Human resources and innovation:
Total Factor Productivity and foreign human capital

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Abstract

This paper analyses the role of migrants in innovation in the three largest European countries – France, Germany and the United Kingdom – in the years 1994-2007, using Total Factor Productivity as a measure of innovation. Unlike previous research, which mainly employs a regional approach, our analysis is at the sectoral level: this allows us to distinguish 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 education, age and diversity of origin, and adopt instrumental variables strategies to address the possible endogeneity of migration. The results show that migrants are relevant in all sectors, but with important differences: highly-educated migrants show a larger positive effect in the high-tech sectors, while middle- and low-educated migrants are more relevant in manufacturing. The diversity of countries of origin contributes to innovation only in the services sectors.

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

JEL Codes: F22, F66, O31, O32

1. Introduction

The contribution of migrant workers to the economic and innovative performances of European countries has recently gained a lot of academic and political 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, greatly fostered the production of innovation in US firms, as proxied by the number of patent applications (Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 2010). This evidence has suggested the importance for Europe of attracting skilled professionals from abroad, in what has often been labeled as the “global race for talent” (Boeri et al., 2012, 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, 2015;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 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 that diversity has a positive effect 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 innovation in Europe. More precisely, it analyzes the role of the human-capital components of the foreign labor force on productivity growth in 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 a measurement of 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 analyse 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, as migrants often move to innovative regions, but are not necessarily employed in the sectors that are actually innovative. On the other hand a possible caveat of our analysis it that, while adopting the sector as the unit of analysis allows a better measurement of the impact of migrants on innovation, it does not account for the existence of possible cross-sectoral spillovers. These might increase the overall impact of migration at a more aggregate level. In this respect the results obtained at the sectoral level can be interpreted as a lower bound with respect to studies that adopt more aggregate units of analysis. The sectoral perspective also 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 diversity is measured, instead, at the sectoral level, that is, among migrants that are active in the same economic sector. We argue that sectors 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 where the native labor force is progressively ageing. Finally, 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. They, also, 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 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 save in the services sector, supporting the idea that the positive effect often found in the literature at the regional level might be due to unmeasured complementarities across sectors.

This paper builds and improve on the existing literature that analyses the effect of migration on innovation at the aggregate (regional or country) level. The results of our analysis are, instead, less directly comparable with the recent literature that analyses the effect of migration and diversity on innovative performances at the firm level (Ozgen, Nijkamp and Poot, 2013; Ozgen et al 2014, Trax et al., 2015; Gosh, Mayda and Ortega, 2016). Indeed results at the firm level typically consider the private returns for individual firms from the hiring of immigrant workers. Our sectoral perspective, instead, is better able to identify the aggregate returns for all firms within a sector, where relevant externalities perhaps play a role: these might consist in the benefits deriving from the inter-firm mobility of (skilled) immigrant workers, as well as the usual knowledge externalities that leak out from innovative firms and that can be appropriated by other firms in the economy.

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 policy implications.

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 medium-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[1] 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 for migration (especially highly-skilled migration) has been 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 to the number of patent applications. Other studies find a positive effect for highly-skilled migration at the city or provincial 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 (2015) finds that highly-skilled migrants positively impact the innovative performances of British firms using provinces as the unit of analysis.[2]

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. In this they partly

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

[2] The positive effect of immigration on productivity growth has also been linked to its role in increasing product diversity at the country level, as shown by a recent literature (Iranzo and Peri, 2009; di Giovanni, Levchenko and Ortega, 2015).

adopt 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 regional level data 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 for migrant diversity on patent production in European regions is found by Dohse and Gold (2014), while Niebuhr (2010) notes a positive effect for 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 for 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 medium-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 of introducing innovations. On the contrary, Gosh et al. (2014) find that skilled immigrants have a positive effect on productivity for publicly traded US firms, especially for R&D intensive firms. Parrotta *et al*. (2014) reported a positive effect for diversity on the production of patents in Danish firms. Ozgen, 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, noted 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 heterogeneous and less coherent picture about the effects of migration both in terms of size and of diversity of countries of origin. This is especially true 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. Partly this can be due to the fact that firm level studies analyze the private returns of hiring immigrant workers for individual firms, while aggregated-level studies measure the returns of immigrant employment for all firms in a specific region or country. 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

Despite its prominent use in aggregate analyses the geographical approach has some important limitations: note least that it overlooks the role of economic sectors for migrant employment. 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 they can 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 given region or country. A region, say, 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 through the performances of each specific industry, by focussing in on 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 only highly-educated workers have. 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 models (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. As shown by Peri (2012) the positive effect of unskilled migration on overall productivity in US states is mostly due to the adoption by firms of technologies that are more efficient and intensive in their use of unskilled workers. Therefore, while for high-technology sectors it seems legitimate to focus only on the contribution of highly-skilled migrants, in the case of other sectors the contribution of low or middle educated foreign workers should also be considered. It should be remembered that 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 advantages of the implementation of a migration policy based on a national quota system, which selects migrants by countries of origin and not on the basis of their education and experience (i.e. a point system). However, here, too, a sectoral perspective highlights 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 migrants from different countries of origin penetrate, over time, 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 diversity among migrants, we build a diversity index (excluding the natives) following the Herfindahl methodology, both at the sector and at the national level.[4] Table (1) shows that while, at the 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 relatively 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 immediately after the education or at a later stage in 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

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

[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 origins (country of birth or citizenship). $\boldsymbol{Diversity\ Index_{jc} = 1 - \sum_{i=1}^{N} Share_{ijc}^{2}}$. Our measure of diversity excludes the native born and captures the diversity among foreign employers only within their sector of activity, allowing us to separate the effect of the share of migrants from its diversity in terms of country of origin. Hence, it is closer to the diversity measure used in Ortega and Peri (2014) than to the one developed in Alesina et al. (2012) as the latter considers natives as well. Higher values of the index imply a more equal distribution of migrants by country of origin.

migration on innovation; otherwise age might become a confounding factor in the results of the analysis.

