I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12226

Does Low Skilled Immigration Increase Profits? Evidence from Italian Local Labour Markets

Giorgio Brunello
Elisabetta Lodigiani
Lorenzo Rocco

MARCH 2019

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12226

Does Low Skilled Immigration Increase Profits? Evidence from Italian Local Labour Markets

Giorgio Brunello
University of Padova, Cesifo, ROA and IZA

Elisabetta Lodigiani
University of Padova and LdA

Lorenzo Rocco
University of Padova and IZA

MARCH 2019

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Does Low Skilled Immigration Increase Profits? Evidence from Italian Local Labour Markets*

We estimate the (causal) effects of low skill immigration on the performance of Italian manufacturing firms. We find that an increase of the local supply of low skilled immigrants by one thousand units – which corresponds to 8.5 percent of the mean value - raises profits on average by somewhat less than half a percentage point, reduces average labour costs by about 0.1 percent and has no effect on TFP. The positive effects on profits are larger for small firms operating in low tech sectors and for firms located in areas specializing in low skill productions. Our evidence suggests that the recent waves of low skilled immigration in Italy may have hampered the transition to an economic structure characterized by high productivity and wage growth.

JEL Classification: J61
Keywords: low skilled immigration, profits, Italy

Corresponding author:
Giorgio Brunello
Department of Economics and Management "M. Fanno"
University of Padova
via del Santo 33
35123 Padova
Italy
E-mail: giorgio.brunello@unipd.it

* We are grateful to Giulio Cainelli for his many suggestions, to Emanuale Ciani, Guglielmo Barone, Guido De Biasio, Andrea Locatelli for their help with the data and to the audiences at the European Investment Bank and 2018 SIEP Conference in Padova for comments. This study is part of the research project "Investigation on the causes of the poor performance of Italian productivity", Department of Economics and Management of the University of Padova, funded by the Italian Ministry of Education, University and Research as part of the program "Dipartimenti di Eccellenza 2018-2022". The usual disclaimer applies.

Introduction

Do firms benefit from low skilled immigration? In the short-run and with flexible wages, an inflow of unskilled immigrants increases the supply of low skilled labour, reduces its price and increase the price of skilled labour (Altonji and Card, 1991; Card, 2001; Dustmann et al, 2008). Firms using intensively unskilled labour, which typically operate in low to medium tech sectors, initially benefit in terms of higher profits. High tech firms, which employ mainly skilled labour, face instead increasing labour costs. Over time, however, as firms expand their production and/or the capital stock, the demand for unskilled labour increases and wages and profits tend to return to the value prior the immigration shock (Borjas, 1995; Olney, 2013; Jaeger et al, 2018).

Yet immigration can still influence firm performance via alternative routes. For instance, birthplace diversity can affect productivity by stimulating innovations and introducing new ideas to solve problems (see Parrotta et al. 2014; Alesina et al., 2016; Docquier et al. 2018); networks of immigrants in firms can reduce information costs and facilitate offshoring activities (e.g., Moriconi et al., 2018), or promote trade in the countries of origin (e.g., Gould, 1994; Combes et al., 2005); suppliers hiring cheap unskilled labour can transfer part of the benefit to downstream firms via lower output prices. Overall, the effects of low skill immigration on profits depends on the time horizon being considered, on the adopted technology and on the interactions among firms in a local labour market.

In this empirical paper, we investigate the effects of low skill immigration on firm performance using firm micro data. We focus on Italy, a relatively large manufacturing economy specialized in traditional sectors that are intensive in unskilled labour, which stands out among OECD destination countries because it disproportionately attracts low-skilled immigrants, who have at most high school education.[1] Using the variation over time and across local labour markets (LLM) in the supply of immigrants, we estimate the effects of immigration on profits, labour costs, capital stock and total factor productivity (TFP) of firms located in these markets. Our sample consists of more than 17 thousand incorporated manufacturing firms observed between 2007 and 2016.

Since immigrants are not randomly allocated across local labour markets, we construct an instrument for the local change in the supply of immigrants using a shift-share approach (see Card, 2001), which exploits the fact that immigrants of a given nationality tend to settle in places where established communities of the same nationality exist (enclave effect).

We find that the average effect of immigration on profits is positive but small. We estimate that increasing the local supply of low skilled immigrants by one thousand units – which corresponds to 8.5 percent of the mean value - raises profits on average by somewhat less than half a percentage point, reduces average labour costs by about 0.1 percent, increases the capital stock (albeit this effect is often not statistically significant) and has no effect on TFP. During the sample period, the stock of immigrants in a local labour market has increased by a massive 83 percent (from 7.55 in 2007 to 13.86 in 2016), but the average profits of firms have risen only by 2.5 percent and average TFP has remained unchanged.

Our results on the effects of immigration on TFP are sharply in contrast with the findings by Mitaritonna et al, 2017, who also use firm micro data to study the effect of immigration in the French economy. A key reason for this difference is that we focus on low skill immigration while they consider a period when the net inflow of immigrants in France was concentrated among the highly skilled.

[1] Previous research on Italy using more aggregate data has shown that an increase in the share of immigrants has contributed to raising value added in manufacturing with respect to services (see De Arcangelis, Di Porto and Santoni, 2015), without having any detectable effect on innovation activities (Bratti and Conti, 2018).

While average effects are small or non-existent, we find substantial heterogeneity in outcomes according to firm size, level of technology and characteristics of the local labour market. We estimate that adding one thousand immigrants to the local labour market increases the profits of small firms operating in low tech sectors by 1.44 percent, more than five times as much as the increase in the profits of larger firms in medium to high tech industries (+0.26 percent). In addition, the capital stock falls with immigration in the former group of firms but increases in the latter group.

Although we do not observe the composition of employment by skill for individual firms, we have this information for the local labour market, dated more than five years before the start of our sample period. When we distinguish between localities with a median or higher than median share of low skilled labour and other localities, we find that the impact of immigration on profits, average labour costs and TFP of the former is much larger. We also find some evidence of a higher impact of immigration on profits in the localities with more abundant credit supply, in line with the fact that, when firms are allowed to freely adjust their capital, they rapidly move towards the efficient combination of inputs and benefit more from the inflow of cheap immigrant labour.

