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FOREIGN HUMAN CAPITAL AND TOTAL FACTOR PRODUCTIVITY: A SECTORAL APPROACH

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We analyze the role of migrants in productivity growth in the three largest European countries—France, Germany and the United Kingdom—in the years 1994–2007, using Total Factor Productivity. Unlike previous research, which mainly employs a regional approach, our analysis is at the sectoral level: this allows to distinguish the real contribution of migrants to productivity from possible inter-sectoral complementarities, which might also foster growth. We control for the share of migrants and the different components of human-capital, such as education, age and diversity, and adopt instrumental variables strategies to address the possible endogeneity of migration. The results show that migrants contribute to the productivity of the sectors in which they are employed, but with important differences: highly-educated migrants show a larger positive effect in high-tech sectors, and to a lesser extent in services sector. The diversity of countries of origin contributes to productivity growth only in the services sectors.

JEL Codes: F22, F66, O31, O32

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1. INTRODUCTION

The contribution of migrant workers to the economic and innovative performances of European countries is an intensely debated topic, both in the academic and in the policy-oriented communities. While recent political developments in European societies tend to highlight possible negative consequences of immigrant inflows on welfare of the receiving countries, evidence in the academic literature provides many examples of positive contribution of immigrants to the economic growth of the communities in which they are located.

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Indeed recent contributions have shown that among the many factors that drive productivity growth immigration is an important one (Peri, 2012; Mitaritonna *et al.*, 2017; Bahar and Rapport, 2018), able to explain some of the differential rates of growth between regions and countries. The contribution of migrants to productivity growth is manyfold. Migrants might, for one, improve the level of innovativeness of economies through the supply of specific skills and competences. Migrants, especially skilled ones, may also foster the diffusion of new ideas, new way of working that spur innovation and eventually lead to economic growth. The existing literature has shown that the inflow of skilled migrants, in particular foreign graduates in science and technology, greatly fostered the production of innovation in the US, as proxied by the number of patent applications (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 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 (Bosetti *et al.*, 2015; Gagliardi, 2015).

Other studies 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; Mitaritonna *et al.*, 2017). This is likely to be the case also for some countries in Europe, 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 migrants could be beneficial for the future growth of these economies.

Lastly, another recent stream of literature has investigated the effect of ethnic diversity of the labor force on the economic performances of firms, regions and countries, finding in most cases that diversity has a positive effect on productivity growth and innovation (Alesina *et al.*, 2016; Ozgen *et al.*, 2012). Therefore, the inflow of new migrants in Europe from different countries, by increasing the overall diversity of the labor force, might also spur growth.

The objective of this paper is to investigate the contribution 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 favored destinations for European and non-European migrants.

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 *et al.*, 2012; Alesina *et al.*, 2016). 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 growth and 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, as well as the sectoral-level dynamics of capital investments (Breschi *et al.*, 2000; Inklaar *et al.*,

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2005; Castellacci, 2010). Using the sector as the unit of analysis leads to an alternative investigation into the link between migration and productivity, because it allows for a measurement of the direct impact of migrants on the productivity growth of the sectors in which they are employed. The existing literature has shown the importance to account for intangible assets when explaining the sectoral dynamics of productivity (Niebel *et al.*, 2017), as well as when cross-country comparisons on income levels are performed (Chen, 2018). Human capital is a relevant component of the intangible assets, hence also the human capital brought by immigrant workers is likely to play an important role in the productivity dynamics of the industries.

By adopting a sectoral perspective we are also able to check for differentiated effects of migrants according to the specific type of sectors in which they are employed, distinguishing between manufacturing and services, and also between high- and low-tech sectors. Previous studies that analyze migration and productivity growth and innovation 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 regions with highest economic growth, but are not necessarily employed in the sectors that are actually innovative.

The sectoral perspective also allows enriching the analysis of the link between ethnic diversity and productivity growth. Existing studies have analyzed diversity at the geographical level that is, measuring the diversity of migrants in a specific region or country (Ager and Brueckner, 2013; Alesina *et al.*, 2016). 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 productivity 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.