[Insert Table 1 here]

4. Data

4.1. Source

In this study to assess the impact of migration on the 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 publicly available 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. In particular we use the available data on Total Factor Productivity (TFP) at the sectoral level, using 31 different sectors (see the list in Table 1) that cover the whole economy. 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 (see Section 2 of the Appendix). The datasets allow for the construction of human capital variables at sector level.

4.2. Descriptive statistics

Table (2) reports a synthetic description of the dataset, presenting the variables of interest for the total pool of observations, manufacturing and services, as well as high-tech and low-tech sectors due to the technological heterogeneity of economic sectors. The first two subgroups overlap with the last two. This allows for the detection of variation in the 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 manufacturing (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 is 7-8.[6]In some sectors migrants constitute up to one quarter of

[5] http://www.euklems.net/ See also Appendix 2 for a description.

[6] In the case of France and the UK countries of birth have been used to identify immigrants. In the case of Germany immigrants are identified by their citizenship, since this is the only information available in the Micro-Census. Given the quite restrictive naturalization law in Germany (longer period to become eligible for German citizenship, limited double

the labor force.[7] Though the percentage of migrants is quite homogenous across sector groups considered (7-8%) the level of education 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 Total Factor Productivity is computed as a residual (Solow, 1957): it indicates the share of output that is not accounted for by the relative contribution of each of the productive inputs in a standard production function. It can, therefore, be considered as a rough proxy of technological change and efficiency growth. Indeed since the early contributions of Griliches (1996), technological change and innovation were found to be an important determinant of TFP. A number of studies have shown that higher levels of innovative activity are associated with higher levels of TFP, both at the industry level (Griffith, Redding and Van Reenen, 2004) and at the firm level (Crepon, Duguet and Mairesse, 1998; Loof and Hesmati, 2001; Hall, 2011).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 changes in the competitive structure of the markets, as well as the lack of proper measurement in the quality of productive inputs.[8] 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

(Contd.)

nationality allowed) the discrepancy in the definition with France and the UK is not likely to play a big role in our analyses.

[7] This is the case for the Food, Beverages and Tobacco sector in the UK for the year 2003 (23%), the sector Hotels and restaurants in Germany for all the years considered (27% on average) and for the same sector in the UK for 2006 (23%). In the UK also the sector Private Households with Employed Persons displays a 22% share of migrants in 2006.

[8] 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 and capital equals its marginal productivity. Notwithstanding all these simplifying assumptions TFP growth still remains a good proxy for 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.

type of innovation that they implement.[9] In this study we use the sectoral TFP provided by the KLEMS database and computed according to the usual accounting framework approach (Jorgenson, Ho and Stiroh, 2005). The main advantage of this measure is the extreme precision of the measurement of the labour and capital inputs, which take into account the specific number of working hours[10], as well as the different types of capital assets and depreciation rates (see Section 2 in the Appendix). This is extremely important because we compare a wide variety of heterogeneous sectors, where the average number of working hours might differ substantially, as well as the type of capital assets. Moreover, in line with what said above, only a very precise measure of TFP allows it to be interpreted as a proxy of innovation and technological change.

Following Griliches (1979) we specify an augmented Cobb-Douglas production function where the level of output at the industry level is determined by the usual physical inputs – labour and capital –as well as by human capital, as proxied by specific characteristics of the labour force, such as education, ethnicity, age and diversity.[11]

$$Y_{sct} = K_{sct}^{\alpha} L_{sct}^{1-\alpha} H_{sct}^{\beta} e^{\varepsilon_{sct}} \tag{1}$$

Where Y indicates total value added, K and L indicate respectively capital and labour inputs and H denotes human capital. Finally ε_{sct} is an idiosyncratic error term. The indexes s, c and t indicate respectively sector, country, and year. Assuming constant returns to scale for capital and labour, we can rearrange equation (1) in the following way:

$$\frac{Y_{sct}}{K_{sct}^{\alpha} L_{sct}^{1-\alpha}} = H_{sct}^{\beta} e^{\varepsilon_{sct}} \tag{2}$$

The left hand side of equation (2) corresponds to the measure of Total Factor Productivity. Our hypothesis is that the composition of human capital (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 labour inputs are already used in the computation of Total Factor Productivity we cannot use the levels of the labour variables to explain the levels of TFP, because this would risk double counting the labour variables. Therefore, we adopt a specification in which the level of TFP is explained by the specific features of the labor force, such as ethnicity and education, rather than by the quantity of labor inputs. We rewrite equation (2) as follows:

$$TFP_{sct} = H_{sct}^{\beta} e^{\varepsilon_{sct}} \tag{3}$$

[9] This is especially important for our study that covers the full range of economic sectors. Other indicators of innovative activity, such as patents, represent a good proxy for innovation only for specific type of industries, in particular medium and high-tech manufacturing sectors. Moreover, it must be stressed that, in most cases, patents indicate an invention, but not necessarily an innovation, since some of them are neither licensed nor produce revenues.

[10] This is particularly important since in some cases the actual number of worked hours might differ substantially between native and immigrant workers.

