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

Etzo, Ivan and Massidda, Carla and Piras, Romano and Mattana, Paolo

May 2016

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 how immigrants impact on Italian economy. The issue is addressed following 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 investigation is carried out at sector level during the 2008–2011 time period. The results show that the main channel through which migration impacts on value added varies on sectoral basis. While at aggregate level, in Manufacturing and in Other Services the impact goes mainly through capital intensity, in the Construction and in the Commerce sectors the principal channel is via total factor productivity.

Keywords: channel output decomposition approach, immigrants.
JEL Classification: F22, F62, J61

1. Introduction

The rising trend in migration inflows observed during the last decades is often perceived as a threat for hosting destinations. In contrast to this view, a recent strand of economic literature has started to think about immigrants as an opportunity for receiving countries to improve the productivity of labor and other inputs of production (Lewis and Peri, 2015; Hunt, 2011; Kerr and Lincoln, 2010). There is multiplicity of reasons why immigrants, both high- and low-skilled ones, could actually be good for the economy.

As for the high-skilled, the positive role is almost universally acknowledged and easily explained in terms of their contribution to human capital accumulation. In addition, high-skilled immigrants are deemed to stimulate entrepreneurship and the exchange of ideas and to contribute, with high-skilled natives, to generate innovations and new firms (Peri et al., 2014).

As regards the less-skilled, fears have prevailed for long time due to alleged crowding-out and substitution effects that would hurt low-skilled natives. Such a picture could actually emerge in a simple partial equilibrium short-run labor market framework that portraits low-skilled immigrants as perfect substitutes of low-skilled natives. As a matter of fact, even in the short-run this conclusion does not necessarily hold as long as immigrants and natives deeply differ in an array of dimensions also when they have the same formal educational level. Among other things, the most common differences reside in individual-specific abilities, such as language fluency, and other social and cultural differences that make immigrants different from natives. Bringing with them these differences, the less-educated immigrants do not necessarily crowd-out natives of comparable education when there are comparative advantages for the two categories of workers to specialize in different tasks. Tasks requiring manual skills (farm laborers, construction workers, child and elderly care, etc.) may be adequately held by foreign workers, while tasks requiring language and communication skills (construction supervisors, farm coordinators, cooks, etc.) can be better held by natives (Peri and Sparber, 2009). Besides pushing a more efficient allocation of skills to tasks, low-skilled immigration can also contribute to productivity gains thanks to lower production costs due to lower wages paid by firms (Peri, 2012). Furthermore, as highlighted by Olney (2013) for US and Etzo et al. (2016) for Italy, firms might find profitable to expand their own businesses by opening new establishments or re-allocating existing ones in response to an increased share of foreign workers.

In the footsteps of these issues built on a traditional labor market framework, recently researches have analyzed the economic impacts of immigration under wider perspectives. One of these is the so called channel output decomposition approach followed by Aleksynska and Tritah (2015), Peri (2012) and Ortega and Peri (2009), by means of which the effect of immigration is measured with respect to per capita output (or value added as in the present study) and to all its components. Aleksynska and Tritah (2015) study the impact of migration in twenty OECD countries during the 1960-2005 time period and find that immigrants have a positive effect on income that works through total factor productivity, whereas the capital output ratio is not affected by immigrants' share. The authors claim that the positive effect is consistent with the literature emphasizing the beneficial effects of workforce diversity on productivity suggested by Alesina et al. (2013) and with the "immigrants greasing the wheels of host countries' labor markets" hypothesis advocated by

Borjas (2001). Ortega and Peri (2009) concentrate on 14 OECD destination countries during the years from 1980 to 2005. Their results suggest that the inflow of immigrants does not seem to reduce capital intensity, nor total factor productivity both in the short and in the long run. In addition, immigration increases employment and total GDP of the receiving countries. As said, these two works look at different samples of OECD countries, on the contrary Peri (2012) studies US States and claims that there is no evidence that immigrants crowd out natives employment and that immigration is associated with total factor productivity growth. He analyzes the impact of migration on production inputs, productivity and its skill bias in a production function framework where heterogeneity and complementarity among workers are allowed. His main empirical findings claim for a positive relationship between immigration and total factor productivity and a negative relationship between immigration and the high-skill bias of aggregate productivity. Accordingly, less-educated immigrants "promote efficient task specialization, thus increasing total factor productivity, and also promote the adoption of unskilled-efficient technologies" (Peri, 2012: 348).

In this paper we aim at giving a contribution on the impact of immigration on the Italian economy taking an approach similar to Peri (2012). The purpose is two-fold: on the one hand we aim at investigating the channels linking the national value added components to an inflow of foreign workers, on the other hand, we try to uncover if these channels operate likewise across sectors. At this scope, we construct a three dimensional panel dataset that observes the value added at aggregate level (excluding Agriculture) and in four sectors (Manufacturing, Construction, Commerce and Other Services) at regional (NUTS 2) level during the 2008–2011 time period. For each sector, we first decompose value added per worker into its four components, namely capital-output ratio, average hours worked, total factor productivity and an index of skill intensity. Then we estimate the impact of migration, measured as the share of immigrant workers over total employment, on these components. We find a preeminent role for the capital to value added ratio and for the productivity-weighted skill-intensity index, followed by total factor productivity. On the contrary, with the exception of Other Services, average hours worked per worker do not play any significant role. These results suggest that the main channel through which migration impact on value added varies depending on the sector of economic activity. At aggregate level, in Manufacturing and in Other Services this happens more via capital intensity rather than total factor productivity. Conversely, in the Construction and in the Commerce sectors the principal channels are reversed and total factor productivity is the driving channel through which immigrants affect per capita value added.