Many commentators suggest that reasons for the dismal performance of Italian productivity include the dominant presence of small firms, a relatively low supply of high skilled labour and an industrial specialization that still insists on low to medium tech productions (see for instance Bugamelli and Lotti, 2018). Our evidence suggests that the recent waves of low skilled immigration, by increasing the profits of small low tech firms and the benefits from operating in local labour markets that specialize in the use of unskilled labour, may have reinforced these reasons rather than facilitated the transition to an economic structure characterized by high productivity and wage growth.

The paper is organized as follows. Section 1 briefly reviews the relevant literature. Section 2 describes the data and Section 3 introduces both the empirical model and the identification strategy. Section 4 presents our results. Robustness checks are discussed in Section 5 and conclusions follow.

1. Literature Review

Compared to the abundant literature on the effects of immigration on native wages (see for instance Dustmann et al., 2016), less has been done so far to explore whether immigration affects firm – level variables, including profits. US studies exploiting the variation in H-1B visas for skilled workers include Ghosh, Mayda and Ortega, 2014, who find that relaxing the cap on these visas would increase the productivity, size and profits of US large and innovative firms. Similar findings are reported by Kerr and Lincoln, 2010 and Peri, Shih and Sparber, 2015. Conversely, Doran, Gelber and Isen, 2016, find that additional H-1B visas have insignificant and at most modest effects on firms' patenting, while reducing average earnings and increasing firm profits.[2]

A few papers have investigated the effects of immigration on firm productivity. Paserman, 2013, exploits cross-firm industry variation in the concentration of skilled immigrants and finds evidence of a negative correlation between the immigrant share and output per worker in low-tech industries, whereas the relationship becomes positive for high-tech industries. Parrotta et al., 2014, study the effects of diversity within firms on total factor productivity, using a rich matched employer-employee dataset for Denmark. Their evidence points toward a negative association between ethnic diversity and firm-level productivity. Trax et al., 2015, use German establishment data to estimate the effect of cultural diversity on total factor productivity and find that higher immigrant concentration in a firm does not lead to higher TFP. However, they show that higher ethnic diversity in the firm or in the region where the firm is

[2] Kirk et al, 2014, also study the effect of reducing US skilled immigrant visas but do not find any impact on innovation.

located have positive effects on firm-level TFP, consistent with the findings in Ortega and Peri, 2014.

Recently, Mitaritonna, Orefice and Peri, 2017, have used micro data of French manufacturing firms to show that a supply-driven increase in the share of foreign-born high skilled workers in a French department have raised the total factor productivity of firms in that department. This positive productivity effect has been also associated with faster growth of capital and exports.

Focusing on the service sector, Ottaviano et al., 2018, investigate whether immigrants affects the labour productivity of firms (measured as gross value added per worker), their exports and imports of services. Exploiting differences in the distribution of immigrants across local labour markets, they find that immigration raises both value added per worker and exports, while imports decrease. They suggest that the key mechanism explaining productivity growth is cost reduction, rather than country-of-origin diversity.

The effects of immigration on firm-level capital stock and choice of techniques has been discussed by Lewis, 2011, Ottaviano and Peri, 2012, Peri, 2016, Blau and Mackie, 2017. Dustmann and Glitz, 2015, use German administrative data to estimate the effect of changes in the local skill mix – due for instance to immigration – on local industries, distinguishing between the expansion of firms adopting technologies that are intensive in the more abundant skill and the adoption of new technologies to accommodate the abundant factor. They find that the latter effect prevails.[3]

2. The Data

Our data, which include gross operating income,[4] value added, labour costs, total employment and the book value of capital stock, are drawn from AIDA – Bureau van Dijk, which covers the universe of Italian incorporated enterprises.

[3] Firms respond to immigration also by increasing the number of establishments (Olney, 2013).
[4] Gross operating income is total revenue minus operating expenses and the costs of running the business. It is gross of taxes and of interest payments.

As in the ORBIS database (see Andrews and Cingano, 2014), reporting employment is not mandatory. Therefore, close to 11 percent of the original records have either missing or zero employment. We also do not observe in these data the composition of employment by skill or by immigrant status.

We consider only incorporated manufacturing firms with at least 500 thousand euro of sales in 2007 and located in Northern or Central Italy.[5] This sub-sample consists of 40,034 firms in 2015, and accounts for 48.2 percent of total manufacturing value added in the relevant regions (see Table A1). We further select the sample by retaining firms with positive values of sales, employment, the capital stock and labour costs which are always present between 2007 and 2016, ending up with 17,269 firms.[6] We deflate all firm variables with the consumer price index and discard extreme values (below the 1st and above the 99th percentile).

For each firm in our data, we use the legal address to identify the local labour market (LLM, or travel to work area) where the firm is located.[7] This assignment procedure is subject to measurement error, because multi-plant firms may have several plants located in areas that do not correspond to the location of the headquarters. We believe that this error is attenuated in our data by the fact that many Italian firms are small and with a single production unit.[8]

As pointed out by Bratti and Conti, 2018, and Del Boca and Venturini, 2005, immigration to Italy is largely low skilled. The proportion of low skilled immigrants, defined as immigrants with high school education or less (see for

[5] We exclude Southern Italy because of its different level of industrialization and because the share of immigrants is much lower than in the rest of the country.

[6] The original sample is reduced to 37,759 firms by dropping anomalies, such as negative values of sales; to 29,235 firms by retaining only firms with at least three consecutive records; to 25,468 firms by dropping Southern regions; to 17,269 firms by dropping missing values and retaining only firms with 10 records between 2007 to 2016.

[7] There are 300 local labour markets in our sample. We use the 2001 definition of local labour markets, as provided by the National Statistical Office (ISTAT).