[11] In the original formulation by Griliches the expenditures in Research and Development are included among the factors that determine the overall level of output. However, since in our analysis we include both manufacturing and services sectors, R&D expenditures are not available for most of the services sectors (OECD STAN, 2016) hence we cannot include them in our model. Indeed, R&D expenditures are only implemented by manufacturing firms, while they are not relevant for the innovation outcomes of most of the economic activtiies in the services sector (Tether, 2005).

TFP is the level of Total Factor Productivity, *H* is the set of variables related to the composition of the labor inputs. In line with existing studies (Ozgen et al., 2012; Bosetti et al., 2015) that tested the impact of migration on innovation outcomes we include the share of migrants among the labour force, the diversity of country of origin among migrants, as well as the share of the tertiary educated and the average age of the labor force. 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:

$$tfp_{sct} = \beta' h_{sct} + \varepsilon_{sct} \tag{4}$$

Through this general empirical specification we will be able to test if the quantity of migrants (share of migrants over 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 national sectors. A further advantage of our empirical approach is that we will be able to check if these effects change according to specific 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:

$$tfp_{sct} = \beta_{1'} sm_{sct} + \beta_{2'} age_{sct} + \beta_{3} agesq_{sct} + \beta_{4'} smte_{sct} + \beta_{5'} diversity_{sct} + \psi_{sc} + \eta_{t} + \varepsilon_{sct} \tag{5}$$

Where *sm* indicates the log of the share of migrants over the total employment of a national sector, *age* is the log of the average age of migrant workers in that 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 national sector (*smte*), and the diversity of migrants' countries of origin in that sector (*diversity*), 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. In order to account for time invariant effects we introduce country-sector specific fixed effects (ψ_{sc}), i.e. we interact the sector dummies of the 31 different sectors included in our analysis with country dummies. We also account for common trends across observations through a full set of time dummies (η_t).Finally ε_{sct} indicates the idiosyncratic shocks of the dependent variable.

The log specification chosen allows for a non linear effect of the share of migrants: it 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 measure is the effect of a percentage increase of a share.[12] We believe that this specification should be more attractive than assuming an homogeneous effect regardless of the existing share of immigrants in a sector. It is, indeed, 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 go to make up only a minimal percentage of those employed.

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 as 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:

$$tfp_{sct} = \beta_{1'} smte_{sct} + \beta_{1'} smmle_{sct} + \beta_{1'} snmle_{sct} + \beta_{2'} agem_{sct} + \beta_{3} agesqm_{sct} + \beta_{2'} agen_{sct} + \beta_{3} agesqn_{sct} + \psi_{sc} + \eta_{t} + \varepsilon_{sct} \tag{6}$$

In equation (6): *smte* indicates the log share of tertiary educated migrants out of total employment in a specific sector and country at time t; at the same level of aggregation *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;[13] *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 country-industry specific fixed effects and time dummies.

5.2. Methodology

In order to estimate equations (5) and (6) 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 sectors. Moreover, the National Systems of Innovation literature (Lundvall, 1993) has stressed as

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

13 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 highly–educated natives was excluded.

additional factors, the role of country-level institutional factors such as: the strength of university-industry relationships; the quality of public funded research; and public support for 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 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.

However the use of fixed effects 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.[14] 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 mobile migrant workers who tend to locate in sectors that have recently experienced expansion. Therefore, in this case too, we might expect some bias in the fixed effects results. Finally for some sectors (especially sectors with relatively fewer employees) national statistical institutes might fail to precisely measure the number of foreign workers employed, inducing some measurement error in our variables of interest. This, in turn, might lead to attenuation bias in fixed effects estimates.

The instrumental variable strategy

In order to account for these problems we follow the well-known identification strategy based on instrumental variables 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 the same nationality have already settled. 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 the same nationality are already settled, but in most cases they also start to work in the same economic activities as compatriots. The existing literature (Danzer and Yaman, 2013; Strom et al. 2013; Tapinos; 1996, Dustmann et al. 2003; Constant, 2005) suggests that this is mostly due to the fact that the main channels to find a job for the newly arrived migrants are their co nationals. In this sector-specific allocation cultural ability matters, of course, but not necessarily primarily: often migrants are

[14] 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 from outside Germany. 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.

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.[15] We call this measure the *ethnic sector share*, computed as follows:

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

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.[16] 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 graphic 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.

[15] In our dataset we classified countries of origin using both specific countries (especially for European countries) and aggregated geographical areas of origins. Indeed, in the original micro data provided by the Labour Force Surveys in France and UK and the Microcensus in Germany only the most important countries of origin are separated out, while countries from where immigration is less frequent are aggregated into areas of origin. The specific classification of countries and areas of origin was not always homogeneous across the three sources of data, in particular in Germany the level of detail was slightly lower. Our primary goal has been to create countries/areas of origin that were consistent across time. Secondly we tried to use the highest level of detail available for each country of destination. On the basis of these considerations we used 30 countries of origin and 14 macro-areas for France and the UK, while for Germany we used 13 countries of origin and 11 macro-areas.

[16] 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.

[Insert Table 4 here]

[Insert Figure 1 here]

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*.[17]Then, for each sector *s* and each country of origin *o*, we computed the share $\lambda_{os}$of migrant workers from a specific country of origin working in that specific sector at the beginning of our period of observation (1994 for France and UK, 1996 for Germany).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).

On the basis of our hypotheses, we expect that the fictional flow of new migrants from a specific country of origin *o* and with education *g*, working in sectors of the 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 tertiary on one side and medium and low on the other) 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 *s* at time *t*. These new flows were used to build the fictional shares of migrants: 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 (5) and for the real shares of high and middle-low educated migrants in equation (6) in an IV setting, since they should be highly correlated with the actual shares of migrants in each sector, but not correlated with the unobserved shocks of TFP.[18]

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[17] 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*.