It is difficult to compare our findings with previous literature regarding Italy. As a matter of fact, starting from 1990s Italy has become an important destination country for an increasing number of immigrants and while various studies looking at the effect of immigrants on Italian labor market have been done (see, inter alia, the recent works of Mocetti and Porello, 2010; Staffolani and Valentini 2010 and Falzoni et al., 2011), very few papers have investigated their role inside a broader economic context as we do in this paper. The present contribution is related to those of Accetturo et al. (2012), Bettin et al. (2014), De Arcangelis et al. (2015a, b) and Etzo et al. (2016). Accetturo et al. (2012) estimate how investment in machinery and equipment responds to an increase in the relative abundance of low-skilled migrant workers. They find a positive relationship that tends to be stronger for small firms and less technologically 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, the latter claim that an increase in the weight of relatively low-skilled immigrants tend to favor low-skill versus high-skill sectors and therefore to impact on the relative composition of the production system. Finally, Etzo et al. (2016) 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.

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

2. Immigration in Italy

In the last decades immigration has become increasingly important for Italy. Foreign citizens, 1,334,889 in the 2001 census, more than tripled in the subsequent ten years reaching 4,027,627 in 2011. In relative terms over Italian population, they were 2.3% in 2001 climbing up to 6.8%, in 2011. As regards the country of origin, the last available data refereed to 2013 show that 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 85.1% of all immigrants (Table 1). Migrants have settled principally in the Centre-North, where they find more favorable conditions in terms of employment opportunities, availability of public services and a vast range of other amenities.

[Table 1]

Data on employment, which are taken from the Italian Labour Force Survey conducted by ISTAT, show that in 2011, at the end of our empirical investigation, total foreign labor force was 2,561,603, while 2,251,481 of them were employed. Immigrants are employed mainly in the Services sectors 60.45%¸ followed by Industry 34.97% and Agriculture 4.58% (Table 2). Among the Services, less than one third are employed in Commerce and more than two third are employed in Other Services. The Industry sector presents a higher share of immigrants employed in Manufacturing but also a remarkable share of immigrants working in Construction. Looking at sectoral employment share, we observe that immigrants are employed proportionally more in Agriculture and Construction with respect to natives (last column of Table 2). As for immigrants' educational level (Table 3), 10.89 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),[1] in 2011 the percentage of the national value added due to foreign workers was about 12.8%, 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).[2] More conservative figures are provided by Fondazione Moressa (2015), that consider only regular employment, and estimates the percentage of value added due to foreign workers at 8.6% in 2014. According these two studies, we can claim that immigrants in Italy account for at least ten per cent of the whole value added production and that their role is crucial in the Construction sector.

3. Research strategy and empirical approach

As stated in the Introduction, in this paper we propose a sector-level perspective to analyze how the Italian economy responds to migration. We focus on the effects of migration on the value added and its components. We consider a panel of 19 Italian regions[3] and analyze the whole economy (excluding agriculture) as well as four sectors (Manufacturing, Construction, Commerce and Other Services) during the 2008–2011 time span.

As theoretical framework, in the footsteps of Peri (2012), we propose a sector-level production function. 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:

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

where Y_{irt} is value added, K_{irt} measures physical capital, X_{irt} corresponds to total hours worked, A_{irt} captures 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. As common practice in the literature, we assume that, within each sector, these two categories of workers combine their labor inputs into a constant elasticity of substitution function. Under these assumptions, $\varphi(h_{irt})$ corresponds to:

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

1 Unioncamere (Italian Union of Chambers of Commerce, Industry, Handicraft and Agriculture) is a public institution that represents the Italian chamber system.

2 These estimates consider both regular and irregular employment.

3 Italian regions are 20, but ISTAT merges the data of the smallest one (Valle D'Aosta) with Piemonte.

where σ_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 $y_{irt}=Y_{irt}/N_{irt}$:

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

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

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

Equation (4) decomposes 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 these premises, for each of the four sectors included in the panel, we test 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:

$$(5)\ lnb_{irt} = d_i + d_r + d_t + \gamma_{b1}z_{1rt} + \gamma_{b2}(z_{2rt}d_2) + \gamma_{b3}(z_{3rt}d_3) + \gamma_{b4}(z_{4rt}d_4) + \varepsilon_{irt}$$

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}) over 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 region (across sectors and time) or year (across sectors and regions); $(z_{irt}d_i)$ are interaction terms meant to capture differences in the slope coefficient across sectors and, finally, ε_{irt} represents a zero-mean random shock.

The empirical model in equation (5) is defined taking 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) calculated for Manufacturing, while the coefficients γ_{b2}, γ_{b3} and γ_{b4} measure the differences between Manufacturing and the other sectors, i.e. Construction, Commerce and Other Services. It follows that immigrants' total impact on the generic *i-th* sector is the sum of the two coefficients $\gamma_{b1}+\gamma_{bi}$. At aggregate level, namely ignoring sector heterogeneity and dropping the interaction terms, equation (5) simplifies into:

$$(5a)\ lnb_{irt} = d_i + d_r + d_t + \gamma_b z_{irt} + \varepsilon_{irt}$$

The empirical implementation of equations (5)-(5a) requires overcoming two main problems. First of all, it needs relevant statistical data and reliable estimates of the production function parameters, specifically the capital-income share and the elasticity of substitution between high- and low-skilled workers at sector level. The direct estimation of these parameters goes beyond the scope of the present paper and, unfortunately, there are very few estimates of them available in the literature at sector level and almost none exists for the case of Italy. With regards to σ, the issue of inter-sector differences is of particular relevance since the elasticity of substitution between high- and low-skilled workers is crucial for computing $\varphi(h_{irt})$. However, as far as we know, no estimates are available for the Italian case and very few attempts are known for other countries. To the best of our knowledge, for Italy some estimates exist only at national level and are those provided by Romiti (2011) who delivers average values of σ around 1.55 at aggregate level, which perfectly fits within the range proposed 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 equations (5)-(5a) assuming that the elasticity of substitution between high- and-low skilled workers is σ=1.55 across all sectors. Next, in order to check for the robustness of the results, we perform a sensitivity analysis in two steps. Firstly, under the assumption that the elasticity of substitution between high- and low-skilled workers is the same for all sectors, we re-estimate the model using the alternative value of σ=1.75 considered by Peri (2012) for USA. Secondly, we introduce sector heterogeneity by imposing sector specific elasticities. At this purpose, we use the estimates provided by Blankenou and Cassou (2011) for USA, that is σ=1.41 for Manufacturing, σ=9.05 for Construction, σ=1.92 for Commerce and σ=1.62 for Other Services.

As for α, Marrocu and Paci (2010), depending on the empirical specification, estimate 0.295 and 0.365 for the whole economy which reassuringly fits very close to international evidence. Unfortunately, there exists no estimates at sector level for Italy, therefore our strategy is to impose the commonly accepted value of 0.33 and then test our results running new regressions that consider sector-level values of this parameter available in the literature at international level. In particular, we consider the shares estimated by Arpaia et al. (2009) for nine EU15 countries (including Italy), that are α = 0.29 for Manufacturing, α=0.26 for Construction, α=0.25 for Commerce and α=0.27 for Other Services.

The second problem refers to the possible endogeneity of the migration variable. In fact, one concern when studying the economic impact of migration is that OLS estimates of equations (5)-(5a) could be inconsistent due to reverse causality and/or omitted variables. In order to overcome this problem and to obtain reliable estimates, the literature suggests to apply the two stages least square (2SLS) estimator. In line with this, we provide and compare estimates obtained with both methods. At this scope, following Altonji and Card (1991) and Card (2001), we construct the instrument by exploiting the correlation between the new immigrants' inflow from a sending country and the past settlements of communities from the same country in the destination area (i.e., city, province or region).

4. The dataset

To construct our dataset, we use data from different sources. The main one is the labor force survey (LFS) provided by the Italian National Institute of Statistics (ISTAT) that delivers data on aggregate employment, hours worked and wages, all measured at regional and sector level. Information regarding the citizenship and skill level is also available from this source. The data on output, which is measured in terms of value added by sector and region, and on physical capital (at national level) 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)[4]. 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[5]. 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[6].

As for the other variables, first we derive A_{irt} and $\beta_{irt.}$ 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:

$$(6)\ \ \beta_{irt} = \frac{(w_{irt}^{H})^{\frac{\sigma_i}{\sigma_i-1}} h_{irt}^{\frac{\sigma_i}{\sigma_i-1}}}{(w_{irt}^{H})^{\frac{\sigma_i}{\sigma_i-1}} h_{irt}^{\frac{1}{\sigma_i-1}} + (w_{irt}^{L})^{\frac{\sigma_i}{\sigma_i-1}} (1-h_{irt})^{\frac{1}{\sigma_i-1}}}$$

$$(7)\ \ A_{irt} = \left(\frac{Y_{irt}^{\frac{1}{1-\alpha_i}} K_{irt}^{-\frac{\alpha_i}{1-\alpha_i}}}{X_{irt}} \right) \times \frac{(w_{irt}^{H})^{\frac{\sigma_i}{\sigma_i-1}} h_{irt}^{\frac{1}{\sigma_i-1}} + (w_{irt}^{L})^{\frac{\sigma_i}{\sigma_i-1}} (1-h_{irt})^{\frac{1}{\sigma_i-1}}}{[w_{irt}^{H} h_{irt} + w_{irt}^{L}(1-h_{irt})]^{\frac{\sigma_i}{\sigma_i-1}}}$$

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

[5] 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 between the total hours worked in year t (by region and industry) and the corresponding total number of workers.

[6] 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. At this purpose we have considered the industries corresponding to the first level of the Statistical Classification of Economic Activities in the European Community (NACE), excluding public administration.

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.[7] 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_i and σ_i necessary to calculate $\varphi(h_{irt})$, A_{irt} and β_{irt} are imposed according to the assumptions discussed in the previous section.

The main summary statistics are reported in Appendix 1 and briefly discussed here. It emerges that the sectors with the highest shares of foreign workers with respect to natives are Construction (18.6%) followed by Other Services (8.2), Manufacturing (7.1%) and Commerce (4.7%). Value added per capita is higher in the services sectors. It is interesting to note that with regards to total factor productivity, the highest values are reported for Constructions and Commerce. Finally, as expected, the highest value for the variable β, which captures the technological skill bias, is reported for Other Services.

5 Results

5.1 OLS estimates

This section provides OLS estimates of the effect of immigration on value added per worker lny_{irt} and its components, namely the capital to value added ratio $(\alpha/(1-\alpha))ln(K_{irt}/Y_{irt})$, average hours worked per worker lnx_{irt}, total factor productivity lnA_{irt} and the productivity-weighted skill-intensity index $ln\varphi_{irt}$. To complete the picture, the impacts of immigration on lnh_{irt} and $ln\beta_{irt}$, that is the two components of φ_{irt}, are also estimated. As explained above, these estimates might be affected by endogeneity and omitted variables problems, therefore they should be taken as a preliminary investigation of the impact of immigration on the Italian economy, before fully addressing this important issue in the next sub section, where a proper instrumental variables technique is applied.