[8] In the robustness section of this paper we run our regressions using only firms with less than 50 employees and confirm our qualitative findings.

example Peri and Sparber, 2009), is the highest among developed economies. As shown in Table 2, in 2010/11 as many as 86 percent of immigrants in Italy were low skilled, compared to 76 percent in France, 44 percent in the UK, 45 percent in Australia and 36 percent in Canada.[9] According to Eurostat, this figure increased to 88.3 percent in 2016, the highest among the 28 EU countries.

The importance of low skilled immigration can be understood by considering that Italy specializes in traditional manufacturing goods that are intensive in low skilled labour, and that its ageing population increasingly demands personal and household services that are typically performed by low skilled workers. In addition, Italy's location makes it a natural place of arrival for immigrants from South-Eastern Europe and North Africa, who are typically low educated (Bratti and Conti, 2018).

Close to 92 percent of immigration to Italy originates from developing countries (91.7 percent in 2016, up from 86.5 percent in 2006) and the top five countries by number of immigrants in 2016 were Romania (22.9 percent), Albania (9.3), Morocco (8.7), China (5.4) and Ukraine (4.6) (source: ISTAT, Demographic Portal). According to the database developed by Artuc, Docquier, Ozden and Parsons, 2015, the share of low skilled immigrants is close to 90% among Romanians and Albanians and equal to 94% among Moroccans and Chinese.

We compute the stock and the share of regular immigrants using the Demographic Balance and Resident Population by Sex and Citizenship (ISTAT, *Bilancio demografico e popolazione residente per sesso e nazionalità*), which contains since 2002 information on regular resident foreigners (by citizenship

[9] Contrary to Greece and Belgium, which have similar proportions of low skilled immigration, the percentage of highly educated in Italy is low also among natives. According to the OECD, the total share of individuals aged 25 to 64 with tertiary education in 2015 was 18 percent in Italy, 30 percent in Greece and 37 percent in Belgium. See OECD, Education at a Glance, 2016. Generally, Italian immigration policies are not skill-selective. Inflows of immigrants from outside the European Union are regulated by a quota system, which is fixed annually by a Decree. This quota is mainly employer driven and does not explicitly target high skilled workers (see Facchini and Lodigiani, 2014).

and sex) in each Italian municipality on January 1 of each year.[10] The average stock of immigrants in a local labour market between 2007 and 2016 was equal to 11,724 individuals, corresponding to 8.64 percent of the local population. This share has increased from 6.02 in 2007 to 9.45 percent in 2016. The distributions of the stock and share across local labour market in 2016 are shown in Figures 1 and 2.

The outcomes studied in this paper include total factor productivity, which we estimate using the procedure proposed by Ackerberg, Caves and Frazer, 2015. Assuming a Cobb Douglas specification, we express log real sales in firm i at time t as function of the log real capital stock, the log of real intermediate goods, the log of total labour costs, the log of total factor productivity (TFP) and a residual. Following Ciani, Locatelli and Pagnini, 2018, we use total labour costs rather than employment because the former allows us to account for differences in labour quality. Since TFP is unobserved by the econometrician, we derive it by using as additional equations the intermediate goods and labour costs functions.[11] The summary statistics for the main variables used in this paper are presented in Table 1.

3. The Empirical Setup

Consider a competitive economy where prices are set in the international market and firm – level output y is given by

$$y_{iqt} = A_{iqt} k_{iqt}^{\gamma} n_{iqt}^{\alpha} m_{iqt}^{\beta} \quad (1)$$

where n and m are skilled (mainly natives) and unskilled labour (including immigrants) employed in the firm, k is the capital stock, A is total factor productivity and the indices i, q and t are for the firm, the local labour market and time. The technology exhibits decreasing returns to scale $(\alpha + \beta + \gamma < 1)$

[10] Unfortunately, these data do not include information on educational attainment.

[11] Olley and Pakes, 1996, and Levinshon and Petrin, 2003, use instead the investment and the intermediate goods function.

and factor prices are w_N for the wage of skilled labour, w_M for the wage of unskilled labour and r for capital. Letting φ be a constant and $\Delta= 1-\alpha-\beta-\gamma$, profit maximization with respect to skilled and unskilled labour yields

$$\pi_{iqt} = \varphi A_{iqt}^{1/\Delta} K_{iqt}^{\gamma/\Delta} w_{Siqt}^{-\alpha/\Delta} w_{Uiqt}^{-\beta/\Delta} - rK_{iqt} = \pi_{iqt}(A_{iqt}, K_{iqt}, w_{Siqt}, w_{Uiqt}, r) \qquad (2)$$

where φ is a constant term. Changes in the local supply of labour – due for instance to a higher inflow of low skill immigrants - affect the profits of firms located in the area by influencing : a) wages; b) the capital stock and the rental price of capital; c) total factor productivity; d) the adopted technology, which includes parameters α, β and γ. Letting M be the stock of immigrants in the local labour market, profits can be written as

$$\pi_{iqt}(M_{qt}) = \pi_{iqt}(A_{iqt}(M_{qt}), K_{iqt}(M_{qt}), w_{Siqt}(M_{qt}), w_{Uiqt}(M_{qt}), r(M_{qt})) \qquad (3)$$

We posit the following empirical relationship between the profits of firm *i* and the local supply of immigrants

$$\pi_{iqt} = \theta_i + \theta_q + \theta_t + \delta_1 M_{qt} + \delta_2 N_{qt} + \rho_{iq} T + v_{iqt} \qquad (4)$$

where N_{qt} is the local stocks of natives, *T* is a linear trend, specific to each locality and to selected firm characteristics, and θ_i, θ_q and θ_t are firm, local and time fixed effects.