[18] As with most of the instrumental variable strategies that exploit the Card (2001) intuition, our strategy would not be valid if we found that TFP shocks are persistent over time and that there are some specific unobservables that lead one ethnic group to specialize in sectors with a specific level of these shocks: for example some nationalities with bigger language problems might only be employed in low-tech sectors with low TFP. If that was the case the original distribution of ethnic shares across sectors in the early 1990s might not be exogenous to the current levels of TFP. In our data, however, we did not find clear specialization patterns in the sectoral distribution of ethnicities in the three countries of destination at the beginning of our period of observation. For example, in 1994-1995 Indians were mainly employed in manufacturing sectors in the UK (Textile and Automotive), while in France they were concentrated in Hotels and Restaurants. Poles were mainly employed in the Mining sector in France in the early 90s, while in the UK they were mainly concentrated in Retail Trade and in Germany they were often employed in Agriculture. On the basis of this evidence we can consider the initial distribution of ethinicities across sectors as exogenous to sectoral TFP dynamics.

6. Results

6.1. Baseline results

In Table (5) we report the results of the estimation of the empirical model described by equation (5), which includes only the components of foreign human capital. It allows us to account 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 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 also country-sector dummies and time dummies and they report results obtained with standard errors robust to heteroscedasticity.[19]

[Insert Table 5 here]

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 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 is statistically significant. In columns (4a) and (5a) we distinguish between High-Tech sectors and Low-Tech sectors[20]: we find that the coefficients of the share of migrant workers is 0.055, 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. *Ex ante* it is difficult to assess what type of bias of fixed effects estimates one should expect in this specific empirical setting. A first possible source of bias is related to the fact that the dynamics of the sectors themselves might affect their probability of attracting migrants. More specifically growing sectors most probably demonstrate higher TFP growth and attract more migrants due to a higher demand for labour. If so, this would lead to an upward bias in fixed effects estimates. Another source of bias of fixed effects could instead be due to measurement errors in the number of immigrants, which would lead to attenuation bias and to a

[19] Standard errors clustered at the level of sectors are not suited to this specific empirical setting due to the very low number of available clusters (Angrist and Pischke, 2009). In all of our specifications the number of clusters is never higher than 31, in some cases (such as in high tech sectors) it can be as low as 6.

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

downward bias in OLS estimates. In a different setting Aydemir and Borjas (2011) indeed found that measurement errors in the share of immigrants could substantially bias downward the estimated impact of immigration on wages: the same might also apply to the impact of migration on innovation.

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 results in Table (5) show that the coefficients of the log share of migrants increase quite substantially. This is in line with most of the literature that uses the ethnic enclave instrument (Hunt and Gauthier-Loiselle, 2010; D'Amuri and Peri, 2014; Bosetti et al., 2015). 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 that attenuation bias due to measurement errors plays a big role, leading to a downward bias in the fixed effects estimates with respect to the true parameters represented by the IV estimator.

A further explanation for the larger coefficient of the IV estimator with respect to fixed effects might be that when treatment effects are heterogeneous IV estimates can be given a local average treatment effect (LATE) interpretation; that is they indicate the treatment effect for the immigrants whose treatment status is affected by the instrument. In other words while fixed effects report the average treatment effect for the whole population of immigrants, the IV report the specific effect of the immigrants who found a job in a specific sector following the ethnic ties. In our case the results suggest that these immigrants have a higher impact on innovation. 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 the Appendix in Table A3.a) indicate that the Card-like instrument used to account for the endogeneity of the log share of migrants 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 lead to only 1.5 percent increase in TFP.

In the fixed effects specification the education level of migrants, proxied by the (log) 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 (6).

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. 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 diversity to have a positive effect, 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.

[Insert Table 6 here]

We then investigate more specifically the role of highly-skilled/middle-low-skilled foreign labor force, which is at the center of the migration policy debate.[21] Table (6) reports the results of an estimation based on the model described in equation (6). 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.

The fixed effects estimation results suggest that highly-skilled migrants play a positive role in 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). In this case the downward bias of the fixed effects suggests that especially for highly skilled immigrants measurement errors in official statistics might substantially decrease their measured impact on productivity and innovation. The first stage F-statistics, reported at the bottom of Table (6) (see also the First-stage results in the Appendix in Tables A3.b and A3.c), 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 (7), 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 relatively low in this case.[22]

[21] We also built two measures of diversity, one for highly-educated migrants and another 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.

[22] The failure of the instrument to predict the stock of the highly-skilled in manufacturing is to be imputed to the low presence of 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. 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 the low-tech subset of manufacturing, while in high-tech manufacturing the F-statistics is well above the conventional threshold. Hence, the weakness of the

The fixed effects estimates suggest that middle-low educated migrants have a positive and statistically significant effect in the economy as a whole, in services and in low tech sectors. However, when we account for the possible endogeneity of migrants we find that the positive effect found with fixed effects estimation disappears in most specifications, suggesting that, unlike highly-skilled migrants, demand pull effects might, instead, bias upward the coefficient of the fixed effects estimates for middle-low educated migrants. Differently from the other sectors the estimate for manufacturing increases in magnitude and becomes statistically significant. In line with Peri's (2012) results this finding suggests that especially in manual-intensive tasks the presence of medium and low skilled immigrants might lead to a substantial increase in TFP, not least due to the adoption by firms of technologies that make a more efficient use of unskilled workers. Overall this result once more demonstrates the important role played by middle-low-skilled migrants in manufacturing.