In the empirical specification we measure the impact of migration (proxied by the share of migrants on total employment) on the growth of Total Factor Productivity, at the sectoral level. We also control for the education level of migrants, their age and the diversity of their countries of origin.[1]

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

[1]By using the share of migrants and its characteristics (age, education and diversity), we adopt a specific measure of diversity, which only measures the diversity of nationalities among the immigrants, contrary to the recent paper by Ager and Bruecnker (2013), which ask a very interesting but different question, and compare polarization and diversity including the natives in the computation of the two indexes.

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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 also when one adopts the sectoral unit of analysis migration -proxied by the share of migrants among workers in each sector- displays a positive effect on Total Factor Productivity growth. This provides a further confirmation of the positive effect of immigration on productivity found in existing studies at the regional or country level. Our specification however allows us also to distinguish whether this positive effect is homogeneous across different sectors. Our results show that this is not the case: the impact of immigrants is stronger in manufacturing than in services, and it is especially large in the high-tech sectors. Also the effect of the education level of immigrants differs a lot among sectors: tertiary-educated migrants have a positive effect on productivity growth especially in high-tech sectors and - to a lesser extent - in services. In some sectors -the manufacturing sectors- also middle and low educated migrants display a mild positive effect. Finally, when we analyze diversity at the sectoral level we find that it 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.

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

The existing literature has provided various empirical and theoretical contributions that allow to identify the mechanisms through which migrants contribute to productivity growth and innovation. An important factor that may lead to a positive productivity effect is related to the diffusion of new ideas that is brought by an inflow of immigrants. Migrant workers, especially skilled ones, may foster the diffusion of tacit knowledge related to the production of new goods, new way of working which eventually leads to increased productivity levels. This is shown for example by Bahar and Rapoport (2018) who use a cross-country dataset to show that the countries that receive an inflow of immigrants from a specific country of origin become more efficient in the production of goods in which the origin country is specialized in. This means that immigrants bring with them tacit knowledge about the production of specific commodities, helping the diffusion of new ideas in the country of destination. Recent contributions extend this perspective by showing that the positive effect of immigration on productivity growth can also be linked to its role in increasing product diversity at the country level (Iranzo and Peri, 2009; Di Giovanni *et al.*, 2015). Another reason behind the positive effect of immigrants on productivity is put forward by Peri and Sparber (2009), who argue that the inflow of immigrants may allow for increased task

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specialization between natives and immigrants, which on its turn may increase better efficiency and productivity increases. Mitaritonna *et al.* (2017) show that immigrants can help boosting productivity by allowing also less productive firms to cut costs and adopt new technologies and increasing specialization, which eventually allows them to increase their productivity. It must be stressed that the literature that looks at the contribution of migrants to productivity growth and innovation has mainly looked at the marginal impact of migrant flows on the productivity of firms and countries, but it has not addressed the issue of whether immigrant workers are comparatively more productive than natives. The studies that look at the wage-gap differential between natives and immigrants suggest that among the many factors that influence this gap (such as for example workplace discrimination) it is also important to include the possibility that immigrants have a lower productivity with respect to natives, due for example to the lack of literacy (Himmler and Jäckler, 2018). Indeed the only study, to our knowledge, that specifically measures the differential contribution of immigrants and natives is the paper by Fassio *et al.* (2019), in which the authors show that the output elasticity of skilled immigrants to patent production in European countries is positive, but lower (about one third) than that of skilled natives.

Since the paper of Dolado *et al.* (1994), which first introduced migrant workers in a production function framework and analyzed 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. Different units of analysis have been adopted to study the impact of migration. The most common approach is to rely on analyses performed at the geographical level (country, regions or provinces)[2]. In many studies a positive effect for migration (especially highly-skilled migration) on productivity growth 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 *et al.* (2016) adopt a country level perspective and find a positive effect for the share of immigrants on GDP and TFP *per capita*. A number of studies has also focused on the impact of immigration on direct measures of technology creation and innovation. Bosetti *et al.* (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 highly-skilled migrants active in the fields of Science and Technology on the number of patent applications in US cities. Gagliardi (2015) finds that highly-skilled migrants positively impact the innovative performances of British firms using provinces as the unit of analysis.