Differently from most literature, which focuses on the share of immigrants, we follow Wozniack and Murray, 2012, and use the stocks of immigrant and native labour supply. In our view, this specification is preferable to the one using shares because, other things equal, wages depend both on the composition and the absolute level of labour supply, and typically the former effect is less important than the latter. Since Eq. (4) includes local labour market time invariant effects, it is unlikely that the relationship between π_{iqt} and M_{qt} is driven by local labor market size.[12]

Assuming that the stock of natives in a locality follows a local trend but varies also with the stock of immigrants because of endogenous migration patterns, Eq. (4) can be re-written as[13]

$$\pi_{iqt} = \theta_i + \theta_q + \theta_t + \beta M_{qt} + \omega_{iq} T + \varepsilon_{iqt} \tag{5}$$

where $\omega_{iq} = \omega_q + \beta X_i$, and X is a vector including the age of the firm and its square, a dummy for firm size and a dummy for the level of technology (low versus medium to high). Taking first differences of (5) we obtain

$$\Delta\pi_{iqt} = \omega_q + \beta X_i + \theta_t + \beta \Delta M_{qt} + \Delta\varepsilon_{iqt} \tag{6}$$

Eq. (6) is the empirical version – in first differences - of Eq. (3): conditional on time invariant local fixed effects and on aggregate time effects, changes in the local stock of immigrants affect firm profits by altering local labour supply. The potential mediators in the transmission of labour supply shocks to profits include changes in local wages, the capital stock, firm productivity and the production technology.

Since immigrants are not randomly distributed across localities, but self-select on local labour market characteristics, including the labour demand by local firms and the local supply of natives, OLS estimates of Eq. (6) are biased. We address the endogeneity of ΔM_{lt} using an instrumental variables strategy, and select the instrument by following the approach proposed - among others - by Card, 2001, and adopted by most of the relevant literature.

Define Z in local labour market *q* and at time *t* as

$$Z_{qt} = \sum_{c=1}^{N} \lambda_{qc91} \Delta IMM_{ct} \tag{7}$$

[12] To dispel this concern, we estimate a specification which augments Eq. (4) with the local share of immigrants, and find that, conditional on the stock of immigrants, the share does not attract a statistically significant coefficient. See Section 4.

[13] We assume $N_{qt} = \theta_q + \theta_t + \mu M_{qt} + z_{iq} T + \omega_{iqt}$. Placing this into (4) yields (5).

where λ_{qc91} is the share of immigrants from country c in locality q and year 1991, well before the beginning of our sample in 2007, and ΔIMM_{ct} is the change in the national number of immigrants from country c in year t. To compute Z_{qt} we follow Barone et al., 2016, and combine data on the residence permits awarded in 1991 (source: Italian Ministry of Interior) by province and country of origin, with data on immigrants by municipality and region of origin (source: Italian Statistical Institute).[14] Figure 3 shows the distribution of Z across local labour markets.

The instrument Z exploits the fact that immigrants tend to locate in areas with a large share of immigrants of the same country of origin (enclave effect). The exclusion restriction requires that, conditional on local labour market and time dummies, local shocks that attracted immigrants at least fifteen years before the start of the sample period are uncorrelated with current local characteristics and shocks, which influence local firms.

We believe that this requirement is likely to hold in our data for at least two reasons. First, we include in Eq. (6) local labour market dummies, which corresponds to local linear trends in Eq. (5). These trends capture evolving local employment opportunities and productivity (see Barone and Mocetti, 2011). Second, in the construction of Z we predict the change in the stock of immigrants in a given local labour market q and time t by redistributing immigrants across localities as of their distribution in 1991.

Importantly, 1991 is the year before the signing of the Maastricht Treaty, which established the principle of freedom of movement and residence in Europe for the European citizens. It also predates by far the Eastern enlargements in 2004 and 2007, which brought some former communist countries, including Poland, Bulgaria and Romania, into the EU. These important historical changes indicate

[14] We use imputation methods to obtain from the data by province and country of origin data by municipality and country of origin. Next, we aggregate municipalities to obtain immigration by country of origin at the local labour market level.

that past and current local shocks are unlikely to be correlated, which supports the validity of the exclusion restriction.[15]

4. Results

Table 3 presents our baseline results. In column (1) we report the first stage effect of the instrument Z on the local stock of immigrants, which is positive and statistically significant.[16] Since the F-test associated to the exclusion of the instrument from the first stage equation is much larger than the threshold value of 10, the selected instrument is not weak.

Columns (2) to (7) show the estimated effect of changes in the local stock of immigrants on real operating profits, the real average labour cost, the real capital stock, total factor productivity, real value added and real total labour costs. We also report in the table the estimated percent change in each outcome when the local stock of immigrants increases by 1 thousand units, or 8.5 percent of the sample mean (11,724). We estimate that increasing M by 1 thousand units raises real operating profits by 0.40 percent and real value added by 0.10 percent, and reduces real per capita labour costs by 0.10 percent. We also find no statistically significant effect on the wage bill, the capital stock and total factor productivity.[17] The estimated effects on profits are small: during the period 2007 to 2016, the average increase in the stock of immigrants in the local labour markets of Northern and Central Italy was equal to 6.3 thousand, which corresponds to a 2.5 percent increase in real operating profits and a 0.6 percent decline in real average labour costs per employee.

Our finding that low skill immigration does not affect TFP does not confirm for Italy the results obtained for France by Mitaritonna et al., 2017, who find

[15] To further corroborate our identification strategy, we submit it to two empirical tests in sub-section 4.2.

[16] In all our regressions, standard errors are clustered at the local labour market level.

[17] The finding that total labour costs increase by 0.014 percent and per capita labour costs per head decline by 0.095 percent implies that employment increases by 0.109 percent. The results for productivity are confirmed when we use the measures proposed by Olley and Pakes and Levinsohn and Petrin.

evidence of a statistically significant positive effect. We believe that these differences could be explained with the fact that we consider mainly low skilled immigration, while they argue that they focus instead on an inflow of highly skilled immigrants.