The share of low and medium educated natives is always positive and significant in most specifications, suggesting 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 among migrants age generally displays a negative effect, whereas among natives age displays a generalized positive effect (with the exception of manufacturing).[23] This would suggest that while among natives age can be associated with experience on the job and hence is often a positive factor influencing TFP, among migrants this is not the case. This could be either because individuals who migrated at a late stage of their career cannot properly exploit their previous experience on the job in the country of destination, or because they do not receive proper training on the job during their career in the destination country. The negative effect of age for immigrants is particularly strong and significant in high-tech sectors, suggesting that these sectors strongly benefit from the inflow of young and highly-educated migrant workers.

Summing up, our analysis shows that when one adopts a sectoral perspective the effect of the migrant labor force comes out differently 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[24], because we are able to control for sectors. But there is no question that our results are 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 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.[25]

(Contd.)

instrument in manufacturing is not, so much due to the different behaviour of highly-skilled migrants in manufacturing, but rather to the limited number of high-skilled migrants in low-tech manufacturing sectors

[23] The negative and significant effect of age in manufacturing for natives is likely to be related to the importance of manual work in these sectors, which typically favour young workers.

[24] 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.

[25] In our analysis we paid a great deal of attention to the possible existence of larger brain waste among migrants than among natives. To our surprise, though, when we built a variable indicating the share of migrants in highly-skilled

Another outcome of our analysis is that a sectoral perspective show that, unlike Alesina, Harnoss and Rapoport (2013), diversity does not always playing a positive role in innovation performances: it has a strong and positive effect on the services sectors, but it has no effect elsewhere in 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 in 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.

6.2.Robustness checks

Linear effects of diversity and migration

An important robustness check of our empirical analysis concerns linear or non-linear effects in the relationship between diversity, the share of migrants and TFP growth. In our baseline specifications we have assumed that diversity linearly affects innovation; however, it could also be the case that the effect of diversity might change according to its specific level. In order to check for this in Table (7) we introduce a new specification in which diversity is included with its squared term: the results of the instrumental variables estimations show that the coefficients of diversity differ according to the specific sectors considered. However the effect of diversity and its squared term are never significantly different from zero. Unlike our baseline specification, we also find that when we include its squared term the positive effect of diversity is no longer significant in the services sectors. Overall the results of Table (7) suggest that the limited impact of diversity found in our baseline specification does not depend on whether we allow diversity to exert linear or non-linear effects on innovation.

In a similar fashion Table (8) we also check whether the choice to use the log share of migrants in our baseline specification, which implicitly assumes a non-linear impact on TFP, is likely to affect the results. In Table (8) we use the simple share of migrants instead of its log transformation. The results show that even when we use the simple share of migrants the results are robust and still point to a positive effect of immigration on TFP. Only in the services sector are there some differences with respect to Table (5), since the effect is still positive, but no longer significant. This is due to the fact that in the services sectors the effect of the share of migrants is stronger when the share of migrants is low.[26] While the baseline results are able to account for these non-linear effects, the linear specification in Table (8) cannot, suggesting that in this case the former is to be preferred.

[Insert Table 7 here]

[Insert Table 8 here]

The role of capital intensity

(Contd.) 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 occupation and the result, given the strong correlation of the two variables, remained the same or, in some cases, they were less significant than education.

[26] We checked this by running two separate regressions: one for observations with a share of migrants larger than the median and one for observations with a share of migrants lower than the median: only in the former case was the effect of migrants significant.

Another possible shortcoming of our analysis is that by using TFP we cannot control for the possible effects that the inflow of new immigrants may have on the capital intensity of the firms in which they are employed. The existing literature shows that, especially for low skilled immigrants, the local availability of new and cheaper labour forces may induce firms to delay specific investments in the renewal or upgrading of their stock of capital (machineries and equipment) and increase, instead, the labour intensity of their productive process by hiring new immigrant workers (Lewis, 2011). In the case of skilled workers the effect is less clear-cut, since in some cases the availability of new skilled labour might even spur firms to invest in new technologies (Paserman, 2013). Moreover, this effect typically changes according to the type of sectors, with different results in high tech and low tech industries.

In our case we do not have specific a priori view about the possible effect of immigrants on the capital intensity of the sectors in our sample, since we have very different type of immigrants (skilled and unskilled) and we also have very different types of sectors, including high and low-tech ones, as well as manufacturing and services. In order to understand if there is an important role for capital in our empirical setting we replicate our analyses using the log of labour productivity instead of Total Factor Productivity: indeed the dynamics of capital intensity will very differently affect labour productivity and TFP[27], if, indeed, capital is an important factor in the relationship between immigration and innovation we should expect substantial differences between results obtained using TFP or Labour Productivity as a dependent variable. In Table (9) we show the results obtained using labour productivity as a dependent variable in both our previous specifications. The results show a very robust pattern with respect to the previous specifications, suggesting that the dynamics of capital intensity do not play a particularly relevant role in our specific setting.

[Insert Table 9 here]

7. Conclusions

The role of innovation is of crucial importance for Europe given the rapid and increasing role played by emerging economies, like India and China. Migration policy could represent a way to 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 activity sector 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. This means we avoid 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

[27] While an increase in capital intensity typically leads to an increase in labour productivity, this is not necessarily the case for TFP, since the overall increase of TFP depends on the specific output elasticities of both labour and capital.

booming in those specific years. Therefore, over the years, migrants from different nationalities will stratify in different sectors according to when they arrive. As a consequence a high level of ethnic diversity in a given 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. Moreover, our sectoral aggregate approach seems better suited to derive policy implications than firm-level micro studies, since the external validity of results based on selected samples of firms in a specific country is necessarily lower than studies implemented at the country level.

