The impact of immigration on output and its components: A sectoral analysis for Italy at regional level

Ivan Etzo[†], Carla Massidda[†], Paolo Mattana[†], Romano Piras[‡]

Abstract

This paper studies the impact of immigrant workers on Italian sectors. The analysis is based on the channel output decomposition approach, by means of which the effect of immigration is measured with respect to per capita value added and its components. The empirical investigation is carried out at sector level during the period 2008–2011. The results show that immigrants exert a positive impact on total output which is mainly driven by the effect on total factor productivity. The main finding is that not all sectors benefit from the productivity gains. The sectors that mostly take advantage of immigrant workers are those featured by the predominance of manual tasks not requiring high communication skills.

Keywords: channel output decomposition approach, immigrant workers, Italy, sectors, regions.
JEL Classification: F22, F62, J61

[‡] University of Cagliari, Department of Social Sciences and Institutions.

1. Introduction

During the last decades, with the rising of international migration flows, the impact of immigrants on the hosting economy has become a hotly debated topic in economic research. In both empirical and theoretical studies, the debate has centered on the impacts of immigrants on the main labor market outcomes, namely wages and employment. The recent literature has not yet reached consensus on whether immigrants have negative, positive or none effect on wages and employment (Borjas et al., 2012; Dustmann et al., 2016; Ottaviano and Peri, 2012). However, differently from the traditional labor market model where immigration is considered as an increase in supply of homogenous labor, it is now widely recognized that immigrant and native workers are heterogeneous and thus do not perfect substitute with each other. Taking into account the skill diversity of immigrant workers bears important implications in that it opens up new perspectives on the analysis of the impact of immigration. In fact, a higher skill differentiation widens the spectrum of possible complementarities between different types of jobs/tasks, increases workers competition and promotes task specialization (Ottaviano and Peri, 2013). Firms can take advantage of the increase in the supply of skills by allocating more efficiently workers in the production process and eventually by changing the production techniques. As a result, an immigrant-induced increase in the supply of skills, by fostering a more efficient allocation of tasks, raises efficiency in production with possible positive effects on output and productivity. Capital adjustments are also possible, in that firms might respond by changing production techniques in order to better exploit the work-force diversity (Lewis, 2011).

Based on these mechanisms, a recent strand of literature proposes an economy-wide perspective and investigates the effects of immigration on total output and its components. A noteworthy result is that immigrant workers exert a positive impact on output which is mainly driven by an increase in total factor productivity (Peri, 2012; Aleksynska and Tritah, 2015). The present paper contributes to this literature by providing new empirical evidence for the Italian regions. In addition, a novel contribution of this study is that it investigates whether the impact of immigrant workers on output and its components varies across sectors. The latter is an important issue because sector heterogeneity in the transmission mechanisms of immigration shocks might lead to sector composition changes (Bettin et al., 2014). At this regard, Italy represents an interesting case for three main reasons. First, immigration has become increasingly important during the last two decades. Foreign citizens, 1.3 millions in the 2001 census, more than tripled in the subsequent ten years overtaking 4 millions in 2011. Second, immigrants in Italy are overwhelmingly low-educated, heterogeneously distributed across regions and disproportionately employed in low-skill intensity sectors. Third, there are noticeable differences across regions with respect to sectoral shares, measured in terms of both value added and total employment, as well as with respect to the share of immigrant workers employed in each sector. Therefore, by providing a regional analysis at sector level this study aims at capturing this heterogeneity which might provide insights on the dynamics underlying the adjustment process to immigration.

To disentangle the channels through which different sectors respond to immigration, we follow a development accounting approach (Hall and Jones, 1999). Accordingly, we decompose the value added per worker into its components (i.e. capital-output ratio, average hours worked, total factor productivity and an index of skill intensity) and we study the impact of the share of immigrant workers (in total employment) on each of these components. We construct a three dimensional panel data set with nine sectors at regional level (NUTS 2) for 19 Italian regions for the period from 2008 to 2011. The empirical investigation requires overcoming the potential endogeneity of the migration variable. Our identification strategy takes advantage of two different instruments to obtain the two stages least square (2SLS) estimates, which are then compared with the OLS results. The first instrument, widely applied in the empirical literature, is constructed by following Altonji and Card (1991) and Card (2001). The second instrument, applied by Gonzales and Ortega (2013), is based on

the geographical accessibility of each region, considering the main transport modes (i.e., land, sea and air). A sensitivity analysis is carried out to check for the robustness of our results with respect to different values of the elasticity of substitution between high- and-low skilled workers. The study provides three main findings. First, it confirms that immigrant workers have a positive effect on value added per worker which is mainly driven by the positive impact on total factor productivity. Second, and new to this paper, it provides evidence that not all sectors benefit from the productivity gains of immigrant-induced work-diversity. Third, and most importantly, it shows that the sectors positively affected by immigrant workers are those characterized by the prevalence of manual-intensive tasks.

The paper is organized as follows. Next Section provides an overview of the relevant literature. Section 3 portraits the main characteristics of the recent upsurge of immigration in Italy. Section 4 discusses the research strategy and presents the empirical approach. Section 5 describes the dataset. Section 6 presents the empirical findings and, finally, Section 7 concludes.

2. Related literature

In contrast with the traditional economic literature focusing on the labor market outcomes (Borjas, 2014), a new strand of research on migration emphasizes the importance to widen the perspective besides the labor market edge, and to consider immigrants as an opportunity for the whole economy (Lewis, 2011; Mazzolari and Neumark, 2012; Lewis and Peri, 2015). This new framework considers immigrants as workers bringing diversified skills compared to natives and takes into account both native workers and firm responses to a change in the supply of these skills. Recent empirical studies contribute to reinforce this perspective and give evidence that, in fact, the impact of immigration goes well beyond wages and employment of natives. For instance, it has been shown that immigrants can contribute to innovation (Kerr and Lincoln, 2010; Hunt, 2011), to increase the supply of low-cost services (Cortes, 2008) and to create incentives for firms to invest or to expand their own businesses by opening new establishments or by re-allocating existing ones (Olney, 2013; Etzo et al., 2015).

Generally speaking, immigrants favor a more efficient allocation of skills to tasks and give to receiving countries the opportunity to reorganize their productive structure and to improve allocative efficiency, which in turn increases total factor productivity (Alesina et al., 2016; Ottaviano and Peri, 2006; 2008; 2013). Efficiency gains arise as long as the different skill endowments bring comparative advantages for the two categories of workers (i.e. natives and immigrants) and induce them to specialize in different tasks (Peri and Sparber, 2009). Tasks requiring manual skills (such as those performed by farm laborers, construction workers, child and elderly care assistant, etc.) may be adequately managed by foreign workers, while tasks requiring language and communication skills (like those performed by construction supervisors, farm coordinators, cooks, etc.) can be better managed by natives. Hence, efficiency gains are the results of specialization and of the choice of appropriate techniques (Peri, 2012).

The few studies that take this economy-wide perspective employ an output decomposition approach based on an aggregate production function (Hall and Jones, 1999). This methodology allows disentangling the impact of immigration on each input and on total factor productivity. In this respect, the works of Ortega and Peri (2009) and Aleksynska and Tritah (2015), for two different samples of OECD countries, and of Peri (2012) for the US, are worth to be mentioned.

Ortega and Peri (2009) concentrate on 14 OECD destination countries during the years from 1980 to 2005. They consider a popular Cobb-Douglas production function where output is a function of labor, physical capital and total factor productivity. Their results suggest that immigration increases employment one for one, implying no crowding-out of natives, and that investment responds rapidly

maintaining the capital-labor ratio constant. Conversely, the effect of immigration on total factor productivity and output per worker is not statistically significant. The main implication of their results is that immigrants only increase the overall size of the economy without impacting on income distribution between workers and capital owners. Aleksynska and Tritah (2015) extend the panel to 20 OECD countries during the period 1960-2005. In their approach, the production function specification considers total output as a function of physical capital, human capital and total factor productivity. Differently from Ortega and Peri (2009), they find a positive effect of immigrants on income per capita that mainly works through total factor productivity. Whilst, they also find no impact of immigrants on the capital-output ratio and on employment. A novel contribution of Aleksynska and Tritah (2015) is the study of immigrants' impact differentiated by age group. They find that the positive effect on income per capita, total factor productivity and human capital starts when immigrants get older. The authors discuss various possible explanations for these findings (e.g. the more efficient distribution of older immigrants among sectors, transaction costs, and endogenous skill upgrading effects on natives) which overall support the concept that immigration represents a complex labor supply shock. However, as it is also recognized by the authors, the issue on the sources of complementarities between immigrants and natives lacks of empirical evidence and, therefore, it needs to be investigated at different level and dimensions.

The economy-wide effects of immigration are also studied by Peri (2012) who analyzes the impact of immigrants on the US states during the period 1960-2006. The production function employed in this study, besides labor, physical capital and total factor productivity, explicitly considers an index of skill intensity.[1] Interestingly, likewise Aleksynska and Tritah (2015) and differently from Ortega and Peri (2009), the results highlight a positive relationship between immigration and output per worker which is mainly driven by the impact of immigration on total factor productivity. Moreover, a negative relationship between immigration and the high-skill bias of aggregate productivity is also found. Peri (2012) interprets this result as evidence that less-educated immigrants promote task specialization and encourage the adoption of unskilled-efficient technologies. Finally, no evidence is found that immigrants crowd out natives' employment, nor that they affect the capital-output ratio.