Using the share rather than the stock of immigrants does no change the qualitative effect on profits (see Table A2). However, when we include in the empirical specification both the stock and the share of immigrants, instrumenting the former with ΔZ and the latter with a version of the instrument that uses the national change in the share rather than in the stock of immigrants, we find that the former attracts a statistically significant and virtually unchanged coefficient, but the latter is not statistically different from zero (column (3) of Table A2).[18] Based on this, we maintain as our preferred specification the one using the change in the stock of immigrants as the key explanatory variable.[19]

In a recent paper, Jaeger et al., 2018, have argued that the short-run negative effect of an inflow of new immigrants on wages is countered by the positive effect of the *ongoing* additional investments in physical capital induced by *past* inflows of immigrants, that are required to restore the steady state capital / labour ratio. Generally, the short-run effect of immigration is partly offset by this adjustment. When the flows of new immigrants are serially correlated over time, a regression of wage changes on the (contemporaneous) flow of immigrants that omits lagged flows produces attenuated (i.e. biased towards zero) estimates that have the correct sign but are severely distorted downwards (in absolute terms), independently of whether the current flow of immigrants is instrumented by the usual shift-share. This happens because the shift-share instrument is almost mechanically correlated with the omitted lagged flows.

[18] This result is not due to weak instruments, as the F-stat in the first stages associated to the stock and share of immigrants is always greater than 10.

[19] In unreported experiments, we have included as an additional regressor a measure of immigration diversity, constructed as one minus the Herfindahl Index across areas of origin. This indicator, however, is never statistically significant, in line with the view that immigration diversity may be relevant when considering high skilled immigrants.

Jaeger et al.'s argument applies to operating profits as well, since wages and profits typically move in opposite directions. In order to address the attenuation bias, Jaeger et al. recommend adding lagged immigration flows to Eq. (7), and instrumenting the lag with the lagged instrument. We follow this suggestion by adding either the first or the third lag (the longest available in our data without losing observations). With the exception of the capital stock, for which we find now a positive and statistically significant effect of immigration, adding the first lag of the stock of immigrants does not alter our qualitative results (see Table 4). We confirm that a higher stock of immigrants increases profits, with the estimated effect being slightly larger than in Table 3 (+0.58 percent versus +0.40 percent when M increases by 1 thousand units).[20]

4.1 Instrument validity

If local labour market shocks affecting local profits are persistent over time, they could correlate with λ_{qc91}, the share of immigrants from country c in LLM q and year 1991, invalidating the instrument. Mitaritonna et al., 2017, propose to verify whether this is a serious threat to identification by splitting the sample into two sub-samples and regressing the trend in the outcome variables during the former sub-sample on the trend in the instrument during the latter sub-period. Statistically significant effects would be problematic, but we find none (see Table A3 in the Appendix).

Our identification strategy could fail because the instrument Z is correlated with the un-observables in Eq. (7), which include current local labour market shocks. We investigate this possibility by applying the method recently developed by Oster, 2017, both to the first stage and to the reduced form estimates associated to (7). The test establishes bounds to the true value of the first stage and the reduced form parameters under two polar cases. In the first case, there are no

[20] Using the third lag rather than the first, we find that the estimated percent change in profits is equal to 0.795 percent. Both in this case and in the case that adds the first lag, the coefficient associated to the lagged lag is not statistically significant from zero, with the exception of the capital stock.

un-observables and both the first stage and the reduced form model associated to Equation (7) are correctly specified. We denote as $\hat{R}$ the estimated R squared in this case. In the second case, there are un-observables but observables and un-observables are equally related to the treatment (δ=1). When un-observables are included, we conservatively assume that the R squared is equal to $R_{max} = \min(1.3\hat{R}, 1)$. If zero can be excluded from the bounding set, then accounting for un-observables would not change the direction of our estimates. Table A4 shows that this is the case both for the first stage (column 1) and for the reduced form (columns 2 to 7).

Following the local-to-zero approach by Conley et al., 2012, we verify that our baseline estimates are robust to small deviations from the excludability condition of the instrument by assuming that the direct effect of Z on firm outcomes is normally distributed with mean zero and standard deviation equal to one twentieth of the effect of ΔM estimated in Table 3. We show in Table A5 that the 95 percent confidence intervals associated to operating profits and average labour costs do not include zero, supporting the view that small deviations from excludability do not alter the sign of the estimated effects.[21]

4.2 Heterogeneous effects

Our baseline results assume that the effect of immigration on profits, wages and productivity are homogeneous across firms. Yet Eq. (2) suggests that in firms that use unskilled labour more intensively the wage changes induced by a local inflow of low skill immigrants have larger effects on profits. These could be small firms or low-tech firms. We consider heterogeneity both at the firm and at the local labour market level. In the former case, we look at firm size and level of technology adopted. In the second case, we consider the relative importance of high skilled jobs and local financial development.

[21] Reported confidence intervals include zero for the capital stock and TFP, in line with our finding that the coefficients associated to these variables are imprecisely estimated in Table 3.

Starting with firm size, we replace the change in the stock of immigrants in Eq. (7) with the interaction of this variable with two dummies, one for small firms (equal to 1 if the value of firm turnover in 2007 was below 10 million euro and to 0 otherwise) and the other for medium to large firms.[22] The estimates in Table 5 indicate that the positive effect of adding one thousand local immigrants on operating profits is about four times as large in small than in medium to large firms (0.887 versus by 0.235 percent, with the difference being statistically significant at the 1 percent level of confidence (p-value of the test = 0.00)).

The estimated impact on real value added is twice as large for small firms than for other firms (0.221 versus 0.056 percent). We also find that a higher local stock of immigrants has a somewhat larger negative effect on real average labour costs for small than for larger firms (-0.105 versus -0.077), although the difference is not statistically significant. The effects on total factor productivity are always very small, but negative for small firms and positive for larger firms. With a Cobb Douglas technology, the larger impact of immigration on the profits of smaller firms in the presence of rather similar effects on average labour costs is consistent with these firms having a higher share of labour on value added (0.71 versus 0.65 in larger firms).

In a separate exercise, we interact the stock of immigrants with dummies indicating small low tech firms, larger low tech firms, small medium to high tech firms and larger medium to high tech firms. Following the EU classification, we define as low tech the following industries: manufacture of food products, beverages, tobacco products, textiles, apparel, leather and related products, wood and of products of wood and cork, except furniture, articles of straw and plaiting materials, paper and paper products, printing and reproduction of recorded media, furniture and other manufacturing, and as medium to high tech the remaining manufacturing sectors.