The analysis is performed using the total number of sectors of the economies of France, Germany and the UK for the years 1994-2007. The outcome measure is the growth of Total Factor Productivity, 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 the well-known procedure first implemented by Card (2001) has been adapted to the 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, as compared to services. Moreover, tertiary-educated migrants have a positive effect on productivity growth mainly in high-tech sectors and to a lesser extent in services. In manufacturing, instead, middle and low educated migrants display a positive effect on TFP growth. Finally, 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.

The analysis is not free of some limitations and these need to be kept in mind. First of all the strategy does not allow for the measurement of possible inter-sectoral spillovers that might increase the aggregate effect of immigration on innovation at the regional or country level. In this respect our results might be considered as a lower bound for the identification of the overall effect of immigration on innovation performances in the three European countries under consideration. Secondly the strategy adopted, by considering only the sectoral affiliation of immigrant workers, does not take into account spatial proximity effects, especially between natives and immigrants. Indeed, it is likely that the effect of immigrants on innovation also depends on the knowledge spillovers that typically take place from close interactions with native workers. Finally the analysis at the sectoral level might be affected by relevant heterogeneities existing among firms within the same sector. It is well known that within the same sector substantial differences might exist between firms in terms of productivity and innovation performances (Dosi et al., 2010, Backman, 2014). Our analysis might not be able to properly account for the existence of specific subsets of very innovative firms which outperform all others.

Keeping in mind these important limitations it is possible to provide some tentative policy implications that draw on the results of our study. Indeed 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 indifferent 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 (e.g. 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 same 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 migrants	0.08	0.08	0.07	0.07	0.08
Composition of migrants by education					
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

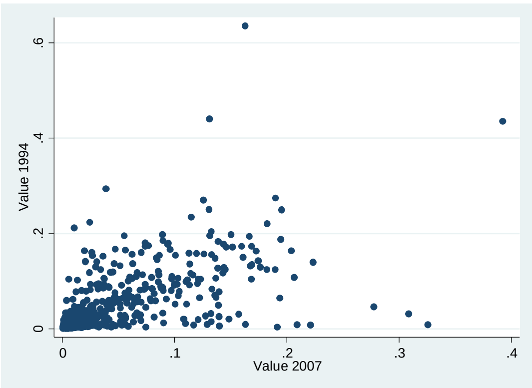
	Mean	Std. Dev.	Min	Max	Definition
TFP	107.82	21.86	26.74	290.87	Total Factor Productivity
Share of migrants	0.073	0.046	0.000	0.29	Share of foreign born in total employed
Education Quality of Migrants	0.228	0.177	0.000	1	Share of high skill foreign born in total foreign born
Share of High Skill Migrants	0.015	0.015	0.000	0.091	Share of tertiary educated foreign born in total employed
Share of M-Low Skill Migrants	0.058	0.042	0.000	0.274	Share of non-tertiary educated foreign born in total employed
Share of M-Low Skill Natives	0.783	0.104	0.318	0.95	Share of non-tertiary educated 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

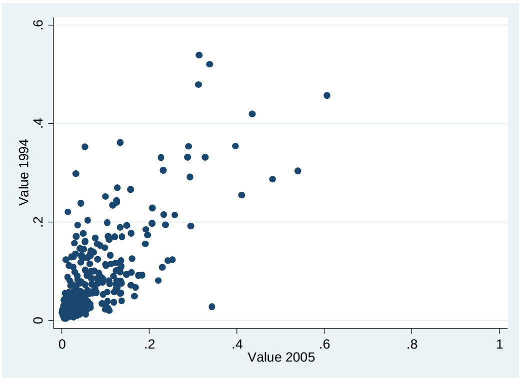
Table 4. Correlation of ethnic sector share over time by countries

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

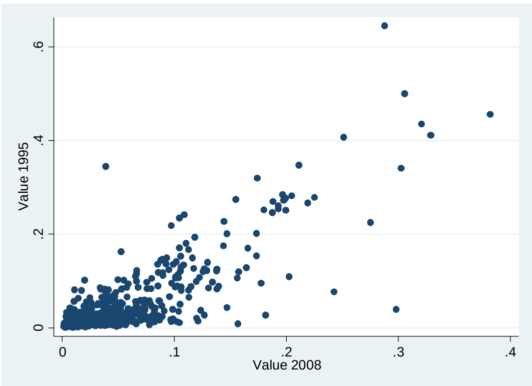
Figure 1.
The relationship between ethnic sector shares (first vs last periods by countries of destination)



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, Education 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 Share of Tertiary Educated 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)
Country-industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 (A3.a) 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)		(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 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 M-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 M-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)
Country-industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 Shareof M-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 High Skill Migrants and the log share of M-Low Skill Migrants. All models include time dummies. First-stage F-statistics are reported. See Tables (A3.b) and (A3.c) for First-Stage coefficients. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness checks: the non-linear effect of Diversity (IV estimates)