Turning our attention to Italy, as it clearly emerges from the above discussion, there are no attempts to address the impact of immigrants at the economy-wide level. In fact, the bulk of the literature concentrates on the effects of immigration on the labor market (see, *inter alia*, Mocetti and Porello, 2010; Staffolani and Valentini, 2010; Falzoni et al., 2011). Very few works investigates the out-of-labor-market impacts of immigration and, among them, only three contributions are worth to be mentioned, being somehow linked with the investigation proposed by the present work. The first is Accetturo et al. (2012) that estimate how investments in machinery and equipment respond to an increase in the relative abundance of low-skilled migrant workers. They find a positive relationship that tends to be stronger for large firms and in skill-intensive sectors. In this perspective, these results can be taken as evidence in favor of a change in production techniques due to low-skilled immigration. Similar findings are obtained by Bettin et al. (2014) and De Arcangelis et al. (2015a, b). The former find evidence of production re-composition in favor of low-skill manufacturing sectors. The latter claim that an increase in the weight of relatively low-skilled immigrants tends to favor low-skill versus high-skill sectors and, therefore, it is likely to impact on the relative composition of the production system. Finally, Etzo et al. (2015) investigate whether firms find profitable to expand their productive capacity and build new establishments in areas where there is abundance of foreign labor force. They find robust evidence that indeed a positive link exists between the share of immigrants and the number of establishments. Such a relationship is stronger in the Construction and Manufacturing sectors.

[1] This index combines more and less educated workers in a constant elasticity of substitution function where the elasticity of substitution is bounded to be higher than zero.

All in all, the literature that offers an economy-wide perspective to analyze the impact of immigration is quite scant. Yet, the works of Ortega and Peri (2009), Peri (2012) and Aleksynska and Tritah (2015) highlight some significant contributions of immigrants on receiving economies. Firstly, two works out of three, namely Peri (2012) and Aleksynska and Tritah (2015), find a strong impact of immigration on output per worker which is mostly due to the positive effect of immigration on total factor productivity. Secondly, all of them find that immigrants do not crowd-out natives in the labor market. Finally, another common finding is that physical capital adjusts rapidly to immigrant-induced labor supply shocks, leaving unchanged the capital-labor ratio or the capital-output ratio.

To conclude, two general considerations can be drawn from the extant literature. On the one hand, the aforementioned studies are in line with the literature emphasizing the beneficial effects of workforce diversity on production (Alesina et al., 2016). On the other hand, they provide empirical support to the hypothesis that immigration stimulates complex adjustment mechanisms that empirical analysis focused on aggregate data alone are not able to unfold. Accordingly, more research is needed to better understand the channels through which immigrants impact on host economy output. For example, none of the studies considering an economy-wide perspective take into account the sectoral composition of output and the fact that immigrants and natives are heterogeneously distributed across sectors. In this respect, Italy represents an interesting country to analyse how the impact of immigration differs across sectors.

3. Immigration in Italy

In the last decades immigration has become increasingly important for Italy. Foreign citizens, that were 1.3 millions in the 2001 census, more than tripled in only ten years overtaking 4 millions in 2011. During the same period the relative size of the immigrant population rose from 2.3% in 2001 to 6.8% in 2011. As regards the country of origin, the last available data (2015) reveals more than 200 nationalities. Romanians, Albanians and Moroccans are the three largest communities followed by Chinese, Ukrainians and Filipinos. The great majority of immigrants comes from the less developed or emerging economies. Overall, the nationalities that account for at least one per cent of foreigners sum up to 83.4% of all immigrants (Table 1). Immigrants have initially settled principally in the Centre-North, attracted by better labor market opportunities. However, in the second half of 2000s immigration grew faster in the southern regions than in the rest of Italy. As regard to employment, during the years of our empirical investigation (i.e. 2008-2011) the number of employed immigrant workers grew on average of about 10.7% at national level, of 9.6% in the North, 11.7% in the Centre and 14.5% in the South.

[Table 1]

The overall share of foreign workers in total employment almost doubled from 2005 (5.2%) to 2011 (10%). In 2011, total foreign labor force was 2.2 millions, 11.6% in the North, 12.7% in the Centre and 4.7 in the South. As shown in Table 2, immigrants are employed mainly in Other Personal services (29.0%), followed by Manufacturing (21.1%), Construction (12.8%) and Hotel and restaurant (9.1%), whereas very small percentages of them are employed in Energy, mining and quarrying (0.2%), Public administration (0.3%) and Financial, insurance and real estate (0.6%). Looking at the relative sectoral employment share (column 3 of Table 2), while in the Manufacturing sector their employment share is similar to that of natives, we observe that immigrants are employed proportionally more than natives in Agriculture, Construction, Hotel and restaurant and, above all, Other personal services and proportionally less than natives in all other sectors. When comparing the employment shares of natives and immigrants, we note that the latter are 37.1% in Other personal services, 31.5% in Agriculture, forestry, fishing and about 20% in

Construction and Hotel and restaurant. Conversely, they account for only 0.2% in Public administration, 1.1% in Financial insurance and real estate and 1.6% in Energy, mining and quarrying.

As for the skill composition, Table 3 presents data on the educational attainment of immigrants and natives, 10.9% have only primary education, 33.72% lower-secondary education, 44.86% upper-secondary education and 10.52% a university degree or more. The last column of Table 3 shows that immigrants are relatively less educated than natives.

[Tables 2 and 3]

Another important way to see the increasing role of immigrants in the Italian economy is to look at their contribution to value added creation. According to Unioncamere estimates (Unioncamere, 2014),[2] in 2011 the percentage of the national value added due to foreign workers was about 12.8%, it almost doubled with respect to 2005, the first year in which this investigation started. When considering the role of immigrants at sectoral level, Construction registers the highest peak with 23.9% of total value added due to immigrants (it was 13.4% in 2005), followed by Agriculture with 18.6% (8.5% in 2005), Services 12% (6.4% in 2005) and Manufacturing with 11.9% (7.3% in 2005).[3] Recent data, provided by Fondazione Moressa (2016), are more conservative in that consider only regular employment, and estimate the percentage of value added due to foreign workers at 8.8% in 2015. According to these two studies, we can claim that immigrants in Italy account for at least ten per cent of the whole value added and that their role is crucial in the Construction sector.

4. Research strategy and empirical approach

The main aim of this paper is to provide a sectoral analysis of the impact of immigration on the value added and its components in Italy. To this end, we consider a panel of 19 Italian regions[4] during the period 2008–2011 and nine sectors, namely Manufacturing, Construction, Commerce, Hotels and restaurants, Transport and communication, Finance insurance and real estate, Professional technical administrative and support services, Education health and social services, Other personal services. The following three sectors have been excluded due to missing data: Agriculture, Energy, mining and quarrying and Public administration. This sector aggregation corresponds to the highest level of the ATECO 2002 classification of economic activities, which is the Italian version of the NACE (Rev. 1.1) classification.

The theoretical framework followed in this study is the production function approach proposed by Peri (2012), which has been modified in order to accommodate the sectoral heterogeneity. More in details, we assume that each sector i of region r in year t produces a homogeneous, perfectly tradable output according to the following Cobb-Douglas production function:

$$(1)\quad Y_{irt} = K_{irt}^{\alpha}[X_{irt}A_{irt}\varphi(h_{irt})]^{(1-\alpha)}$$

where Y_{irt} is value added, K_{irt} measures physical capital, X_{irt} corresponds to total hours worked, A_{irt} is total factor productivity, $h_{irt}=H_{irt}/X_{irt}$ is the share of total hours worked (X_{irt}) supplied by high-skilled workers (H_{irt}) and, finally, $\varphi(h_{irt})$ represents an index of skill intensity which depends on the elasticity of substitution between high- and low-skilled workers. Furthermore, we assume that,

[2] Unioncamere (Italian Union of Chambers of Commerce, Industry, Handicraft and Agriculture) is a public institution that represents the Italian Chamber system.
[3] These estimates consider both regular and irregular employment.
[4] Italian regions are 20, but ISTAT merges the data of the smallest one, that is Valle D'Aosta, with the neighbouring Piemonte.

within each sector, these two categories of workers combine their labor inputs into a constant elasticity of substitution function, which is defined as follows:

$$(2)\ \varphi\,(h_{irt}) = \left[(\beta_{irt}h_{irt})^{\frac{\sigma_i-1}{\sigma_i}} + \left((1-\beta_{irt})(1-h_{irt})\right)^{\frac{\sigma_i-1}{\sigma_i}}\right]^{\left(\frac{\sigma_i}{\sigma_i-1}\right)}$$

where $\sigma_i>0$ is the elasticity of substitution between high- and low-skilled workers, β_{irt} measures the degree of productivity skill bias and, by definition, $(1-h_{irt})=L_{irt}/X_{irt}$ is the share of total hours worked (X_{irt}) supplied by low-skilled workers (L_{irt}).

Let us define N_{irt} as total employment in sector i of region r in year t, and re-write the production function (1) in terms of value added per worker $y_{irt}=Y_{irt}/N_{irt}$:

$$(3)\ y_{irt} = \left(\frac{K_{irt}}{Y_{irt}}\right)^{\left(\frac{\alpha}{1-\alpha}\right)} [x_{irt}A_{irt}\varphi(h_{irt})]$$

where x_{irt} measures the average hours worked per worker ($x_{irt}=X_{irt}/N_{irt}$). Taking logarithms on both sides of equation (3) and rearranging terms we get:

$$(4)\ lny_{irt} = \left(\frac{\alpha}{1-\alpha}\right) ln\frac{K_{irt}}{Y_{irt}} + lnx_{irt} + lnA_{irt} + ln\varphi(h_{irt})$$

Equation (4) is an identity, which decomposes the value added per worker into (i) capital to value added ratio, (ii) average hours worked per worker, (iii) total factor productivity and (iv) the productivity-weighted skill-intensity index $\varphi(h_{irt})$. Accordingly, any potential impact that immigrants might have on value added per worker must go through these four components.