[22] This definition is close to the one adopted by the European Union, which classifies firms as micro or small when turnover is at most 2 or 10 million euro. The interactions between ΔM and the firm size dummies are instrumented with the interactions of ΔZ with the dummies.

Results are reported in Table 6. We find that the estimated positive impact of low skilled immigration on real operating profits is highest for small firms in low tech sectors and lowest in larger firms in medium and high tech sectors (1.44 versus 0.264 percent, difference statistically different from zero at the 1 percent level of confidence). There is also evidence that average labour costs fall more in small low tech firms, and that the capital stock also falls in these firms, while it increases in larger firms independently of the sector. Combining these findings with those in Table 5, we conclude that firms size appears to be a more important source of heterogeneity in the response of firms to changes in local immigration than the level of technology.

We expect that, ceteris paribus, firms with a higher intensity of unskilled labour benefit more than other firms – in terms of lower labour costs and higher profits – from low skilled immigration. Unfortunately, our firm data do not include the composition of employment by skill, education or immigrant status. This information is available, however, at the local labour market level from the 2001 Census. For each locality, we compute the average share of low skilled employees as the share of individuals not employed in managerial, professional or technical jobs. In order to avoid that this share captures other local labour market factors, such as the level of income or wealth, we regress it on local real labour income, real housing wealth and regional dummies, take the residuals and define two dummies, one for local labour markets with values of these residuals below the median and the other for localities with values at or above the median. We then interact these dummies with the change in the local stock of immigrants. Figure 4 shows that the distribution of local labour markets with a relatively high share of unskilled labour is fairly dispersed, with no particular concentration in any specific region of the country.

Results are reported in Table 7. We find that the percent change in operating profits induced by adding one thousand immigrants to the local labour market is more than ten times larger (5.26 versus 0.444 percent) in areas with a median or higher than median share of low skilled workers than in the other areas. The gap is even larger for average labour costs, that fall by 5.33 percent in the former and by only 0.14 percent in the latter. Finally, total factor productivity falls in all localities, but especially in those with a high share of unskilled labour. These estimates suggest that the inflows of low-skilled immigrants in areas that specialize in productions intensive in low-skilled labour increase profits and employment significantly, by reducing average labour costs rather than by promoting productivity and innovation.[23]

One reason why profits increase with immigration is that firms facing lower labour costs – especially those located in areas that use intensively low skilled labour - have an incentive to expand their production using the current technology. This expansion is likely to be facilitated where access to credit is easier. We measure financial access with two indicators, the number of bank branches and loans per capita in the local area. As for the share of low skilled jobs, we regress both indicators on regional dummies, local income and housing wealth, take the residuals and define two dummies, one for areas with lower than median values and the other for areas with median or above median values. We study the effects on operating profits by interacting these dummies with the local change of immigrants. Results reported in Table 8 show that profits increase more with immigration in areas with higher financial development,[24] although the difference in the effects across areas is not statistically distinguishable from zero.[25]

5. Robustness

In our baseline estimates, we have used the change in the local stock of immigrants, independently of their age. When we restrict our estimates to

[23] The percent increase in employment in areas with a higher than median share of unskilled labour is 5.9 percent (5.33+0.575). The share of low tech firms operating in local areas with a higher share of low skill labour is equal to 41%, compared to 30% in the other areas.

[24] Not reported in the table, there is also evidence that the capital stock reacts significantly more to immigration in areas where the access to credit is easier.

[25] We have also explored whether the impact of immigration on profits varies across areas with different levels of social capital, measured with blood donations per capita, and across local areas with and without industrial districts, but found no evidence that this is the case.

immigrants aged 15 to 64, however, results are very similar (see Table A6). Our findings are also confirmed when we add to the sample the firms located in Southern Italy (Table A7).

By assigning firms to the local labor market where they have their legal residence, we disregard that medium and large firms may have more than one plant located in different local labor market. To attenuate this concern, we restrict our sample to firms with less than 50 employees, about 76 percent of the original sample, which are less likely to be multi-plant. As shown in Table A8, are results are qualitatively unchanged.

Finally, in our baseline sample, we have considered only firms which are always present between 2007 and 2016. We verify whether our results hold also in a larger sample, which includes all firms present in the data for at least seven years out of the available ten (more than 95 percent of the total). In spite of the fact that our sample size increases by about one third, our key findings remain qualitatively similar (Table A9).

Conclusions

Contributing to a small literature, this paper has investigated the (causal) effects of low skill immigration on the performance of Italian manufacturing firms. We have found that a higher local stock of immigrants raises profits and reduces average labour costs, especially among small firms operating in low tech sectors and among firms located in areas specializing in low skill productions.

We have not confirmed for Italy the results by Mitaritonna et al. 2017, who report that higher immigration increases TFP in France. Our evidence suggests instead no effects on average, and negative effects for small low tech firms and for firms operating in areas specializing in low skill activities. Partially in contrast with the results by Jaeger et al., 2018, who conjecture that immigration triggers an upwards adjustment of physical capital, we have also found that small low tech firms reduce their stock of capital but expand employment when low skilled immigration increases.

The poor recent performance of Italian productivity has been attributed – among other things - to the dominant presence of small firms, a relatively low supply of high skilled labour and an industrial specialization that still insists on low to medium tech productions. Our results suggest that the recent waves of low skilled immigration may be reinforcing these weaknesses, by increasing the profits especially of small (low tech) firms and by reducing both their average labour costs and the pressure to invest and innovate.

References

Alesina, A., Harnoss, J. & Rapoport, H. (2016), Birthplace diversity and Economic Prosperity**,** *Journal of Economic Growth*, 21 (2): 101-138.

Altonji, J. and Card, D. (1991).The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives, NBER Chapters, in: Immigration, Trade, and the Labor Market, pages 201-234 National Bureau of Economic Research, Inc.