VARIABLES	(1) Total IV	(2) Manufacturing IV	(3) Services IV	(4) High-Tech Sectors IV	(5) Low-Tech Sectors IV
log Share of Migrants	**0.217*** **	**0.230*** **	**0.083** **	**0.311*** **	**0.179*** **
	(0.036)	**(0.055)**	**(0.036)**	**(0.058)**	**(0.041)**
log Share of Tertiary Educated Migrants	0.007	-0.003	-0.002	**0.068** **	-0.003
	(0.011)	(0.018)	(0.012)	**(0.030)**	(0.012)
Diversity Index	0.118	-0.526	0.363	-12.250	0.417
	(0.330)	(1.687)	(0.288)	(11.528)	(0.339)
Diversity Index Squared	-0.126	0.163	-0.086	7.511	-0.359
	(0.251)	(1.105)	(0.242)	(6.673)	(0.260)
log Age of Migrants	-5.002	-12.461**	6.931*	-38.055***	-1.426
	(3.538)	(6.209)	(3.674)	(12.159)	(3.705)
log Age of Migrants squared	0.686	1.721**	-0.973*	5.183***	0.200
	(0.481)	(0.842)	(0.500)	(1.649)	(0.504)
Constant	14.408**	28.255**	-7.693	80.512***	7.602
	(6.606)	(11.863)	(6.879)	(24.425)	(6.941)
Country-industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,142	472	670	228	914
Number of sectors	91	38	53	18	73
First stage F statistics	317.59	145.08	247.34	129.98	220.6

Note: The dependent variable is the log of Total Factor Productivity. The table reports the results of a two-stage least squares estimator with country-industry 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. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8. Robustness checks: simple share of migrants (IV estimates)

VARIABLES	(1) Total IV	(2) Manufacturing IV	(3) Services IV	(4) High-Tech Sectors IV	(5) Low-Tech Sectors IV
Share of Migrants	**0.093*** **	**0.073** **	0.015	**0.074*** **	**0.109*** **
	(0.026)	**(0.034)**	(0.011)	**(0.015)**	**(0.040)**
log Share of Tertiary Educated Migrants	0.025	0.015	-0.007	**0.084** **	0.021
	(0.020)	(0.030)	(0.013)	**(0.036)**	(0.025)
Diversity Index	0.107	0.319	0.404	-1.101	0.218
	(0.385)	(0.634)	(0.296)	(13.909)	(0.445)
Diversity Index Squared	0.175	-0.283	0.004	1.548	0.054
	(0.315)	(0.448)	(0.257)	(8.039)	(0.370)
log Age of Migrants	-5.279	-10.459**	8.561**	-28.917*	-4.673
	(3.364)	(4.134)	(3.787)	(14.801)	(3.900)
log Age of Migrants squared	0.753	1.486***	-1.194**	4.009**	0.669
	(0.461)	(0.569)	(0.516)	(2.004)	(0.536)
Constant	12.897**	22.429***	-11.165	56.136*	11.624
	(6.173)	(7.610)	(7.095)	(30.050)	(7.121)
Country-industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,148	478	670	228	920
Number of sectors	92	39	53	18	74
First stage F statistics	24.61	10.72	63.14	60.06	11.93

Note: The dependent variable is the log of Total Factor Productivity. The table reports the results of a two-stage least squares estimator with country-industry fixed effects, using the Card-like instruments, as described in Section 5.2. The instrumented variable is the share of immigrants. All models include time dummies. First-stage F-statistics are reported. See Table (A3.d) for First-Stage coefficients. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 9. Labour Productivity and Foreign Labor Force (IV estimates).

VARIABLES	(1) Total IV	(2) Manufacturing IV	(3) Services IV	(4) High-Tech Sectors IV	(5) Low-Tech Sectors IV	(6) Total IV	(7) Manufacturing IV	(8) Services IV	(9) High-Tech Sectors IV	(10) Low-Tech Sectors IV
log Share of Migrants	**0.266*** **	**0.297*** **	**0.102** **	**0.328*** **	**0.238*** **	-	-	-	-	-
	(0.039)	**(0.059)**	**(0.042)**	**(0.061)**	**(0.046)**	-	-	-	-	-
log Share of Tertiary Educated Migrants	0.012	0.001	0.006	**0.057***	0.005	-	-	-	-	-
	(0.012)	(0.019)	(0.015)	**(0.031)**	(0.014)	-	-	-	-	-
Diversity Index	0.012	-0.249	0.285	-17.788	0.303	-	-	-	-	-
	(0.363)	(1.801)	(0.341)	(12.270)	(0.378)	-	-	-	-	-
Diversity Index Squared	-0.118	-0.108	-0.048	10.593	-0.349	-	-	-	-	-
	(0.276)	(1.180)	(0.287)	(7.103)	(0.290)	-	-	-	-	-
log Share of High Skill Migrants	-	-	-	-	-	**0.219*** **	-0.318	**0.118*** **	**0.293*** **	**0.266*** **
	-	-	-	-	-	**(0.066)**	(0.389)	**(0.040)**	**(0.074)**	**(0.078)**
log Share of M-Low Skill Migrants	-	-	-	-	-	0.074	**0.433** **	-0.029	0.144	0.042
	-	-	-	-	-	(0.068)	**(0.209)**	(0.056)	(0.142)	(0.075)
log Share of M-Low Skill Natives	-	-	-	-	-	0.597***	0.544	-0.001	0.884**	0.905***
	-	-	-	-	-	(0.230)	(0.914)	(0.181)	(0.437)	(0.340)
Constant	18.843***	30.599**	-3.952	84.444***	12.515	-62.690*	292.707**	-125.961***	-136.397	-35.056
	(7.201)	(12.387)	(8.021)	(24.794)	(7.651)	(34.286)	(116.507)	(29.838)	(120.825)	(41.089)
Country-industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,142	472	670	228	914	1,140	471	669	228	912
Number of sectors	91	38	53	18	73	91	38	53	18	73
First stage F statistics	317.59	145.08	247.34	129.98	220.6					
log Share of High Skill Migrants	-	-	-	-	-	31.07	2.66	58.41	27.81	19.91
log Share of M-Low Skill Migrants	-	-	-	-	-	78.95	33.88	62.88	18.83	61.27

