personal services	0.89	0.09	1.72	1.61	1.54	1.73	0.42	1.76	1.14	0.65
Private households with employed persons	0.47	0.38	0.11	0.31	0.55	0.30	1.91	1.37	1.22	0.84
Source: LFS, France										

Table A1.c Specialization of immigrants across sectors: Germany, the largest origin groups

Sector	Turkey	Austria	Greece	Italy	Poland	Former Yugos.	Former USSR	Europe (west)	Europe (east)
Agriculture, hunting, forestry and fishing	0.69	0.49	0.25	0.61	2.27	1.04	1.38	1.61	1.45
Mining and quarrying	2.66	0.53	0.61	0.82	0.46	1.18	0.00	1.92	0.42
Food, beverages and tobacco	1.62	0.75	0.97	0.68	0.89	1.01	1.15	0.55	0.79
Textile, leather and footwear	1.52	0.77	1.31	1.01	0.49	1.11	1.00	0.00	1.62
Wood and products of wood and cork	0.66	1.06	0.43	0.70	1.83	1.27	2.34	0.53	2.52
Pulp, paper, printing and publishing	0.98	1.25	1.27	1.09	0.50	0.80	1.07	0.78	1.09
Coke, refined petroleum and nuclear fuel	0.00	0.00	0.00	0.00	4.32	0.00	0.00	2.40	0.00
Chemicals and chemical products	0.87	1.43	1.30	1.28	0.98	0.81	0.65	1.87	0.63
Rubber and plastic products	1.69	0.43	1.64	1.18	0.77	0.69	1.04	0.26	1.07
Other non-metallic mineral products	1.78	0.49	1.13	0.99	1.17	0.97	0.82	0.20	0.46
Basic metals and fabricated metals	1.60	0.45	1.30	1.26	0.80	1.15	0.98	0.55	0.85
Machinery, nec	0.94	1.11	1.19	1.16	1.00	0.99	1.14	1.07	1.01
Electrical and optical equipment	0.88	1.24	1.16	0.84	0.90	0.95	1.01	1.04	1.32
Transport equipment	1.58	0.85	1.27	1.39	0.53	1.04	0.69	0.37	0.80
Manufacturing nec; recycling	1.35	1.40	0.89	1.20	0.79	0.83	1.38	0.66	0.59
Electricity, gas and water supply	0.46	2.42	0.49	1.31	0.77	1.06	1.10	2.98	1.22
Construction	1.09	0.81	0.59	1.01	1.72	1.82	0.79	0.68	1.09
Sale, maintenance and repair of motor vehicles	1.17	0.89	1.38	1.14	1.14	1.12	1.32	0.71	0.94
Wholesale trade and commission trade	1.17	1.30	0.82	0.89	0.79	0.76	0.89	1.20	0.51
Retail trade, except of motor vehicles; etc.	1.16	1.08	0.84	0.95	0.87	0.92	0.89	1.06	0.88
Hotels and restaurants	0.77	0.57	1.65	1.55	0.57	0.96	0.54	0.47	1.02
Transport and storage	1.26	0.76	1.03	0.92	0.72	0.84	1.21	1.22	1.01
Post and telecommunications	1.46	1.13	0.50	0.98	1.23	0.70	0.58	0.73	1.14
Financial intermediation	0.56	2.88	0.75	1.27	0.98	0.98	0.72	2.24	0.63
Real estate activities	0.26	2.27	0.00	0.66	1.23	1.09	0.83	1.80	2.69
Renting of machinery and equipment	0.83	0.94	0.80	0.68	1.06	1.00	1.19	1.25	1.00
Public adm. and defense; compulsory soc. sec.	0.73	1.18	0.97	0.95	1.12	0.82	0.87	2.89	0.91
Education	0.48	1.46	0.65	0.59	1.04	0.40	1.26	1.67	1.28
Health and social work	0.56	0.90	0.81	0.78	1.47	1.37	1.34	1.25	1.13
Other community, social and personal services	0.84	1.85	0.88	0.86	0.97	0.59	1.19	1.23	0.98
Private households with employed persons	0.37	1.06	0.56	0.37	2.78	0.66	1.88	0.71	0.70

Source: Microcensus, Germany

Appendix Section 2

Data description

UK Labour Force Survey

The British Quarterly Labour Force Survey (QLFS) is a sample survey of households living at private addresses in Great Britain. The QLFS is conducted, as the name suggests, on a quarterly basis and aims to obtain a sample of around 60,000 households. The survey contains data on: employment and self-employment; full-time and part-time employment; second jobs; employment by age and sex; ILO unemployment by age and sex; economic activity by age and sex; occupations and industry sectors; regional economic activity; average actual weekly hours of work (by industry sector); economic inactivity by age and sex; economic inactivity by reason including discouraged workers; temporary employees; part-time and self-employed by occupation/industry; average weekly hours of work; ILO unemployment by occupation/industry; duration of ILO unemployment; average gross earnings by occupation, industry sector/region; ethnic group economic activity; household population by age and sex; economic activity for counties and larger Unitary Authorities and Local Authority Districts; long-term unemployed by occupation and industry sector; and labour market structure.

QLFS contains information on earnings just after 1993; pre-1998, earnings data is available only for fifth wave respondents, post 1998 earnings data is collected in the first and in the final wave; country of birth within the UK only began to be collected in QLFS from 2001

Spatial Coverage: UK, Standard Regions

Temporal Coverage: 1992-2011

French Labor Force Survey

The French Labor Force Survey was launched in 1950 and became an annual survey in 1982. Redesigned in 2003, the survey is now continuous providing quarterly results. The survey covers private households in metropolitan France. It includes a part of the population living in collective households, and persons who have family ties with private households. Participation in the survey is compulsory. The resident population comprises persons living in metropolitan France.

The survey provides longitudinal data on households and individuals. Persons aged 15 years or over are interviewed. Data refer to the number of persons who were working during the survey week including employees, self-employed as well as family workers. Data include persons who have a job but are not at work due to illness (less than 1 year), vacation, labour dispute, educational leave, etc.

Spatial Coverage: France (II de France, the overseas departments and territories are excluded), Districts.

Temporal Coverage: 1968-2011

German Microcensus

The Microcensus provides official statistics of the population and the labor market in Germany. The Labor Force Survey of the European Union (EU Labor Force Survey) forms an integral part of the Microcensus. The Microcensus supplies statistical information in a detailed subject-related and regional breakdown on the population structure, the economic and social situation of the population, families, consensual unions and households, on employment, job search, education/training and continuing education/training, the housing situation and health. Furthermore, wage information is only given in intervals. The German Microcensus includes 1% of the resident population in the former West Germany, and is a large, representative, random sample containing comprehensive information on individual and household characteristics.

Spatial Coverage: Germany, NUTS 3.

Temporal Coverage: 1971-2009.