Andrews, D. and Cingano, F. (2014). Public Policy and Resource Allocation: Evidence from Firms in OECD Countries. *Economic Policy*, 29 (78), 253-296.

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *American Economic Review*, 83 (6), 2411-2451.

Artuc, E., Docquier, F., Özden, Ç., and Parsons, C. (2015), A Global Assessment of Human Capital Mobility: The Role of Non-OECD Destinations, World Development, 65, 6-26.

Blau, F. and C. Mackie (2017), National Academies of Sciences, Engineering, and Medicine. The Economic and Fiscal Consequences of Immigration. Washington, DC: The National Academies Press.

Barone, G. and Mocetti, S. (2011). "With a litthe help from abroad: the effect of low-skilled immigration on female labour supply." *Labour Economics*, 18, 664-675.

Barone, G., D'Ignazio, A., De Blasio, G. and Naticchioni, P. (2016). Mr. Rossi, Mr. Hu and politics. The role of immigration in shaping natives' voting behavior, *Journal of Public Economics*, Elsevier, 136(C), 1-13.

Borjas, G. J. 1995. "The Economic Benefits from Immigration." *Journal of Economic Perspectives*, 9 (2), 3-22

Bratti, M. and C. Conti (2018). The effect of immigration on innovation in Italy. *Regional Studies*, 52:7, 934-947

Bugamelli, M and Lotti, F (eds.), (2018), Productivity Growth in Italy: A Tale of Slow Motion Change, Bank of Italy Occasional Papers.

Card, D. (2001). "Immigrant Inflows, Native Outflows and the Local Labour Market Impacts of Higher Immigration." *Journal of Labor Economics,* 19(1). 22–64.

Ciani, E., Locatelli, A., and Pagnini, M. (2018). Evoluzione territoriale della TFP: analisi dei dati delle società di capitali manifatturiere tra il 1995 e il 2015.Questioni di Economia e Finanza, Occasional Papers 438, Bank of Italy.

Combes, P., Lafourcade, M. and Mayer, T. (2005). "The trade-creating effects of business and social networks: evidence from France," *Journal of International Economics*, 66(1), 1-29.

Conley, T., Hansen, C.B., and Rossi P., 2012. “Plausibly Exogenous.” *The Review of Economics and Statistics*, 94(1), 260-272.

De Arcangelis, G., Di Porto, E., and Santoni, G. (2015). Migration, Labour Tasks and Production Structure. *Regional Science and Urban Economics*, 53, 156–169.

Del Boca, D., and Venturini, A. (2005). Italian migration. In K. Zimmermann (Ed.), European migration: What do we know? (pp. 303–336). Oxford: Oxford University Press.

Doran, K. , Gelber, A. and Isen, A. (2016), The Effects of High-Skilled Immigration Policy on Firms: Evidence from Visa Lotteries, NBER Working Paper, February 2016.

Docquier, F., Turati, R., Valette, J. and Vasilakis, C. (2018). Birthplace Diversity and Economic Growth: Evidence from the US States in the Post-World War II Period, IZA Discussion Paper 11802, Institute for the Study of Labor (IZA).

Dustmann, C., Glitz, A. and Frattini, T. 2008. The labour market impact of immigration, *Oxford Review of Economic Policy*, Oxford University Press, vol. 24(3), 478-495.

Dustmann, C., and A. Glitz (2015). How Do Industries and Firms Respond to Changes in Local Labor Supply? *Journal of Labor Economics* 33(3), 711–50.

Dustmann, C., Schönberg, U. and Stuhler, J. (2016). The Impact of Immigration: Why Do Studies Reach Such Different Results? *Journal of Economic Perspectives*, 30(4), 31-56.

Facchini, G., and Lodigiani, E. (2014). “Attracting skilled immigrants: An overview of recent policy developments in advanced countries”. *National Institute Economic Review*, 229: R3-R2.1

Ghosh, A. , Mayda, A.M. and Ortega, F. (2014), The Impact of Skilled Foreign Workers on Firms: An Investigation of Publicly Traded U.S. Firms. IZA Discussion Paper No. 8684.

Gould, D., (1994). Immigrant links to home country: empirical implications for US bilateral trade flows. *Review of Economics and Statistics* 76, 302–316.

Kerr W. and Lincoln, W. (2010). "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention," *Journal of Labor Economics*, 28(3), pages 473-508, July.

Kirk, D. Gelber, A, Isen, A, (2014) The Effects of High skilled Immigration Policy on Firms: Evidence from H-1B Visa Lotteries, NBER Working Paper 20688

Jaeger, D. A., Ruist, J. and Stuhler, J. (2018). "Shift-Share Instruments and the Impact of Immigration." IZA Discussion Papers 11307, Institute for the Study of Labour (IZA).

Levinsohn, J. and A. Petrin (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies*, 70 (2), 317-341.

Lewis, E. (2011). Immigration, Skill Mix, and Capital Skill Complementarity, *The Quarterly Journal of Economics*, 126, 1029–1069.

Mitaritonna, C., Orefice, G. and Peri, G. (2017). "Immigrants and Firms' Outcomes: Evidence from France." *European Economic Review*, 96, 1-82.

Moriconi, S., Peri, G., and Pozzoli, D. (2018). The Role of Institutions and Immigrant Networks in Firms' Offshoring Decisions. IZA Discussion Paper 118, Institute for the Study of Labour (IZA).

Olley, S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry, *Econometrica*, 64 (6), 1263-1298.

Olney, W. (2013). Immigration and firm expansion. *Journal of Regional Science*, 53 (1) , 142–157.

Ortega, F. and G. Peri (2014). Openness and income: The roles of trade and migration. *Journal of International Economics*, 92 (2), 231-251.

Oster, E. (2017). "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics*.

Ottaviano, G. I., and Peri, G., 2012. "Rethinking the effect of immigration on wages*." Journal of the European Economic Association*, 10, 152–197.

Ottaviano, G. I.P., Peri, G. and G. C. Wright (2018), Immigration, trade and productivity in services: Evidence from U.K. firms, *Journal of International Economics*, 112, 88-108.