Results are reported in Table 4. It is worth noticing 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 immigration share. In the Table, column (1) reports the estimates at aggregate level for the whole economy as in equation (5a), which excludes the interaction terms, while columns from (2) to (5) present the results for each sector in the panel as specified in equation (5).

In column (1), with the exception of the skill intensity index $\varphi(h_{irt})$ that reports a negative coefficient (-0.004), the overall picture suggests the existence of a positive and significant relationship between the share of immigrant workers and all components of the value added per worker. In details, the total positive effect of immigration share on lny_{irt} (0.019) is almost all attributable to the effect of migration on total factor productivity (0.017) and to the capital-value

[7] 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*.

added ratio (0.005). Only a minor role (0.001) is detected for average hours worked per worker lnx_{irt}.

Let us now turn to the sector level perspective (columns from 2 to 5 in Table 4) and focus on the effect of migration on Manufacturing, Construction, Commerce and Other Services. As explained earlier, while the effect of migration on Manufacturing is detected by the coefficient γ_{b1}, the total impact of the share of immigrant workers on the *i-th* sector is obtained summing γ_{b1} (column 2) with the slope coefficient estimated for the corresponding interaction term (γ_{bi}). For the sake of clarity, the Table reports, for each sector, the sum of the two coefficients of equation (5), namely γ_{b1}+γ_{bi}. Displayed in this way, results are more easily readable and show interesting differences across sectors in response to a variation of the immigrant workers share.

At first glance we observe that sector-level estimates confirm the aggregate picture of column (1). As we can notice, across all sectors immigration has a positive correlation with lny_{irt} (ranging from 0.011 in Manufacturing to 0.041 in Commerce) and a negative correlation with $\varphi(h_{irt})$ (in the range from -0.004 in Manufacturing and Construction to -0.011 in Other Services). Except for Construction (where it is not statistically significant), a positive coefficient is also obtained for the capital to value added ratio (0.008 in Manufacturing and Commerce, 0.012 in Other Services) and, when statistically significant, for average hours worked per worker lnx_{irt} and total factor productivity lnA_{irt}. Finally, it is confirmed also at sector level the negative correlation with respect to lnh_{irt}, the share of total hours worked supplied by high-skilled, and $ln\beta_{irt}$, the degree of productivity skill bias.

5.2 Instrumental variables estimates (2SLS)

As discussed in Section 3, the potential endogeneity of the migration variable suggests the implementation of the 2SLS technique. The source of endogeneity could be some omitted variables which might affect both our dependent variables and the immigrants' decision to move into a specific region. That is, some foreign workers might have chosen to move to a specific region attracted by the favorable economic conditions and the consequently increase in employment opportunities. To control for these potential sources of bias, the implementation of the 2SLS estimator requires the adoption of an instrument. Following Altonji and Card (1991) and Card (2001), we construct our instrument by exploiting the correlation between the new immigrants' inflow from a given sending country and the corresponding compatriot communities which have already 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 and region on the basis of the value added share of each sector in the corresponding sending country.[8] Accordingly, the resulting variable predicting the yearly number of immigrants in each region and sector has been built as follows:

$$(8)\ p\_sh\_imm_{r,i,t} = \frac{\sum_{r,i}\left(sh\_imm_{j,r,2002} * imm_{j,t} * \overline{w\_ind_{j,i}}\right)}{pop_{r,i,t}}$$

[8] Data are retrieved from ILO database, for each sending country the sum of the industry shares equal to one.

where, $sh\_imm_{j,r,2002}$ is the share of immigrants from country j residing in region r in 2002 over the total number of immigrants from country j residing in Italy in 2002,[9] $imm_{j,t}$ is the total number of immigrants from country j residing in Italy in year t and $\overline{w\_ind_{j,i}}$ is the average value added share of sector i in country j. 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, which has been distributed to each sector according to the corresponding employment share (i.e., $pop_{r,i,t}$). The first stage regression results show that the predicted share of immigrants has a positive and statistically significant coefficient and significant power (F-test of 20.3).

Regression results are reported in Table 5. As for the signs of estimated coefficients, the general picture mostly confirms OLS results. The positive effect of immigrants' share on per capita value added is confirmed, while the estimated impact is magnified across sectors as well as at aggregate level.

Let us now concentrate on the sector-level perspective, starting with Manufacturing (column 2). The estimated coefficients show a statistically significant impact of immigration on all the dependent variables, but for lnx_{irt}. In details, it emerges that a one-percentage point increase in the share of immigrants increases value added per worker by 3.3%. Splitting this effect into its four components, a positive impact is estimated for the immigration share on both the capital to value added ratio (2.3%) and total factor productivity (1.4). Conversely, negative coefficients are estimated for the effect of immigration share on the degree of productivity skill index (-0.03%), and for its components, i.e. lnh_{irt} (-2.6%) and $ln\beta_{irt}$ (-5%).

Looking at column (3) we first notice that Construction does not exhibit strong differences with respect to Manufacturing in terms of both sign and significance of the estimated coefficients. Some differences only appear in terms of magnitude. In this respect, it is interesting to note that, while the estimated impact of migration on value added per worker is almost the same in the two sectors, there are differences in two of its components. In particular, for Construction we estimate a lower coefficient with respect to the capital to value added ratio (1.4% in Construction, 2.3% in Manufacturing) and a slightly higher semi-elasticity as regards total factor productivity (1.9% in Construction and 1.4% in Manufacturing). These results might highlight that immigration exerts a weaker impulse on physical capital investment in Construction since immigrants are more likely to substitute capital in the production process. Finally, as regards the coefficients reported for the index of skill intensity $ln\varphi_{irt}$ and for its two components, lnh_{irt} and $ln\beta_{irt}$, the differences between Construction and Manufacturing are not very relevant.