Another way through which immigration can foster productivity growth is through increased diversity of the labor force. Alesina and LaFerrara (2005) suggest that a more diverse workforce may also allow for better problem solving abilities. In

[2]An interesting direction of the research include also firm level studies, which unfortunately do not always provide clear indications of the relation between migration and productivity, because the results often change according to the specific national sample chosen for the analysis. For a survey see Venturini *et al*. (2017).

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other words a more cognitively diverse group of people maybe be able to find better solutions to complex problems (Hong and Page, 1998). This is very much in line with the findings of existing research on multicultural teams in business studies (Stahl *et al.*, 2010). Lazear (1999) shows that different skills may increase the productivity of a production unit, although he also highlights that over certain levels of diversity too much differences in languages and cultures may actually decrease the benefits of diversity.

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. Alesina *et al*. (2016) find that the diversity of migrants in terms of country of birth is positively associated with TFP at the country-level, and the effect is more prominent for the diversity of highly-skilled migrants. In most of the cases the studies find that it's the overall variety of nationalities that fosters economic growth. Ager and Brückner (2013) find that also about a century ago cultural diversity fostered economic growth in the United States, in the so-called "age of mass migration." However they also find that, while diversity measured as fractionalization, increases output, polarization, which proxies the presence of a large group of immigrants from the same country of origin, instead has a negative effect on the output growth of the US counties in the period 1870–1920. Many studies measure the impact of diversity on direct measures of innovation. Using regional level data for European countries Ozgen *et al*. (2012) find that patent applications are positively associated with the diversity of the immigrant community in the region. 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, among the studies that adopt a geographical approach to study the relationship between migration and productivity some find a positive effect for (mainly skilled) migration, 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 growth performances.

In the next section we will show how adopting a sectoral perspective can offer a complimentary perspective with respect to the existing literature.

3. The Rationale for a Sectoral Analysis of Migration and Productivity

Despite its prominent use in aggregate analyses the geographical approach has some important limitations: not least that it overlooks the role of economic sectors for migrant employment. The literature on Technological Regimes (Breschi *et al.*, 2000; Castellacci, 2010) 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, the innovative activities that lead to productivity growth 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 productivity in several respects.

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3.1. *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 economic 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 productivity growth: 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 focusing in on their direct contribution to productivity. On the basis of these considerations it seems important to check if the estimated effects of immigration on productivity, found in analyses that adopt a geographical approach, still hold when a sectoral analysis is implemented.

3.2. *The Effect of Migrants' Education*

The literature on the effect of migration on productivity 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 growth 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 and productivity growth are often achieved 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 productivity 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.

3.3. *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 advocate implementation of a migration policy based on a national quota system (which selects migrants by countries of origin) over selection systems based on education and experience. However, here, too, a sectoral perspective

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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[4].

If that is the case the positive effect of the diversity of migrants on productivity and innovation 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.[5] 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.

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

[4]For the empirical evidence of the spilover effects see Goodridge *et al.* (2016).

[5]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). $\textit{Diversity Index}_{jc} = 1 - \sum_{i=1}^{N} \textit{Share}_{ijc}^{2}$. 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 (2012) than to the one developed in Alesina *et al.* (2016) as the latter considers natives as well. Higher values of the index imply a more equal distribution of migrants by country of origin.

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TABLE 1
Diversity Index (Within Migrants)

Sector	1994-1996 UK	1994-1996 France	1994-1996 Germany	2005-2007 UK	2005-2007 France	2005-2007 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 administration	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.

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3.4. *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, 2015). The different average age of native and immigrant workers should then be taken into account in any analysis of the effect of migration on innovation; otherwise age might become a confounding factor in the results of the analysis.