Under this theoretical framework, we can study whether a variation in the share of immigrant workers impacts on each right-hand side term of equation (4) and if this impact differs across sectors. For this scope, we propose the following econometric model:

$$(5)\ lnb_{irt} = d_i + d_r + d_t + \gamma_{b1}z_{1rt} + \textstyle\sum_{i=2}^{9}\gamma_{bi}(z_{irt}d_i) + \varepsilon_{irt}$$

where b_{irt} represents each right-hand side component of equation (4); $z_{irt}=(N^F_{irt}/N_{irt})$ is the share of immigrant workers (N^F_{irt}) in total employment; d_i, d_r, d_t are sector, region and time specific effects that account for idiosyncratic factors that might affect a particular sector (across regions and years) or a region (across sectors and years) or a year (across sectors and regions); $(z_{irt}d_i)$ are interaction terms which are meant to capture differences in the slope coefficient across sectors and, finally, ε_{irt} represents a zero-mean random shock[5].

The empirical model in equation (5) is estimated using Manufacturing as the reference sector. Accordingly, γ_{b1} measures the impact of the share of immigrant workers, z_{1rt}, on each of the right-hand side component of equation (4) for Manufacturing, while the coefficients γ_{bi} measure the difference between Manufacturing and sector i. It follows that the impact of immigrants on the *i-th* sector is the sum of these two coefficients, namely $\gamma_{b1}+\gamma_{bi}$. For the sake of comparability, in order to

[5] The empirical model in equation (5) could be seen as a linear system of equations. Accordingly, it might be estimated using seemingly unrelated regressions (SUR) in order to gain efficiency from taking account of correlation between error terms across equations. However, it can be demonstrated that when the same regressors appear in the right hand side of each equation (i.e. our case), estimating the model using OLS equation by equation is equivalent to SUR (see for instance Wooldridge, 2010).

obtain a measure of the aggregate effect of immigration, equation (5) is also estimated without the interaction terms.[6]

The empirical implementation of equation (5) requires coping with two main issues: the first refers to the data, the second is the potential endogeneity of immigrants with respect to the response variables. The latter issue will be addressed in the next sub-section. As for the first, the construction of the dataset needs to collect relevant data and reliable estimates of the production function parameters, specifically with regard to the capital-income share and the elasticity of substitution between high- and low-skilled workers at sector level. The estimation of these parameters goes beyond the scope of the present paper and, unfortunately, there are very few estimates available in the literature at sector level and almost none exists for the case of Italy. Therefore, our strategy is as follows. As for α, since it affects only the scale factor of the capital to value added ratio, we impose the standard value of 0.33 for all sectors.[7] With regards to σ, inter-sector differences might be important since the elasticity of substitution between high- and low-skilled workers enters the computation of both $\varphi(h_{irt})$ and A_{irt}. However, to the best of our knowledge, no estimates are available for Italy and very few attempts have been made to provide estimates for other countries. As for the aggregate measure of σ, Romiti (2011) estimates an average value of σ equal to 1.55 for Italy, which is within the range estimated for other countries (most estimates in the literature cluster between 1.5 and 2.0, see Ciccone and Peri, 2005). Therefore, our strategy is to estimate the model in equation (5) assuming that the elasticity of substitution between high- and-low skilled workers is σ=1.55 for all sectors. Next, in order to check for the robustness of our results, we perform a sensitivity analysis as follows. First, under the assumption that the elasticity of substitution between high- and low-skilled workers is the same across sectors, we re-estimate the model using the alternative value of σ=1.75, which is the one used by Peri (2012) for the US. Second, we introduce sector heterogeneity by imposing sector specific elasticities values (i.e. σ_i). To this aim, we use the values of the elasticity of substitution between high- and low-skilled workers at sector level estimated by Blankenau and Cassou (2011) for the US. Interestingly, the authors find that for nine out of ten industries the estimated parameter is higher than the aggregate estimate. Moreover, their findings highlight the existence of noticeable differences across sectors. The values of σ_i are the following: σ = 1.41 for Manufacturing, σ = 9.05 for Construction, σ = 1.92 for Commerce, σ = 2.06 for Hotel and restaurant, σ = 2.22 for Transport and communication, σ = 1.15 for Finance, insurance and real estate, σ = 1.07 for Professional, technical, administrative and support services, σ = 2.5 for Education, health and social services and, finally, σ = 46.9 for Other personal services (Blankenau and Cassou 2011, Table 1). We are aware that there exist structural differences between Italy and the US (e.g. firm size and the average skill intensity of the production processes, among the others) which might affect the sector specific value of σ. In particular, the Italian manufacturing sector is characterized by the presence of a larger number of small firms adopting production processes which are less skill intensive. Therefore, it is likely that the elasticity of substitution between high- and low-skilled workers in Manufacturing is higher in Italy rather than in the US. However, we also believe that, overall, these estimates are appropriate to carry out a sensitivity analysis in that they represent a good approximation which allows the analysis to capture the heterogeneity existing across Italian industries with respect to σ.

4.1. Endogeneity and instruments

The second, and most fundamental problem is the possible endogeneity of the migration variable. In fact, not only immigrant workers can affect output, but they might also be attracted by those regions which are experiencing better economic performances (e.g. an increase of labor market opportunities). Moreover, there might be unobservable factors correlated with both immigrant

[6] Dropping the interaction terms, the equation (5) simplifies to $lnb_{irt} = d_i + d_r + d_t + \gamma_b z_{irt} + \varepsilon_{irt}$.

[7] This value is within the range of values (i.e., 0.29 and 0.36) estimated for Italy by Marrocu and Paci (2010).

workers and output and/or its components. Think, for example, of the state of technology or the relative factor prices. The fixed effects panel data model in equation (5) controls for all of those factors which do not vary over time. However there might be other omitted variables which are time variant. For example, a positive sector-region specific productivity shock in one year raises the labor demand and, as a consequence, might also pull immigrants towards that region and sector. As it is well known, in presence of reverse causality and/or omitted variables bias, the OLS estimates of equation (5) are biased. Hence, in order to obtain consistent estimates, we apply the two stages least square (2SLS) estimator.

In this regard, we predict the exogenous share of immigrants by building two different instruments. The first one is widely applied in the migration literature and it is constructed by following Altonji and Card (1991) and Card (2001). This instrument is based on the idea that the destination choice of current immigrants within the country is highly correlated with the number of compatriots that have already established in that specific destination (i.e., city, province or region). The second instrument is based on both the geographical accessibility of each region and the preferences of immigrants with respect to the main transport modes (i.e., land, sea and air). This instrument has successfully been applied by Gonzales and Ortega (2013) to explain the impact of immigration on house prices in Spain. It is worth to point out that, from a geographical point of view, Italy is very similar to Spain, in that it is a peninsula in the Mediterranean sea which represents a gate to Europe for those immigrants arriving by sea from the north African countries. The next subsections describe the constructions of the two instruments.

4.2. Ethnic networks

Following Altonji and Card (1991) and Card (2001), we construct the first instrument by exploiting the positive correlation between the actual flows of immigrants from a given sending country and the corresponding compatriot communities that have settled in the destination region in the past. In order to construct the instrument at sector level, we modify the standard version of the instrument by distributing the predicted number of immigrants in each sector *i* and region *r* on the basis of the pre-sample share of foreign workers employed in sector *i* and holding the same citizenship *j* in total foreign workers employed in region *r*. In other words, it is assumed that new immigrants are more likely to search for a job in the same sectors where their compatriots already work and, ultimately, that the social (ethnic) networks determine the labor supply at sector level. Accordingly, the resulting variable predicting the yearly number of immigrants in each region *r* and sector *i* is built as follows:

$$(6)\ p\_sh\_imm^{n}_{r,i,t} = \frac{\sum_{r,i}\left(sh\_imm_{j,r,2002} * imm_{j,t} * \overline{w\_ind_{j,i}}\right)}{pop_{r,i,t}}$$

where, $sh\_imm_{j,r,2002}$ is the share of immigrants from country *j* residing in region *r* in 2002 in total number of immigrants from country *j* residing in Italy in 2002,[8] $imm_{j,t}$ is the total number of immigrants from country *j* residing in Italy in year *t* and $\overline{w\_ind_{j,i}}$ is the average share (over the pre-sample period 2006-2007) of immigrants from country *j* employed in sector *i* over the total foreign workers employed in region *r*. In order to obtain the predicted exogenous component of the share of immigrants, the numerator has been divided by the total population (working age) resident in each region, that has been distributed to each sector according to the corresponding employment share (i.e., $pop_{r,i,t}$).

[8] The 2002 is the first year for which data of immigrants by country of origin are available at regional level. Usually the lagged year goes back a couple of decades, however immigration in Italy has experienced some important shocks in both the paths and trends of international immigration between 2002 and 2007 which can justify the adoption of this short lag. The main source of these shocks is the enlargement of the EU to central and eastern European countries.

4.3. Geographical accessibility

The second instrument exploits the different accessibility degree between Italian regions. Immigrants can cross the Italian borders by means of the three main transportation modes, namely by land, by air and by sea. The choice between them, among several factors, ultimately depends on travel distance to Italy from the origin country and on transport costs. Immigrants from Albania and Morocco, which rank 2nd and 3rd in terms of total number of immigrants in Italy, for instance, can easily reach the southern Italian regions by sea, which is less expensive than travelling by plane. On the contrary, immigrants from Romania, that is the top sending country, might find more convenient to cross by land the Italian border (i.e. by car or train). In sum, immigrants might prefer to settle in those regions which are easier to access from their own country. Accordingly, we build the instrument considering the different accessibility degree with respect to the three main transportation modes. In the footsteps of Gonzales and Ortega (2013), we follow three steps. In the first step, three indicators are developed to measure the accessibility of each region *r* with respect to the transportation mode *m*, where *m* stands for *land*, *air*, *sea*. Each indicator is computed so that the sum over all regions is equal to one. To compute the *land* indicator, we use the average of the shortest road-distances from each region to the borders of France, Switzerland and Austria[9]. The *air* indicator is constructed by computing the regional shares in total foreign arrivals at the Italian airports in 2007. Similarly, the *sea* indicator is constructed by computing the regional shares in total arrivals at the main regional harbors. In the second step, the indicator measuring the preference of country *j* citizens for transportation mode *m* is constructed by using survey data on international arrivals provided by the Bank of Italy. We choose the average of 2006 and 2007 as pre-sample years. Third, the overall accessibility measure for each country-region pair is constructed as follows:

$$(7)\quad \omega_{r,j} = a_{r,land}\, p_{j,land} + a_{r,air}\, p_{j,air} + a_{r,sea}\, p_{j,sea}$$

where, $p_{j,m}$ and $a_{r,m}$ measure the country preferences and the region accessibility for transportation mode *m*, respectively. The final step is similar to equation (6) with the only difference being that now the total number of country *j* immigrants arrived in Italy in year *t* are distributed according to the overall country-region accessibility measure $\omega_{r,i,t}$, as follows:

$$(8)\quad p\_sh\_imm^{a}_{r,i,t} = \frac{\sum_{r,i}\left(\omega_{r,j} * imm_{j,t} * \overline{w\_ind_{j,i}}\right)}{pop_{r,i,t}}$$

where, now $p\_sh\_imm^{a}_{r,i,t}$ indicates the immigrant population share (working age) in region *r* sector *i* and year *t*, predicted using the geographical accessibility instrument.