As regards Commerce, the correlation between immigration share and value added per worker is positive and stronger than any other sector (6.3%). This result is mainly due to the strong correlation between the immigrants' share and total factor productivity (5.2%) which makes Commerce the sector with the highest productivity gains from immigration. As previously discussed, in Italy immigrants are mainly low-skilled, hence this finding probably means that Commerce is the sector that better exploits the advantages arising from a more efficient allocation

[9] The 2002 is the first year for which data of immigrants by country of origin are available at regional level.

of skills to tasks: manual-intensive tasks for immigrants and communication-intensive tasks for natives. Other differences also emerge for the other estimated coefficients. Among them, it is worth noticing the estimated coefficient for the degree of skill bias of productivity $ln\beta_{irt}$ (-16.1%) that is considerably higher in absolute value than in Manufacturing and Construction, but still lower than in Other Services. All in all, our results suggest that the differences between two highly heterogeneous sectors, such as Manufacturing and Commerce, are also reflected in the mechanisms that determine the impacts of immigration flows in the economic performance of receiving regions. These mechanisms seem pointing out that Commerce is the sector where migration inflows have more chance to impact on the real side of the economy.

Finally, looking at Other Services there are two main peculiarities to be noticed. On the one hand, we find the strongest reaction of the capital to value added ratio (3.3%), while no impact is detected for total factor productivity. These two results, taken together with the positive coefficient (0.4%) of average hours worked per worker lnx_{irt}, (this is the only sector where this variable contributes to the effect of migration shocks on income per worker) almost compensate each other, so that the sensitivity of value added per workers to the share of immigrant workers over total employment does not diverge from Manufacturing and Construction. On the other hand, $ln\varphi_{irt}$, lnh_{irt} and $ln\beta_{irt}$ report the highest (in absolute value) estimated coefficients compared to the other sectors, which make Other Services the sector in which immigration exerts the strongest influence in promoting unskilled-efficient production techniques.

Compared with previous results, our findings partly confirm those of Peri (2012) and of Aleksynska and Tritah (2015). In line with them, we find a positive effect of the share of immigrants' workers on value added per worker and on total factor productivity. In addition, we also confirm the negative impact on the technology skill bias index found by Peri (2012). Differently from both these papers, however, our results highlight also a positive role of immigrants' workers on the capital to value added ratio. Concerning the positive effect on total factor productivity, immigrants could be a channel to induce tasks specialization among workers (natives and immigrants) and increase overall productivity through competition in the labor markets. As for the negative role on the technology skill bias, it might be the case that immigrants lead firms to adopt less skill-intensive technologies. With respect to Italy, though with different methodological approaches, similar results have been found by Accetturo et al. (2012), Bettin et al. (2014) and De Arcangelis et al. (2015a, b). Here a novel result is the positive effect of migration on the capital to value added ratio meaning that firms tend to invest quickly as soon as new labor force becomes available. Finally, and this too is a novel result in the literature, the sector-level analysis highlights that the response to immigration is different in terms of statistical significance and magnitude.

5.3 Sensitivity analysis of 2SLS estimates to σ and α

Results reported in Tables 4 and 5 are obtained for σ=1.55 and α=0.33. This choice implies that all sectors are assumed to be homogenous with respect to both parameters. In this section, we run additional 2SLS regressions using alternative values of σ and α in order to check whether and to what extent the homogeneity assumption affects our estimates.

We start by re-running equation (5) to test its empirical performance for different values of σ. First, we hold the homogeneity assumption and impose σ=1.75 across sectors, this is a median value proposed by Peri (2012) based on several estimates for the US. Results for the variables involved by the choice of σ are reported in Table 6 where, for the sake of clarity, also the estimates of Table 5 are reported. As it emerges, the results remain substantially unchanged. As second step, we impose different values of σ to the different sectors according to the values estimated by Blankenou and Cassou (2011), namely σ=1.41 for Manufacturing, σ=9.05 for Construction, σ=1.92 for Commerce and σ=1.62 for Other Services. Results are reported in Table 7 where, again, estimates are reported only for the variables involved by the choice of σ. As it emerges from the table, again the results remain substantially unchanged, with the exception of the impact estimated for the productivity skill bias in Manufacturing, which is not statistically significant anymore.

Finally, we test for alternative values of α, leaving σ=1.55 for all sectors.[10] At this scope, we use the values estimated by Arpaia et al. (2009) for nine EU15 countries (including Italy), these are α=0.29 for Manufacturing, α=0.26 for Construction, α=0.25 for Commerce and α=0.27 for Other Services. Results are reported in Table 8 only for the variables involved by the choice of α. With regards to total factor productivity the estimated coefficients increase in magnitude and Commerce is confirmed as the most affected sector. The opposite arises with respect to the capital to value added ratio, for which the estimated coefficients are lower than the baseline regression (with α=0.33 for all sectors). Still, they are all statistically significant and the Other Services continues to show the highest impact to the share of immigrant workers.

Summing up, according to the sensitivity analysis developed in this sub-section, the main findings of our study seem to be sufficiently robust with respect to the values imposed to σ and α.

6 Conclusion

This paper has delivered an empirical investigation on the response given by the Italian economy to an increase in immigrant workers. We have followed the channel output decomposition approach advocated by Aleksynska and Tritah (2015), Peri (2012) and Ortega and Peri (2009) by means of which the effect of immigration is measured with respect to per capita value added and to its components. We have constructed a three dimensional panel dataset for the main Italian sectors at regional level, through time (2008–2011). In particular, four components of value added per worker are considered: the capital to value added ratio, average hours worked per worker, total factor productivity and a productivity-weighted skill-intensity index. The impact of the share of immigrant workers over total employment is estimated separately for each component.