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 measures the level of Total Factor Productivity and comes from the publicly available EU KLEMS Growth and Productivity Accounts database[6] (see Appendix 2 for a more detailed description of the data). 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. While there is not a unique way of estimating or computing TFP, and several different methods have been introduced in the literature (Gu and Yang, 2016), the TFP data -which is computed and not estimated- provided by the KLEMS project has several advantages, as described by O'Mahony and Timmer (2009): in particular it allows for 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, we used individual level data coming from the Labor Force Surveys for France and the UK and by the Micro-Census for Germany (see Section 2 of the Appendix). These datasets allow for constructing human capital variables at sector level, as they contain information on the country of origin, age, education level and sector of employment of individuals. This allowed to build a dataset which contains information on the composition of labor force both in terms of origin and education level at the 2-digit sector level. As a result for each sector we computed the share of migrants among total employed, the share of tertiary educated both among natives and migrants and the average age of both groups.

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

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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.

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.[7] 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 percent), closely followed by manufacturing (2.79 percent). Instead, the slowest growth of TFP is observed in services (0.68 percent). 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 percent. On average, migrants are only slightly younger than natives. Not surprisingly the highest share of tertiary-educated individuals is in high-tech, which usually 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 percent.[8]In some sectors migrants constitute up to one quarter of the labor

[7]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.

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

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force.[9] Though the percentage of migrants is quite homogenous across sector groups considered (7–8 percent) the level of education of migrants varies significantly. 28 percent of migrants in high-tech are tertiary-educated, which is well above the average of the whole pool of sectors considered (23 percent). High-tech sectors have the youngest and most educated employees; whereas manufacturing is characterized 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.

5. Model and Methodology

5.1. *The Empirical Strategy*

We want to test the impact of the share of migrants on the productivity growth of different sectors, controlling for specific characteristics of the immigrants such as age, education and country of origin, since we believe that these will have differentiated effects according to the sector types considered. We adopt a simple model in which productivity growth is measured by Total Factor Productivity.

There are important limitations to keep in mind when using TFP growth as a proxy for technological change, 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.[10] Despite these limitations the use of TFP has important advantages since it directly captures the economic impact of technological change and it can be computed for all sectors in the economy, regardless of the specific type of innovation that they implement.[11] In this study we use the sectoral TFP provided by the KLEMS database and computed according to the usual accounting framework approach (Jorgenson *et al.*, 2005; Hartwig, 2011). The main advantage of this measure is the extreme precision of the measurement of the labor and capital inputs, which take into account the specific number of working hours, 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

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

[10]Other shortcomings, from the use of the growth of computed Total Factor Productivity, depend on underlying assumptions about the presence of constant returns to scale in the economy (see also Maynard, 2016) and from the adoption of the Euler Theorem according to which the overall compensation of labor 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.

[11]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.

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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—labor and capital –as well as by human capital, as proxied by specific characteristics of the labor force, such as education, ethnicity, age and diversity.[12]

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

where Y indicates total value added, K and L indicate respectively capital and labor 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. 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 labor inputs are already used in the computation of Total Factor Productivity we cannot use the levels of the labor variables to explain the levels of TFP, because this would risk double counting the labor 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:

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

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) we include the share of migrants among the labor force, the diversity of country of origin among migrants, in addition 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:

[12]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, 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 activities in the services sector (Tether, 2005).

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

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.

5.2. *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 total employment of a national sector, *age* is the log of the average age of migrant workers employed 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 employed 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 an 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.[13] 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

[13]As an example, if in a given sector the share of migrants increases from 5 percent to 6 percent, this will correspond to a 20 percent increase of the share of migrants in that sector. Conversely, if in a given sector the share of migrants increases from 20 percent to 21 percent this will correspond to a 5 percent increase in the share of migrants.

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sector in which migrants dominate and in a sector in which they go to make up only a minimal percentage of those employed.