5. Data sources and variables construction

The dataset has been constructed by using data from different sources. Data availability has limited the period of our analysis, which is from 2008 to 2011. More in detail, the information on wages by nationality are only available since 2008, whereas the immigrants time series after 2011 are not comparable due to post-census adjustments.

The main source is the labor force survey (LFS) provided by ISTAT that delivers data on aggregate employment, hours worked and wages, all measured at regional and sector level. Also citizenship and workers' skill level are retrieved from LFS. The data on output, measured in terms of value

[9] For each region we average the shortest road-distances across all province capital cities. Different road types are considered, not only highways.

added (per worker) by sector and region, and on physical capital are taken from ISTAT national accounts.

To construct yearly employment and hours worked, we aggregate the quarterly LFS micro data using the personal weight (COEF)[10]. The skill level is measured by means of educational attainment; accordingly, low-skilled workers (L_{irt}) are those with upper-secondary education or less (ISCED 1, 2, 3 and 4), whilst high-skilled workers (H_{irt}) are those with a university degree or more (ISCED 5 and 6). Foreign workers are those not holding Italian citizenship. Total employment (N_{irt}) is the sum of domestic workers (N_{irt}^{D}) and foreign workers (N_{irt}^{F}), all measured in region r, sector i and year t. Total hours worked X_{irt} have been computed as the sum of total hours worked by high-skilled (H_{irt}) and low-skilled (L_{irt}) workers[11]. Real value added per worker (y_{irt}) is constructed dividing the real value added by total employment. The physical capital stock by sector is available only at national level, thus we construct the regional variable by distributing the national sector amount in each region r and sector i according to the corresponding value added weight of each sector i in region r[12].

As for the remaining variables, we first derive A_{irt} and β_{irt} and then compute the index of skill intensity $\varphi(h_{irt})$. Accordingly, we consider equation (1) together with the condition that the average hourly wage of high- and low-skilled workers ($w^{H}{}_{irt}$ and $w^{L}{}_{irt}$) equals the marginal productivity of H_{irt} and L_{irt}, respectively. Thus, by following the same procedure explained in Peri (2012), we get the following two expressions:

$$(9)\ \ \beta_{irt} = \frac{(w_{irt}^{H})^{\frac{\sigma_i}{\sigma_i-1}} h_{irt}^{\frac{\sigma_i}{\sigma_i-1}}}{(w_{irt}^{H})^{\frac{\sigma_i}{\sigma_i-1}} h_{irt}^{\frac{1}{\sigma_i-1}} + (w_{irt}^{L})^{\frac{\sigma_i}{\sigma_i-1}} (1-h_{irt})^{\frac{1}{\sigma_i-1}}}$$

$$(10)\ \ A_{irt} = \left(\frac{Y_{irt}^{\frac{1}{1-\alpha}} K_{irt}^{-\frac{\alpha}{1-\alpha}}}{X_{irt}} \right) \times \frac{(w_{irt}^{H})^{\frac{\sigma_i}{\sigma_i-1}} h_{irt}^{\frac{1}{\sigma_i-1}} + (w_{irt}^{L})^{\frac{\sigma_i}{\sigma_i-1}} (1-h_{irt})^{\frac{1}{\sigma_i-1}}}{[w_{irt}^{H} h_{irt} + w_{irt}^{L}(1-h_{irt})]^{\frac{\sigma_i}{\sigma_i-1}}}$$

where $w^{H}{}_{irt}$ and $w^{L}{}_{irt}$ are constructed by using the monthly wage taken from LFS that we divide first by total workers and then by the average hours worked during the year.[13] Once β_{irt} has been computed, the index of skill intensity $\varphi(h_{irt})$ is obtained as defined in equation (2). The value of α and σ_i necessary to calculate $\varphi(h_{irt})$, A_{irt} and β_{irt} are imposed according to the assumptions discussed in Section 4. The data used to construct the "ethnic networks" instrument have been retrieved from the ISTAT database. As for the "geographical accessibility" instrument, the data on the arrivals of

[10] The number of workers in year t (by region and industry) is constructed as the average of total workers in each quarter. Self employed are not considered.

[11] We have used the variable ORELAV which measures the hours worked in a week and multiplied it by 13 (i.e. the average number of weeks in a quarter) to obtain the total number of hours worked in each quarter and then we computed the sum to obtain the total number of hours worked in year t. Hours per worker, for both natives and immigrants in each education cell, is computed as the ratio of total hours worked in year t (by region and industry) to the corresponding total number of workers.

[12] The industry weights are constructed with respect to each industry, so that the sum of the weights for each industry over the 19 regions is equal to one.

[13] For each quarter we multiply (for each type of worker) the variable RETRIC by COEFF and by three and then take the sum by region and industry. We then sum all the quarters' pays to obtain the annual pay. The annual pay is then divided by average number of workers in order to obtain the average pay per worker, which is finally divided by the annual hours worked by high (low) skilled worker in region r, industry i and year t.

foreign citizens by transport mode are taken from the Bank of Italy (2006; 2007), whereas the rest of the data comes from the ISTAT database.

6. Results

6.1 OLS estimates

This section provides results from the OLS estimation of equation (5). As discussed in previous sections, we investigate the impact of the share of immigrant workers on value added per worker ($ln\ y_{irt}$) and on its four components for 19 Italian regions and nine sectors. Accordingly, we consider the capital to value added ratio ((α/1-α) $ln\ (K_{irt}/Y_{irt})$), the average hours worked per worker ($ln\ x_{irt}$), the total factor productivity (lnA_{irt}) and the productivity-weighted skill-intensity index ($ln\ \varphi(h_{irt})$). We also estimate the impact of immigrant workers on both $ln\ h_{irt}$ and $ln\ \beta_{irt}$, namely the two components of $\varphi(h_{irt})$. These estimates might be affected by endogeneity and omitted variables bias, therefore we take them as a preliminary assessment of our empirical investigation.

The results are shown in Table 4, where columns from (2) to (10) report the coefficients estimated for each industry as specified in equation (5). To complete the picture, in column (1), we also report the estimates obtained by dropping the interaction terms from equation (5). As explained in Section 4, by so doing we estimate the overall effect of immigrant workers on the nine sectors together. It is worth noting from the outset that, since the model is specified in log-level format, the estimated parameters are semi-elasticities. Hence, after multiplying them by 100, they measure the percentage change on each of the dependent variables given by one-percentage point variation in the immigrant workers share.

Starting from the overall impact (column 1), it emerges a positive and significant relationship between the share of immigrant workers and the value added per worker $ln\ y_{irt}$ (0.005) which is entirely due to the effect of immigrants on total factor productivity (0.006). On the contrary, the effect on the other components appears to be negligible and not statistically significant.

[Table 4]

Let us now turn to the sector level perspective (columns from 2 to 10 in Table 4). As explained earlier, while the effect of migration on Manufacturing is measured by the coefficient γ_{b1} (column 2), the total impact of the share of immigrant workers on the *i-th* sector is obtained summing γ_{b1} with the slope coefficient estimated for the corresponding interaction term (γ_{bi}). For the sake of clarity, the results reported in the table are those obtained from the linear combination of the two coefficients of equation (5), namely γ_{b1}+γ_{bi}.

At first glance, we observe a great deal of heterogeneity across sectors. First of all, an increase in the share of foreign workers has a positive impact on the value added per worker only in three sectors: Constructions (column 3), Commerce (column 4) and Hotel and restaurant (column 5). On the contrary, immigrants seem to affect negatively the value added per worker in two service sectors, namely the Professional, technical, administrative and support services (column 8), and the Education, health and social services (column 9). As for the impact of immigrants on the components of the value added per worker, again the main channel appears to be total factor productivity. Furthermore, results in Table 4 show that in some sectors the impact of immigrants on value added per worker is not significant. In this respect, while for Finance, insurance and real estate sector (column 7) this outcome does not come as a surprise given the low share of foreign workers (1.1%, see Table 2), for other sectors the same outcome might appear startling, particularly for Manufacturing. At this regard, it should be considered that Manufacturing is a quite

heterogeneous group, especially with respect to some important firm's characteristics like the size and the average skill intensity of jobs. Accordingly, the estimated outcome might be the result of counterbalancing effects among the different branches of activities.[14] An additional caveat when it comes to discuss the OLS estimates for Manufacturing, as well as for all the other sectors, is related to the sign of the endogeneity bias. It is worth noting that, during periods of economic downturn, the endogeneity bias resulting from the reverse causality could be negative instead of the more usual positive bias, which is supposed to affect the OLS estimates. This might be particularly true for Manufacturing, where the exporting firms (the so called Made in Italy) can hire foreign workers to reduce the labor costs, thus keeping the competitiveness without relocating the production abroad (Murat and Paba, 2004). The production processes of these firms are characterized by the prevalence of manual tasks which do not require high language and communication skills. That is to say, firms experiencing negative growth rates might have increased the share of foreign workers in order to cut their labor costs. In this case, the endogeneity bias resulting from the reverse causality would be negative.