We have found that immigrant workers have a positive impact on value added per worker thanks to their positive influence on the process of capital accumulation and total factor productivity. At the same time, they negatively affect the skill-intensity index along with its two components, namely the share of highly educated workers and the skill bias of technology. Taken jointly, these results

[10] We have also performed regressions with different values of σ together with different values of α and obtained substantially unchanged results. Results are available upon request.

suggest that immigration in Italy stimulates productivity gains by promoting production techniques that are more unskilled-efficient. This result is perfectly consistent with the fact that immigration in Italy is characterized by a very high percentage of low-skilled workers which presumably have been employed in the less qualified jobs disregarded by the native labor supply. Therefore, comparative advantages in tasks specialization seem the primary source of productivity gains due to immigration in Italy. It is also possible that immigration is giving an indirect contribution to total factor productivity by reducing labor costs and by allowing firms to invest more in new technologies.

A further important result is that an increase in the share of immigrant workers might impact differently depending on the sector which employs the resource. We have found that in Construction more immigrant workers mean a slower capital accumulation process and, therefore, this might be a signal of a substitution effects between capital and labor. Conversely, we have found that in Commerce more immigrant workers mean higher productivity gains and stronger skill bias and, hence, complementarities between immigrants and natives. Finally, in other Services more immigrant workers mean faster growth in the average hours worked. In this scenario, Commerce seems to be the economic sector where migration inflows have more chance to impact on total factor productivity and, thus, on value added per worker.

To sum up, the results of this study can be considered important improvements in the knowledge of the channels along which immigrant workers impact on host countries. First of all, they represent new evidence for Italy, a country where the immigration phenomenon has assumed unprecedented dimensions. Secondly, they support previous empirical literature advancing the idea that low-skilled immigrants can be an opportunity for receiving countries. Finally, they highlight that the responses to an increase in the share of immigrants can differ among sectors and, therefore, that the overall economic impacts depend on the sector where the immigrants find occupation. In this perspective, positive economic impacts of immigration on host countries seem to strictly depend on the efficient allocation of all available resources and on the correct matching of skills with tasks. At this scope, 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 in order to enable firms to adjust their factor mix to the availability of immigrant workers that, presumably, have different skills with respect to natives. The resulting better inputs allocation would contribute to firms' expansion with possible positive effects on labor markets outcomes for both natives and immigrants.

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. (2013). Birthplace Diversity and Economic Prosperity. NBER Working Papers N. 18699.

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, pages 201–234. Elsevier.

Arpaia A, Pérez E. and Pichelman K. (2009) Understanding labour income share dynamics in Europe. European Economy Economic Papers N. 379.

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. (2001) Does Immigration Grease the Wheels of the Labor Market? Brookings Papers on Economic Activity, 32: 69-134.

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: 381–422.

Cortes P. and Tessada J. (2011). Low-skilled immigration and the labor supply of highly skilled women. American Economic Journal: Applied Economics 3: 88–123.

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.

Etzo I., Massidda C. and Piras R. (2016). The impact of immigration on firms' establishments and employees in Italy. Mimeo.

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.

Fondazione Moressa (2015) Rapporto annuale sull'economia dell'immigrazione. Stranieri in Italia: attori dello sviluppo. Il Mulino, Bologna.

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.

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, pages 625-685. Elsevier.

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.

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 labor mobility: Evidence from OECD countries 1980-2005. Human Development Reports, Research Paper N. 6.

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. (2013). New frontiers of immigration research: Cities and Firms. Journal of Regional Science, 53: 1–7.

Peri G., Shih K. Y. and Sparber C. (2014). Foreign STEM Workers and Native Wages and Employment in U.S. Cities. NBER Working Papers N. 20093.

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.

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.

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. Labor, 24: 295–310.