Note: The dependent variable is the log of Labour Productivity. All models include additional control variables, as in Tables (5) and (6).All models include time dummies. The table reports the results of a two-stage least squares estimator with country-industry fixed effects, using the Card-like instruments, as described in Section 5.2. In columns (1) to (5) the instrumented variable is the log share of immigrants, in columns (6) to (10) the instrumented variables are the log share of high skill immigrants and the log share of middle- low skill immigrants. First-stage F-statistics are reported. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 11. Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12
1	log TFP	1.000											
		0.000											
2	log Share of Migrants	-0.003	1.000										
		0.930	*0.000*										
3	log Share of High Skill Migrants	-0.105	0.493	1.000									
		0.000	*0.000*	*0.000*									
4	log Share of M-Low Skill Migrants	0.049	0.950	0.252	1.000								
		0.096	*0.000*	*0.000*	*0.000*								
5	log Share of M-Low Skill Natives	0.129	0.028	-0.365	0.197	1.000							
		0.000	*0.334*	*0.000*	*0.000*	*0.000*							
6	Diversity Index	-0.075	0.241	0.329	0.142	-0.119	1.000						
		0.011	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*						
7	Diversity Index squared	-0.052	0.228	0.404	0.111	-0.181	0.967	1.000					
		0.078	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*					
8	log Education Quality of Migrants	-0.112	-0.257	0.715	-0.479	-0.434	0.176	0.272	1.000				
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*				
9	log Age of Migrants	-0.015	-0.170	-0.144	-0.139	0.013	-0.112	-0.177	-0.023	1.000			
		0.617	*0.000*	*0.000*	*0.000*	*0.669*	*0.000*	*0.000*	*0.425*	*0.000*			
10	log Age of Migrants Squared	-0.012	-0.174	-0.147	-0.142	0.013	-0.121	-0.186	-0.024	1.000	1.000		
		0.690	*0.000*	*0.000*	*0.000*	*0.655*	*0.000*	*0.000*	*0.421*	*0.000*	*0.000*		
11	log Age of Natives	0.100	-0.006	0.024	-0.039	-0.143	-0.103	-0.103	0.036	0.206	0.208	1.000	
		0.001	*0.831*	*0.415*	*0.187*	*0.000*	*0.000*	*0.000*	*0.215*	*0.000*	*0.000*	*0.000*	
12	log Age of Natives Squared	0.100	-0.003	0.026	-0.036	-0.143	-0.102	-0.101	0.037	0.204	0.206	1.000	1.000
		0.001	*0.908*	*0.370*	*0.217*	*0.000*	*0.001*	*0.001*	*0.211*	*0.000*	*0.000*	*0.000*	*0.000*

P-values are reported in italics below correlations’ coefficients.

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

KLEMS data and the computation of TFP

The KLEMS database includes measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all European Union member states from 1970 onwards. The methodology used to compute the KLEMS sectoral TFP relies on the usual growth accounting framework (Jorgenson, Ho and Stiroh, 2005), according to which TFP growth is computed as:

$$\Delta \ln TFP_{st} = \Delta \ln Y_{st} - \alpha \Delta \ln K_{st} - \beta \Delta \ln L_{st}$$

Where Y represents the total value added of a sector, K represent capital services and L denotes labour services. The indexes s, and t indicate respectively sector and year. All productive inputs are weighted by their specific revenue share α and β. On the basis of this formula KLEMS provides a TFP index for each national sector from 1991 to 2007. The great advantage of the KLEMS measure of TFP is that the measurement of labor and capital inputs is extremely precise. Labour inputs are measured taking into account the specific number of working hours of the employees of each sector and several other characteristics of the labour force. The capital services distinguishes between 9 different asset types, among which machinery and equipment, computing equipment, transport equipment, and intangible assets. The capital services are also computed using different depreciation rates for each asset types and for different sectors (for further details see Mahony and Timmer, 2009).

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.

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 continuously 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 one 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.

Appendix Section 3

Table A3.a. First stage of the 2SLS in Table (5): 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***
	(0.033)	(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 A3.b.. First stage of the 2SLS in Table (6): the dependent variable is the log share of high skill 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 high skill 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 A3.c. First stage of the 2SLS in Table (6): the dependent variable is the log share of middle low skill migrants

VARIABLES	(1) Total Economy	(2) Manufacturing	(3) Services	(4) High-Tech Sectors	(5) Low-Tech Sectors
Predicted (log) share of M-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 midlle-low skill 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 A3.d. First stage of the 2SLS in Table (8): the dependent variable is the share of migrants

VARIABLES	(1) Total Economy	(2) Manufacturing	(3) Services	(4) High-Tech Sectors	(5) Low-Tech Sectors
Predicted share of migrants	0.085***	0.073***	0.317**	0.467***	0.063***
	(0.017)	(0.022)	(0.040)	(0.060)	(0.018)
Set of exogenous variables included in the second stage	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,148	478	670	228	920
Number of sectors	91	38	53	18	73
F statistics (I stage)	24.61	10.72	63.14	60.06	11.93

Note: This table reports the first stage statistics for the Card-like instrument in Table (8), where we instrument the share of migrants in each sector. The construction of the instrument is explained in detail in Section 5.2. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1