[Table 5]

6.2 Two stage least square (2SLS) estimates

We correct the potential endogeneity of OLS estimates using the 2SLS instrumental variables method. As explained in the previous section, we argue that the sign of the endogeneity bias might be either positive or negative. It is worth pointing out that, in the latter case, both of the two instruments we use to carry out the estimates specifically correct for this bias by distributing the predicted number of immigrants (from country j assigned to region r) among the sectors according to the average share of compatriots employed in each sector in a pre-sample period (years: 2006 and 2007).

6.2.1 First stage results

The results from the first stage regressions are reported in Table 5. The dependent variable is the share of foreign workers in total employment, while the main regressors are, alternatively, the "ethnic networks instrument" (columns 1 and 2) and the "geographical accessibility instrument" (columns 3 and 4), which have been constructed as explained in Section 4. The estimated coefficients are statistically significant for all models. The bottom part of the table reports tests of both underidentification and weak identification. The Kleibergen and Paap (2006) rank LM statistic is robust in the presence of heteroskedasticity, autocorrelation or clustering. The test always rejects the null of underidentification, indicating that all instruments are relevant. For the models estimated without the interaction terms, we also report the heteroskedastic and clustering robust weak identification test, that is the Kleibergen and Paap (2006) rank Wald F-statistics[15]. Both statistics are well above the critical value tabulated by Stock and Yogo (2005). As a result of the different tests, thus, both the "ethnic networks" instrument and the "geographical accessibility" instrument appear to have significant power.

6.2.2 Instrumental variables estimates

The outcomes from the 2SLS estimates obtained using the "ethnic networks" and the "geographical accessibility" instruments are reported in Tables 6 and 7, respectively. In order to simplify the analysis of the results, we limit the discussion of the effects estimated for the output components only to those sectors for which the impact of immigrants on value added per worker is statistically significant.

[14] Unfortunately the data do not allow a further disaggregation.

[15] The Stock and Yogo (2005) critical values are available only for models including up to two endogenous regressors. For this reason, the statistics has not been computed for the models with the interaction terms.

[Table 6]

We start by discussing the results obtained with the "ethnic networks" instrument. As we can see in column 1 of Table 6, when estimating the model without the sector interaction terms, the outcomes are similar to those showed in column 1 of Table 4. In particular, the impact of immigrants on value added per worker has a positive sign and it is explained entirely by the impact on total factor productivity. However, when observing the sector specific slope coefficients (Table 6, columns from 2 to 10), there emerges some noteworthy differences. Firstly, in addition to Construction, Commerce and Hotel and restaurant, now the estimated impact of the immigration share on the value added per worker is positive and statistically significant also for Manufacturing (column 2), Transport and communication (column 6) and Other personal services (column 10). Secondly, there appears no sector for which the estimated impact of the share of foreign workers on value added per worker is negative and statistically significant. These differences between OLS and 2SLS results can be explained, as discussed above, by our hypothesis that the sign of the bias, when using the endogenous variable in the OLS estimates, might be either positive or negative. As for the estimates regarding the four output components, the results confirm that total factor productivity is the main channel through which immigrants exert a positive impact on value added per worker. Moreover, the estimated negative effects on both h_{irt} and β_{irt} for Commerce and for Transport and communication reveal that, in these two sectors, not only do immigrants reduce the share of total hours worked by high skilled workers (h_{irt}), but they also reduce the skill bias of technology (β_{irt}). In other words, it would seem that in these two sectors foreign workers discourage the adoption of skill intensive techniques and induce a rise in the demand for low-skilled workers. Lastly, Manufacturing is the only sector where the positive impact of immigrants on value added per worker is conveyed also by a positive effect on the capital to value added ratio, not just by total factor productivity.

[Table 7]

The results of the instrumental variable regressions obtained using the "geographical accessibility" instrument are shown in Table 7. With regards to the effects of foreign workers estimated without the sector interaction terms (column 1), the OLS outcomes are generally confirmed. However, sector specific estimates (columns from 2 to 10) differ substantially from those reported in Table 4. The main difference is that for the Hotel and restaurant sector, the effect of immigrants on value added per worker is not statistically significant (column 5). Conversely, it is confirmed that, when significant, the effect of immigrants on value added per worker is always positive and is mainly driven by the positive impact on total factor productivity. The two exceptions are Manufacturing (column 2) and Transport and communications (column 6). For the latter, the positive effect of foreign workers on total factor productivity is mitigated by a non trivial negative effect on the skill-intensity index $\varphi(h_{irt})$ and its determinants, namely h_{irt} and β_{irt}. As regards the former, the negative effect on the skill-intensity index $\varphi(h_{irt})$ is counterbalanced by a positive and statistically significant effect on the capital to value added ratio.

Overall, comparing the outcomes of the 2SLS estimates, the findings which appear to be robust to the use of the two alternative instruments are the following. First, the positive effect of a rise in the share of foreign workers on value added per worker shown by the model without the interaction term, conceals noticeable differences across sectors. More specifically, foreign workers have a positive effect on value added per worker in four sectors: Manufacturing, Construction, Commerce and Transport and communication. Among them, Commerce is the one with the strongest impact. Second, the share of foreign workers never affects three sectors, namely Finance insurance and real estate, Professional, technical, administrative and support services and Education health and social services. Third, total factor productivity is the main channel through which immigrant workers

affect positively the value added per worker. Fourth, a positive effect on capital to value added ratio is found for Manufacturing, suggesting the presence of non trivial complementarities between capital and labor. Accordingly, Manufacturing firms seem to respond quickly to an immigrant-induced increase in labor supply by adjusting their capital intensity as argued, among others, by Ottaviano and Peri (2008). Finally, the negative coefficient of the skill bias of technology, estimated for the Transport and communication sector, would suggest that in this sector immigrant workers could have slowed down the adoption of high skilled technologies.

6.3 Sensitivity analysis of 2SLS regressions for σ

The results showed in Tables 6 and 7 are obtained assuming that the elasticity of substitution between high and low skilled workers is the same across sectors, that is $\sigma = 1.55$. This assumption might be too strong, especially for those sectors which are particularly high (or low) skill-intensive. Therefore, in this section we test for the robustness of the previous results by re-estimating the model in equation (5) changing the value of σ. Notice that a different value of σ affects the construction of only three variables: total factor productivity, the skill intensity index $\varphi(h_{irt})$ and the skill bias of technology β_{irt}. Therefore, the sensitivity analysis is restricted to these variables. Moreover, for simplicity, the discussion is limited to those sectors for which a statistically significant impact on the value added per worker is reported in Tables 6 and 7.

As a first step, we assign an alternative value to σ, equal for all sectors. We set $\sigma = 1.75$, that is the value used by Peri (2012), which corresponds to the median value of the estimates available in the literature for the US economy. The estimates obtained by using the "ethnic network" instrument are reported in the upper part of Table 8. Starting from total factor productivity, which is the main channel through which immigrants seem to exert the positive impact on the value added per worker, the results appear quite similar to those reported in Table 6, with respect to both the point estimates and the significance level. As a consequence, also the differences in the outcomes for the skill intensity index $\varphi(h_{irt})$ and the skill bias of technology β_{irt} appear to be not meaningful. Similarly, no relevant differences are observed with regards to the estimates obtained using the "geographical accessibility" instrument, reported in the bottom part of Table 8. Thus, it clearly emerges that an increase in the elasticity of substitution between high- and low-skilled workers does not change the main findings discussed in Section 6.2.

[Tables 8 and 9]

As a second step, we relax the assumption that σ is equal across sectors and use the values that Blankenou and Cassou (2011) estimate for the US. The results from the 2SLS regressions are reported in Table 9. Again, the discussion of the main findings is in terms of comparison with those in Tables 6 and 7 (i.e. with $\sigma = 1.55$). Starting with the estimates obtained using the "ethnic network" instrument, and with regard to the impact of immigrants on total factor productivity, there emerges no meaningful differences compared with the previous results (Table 6). As for differences in the point estimates, higher values of the coefficients estimated for the total factor productivity are counterbalanced by higher values of the coefficients estimated for the skill intensity index $\varphi(h_{irt})$. Conversely, some differences arise when using the "geographical accessibility" instrument. More specifically, the effect of immigrants on total factor productivity for both Hotel and restaurant (column 5) and Other personal services (column 10) is now (highly) statistically significant (with positive sign), thus in line with the results found with the "ethnic network" instrument. Moreover, the estimates are now significant for Finance insurance and real estate (column 7), and for Professional, technical, administrative and support services (column 8), with positive and negative sign, respectively. Again, not surprisingly, the higher coefficients estimated for total factor productivity are counterbalanced by the higher coefficients (in absolute value) estimated for the skill intensity index $\varphi(h_{irt})$ and for the skill bias of technology β_{irt}.

Summing up, considering all the results together, that is the 2SLS estimates and the sensitivity analysis, our findings suggest that immigrants exert a positive impact on both value added per worker and total factor productivity in at least four sectors, namely Manufacturing, Construction, Commerce and Transport and communication. Overall, these sectors represent 46% of total employment and 42% of total value added for the Italian economy in 2011.

7. Concluding remarks

This paper performs a sectoral analysis of the channels through which receiving economies respond to immigration. To this aim, we empirically investigate the economic impact of immigrant workers on Italian sectors at regional level during the period 2008–2011. The period of our analysis has been characterized by a huge increase of immigration in Italy, which in turn affected the labor supply. The share of foreign workers in total employment, in fact, roughly doubled during the second half of Noughties, from 5.2% in 2005 to 10% in 2011 (ISTAT). Interestingly, although the majority of foreign workers are employed in the Northern regions, the Center and the South are the areas of the country where the share of foreign workers in total employment has experienced the fastest growth during the period of our analysis. Moreover, almost 90% of immigrant workers are low-skilled and unevenly distributed across sectors.