Table A1. Summary statistics

Variables		Manufacturing					Construction					Commerce					Other Services				
		Mean	Std. Dev.	Min	Max	Observations	Mean	Std. Dev.	Min	Max	Observations	Mean	Std. Dev.	Min	Max	Observations	Mean	Std. Dev.	Min	Max	Observations
$z_{irt}=(N^F_{irt}/N_{irt})$	overall	7.11	4.36	1.13	15.49	N = 76	18.60	11.31	1.65	38.85	N = 76	4.66	2.11	0.46	11.65	N = 76	8.24	4.37	1.56	18.05	N = 76
	between		4.34	1.34	14.52	n = 19		11.22	3.36	36.75	n = 19		1.75	1.08	7.83	n = 19		4.26	2.68	14.59	n = 19
	within		0.95	3.84	10.80	T = 4		2.68	12.32	24.72	T = 4		1.23	1.75	8.48	T = 4		1.29	4.83	11.69	T = 4
y_{irt}	overall	66134	9130	49679	87035	N = 76	64272	15909	40430	98781	N = 76	101385	17890	69410	142872	N = 76	82629	8017	64771	99988	N = 76
	between		8465	53208	78853	n = 19		15553	42484	96173	n = 19		17125	72483	139210	n = 19		8038	67068	96453	n = 19
	within		3815	55188	76028	T = 4		4567	55343	80753	T = 4		6208	87996	120095	T = 4		1501	78892	86164	T = 4
$(\alpha/(1-\alpha))\ (K_{irt}/Y_{irt})$	overall	0.60	0.10	0.42	0.81	N = 76	0.08	0.03	0.04	0.11	N = 76	0.24	0.02	0.19	0.30	N = 76	0.86	0.04	0.79	1.03	N = 76
	between		0.10	0.46	0.79	n = 19		0.00	0.08	0.08	n = 19		0.01	0.22	0.28	n = 19		0.04	0.80	1.02	n = 19
	within		0.03	0.53	0.65	T = 4		0.03	0.04	0.11	T = 4		0.02	0.21	0.27	T = 4		0.01	0.85	0.87	T = 4
A_{irt}	overall	16.41	2.36	12.34	21.64	N = 76	28.50	7.07	17.71	44.68	N = 76	38.66	6.83	26.46	55.18	N = 76	16.40	1.55	13.43	20.48	N = 76
	between		2.09	13.09	20.11	n = 19		6.65	18.80	41.80	n = 19		6.42	27.91	52.86	n = 19		1.55	13.84	19.79	n = 19
	within		1.16	13.93	19.01	T = 4		2.75	24.24	38.09	T = 4		2.65	33.76	46.24	T = 4		0.32	15.61	17.09	T = 4
x_{irt}	overall	2007	30	1927	2085	N = 76	2012	35	1927	2087	N = 76	1897	54	1805	2043	N = 76	1763	36	1697	1844	N = 76
	between		21	1963	2042	n = 19		31	1956	2062	n = 19		46	1848	2018	n = 19		33	1714	1828	n = 19
	within		22	1950	2071	T = 4		17	1972	2048	T = 4		30	1802	1992	T = 4		14	1736	1797	T = 4
$\varphi(h_{irt})$	overall	1.10	0.03	1.05	1.18	N = 76	1.04	0.02	1.01	1.10	N = 76	1.09	0.02	1.04	1.14	N = 76	1.21	0.01	1.19	1.23	N = 76
	between		0.03	1.06	1.17	n = 19		0.01	1.02	1.07	n = 19		0.02	1.06	1.12	n = 19		0.01	1.19	1.22	n = 19
	within		0.01	1.08	1.13	T = 4		0.01	1.01	1.07	T = 4		0.01	1.05	1.12	T = 4		0.00	1.20	1.22	T = 4
$\beta_{irt.}$	overall	0.07	0.04	0.02	0.19	N = 76	0.02	0.01	0.00	0.06	N = 76	0.05	0.02	0.02	0.11	N = 76	0.31	0.04	0.22	0.38	N = 76
	between		0.04	0.02	0.16	n = 19		0.01	0.01	0.04	n = 19		0.02	0.02	0.09	n = 19		0.03	0.24	0.36	n = 19
	within		0.01	0.03	0.10	T = 4		0.01	-0.01	0.04	T = 4		0.01	0.03	0.09	T = 4		0.02	0.27	0.35	T = 4
h_{irt}	overall	0.08	0.03	0.04	0.17	N = 76	0.03	0.02	0.00	0.08	N = 76	0.07	0.02	0.03	0.12	N = 76	0.23	0.02	0.18	0.29	N = 76
	between		0.03	0.04	0.16	n = 19		0.01	0.01	0.05	n = 19		0.02	0.04	0.10	n = 19		0.02	0.19	0.27	n = 19
	within		0.01	0.06	0.11	T = 4		0.01	0.00	0.06	T = 4		0.01	0.04	0.10	T = 4		0.01	0.21	0.26	T = 4

Table 1 - Immigrants residing in Italy. First 23 nationalities (2013).

Nationality	Units	Share	Cumulative Share	Nationality	Units	Share	Cumulative Share
Romania	933354	21.27	21.27	Ecuador	82791	1.89	70.66
Albania	464962	10.60	31.87	Pakistan	80658	1.84	72.50
Morocco	426791	9.73	41.60	Senegal	80325	1.83	74.33
Chinese, Pop. Rep.	223367	5.09	46.69	Sri Lanka	79530	1.81	76.14
Ukraine	191725	4.37	51.06	Egypt	76691	1.75	77.89
Philippines	139835	3.19	54.24	Macedonia	76608	1.75	79.64
Moldova	139734	3.18	57.43	Nigeria	56476	1.29	80.93
India	128903	2.94	60.37	Ghana	48575	1.11	82.03
Peru	99173	2.26	62.63	Bulgaria	47872	1.09	83.12
Bangladesh	92695	2.11	64.74	Serbia	43816	1.00	84.12
Poland	88839	2.02	66.76	Kosovo	43751	1.00	85.12
Tunisia	88291	2.01	68.78	**Total**	**3734762**		

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 – Immigrants and Italians main characteristics: sectoral employment (2011).

	Italians	Immigrants	Italians/Immigrants
Agriculture	**3.60**	**4.58**	**0.79**
Industry	**27.68**	**34.97**	**0.79**
Manufacturing	*20.40*	*20.01*	*1.02*
Construction	*7.28*	*14.96*	*0.49*
Services	**68.72**	**60.45**	**1.14**
Commerce	*19.89*	*17.53*	*1.13*
Other Services	*48.83*	*42.92*	*1.14*

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

Table 3 – Immigrants and Italians main characteristics: education level (2011).

	Italians	Immigrants	Italians/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.