5.3. *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:

$$\begin{aligned} tfp_{sct} = {} & \beta_1 smte_{sct} + \beta_2 smmle_{sct} + \beta_3 snmle_{sct} + \beta_4 agem_{sct} + \beta_5 agesqm_{sct} + \beta_6 agen_{sct} \\ & + \beta_7 agesqn_{sct} + \psi_{sc} + \eta_t + \varepsilon_{sct} \end{aligned} \tag{6}$$

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;[14] *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. In Table 3 we indicate how we built the variables included in the model and we report descriptive statistics.In the Appendix (Table A1.d) we also show the correlation table for the variables included in the table.

5.4. *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 additional factors, the role

[14]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.

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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.

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.[15] Moreover, the fixed effects estimator is only consistent under the strict exogeneity assumption, according to which past

[15]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 investment 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.

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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.

5.5. *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 (Tapinos, 1996, Dustmann *et al.*, 2003; Constant *et al.*, 2005; Danzer and Yaman, 2013; Strom *et al.*, 2018) 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 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.[16] We call this measure the *ethnic sector share*, computed as follows:

[16]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.

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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

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

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.[17] 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.

5.6. *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

[17]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.

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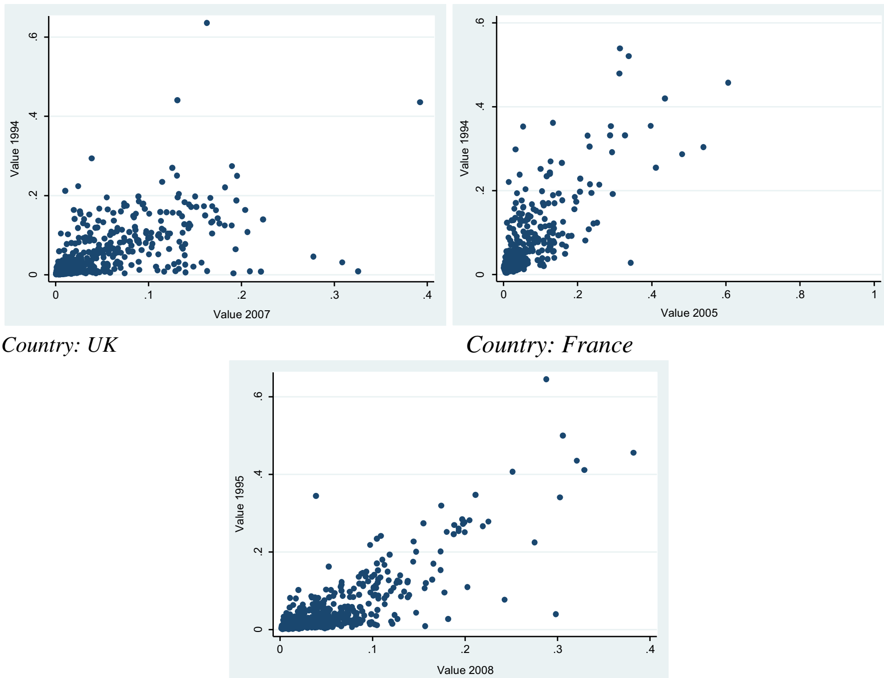

Country: UK *Country: France*

Country: Germany

Figure 1. The Relationship Between Ethnic Sector Shares (First vs Last Periods by Countries of Destination).
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. [Colour figure can be viewed at wileyonlinelibrary.com]

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.[18] Then, for each sector s and each country of origin o, we computed the share λ_{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 s of the specific country of destination, will be equal to:

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

[18]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*.

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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.[19]

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.[20]

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)

[19]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 unobservable 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 ethnicities across sectors as exogenous to sectoral TFP dynamics.

[20]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. As an additional robustness check we also ran our model with bootstrapped standard errors: the results are in line with those presented in the paper.

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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.

***$p < 0.01$;**$p < 0.05$;*$p < 0.1$.

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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: we find that the coefficients of the share of migrant workers is in line with the results for the total economy, but it is significant only in Low-Tech sectors.

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 labor. 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 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 productivity.

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 productivity. 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).

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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, but only at the 10 percent level. 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.[21] 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.[22]

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 productivity (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.