The empirical strategy is based on an aggregate production function approach which allows to identify the impact of immigration on output and its components. The former is expressed in terms of value added per worker, while the components are the capital to value added ratio, the average hours worked per worker, the total factor productivity and a productivity-weighted skill-intensity index.

According to our empirical findings, with respect to the effect of immigrants on value added per worker, sectors can be divided into three groups.

In the first one, we find that an increase of foreign workers neither affects value added per worker nor total factor productivity. This group includes Finance, insurance and real estate, Professional, technical, administrative and support services, and Education, health and social services. These are also the sectors with the highest shares of skilled workers. Accordingly, in these sectors the prevalence of skill intensive production tasks and/or managerial jobs requiring high communication skills severely limits the advantages of employing (low-skilled) foreign workers. These findings are robust to both the use of alternative instruments and the use of sector-specific values of the elasticity of substitution between high- and low-skilled workers (σ_i).

The second group of sectors comprises Hotel and restaurant and Other personal services. For these sectors, we find a positive impact of immigration on both value added per worker (and total factor productivity). The outcome is statistically significant and robust to the use of sector-specific values of σ only when the estimates are carried out using the "ethnic networks" instrument.

The third group is the one for which the empirical evidence in favor of a positive impact of immigration on output is robust to the use of both instruments and to the sensitivity analysis. This group includes Manufacturing, Construction, Commerce and Transport and Communication. For these four sectors, the positive effect is mainly explained by the positive impact on total factor productivity. Commerce is the sector where the effect of immigrants is stronger. Moreover, for Construction and Commerce, we find robust evidence that immigrants negatively affect the skill-intensity index through its two determinants, namely the share of highly educated workers and the skill bias of technology. Taken together, these results suggest that, particularly in these two sectors, immigrants stimulate productivity gains by promoting production techniques that are unskilled-efficient. This explanation is consistent with the fact that a very high share of immigrant workers are low-skilled in terms of educational attainment. As a result, the low-skilled foreign workers specialize in manual tasks, possibly without crowding out low-skilled natives, which, conversely, specialize in communication-intensive tasks. Therefore, comparative advantages in tasks specialization seem the primary source of productivity gains due to immigration for these two

sectors. Similar results hold for Transport and communication, but only for the 2SLS estimates using the "geographical accessibility" instrument. It is also possible that immigration is providing an indirect contribution to total factor productivity by reducing labor costs and by allowing firms to invest more in new technologies. This might be the case for both Manufacturing and Transport and communication, for which we have not found (robust) evidence of a negative effect of immigrants on the skill bias of technology. However, at this regard, it should be considered that the results might be affected by the sectoral aggregation level of the data. In fact, both sectors comprise firms, and thus activities, which are quite heterogeneous with each other, in particular with regard to the technology intensity of the production processes.

It is worth to note that the third group of sectors accounts for 42% of the Italian total value added. Therefore, it emerges that the overall positive impact estimated without considering sector specific effect is probably driven only by these sectors. The latter result conforms to previous empirical evidence in favor of the positive effect of the share of immigrant workers at aggregate level, on both value added per worker and total factor productivity (Peri, 2012; Aleksynska and Tritah, 2015).

Overall, the present study provides the following contributions to the empirical literature on the economic impact of immigration. First, it provides additional empirical evidence on the positive effects of immigration on the host economy. More specifically, the findings highlight a positive impact on value added per worker which is mainly driven by the positive impact on total factor productivity. Second, it presents a novel sectoral analysis, whose results emphasize how the impact of immigrants crucially depends on the sector where they are employed. Third, it shows that the sectors that mostly take advantage of immigrant workers are those characterized by the predominance of manual tasks (i.e. tasks that do not require high communication skills).

Based on our findings, some policy implications can be drawn. As long as immigrants contribute to a better functioning of labor markets and to the overall efficiency of the economic system, economic policy should pursue the maintenance of flexible labor markets. This would help firms to adjust their factor mix to the availability of immigrant workers that, presumably, have different skills with respect to natives. The resulting increase in allocative efficiency is likely to exert a significant positive effect to total output and productivity.

References

Accetturo A., Bugamelli M. and Lamorgese A. (2012). Welcome to the machine: firms' reaction to low-skilled immigration. Banca d'Italia, Temi di discussione N. 846.

Aleksynska M. and Tritah A. (2015). The heterogeneity of immigrants, host countries' income and productivity: A channel accounting approach. Economic Inquiry, 53, 150-172.

Alesina A., Harnoss J. and Rapoport H. (2016). Birthplace diversity and economic prosperity. Journal of Economic Growth, 21, 101-138.

Altonji J. G. and Card D. (1991). The effects of immigration on labor market outcomes of less-skilled natives. In Abowd J. and Freeman R. (Eds) Immigration, trade, and labor markets (pp. 201–234). Elsevier.

Bank of Italy (2006, 2007). Indagine sul turismo internazionale dell'Italia. Retrieved in September 2016, from Bank of Italy web site: http://www.bancaditalia.it/statistiche/rapp_estero/turismo-int

Bettin G., Lo Turco A. and Maggioni D. (2014). A firm-level perspective on migration. The role of extra-EU workers in Italian manufacturing. Journal of Productivity Analysis, 42, 305–325.

Borjas G. J. (2014). Immigration economics, Harvard University Press.

Borjas G. J. (2001). Does immigration grease the wheels of the labor market? Brookings Papers on Economic Activity, 32, 69-134.

Borjas, G. J., Grogger J., and Hanson G. H. (2012). Comment: On estimating elasticities of substitution. Journal of the European Economic Association, 10, 198-210.

Card D. (2001). Immigrant inflows, native outflows, and the local market impacts of higher immigration. Journal of Labor Economics, 19, 22-64.

Blankenou W. F. and Cassou S. P. (2011). Industry estimates of the elasticity of substitution and the rate of biased technological change between skilled and unskilled labour. Applied Economics, 43, 3129-3142.

Ciccone A. and Peri G. (2005). Long-run substitutability between more and less educated workers: evidence from U.S. states, 1950–1990. The Review of Economics and Statistics, 87, 652-663.

Cortes P. (2008). The effect of low-skilled immigration on U.S. prices: Evidence from CPI data. Journal of Political Economy, 116, 381–422.

De Arcangelis G., Di Porto E. and Santoni G. (2015a). Immigration and manufacturing in Italy. Evidence from the 2000s. Economia e Politica Industriale, 42: 163-187.

De Arcangelis G., Di Porto E. and Santoni G. (2015b). Migration, labor tasks and production structure. Regional Science and Urban Economics, 53, 156–169.

Dustmann C., Schönberg U. and Stuhler J. (2016). The impact of immigration: Why do studies reach such different results? Journal of Economic Perspectives, 30, 31-56.

Etzo I., Massidda C. and Piras R. (2015). The impact of immigrants settlements' on Italian firms. Paper presented to Italian Economic Association, 56th Annual Conference, Naples (Italy) 22-24 October 2015.

Falzoni A. M., Venturini A. and Villosio C. (2011). Skilled and unskilled wage dynamics in Italy in the 1990s: changes in individual characteristics, institutions, trade and technology. International Review of Applied Economics, 25, 441-463.

Gonzales L. and Ortega F. (2013). Immigration and housing booms: evidence from Spain. Journal of Regional Science, 53, 37-59.

Fondazione Moressa (2016). Rapporto annuale sull'economia dell'immigrazione. L'impatto fiscale del'immigrazione. Il Mulino, Bologna.

Hall R. E. and Jones C. I. (1999). Why do some countries produce so much more output per worker than others? Quarterly Journal of Economics, 114, 83-116.

Hunt J. (2011). Which immigrants are most innovative and entrepreneurial? Distinctions by entry visa. Journal of Labor Economics, 29, 417-457.

Kerr W. R. and Lincoln W. F. (2010). The supply side of innovation: H-1b visa reforms and US ethnic invention. NBER working paper N. 15768.

Kleibergen F. and Paap R. (2006). Generalized reduced rank tests using the singular value decomposition. Journal of Econometrics, 133, 97-126.

Lewis E. G. and Peri G. (2015). Immigration and the economy of cities and regions. In Duranton G, Henderson V. J. and Strange W. C., (Eds) Handbook of regional and urban economics, (Vol. 5, pp 625-685). Elsevier.

Lewis E. G. (2011). Immigration, skill mix, and capital skill complementarity. Quarterly Journal of Economics, 126, 1029-1069.

Marrocu E. and Paci R. (2010). The effects of public capital on the productivity of the Italian regions. Applied Economics, 42, 989-1002.

Mocetti S. and Porello C. (2010). How does immigration affect native internal mobility? New evidence from Italy. Regional Science and Urban Economics, 40, 427-439.

Mazzolari F. and Neumark D. (2012). Immigration and productivity diversity. Journal of Population Economics, 25, 1107-1137.

Olney W. (2013). Immigration and firms expansion. Journal of Regional Science, 53, 142–157.

Ortega F. and Peri G. (2009). The causes and effects of international migration: Evidence from OECD countries 1980-2005. NBER Working Papers N. 14833.

Ottaviano G. I. P. and Peri G. (2006). Rethinking the gains from immigration. Theory and evidence from USA. FEEM Working Paper N. 52.