Dependent Variables	Total	Manufacturing	Construction with interaction	Commerce with interaction	Other Services with interaction
	(1)	(2)	(3)	(4)	(5)
$ln\ y_{irt}$	0.019***	0.011**	0.023***	0.041***	0.014**
	[0.004]	[0.004]	[0.004]	[0.005]	[0.006]
$(\alpha/(1-\alpha))\ ln\ (K_{irt}/Y_{irt})$	0.005***	0.008***	0.002	0.008**	0.012**
	[0.001]	[0.002]	[0.002]	[0.003]	[0.005]
$ln\ x_{irt}$	0.001**	0.000	0.001**	-0.001	0.005***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
$ln\ A_{irt}$	0.017***	0.006	0.024***	0.040***	0.007
	[0.017]	[0.004]	[0.005]	[0.007]	[0.009]
$ln\ \varphi_{irt}$	-0.004***	-0.004***	-0.004***	-0.006***	-0.011***
	[0.001]	[0.001]	[0.000]	[0.001]	[0.002]
$ln\ h_{irt}$	-0.037***	-0.042***	-0.026***	-0.054***	-0.108***
	[0.005]	[0.009]	[0.004]	[0.011]	[0.015]
$ln\ \beta_{irt}$	-0.076***	-0.082***	-0.055***	-0.117***	-0.222***
	[0.014]	[0.020]	[0.010]	[0.023]	[0.030]

Notes: observations 380. Heteroskedasticity robust standard errors clustered by region 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 $(z_{irt} \times d_i)$. The Table reports the total impact of migration on the *i-th* industry as the sum of the coefficient of Manufacturing and the interaction term, namely $\gamma_{b1} + \gamma_{bi}$.

Table 5. 2SLS estimates

	Total	Manufacturing	Construction with interaction	Commerce with interaction	Other Services with interaction
	(1)	(2)	(3)	(4)	(5)
ln yirt	0.033***	0.033***	0.032***	0.063***	0.036**
	[0.007]	[0.007]	[0.008]	[0.010]	[0.016]
$(\alpha/(1-\alpha))\ ln\ (K_{irt}/Y_{irt})$	0.022***	0.023***	0.014***	0.024**	0.033**
	[0.004]	[0.004]	[0.005]	[0.010]	[0.015]
$ln\ x_{irt}$	-0.001	-0.001	-0.001	-0.003	0.004**
	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
$ln\ A_{irt}$	0.014***	0.014***	0.019*	0.052***	0.013
	[0.004]	[0.004]	[0.010]	[0.011]	[0.013]
$ln\ \varphi_{irt}$	-0.003**	-0.003***	-0.004***	-0.008***	-0.012***
	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
$ln\ h_{irt}$	-0.001***	-0.026***	-0.021**	-0.080***	-0.128***
	[0.000]	[0.004]	[0.008]	[0.021]	[0.023]
$ln\ \beta_{irt}$	-0.043***	-0.050***	-0.044**	-0.161***	-0.256***
	[0.013]	[0.011]	[0.017]	[0.044]	[0.043]

Notes: F-test (First-stage) = 20.3; observations 380. Heteroskedasticity robust standard errors clustered by region 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 $(z_{irt} \times d_i)$. The Table reports the total impact of migration on the *i-th* industry as the sum of the coefficient of Manufacturing and the interaction term, namely $\gamma_{b1} + \gamma_{bi}$.

Table 6. Sensitivity analysis for $\sigma = 1.75$

	Manufacturing		Construction with interaction		Commerce with interaction		Other Services with interaction	
	$\sigma = 1.55$	$\sigma = 1.75$	$\sigma = 1.55$	$\sigma = 1.75$	$\sigma = 1.55$	$\sigma = 1.75$	$\sigma = 1.55$	$\sigma = 1.75$
$ln\ A_{irt}$	0.014***	0.012***	0.019*	0.018*	0.052***	0.048***	0.013	0.006
	[0.004]	[0.004]	[0.010]	[0.010]	[0.011]	[0.011]	[0.013]	[0.013]
$ln\ \varphi_{irt}$	-0.003***	-0.001***	-0.004***	-0.002***	-0.008***	-0.004***	-0.012***	-0.005***
	[0.001]	[0.000]	[0.001]	[0.000]	[0.002]	[0.001]	[0.002]	[0.001]
$ln\ \beta_{irt}$	-0.050***	-0.036***	-0.044**	-0.031**	-0.161***	-0.116***	-0.256***	-0.185***
	[0.011]	[0.008]	[0.017]	[0.013]	[0.044]	[0.032]	[0.043]	[0.000]

Notes: see Table 5 and the main text for more details.

Table 7. Sensitivity analysis with different values of σ (different in each industry).

	Manufacturing	Construction with interaction	Commerce with interaction	Other Services with interaction
	$\sigma = 1.41$	$\sigma = 9.05$	$\sigma = 1.92$	$\sigma = 1.62$
$ln\ A_{irt}$	0.018***	0.022**	0.055***	0.015
	[0.004]	[0.008]	[0.009]	[0.012]
$ln\ \varphi_{irt}$	-0.007***	-0.006***	-0.011**	-0.014***
	[0.001]	[0.002]	[0.004]	[0.004]
$ln\ \beta_{irt}$	0.025	-0.044**	-0.063**	-0.102***
	[0.017]	[0.019]	[0.024]	[0.035]

Notes: see Table 5 and the main text for more details.

Table 8. Sensitivity analysis with different values of α (different in each industry).

	Manufacturing	Construction with interaction	Commerce with interaction	Other Services with interaction
	$\alpha = 0.29$	$\alpha = 0.26$	$\alpha = 0.25$	$\alpha = 0.27$
$ln\ A_{irt}$	0.029***	0.027***	0.066***	0.033*
	[0.006]	[0.009]	[0.012]	[0.016]
$(\alpha/(1-\alpha))\ ln\ (K_{irt}/Y_{irt})$	0.008***	0.007***	0.010**	0.014*
	[0.002]	[0.002]	[0.004]	[0.008]

Notes: see Table 5 and the main text for more details.