[21]Following the existing literature (Niebhur, 2010), we have also tried to account for possible non linear effects of diversity by including a squared term in our specification. The results do not change from the ones presented in the paper, as diversity is always non significantly different from zero, also when we account for its non-linear effect.

[22]In line with the results found by other studies who measured diversity as separated from polarization (Ager and Brueckner, 2013), we have also checked whether the inclusion of a polarization index would substantially affect the impact of diversity. In order to have comparable measures with respect to the existing studies on diversity and polarization we computed the diversity and polarization index including the natives in the computation and excluding the migrant share from the independent variables of our model. The results show that there is no substantial effect of neither of the two indexes on our measure of productivity growth. This confirms the non-significant effect of diversity on productivity at the sectoral level.

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We then investigate more specifically the role of highly-skilled/middle-low-skilled foreign labor force.[23] 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 previous 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 6, among manufacturing sectors the Card-like instrument for highly-educated migrants does not have sufficient explicative power. Therefore, the reliability of the results of the second stage for highly-educated migrants is relatively low in this case.[24]

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

[23]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.

[24]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 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.

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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 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

$^{***}p < 0.01$;$^{**}p < 0.05$;$^{*}p < 0.1$.

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for middle-low educated migrants. Differently from the other sectors the estimate for manufacturing increases in magnitude and becomes statistically significant, even if only at the 10 percent level. 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.

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). 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. On average, the share of migrants out of total employment is not higher than 10 percent in the three countries considered. Our results tell us that an increase from 10 percent to 11 percent—which amounts to a 10 percent increase of the share of migrants—would lead to a 3 percent increase in TFP in high-tech sectors but of only 0.8% in services. Our results are lower than Ortega and Peri (2014)'s elasticity of 6 percent,[25] 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 productivity growth.[26]

[25]Ortega and Peri (2012) 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.

[26]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 occupations we found that the correlation with the share of highly-educated migrants was very high, around 98 percent. 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 productivity dynamics. 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.

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Another outcome of our analysis is that a sectoral perspective shows that, unlike Alesina *et al*. (2016), diversity does not always play a positive role in productivity performances: it has a strong and positive effect on the services sectors, but it has no effect elsewhere in the economy. We propose that the explanation for the difference in our results for the limited role of diversity may 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*

6.2.1. Labor Productivity and the Role of Capital Intensity

A 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 labor force may induce firms to delay specific investments in the renewal or upgrading of their stock of capital (machineries and equipment) and increase instead the labor intensity of their productive process by hiring new immigrant workers (Lewis, 2011). In the case of skilled workers instead the effect is less clear-cut, since in some cases the availability of new skilled labor might even spur the investments of firms in new technologies (Paserman, 2013). Moreover this effect typically changes according to the type of sectors, with different results found between high tech or low tech industries.

In our case we do not have specific a priori about the possible effect of immigrants on the capital intensity of the sectors in our sample, since we have very different types 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 of capital in our empirical setting we replicate our analyses using the log of labor productivity instead of Total Factor Productivity: indeed the dynamics of capital intensity will affect very differently labor productivity and TFP: while an increase in capital intensity typically leads to an increase in labor productivity, this is not necessarily the case for TFP, since the overall increase of TFP depends on the specific output elasticities of both labor and capital. If indeed capital is an important factor in the relationship between immigration and productivity we should expect substantial differences between the results obtained using TFP or Labor Productivity as a dependent variable. We use the same source of data that we used for TFP, i.e. the sectoral levels of labor productivity provided by the EU KLEMS Growth and Productivity Accounts database. In Table 7 we show the results obtained using labor productivity as a dependent variable in both our previous specifications. We only show the result of the IV specification, as this is our preferred one. The results in columns (1) to (5) show that when we run the specification of equation (5) the results are very stable, we find a moderate increase (about 20 percent) of the coefficient of the share of migrants in all sectors. When we estimate equation (6) we

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find instead that the results are roughly the same as those found in Table 6. These results suggest that the dynamics of capital intensity do not play a very relevant role in our specific setting. At the same time, in the case of equation (5) it suggests that the coefficient of the share of migrants obtained using TFP as a dependent variable can be considered as a lower bound, with respect to the overall impact of migrants on productivity (Table 7).