Ottaviano G. I. P. and Peri G. (2008). Immigration and national wages: Clarifying the theory and the empirics. NBER Working Papers N. 14188.
Ottaviano G. I. P. and Peri G. (2012). Rethinking the effect of immigration on wages. Journal of the European Economic Association, 10, 152–97.
Ottaviano G. I. P. and Peri G. (2013). New frontiers of immigration research: Cities and firms. Journal of Regional Science, 53, 1-7.
Peri G. (2012). The effect of immigration on productivity: Evidence from U.S. States. The Review of Economics and Statistics, 94, 348-358.
Peri G. and Sparber C. (2009). Task specialization, immigration, and wages. American Economic Journal: Applied Economics, 1, 135-69.
Romiti A. (2011). Immigrants-natives complementarities in production: evidence from Italy. CERP Working Paper N. 105.
Staffolani S. and Valentini E. (2010). Does immigration raise blue and white collar wages of natives? The case of Italy. Labour, 24, 295–310.
Stock J. H. and Yogo M. (2005). Testing for weak instruments in linear IV regression. In Andrews D.W.K. and Stock J.H. (Eds.) Identification and inference for econometric models: Essays in honor of Thomas Rothenberg (pp. 80-108). Cambridge: Cambridge University Press,.
Unioncamere (2014). Audizione dell'Unioncamere - Comitato parlamentare di controllo sull'attuazione dell'accordo di Schengen, di vigilanza sull'attività di Europol, di controllo e vigilanza in materia di immigrazione, 20 march 2014.
Wooldridge, Jeffrey M. (2010). Econometric analysis of cross section and panel data. Second Edition, The MIT Press, Cambridge, Massachusetts.

Table 1 - Immigrants residing in Italy. First 23 nationalities (31/12/2015).

Nationality	Units	Share	Cumulative Share	Nationality	Units	Share	Cumulative Share
Romania	1151395	22.91	22.91	Sri Lanka	102316	2.04	68.68
Albania	467687	9.31	32.21	Pakistan	101784	2.03	70.70
Morocco	437485	8.70	40.92	Senegal	98176	1.65	72.66
Chinese, Pop. Rep.	271330	5.40	46.32	Poland	97986	1.95	74.61
Ukraine	230728	4.59	50.91	Tunisia	95645	1.90	76.51
Philippines	165900	3.30	54.21	Ecuador	87427	1.74	78.25
India	150456	2.99	57.20	Nigeria	77264	1.54	79.79
Moldova	142266	2.83	60.03	Macedonia	73512	1.46	81.25
Bangladesh	118790	2.36	62.39	Bulgaria	58001	1.15	82.40
Egypt	109871	2.19	64.58	Ghana	48637	1.00	83.37
Peru	103714	2.06	66.64	**Total**	**419370**		

Source: own computation based on Istat (Data warehouse: http://stra-dati.istat.it/). Data are reported for those countries which represent at least 1% of foreign citizens.

Table 2 – Native and immigrant workers: employment by industry (year: 2011).

		% sectoral employment			Employment share	
cat12	Sectors	Natives	Immigrants	Natives/ Immigrants	Natives	Immigrants
1	Agriculture, forestry, fishing	3.2	5.2	0.62	68.5	31.5
2	Energy, mining and quarrying	1.1	0.2	5.50	98.4	1.6
3	Manufacturing	20.7	21.1	0.98	92.2	7.8
4	Construction	7.3	12.8	0.57	79.6	20.4
5	Commerce	11.6	6.0	1.93	94.4	5.6
6	Hotel and restaurant	5.1	9.1	0.56	79.9	20.1
7	Transportation and communication	5.9	4.9	1.20	92.7	7.3
8	Financial, insurance and real estate	3.1	0.6	5.17	98.9	1.1
9	Professional, scientific and technical activities	8.1	6.3	1.29	93.9	6.1
10	Public administration	9.6	0.3	32.00	99.8	0.2
11	Education; Health and social work activities	17.0	4.6	3.70	97.3	2.7
12	Other personal services	7.4	29.0	0.26	62.9	37.1
		100.00	100.0			

Source: own computation based on the LFS data (ISTAT).

Table 3 – Native and immigrant workers: education level (2011).

	Natives (%)	Immigrants (%)	Natives/Immigrants
Primary education (ISCED 1)	4.65	10.89	0.43
Lower-secondary (ISCED 2)	29.86	33.72	0.88
Upper secondary (ISCED 3, 4)	46.83	44.86	1.04
University degree and more (ISCED 5, 6)	18.66	10.52	1.77

Source: own computation based on Istat (Data warehouse: http://stra-dati.istat.it/ and http://dati.istat.it/).

Table 4. OLS estimates

	1	2	3	4	5	6	7	8	9	10
Sectors	*Total*	*Manuf.*	*Constr.*	*Commerce*	*Hotel and restaurant*	*Transport. and communicat.*	*Finance, insurance and real estate*	*Prof., technical, administrative and support services*	*Education, health and social services*	*Other personal services*
Dependent Variables										
$ln\ y_{irt}$	0.005 **	0.005	0.010 **	0.018 *	0.011 **	-0.004	-0.049	-0.018 ***	-0.049 ***	0.002
	(0.002)	(0.006)	(0.004)	(0.009)	(0.005)	(0.005)	(0.036)	(0.004)	(0.011)	(0.002)
$(\alpha/(1-\alpha))\ ln\ (K_{irt}/Y_{irt})$	0.000	0.001 *	0.001 *	0.001	0.001	-0.002	-0.010 *	0.003 **	0.011 ***	0.000
	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)
$ln\ x_{irt}$	0.000	0.001	-0.001	-0.005 **	-0.006 ***	0.000	0.001	0.006 **	0.010 **	0.001
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
$ln\ A_{irt}$	0.006 **	0.006	0.011 **	0.026 **	0.017 **	0.004	-0.032	-0.027 **	-0.059 ***	0.002
	(0.003)	(0.006)	(0.004)	(0.010)	(0.005)	(0.005)	(0.033)	(0.005)	(0.012)	(0.002)
$ln\ \varphi_{irt}$	-0.001	-0.003 *	-0.001 **	-0.004	-0.001	-0.005 *	-0.008 **	0.000	-0.012 ***	-0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)
$ln\ h_{irt}$	0.005	-0.014	0.014 **	-0.007	0.013	-0.030 **	-0.074 ***	-0.014 **	-0.117 ***	-0.004
	(0.005)	(0.007)	(0.005)	(0.023)	(0.008)	(0.010)	(0.018)	(0.006)	(0.017)	(0.004)
$ln\ \beta_{irt}$	0.005	-0.035 *	0.021 *	-0.023	0.020	-0.054 *	-0.104	-0.021 **	-0.199 ***	-0.009
	(0.009)	(0.014)	(0.012)	(0.042)	(0.015)	(0.026)	(0.037)	(0.013)	(0.033)	(0.011)

*Notes: observations 684. Heteroskedasticity robust standard errors clustered by region and sectors in brackets. Constant term, industry, region and time effects included but not reported. *** significant 1%, ** significant 5%, * significant 10%. For the i-th industry, the interaction term is (z_irt×d_i). The Table reports the estimated impact of the share of foreign workers on the i-th industry as the linear combination of the coefficient of Manufacturing and the interaction term, namely γb1 + γbi.*

Table 5. First Stage results

	Dependent variable: share of immigrant workers (z_{irt})			
Instrument:	Ethnic networks		Geographical accessibility	
	1	2	3	4
Coefficient	0.33 ***	0.22 ***	0.38 ***	0.26 **
Standard error	(0.06)	(0.08)	(0.07)	(0.11)
Interactions (instrument x sector)	NOT	YES	NOT	YES
Underidentification test (Kleibergen-Paap rk LM statistic)				
Chi-sq(1)	25.89 ***	7.01 ***	14.71 ***	7.55 ***
Weak identification test (Kleibergen-Paap rk Wald F statistic)	34.55		31.99	
Stock-Yogo weak ID test critical values: 10% maximal IV size	16.38	na	16.38	na

*Notes: observations 684. Heteroskedasticity robust standard errors clustered by region and sectors in brackets. Constant term, industry, region and time effects included but not reported. The reported test statistics for underidentification and weak identification are robust to both heteroskedasticity, autocorrelation, and clustering. *** significant 1%, ** significant 5%, * significant 10%.*

Table 6. 2SLS estimates (instrument: ethnic networks)

	1		2		3		4		5		6		7		8		9		10	
Sectors:	Total		Manuf.		Constr.		Commerce		Hotel and restaurant		Transport. and communicat.		Finance, insurance and real estate		Prof., technical, administrative and support services		Education, health and social services		Other personal services	
Dependent Variables																				
ln y_{irt}	0.023	***	0.041	***	0.028	***	0.099	**	0.045	***	0.022	*	-0.045		0.013		0.072		0.016	**
	(0.004)		(0.016)		(0.008)		(0.041)		(0.012)		(0.013)		(0.065)		(0.016)		(0.070)		(0.006)	
$(\alpha/(1-\alpha))$ *ln* (K_{irt}/Y_{irt})	0.001		0.005	**	0.002		0.004		0.003		0.000		-0.015	*	0.005		0.023	**	0.002	
	(0.001)		(0.002)		(0.001)		(0.006)		(0.002)		(0.003)		(0.008)		(0.003)		(0.010)		(0.001)	
ln x_{irt}	-0.001		0.006	*	0.002		0.005		-0.003		0.002		0.012		0.009	**	0.033	**	0.003	
	(0.001)		(0.003)		(0.002)		(0.007)		(0.003)		(0.002)		(0.009)		(0.004)		(0.014)		(0.002)	
ln A_{irt}	0.024	***	0.039	**	0.029	***	0.111	**	0.052	***	0.029	**	-0.009		0.007		0.069		0.014	**
	(0.005)		(0.017)		(0.008)		(0.038)		(0.012)		(0.013)		(0.062)		(0.017)		(0.081)		(0.006)	
ln φ_{irt}	-0.001		-0.009		-0.005	**	-0.021	**	-0.006	**	-0.009	**	-0.034		-0.008		-0.052	*	-0.003	
	(0.001)		(0.006)		(0.002)		(0.008)		(0.004)		(0.004)		(0.017)		(0.006)		(0.029)		(0.002)	
ln h_{irt}	0.022	**	-0.026		0.009		-0.081	**	0.002		-0.041	**	-0.191	**	-0.035	*	-0.232	**	-0.010	
	(0.010)		(0.022)		(0.011)		(0.035)		(0.019)		(0.018)		(0.074)		(0.021)		(0.099)		(0.008)	
ln β_{irt}	0.037	**	-0.059		0.010		-0.156	**	0.002		-0.078	*	-0.312	**	-0.072		-0.452	**	-0.017	
	(0.018)		(0.049)		(0.024)		(0.073)		(0.037)		(0.041)		(0.142)		(0.047)		(0.225)		(0.017)	