7. Conclusions

In this paper we have analyzed whether and to what extent migrants contribute to the productivity growth of thee 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 high productive sectors. Moreover, by measuring ethnic diversity at the sectoral level, we are able to disentangle the actual effect of diversity from the effect of the so-called Jacobian externalities, that is complementarities between sectors. Since migration typically occurs through successive waves of migrants from distinct countries of origin, in each period the flow of migrants will be absorbed by the sectors that are booming in those specific years. Therefore, over the years, migrants from different nationalities will 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 appropriate to derive policy implications.

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. 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

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TABLE 7
LABOR PRODUCTIVITY AND FOREIGN LABOR FORCE (IV ESTIMATES)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total	Manufacturing	Services	High-Tech Sectors	Low-Tech Sectors	Total	Manufacturing	Services	High-Tech Sectors	Low-Tech Sectors
Variables	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
log Share of Migrants	0.267***	0.297***	0.102**	0.340***	0.243***	-	-	-	-	-
	(0.039)	(0.058)	(0.042)	(0.063)	(0.046)	-	-	-	-	-
log Share of Tertiary Educated Migrants	0.012	0.001	0.005	0.041	0.004	-	-	-	-	-
	(0.012)	(0.019)	(0.015)	(0.030)	(0.014)	-	-	-	-	-
Diversity Index	-0.138	-0.414**	0.230**	0.492	-0.137	-	-	-	-	-
	(0.099)	(0.188)	(0.101)	(0.472)	(0.105)	-	-	-	-	-
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.

***$p < 0.01$;**$p < 0.05$;*$p < 0.1$.

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Total Factor Productivity growth. This is a first important results, which confirms that the effect of immigrants on productivity depends on the direct contribution of immigrants to the productivity of the sectors in which they are employed. The second relevant result is that the impact of this 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 mild 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, at least for non-services-based activities, 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 productivity also depends on the knowledge spillovers that typically take place from close interactions with native workers. A further limitation of our analysis is that it does not specifically inquire whether the contribution of immigrants differs from the natives' one, even if we control for it. This is a very interesting field of research which however lies outside the scope of this paper, but which would provide important information to policy makers. Lastly, our production function approach is well suited to identify the supply effect of immigration at the sectoral level, but it is not able to properly account for the aggregate welfare effects of the inflow of immigrants on the countries of destination. Indeed an inflow of immigrants will also have an impact on the demand for housing, healthcare and schooling. This demand factors, which we do not account for in this model, should necessarily be considered when the overall impact of immigration is to be assessed.

Keeping in mind these important limitations it is possible to provide some tentative policy implications that can be drawn from the results of our study. First of all our analysis shows that migrants directly contribute to the productivity of the sectors in which they are employed: this implies that policies aimed at drastically decreasing the inflow of immigrants should consider that this might also have some impact on productivity growth. However our analysis also shows that, when one distinguishes by education level, the impact of migrants on productivity varies considerably according to the sectors in which they are employed. The positive effect of tertiary-educated migrants is especially strong in the high-tech sectors and—to a lesser extent—the services sectors. This suggests that, in order to foster productivity, 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. Moreover our findings suggest that a migration policy intended to foster the productivity of European

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countries should be strongly demand-driven, that is, it should take into account the specific needs of firms active in different sectors. While tertiary-educated migrants are important for specific sectors with high knowledge content, countries in which manufacturing (in particular mid-low tech manufacturing) still has an important role in the overall economy may not benefit much from this category of foreign workers. Hence policy makers should consider introducing 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 analyzed 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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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Appendix Section 1

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

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

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

Table A1.d: Correlation table

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Appendix Section 2

2.1: Data description
2.1.1: KLEMS data and the computation of TFP
2.1.2: UK Labour Force Survey
2.1.3: French Labor Force Survey
2.1.4: German Microcensus

Appendix Section 3

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

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