*Notes: observations 684. Heteroskedasticity robust standard errors clustered by region and sectors in brackets. Constant term, industry, region and time effects included but not reported. *** significant 1%, ** significant 5%, * significant 10%. For the i-th industry, the interaction term is (z_irt×d_i). The Table reports the estimated impact of the share of foreign workers on the i-th industry as the linear combination of the coefficient of Manufacturing and the interaction term, namely γb1 + γbi. A Wald tests of joint significance of the coefficients estimated for the i-th industry has been performed for each regression. The results are the following. ln y : F(9, 170) = 5.84*** ; (α/(1-α)) ln (K/Y): 4.56*** ; ln x: F(9, 170) = 3.16*** ; ln A: F(9, 170) = 7.08*** ; ln φ : F(9, 170) = 3.28*** ; ln h: F(9, 170) = 4.58*** ; ln β : F(9, 170) = 3.22***.*

Table 7. 2SLS estimates (instrument: geographical accessibility)

	1	2	3	4	5	6	7	8	9	10
Sectors:	*Total*	*Manuf.*	*Constr.*	*Commerce*	*Hotel and restaurant*	*Transport. and communicat.*	*Finance, insurance and real estate*	*Prof., technical, administrative and support services*	*Education, health and social services*	*Other personal services*
Dependent Variables										
ln y_{irt}	0.011 **	0.037 **	0.012 **	0.057 **	0.015	0.018 **	-0.023	-0.009	0.020	0.006
	(0.004)	(0.018)	(0.006)	(0.022)	(0.017)	(0.009)	(0.046)	(0.012)	(0.062)	(0.004)
$(\alpha/(1-\alpha))$ *ln* (K_{irt}/Y_{irt})	0.002 *	0.011 *	0.003 *	0.005	0.003	-0.002	-0.009 *	0.007 *	0.032 *	0.003 *
	(0.001)	(0.006)	(0.001)	(0.006)	(0.003)	(0.003)	(0.005)	(0.004)	(0.016)	(0.001)
ln x_{irt}	0.000	0.005	0.000	-0.002	-0.002	0.001	0.003	0.012 ***	0.030 *	0.001
	(0.001)	(0.004)	(0.001)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.016)	(0.001)
ln A_{irt}	0.012 **	0.036 *	0.015 **	0.068 **	0.025	0.031 **	0.004	-0.021	0.045	0.007
	(0.005)	(0.022)	(0.007)	(0.024)	(0.019)	(0.012)	(0.041)	(0.015)	(0.097)	(0.005)
ln φ_{irt}	-0.003	-0.014 *	-0.006 **	-0.015	-0.011 **	-0.012 **	-0.020	-0.007	-0.086 *	-0.004 **
	(0.002)	(0.008)	(0.002)	(0.010)	(0.003)	(0.004)	(0.014)	(0.006)	(0.051)	(0.002)
ln h_{irt}	0.004	-0.044	0.001	-0.067 **	-0.020	-0.050 **	-0.129 **	-0.051 **	-0.361 **	-0.017 **
	(0.009)	(0.032)	(0.009)	(0.033)	(0.017)	(0.018)	(0.053)	(0.022)	(0.172)	(0.007)
ln β_{irt}	0.002	-0.115	-0.004	-0.103	-0.054 *	-0.105 **	-0.202 *	-0.106 **	-0.742 *	-0.036 **
	(0.018)	(0.072)	(0.022)	(0.076)	(0.032)	(0.042)	(0.116)	(0.051)	(0.394)	(0.015)

*Notes: observations 684. Heteroskedasticity robust standard errors clustered by region and sectors in brackets. Constant term, industry, region and time effects included but not reported. *** significant 1%, ** significant 5%, * significant 10%. For the i-th industry, the interaction term is (z_irt×d_i). The Table reports the estimated impact of the share of foreign workers on the i-th industry as the linear combination of the coefficient of Manufacturing and the interaction term, namely γb1 + γbi. A Wald tests of joint significance of the coefficients estimated for the i-th industry has been performed for each regression. The results are the following. ln y : F(9, 170) = 3.35*** ; (α/(1-α)) ln (K/Y): 4.92*** ; ln x: F(9, 170) = 2.43** ; ln A: F(9, 170) = 4.53*** ; ln φ : F(9, 170) = 2.79*** ; ln h: F(9, 170) = 3.36*** ; ln β : F(9, 170) = 2.13**.*

Table 8. Sensitivity analysis for σ = 1.75

	2		3		4		5		6		7		8		9		10	
Sectors:	Manuf.		Constr.		Commerce		Hotel and restaurant		Transport. and communicat.		Finance, insurance and real estate		Prof., technical, administrative and support services		Education, health and social services		Other personal services	
Dependent Variables																		
2SLS regressions with "ethnic network" instrument																		
ln A_{irt}	0.034	**	0.026	***	0.098	***	0.048	***	0.023	*	-0.029		0.002		0.035		0.012	**
	(0.015)		(0.007)		(0.037)		(0.012)		(0.013)		(0.062)		(0.015)		(0.068)		(0.006)	
ln φ_{irt}	-0.003		-0.002	*	-0.008	**	-0.002		-0.004	**	-0.013	**	-0.003		-0.019	*	-0.001	
	(0.002)		(0.001)		(0.003)		(0.001)		(0.002)		(0.007)		(0.002)		(0.011)		(0.001)	
ln β_{irt}	-0.040		0.009		-0.106	**	0.004		-0.053	*	-0.211	**	-0.050		-0.310		-0.011	
	(0.035)		(0.018)		(0.053)		(0.026)		(0.030)		(0.098)		(0.033)		(0.157)		(0.012)	
2SLS regressions with "geographical accessibility" instrument																		
ln A_{irt}	0.026	*	0.011	*	0.058	***	0.017		0.024	**	-0.008		-0.025	*	-0.011		0.004	
	(0.015)		(0.007)		(0.022)		(0.019)		(0.011)		(0.046)		(0.014)		(0.075)		(0.004)	
ln φ_{irt}	-0.005		-0.002	**	-0.005		-0.004	***	-0.004	***	-0.008	*	-0.003		-0.030		-0.002	**
	(0.003)		(0.001)		(0.004)		(0.001)		(0.002)		(0.005)		(0.002)		(0.019)		(0.001)	
ln β_{irt}	-0.080		-0.001		-0.067		-0.036		-0.073	**	-0.137	*	-0.076	**	-0.512	*	-0.025	**
	(0.051)		(0.016)		(0.054)		(0.023)		(0.031)		(0.081)		(0.036)		(0.274)		(0.011)	

*Notes: observations 684. Heteroskedasticity robust standard errors clustered by region and sectors in brackets. Constant term, industry, region and time effects included but not reported. *** significant 1%, ** significant 5%, * significant 10%. For the i-th industry, the interaction term is (z_irt×d_i). The Table reports the estimated impact of the share of foreign workers on the i-th industry as the linear combination of the coefficient of Manufacturing and the interaction term, namely γb1 + γbi.*

Table 9. Sensitivity analysis with sector-specific values of σ

	2		3		4		5		6		7		8		9		10	
Dependent Variables / Sectors:	Manuf.		Constr.		Commerce		Hotel and restaurant		Transport. and communicat.		Finance, insurance and real estate		Prof., technical, administrative and support services		Education, health and social services		Other personal services	
								2SLS regressions with "ethnic network" instrument										
ln A_{irt}	0.088	**	0.061	***	0.234	***	0.096	***	0.063	**	0.162		-0.023		0.286		0.045	***
	(0.043)		(0.018)		(0.060)		(0.031)		(0.026)		(0.148)		(0.080)		(0.250)		(0.011)	
ln φ_{irt}	-0.058		-0.036	*	-0.144	**	-0.050		-0.044	*	-0.205	*	0.022		-0.270		-0.034	**
	(0.038)		(0.019)		(0.058)		(0.031)		(0.025)		(0.105)		(0.077)		(0.219)		(0.012)	
ln β_{irt}	-0.224		-0.162	**	-0.616	***	-0.181		-0.196	*	-0.929	**	0.112		-1.232		-0.155	***
	(0.157)		(0.075)		(0.212)		(0.130)		(0.108)		(0.386)		(0.308)		(0.937)		(0.044)	
								2SLS regressions with "geographical accessibility" instrument										
ln A_{irt}	0.169	**	0.060	***	0.233	***	0.108	***	0.134	**	0.109	*	-0.169	*	0.476		0.037	***
	(0.074)		(0.012)		(0.059)		(0.018)		(0.047)		(0.080)		(0.087)		(0.448)		(0.008)	
ln φ_{irt}	-0.147		-0.050	***	-0.180	***	-0.094	***	-0.114		-0.125	**	0.141	*	-0.517		-0.034	***
	(0.131)		(0.015)		(0.049)		(0.032)		(0.078)		(0.060)		(0.080)		(0.435)		(0.006)	
ln β_{irt}	-0.546		-0.211	***	-0.702	***	-0.368	***	-0.461		-0.598	***	0.522	*	-2.251		-0.153	***
	(0.464)		(0.058)		(0.183)		(0.131)		(0.294)		(0.224)		(0.288)		(1.852)		(0.027)	

*Notes: observations 684. Heteroskedasticity robust standard errors clustered by region and sectors in brackets. Constant term, industry, region and time effects included but not reported. *** significant 1%, ** significant 5%, * significant 10%. For the i-th industry, the interaction term is (z_irt×d_i). The Table reports the estimated impact of the share of foreign workers on the i-th industry as the linear combination of the coefficient of Manufacturing and the interaction term, namely γb1 + γbi.*