Parrotta, P., Pozzoli, D., and Pytlikova, M. (2014). Does labor diversity affect firm productivity? *European Economic Review*, 66:144–179.

Paserman, M. (2013). Do high-skill immigrants raise productivity? Evidence from Israeli manufacturing firms, 1990-1999. *IZA Journal of Migration*, 2 (1), 1-31.

Peri, G. and Sparber, C. (2009). "Task Specialization, Immigration and Wage, *American Economic Journal: Applied Economics* 1(3), 135–169.

Peri, G. (2016). Immigrants Productivity and Labor Markets, *Journal of Economic Perspectives*, 30 (4), 1-30.

Peri, G., Shih, K., and Sparber, C. (2015). STEM Workers, H-1B Visas, and Productivity in US Cities. *Journal of Labor Economics* 33.S1, S225-S255.

Rauch, J., Trindade, V. (2002). Ethnic Chinese networks in international trade. *Review of Economics and Statistics*, 84 (1), 116–130.

Trax, M., Brunow, S. and Suedekum, J. (2015). Cultural diversity and plant-level productivity, *Regional Science and Urban Economics*, 53, 85-96.

Wozniack, A. and T. Murray (2012). Timing is everything: Short-run population impacts of immigration in US cities. *Journal of Urban Economics* 72, 60–78.

Table 1. Summary statistics

Variable	Mean	Standard Deviation	Number of observations
Real operating income	0.568	1.208	155,431
Real value added	2.595	3.934	155,431
Real labour cost	1.651	2.482	155,431
Real labour cost per employee	0.039	0.023	155,431
Real capital stock	9.912	16.331	155,431
Number of employees	39.189	56.651	155,431
Total factor productivity	0.221	0.044	152,141
Number of firms	17,269		
Stock of immigrants in LLM	11.724	31.559	300
Share of immigrants in LLM	8.642	2.720	300

Notes: LLM is for local labour market. All values are expressed in million euro, with the exception of the number of employees and firms (units), the stock of immigrants (thousands) and the share of immigrants (percent).

Table 2. Share of immigrants by level of education in Italy and in selected OECD countries. 2010/11

Country	Primary/lower secondary	Upper Secondary	Tertiary
Italy	0.47	0.39	0.14
Australia	0.12	0.33	0.48
Belgium	0.23	0.11	0.14
Canada	0.11	0.25	0.64
Germany	0.43	0.35	0.21
Denmark	0.17	0.24	0.21
Spain	0.45	0.31	0.24
Finland	0.58	0.21	0.21
France	0.51	0.24	0.24
UK	0.21	0.22	0.58
Greece	0.47	0.39	0.14
Ireland	0.12	0.41	0.41
Luxembourg	0.30	0.20	0.27
Netherlands	0.41	0.29	0.30
Norway	0.22	0.23	0.34
Sweden	0.18	0.30	0.36
USA	0.40	0.33	0.27

Source: OECD DIOC database.

Table 3. First stage and IV estimates of the effects of changes in the local stock of immigrants (M). Dependent variables: changes in firm outcomes

	First stage	Δ Real operating profits	Δ Real average labour costs	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour costs
ΔZ	0.246***						
	(0.040)						
ΔM		2. 288***	-0.038**	1.548	-0.001	2. 640***	0.222
		(0.241)	(0.015)	(1.208)	(0.010)	(0.464)	(0.321)
Percent change when M increases by 1 thousand units		0.403***	-0.095**	0.016	-0.005	0.102***	0.014
		(0.042)	(0.039)	(0.012)	(0.005)	(0.018)	(0.019)
Observations	155,422	155,422	155,422	155,422	152,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F first stage	35.55						

Notes: Real operating profits, average and total labour cost, capital stock, value added and TFP are measured in thousand euro. M: stock of immigrants in the local labour market (thousands). Z: selected instrument. Standard errors clustered by LLM within parentheses. The sample includes only firms always present in the data during the period 2007-2016. Firm-level controls include dummies for firm size and level of technology and firm age and its square.

Table 4. First stage and IV estimates of the effects of changes in the current and lagged stock of immigrants (M). Dependent variables: changes in firm outcomes.

	First stage current ΔM	First stage lagged ΔM	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour cost
ΔZ	0.245***	-0.068***						
	(0.040)	(0.013)						
ΔZ(-1)	-0.006	0.198***						
	(0.010)	(0.050)						
ΔM			2.556***	-0.032**	6.215***	0.000	2.905***	0.298*
			(0.378)	(0.015)	(1.384)	(0.020)	(0.446)	(0.176)
ΔM(-1)			0.744	0.018	12.944***	0.002	0.733	0.210
			(0.596)	(0.028)	(1.998)	(0.010)	(0.595)	(0.853)
Percent change when M increases by 1 thousand units (long run effect)			0.580***	-0.034	0.193***	0.009	0.140***	0.030
			(0.160)	(0.094)	(0.029)	(0.022)	(0.026)	(0.053)
Observations	155,422	155,422	155,422	155,422	155,422	155,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F first stage	719.7	394.9						

Notes: see Table 3

Table 5. IV estimates of the percent change in firm outcomes with respect to changes in the local stock of immigrants. Interacted with a dummy equal to one for small firms and to zero otherwise.

	Δ Real operating profits	Δ Real average labour cost	Δ Real capital stock	Δ TFP	Δ Real value added	Δ Real total labour cost
Percent change when M increases by 1 thousand units – smaller firms	0.887***	-0.105***	-0.009	-0.008	0.221***	0.018
	(0.112)	(0.038)	(0.043)	(0.006)	(0.033)	(0.027)
Percent change when M increases by 1 thousand units – larger firms	0.235***	-0.077*	0.024***	0.002	0.056***	0.012
	(0.024)	(0.044)	(0.005)	(0.006)	(0.014)	(0.017)
P-value test differences	0.00	0.17	0.40	0.00	0.00	0.69
Observations	155,422	155,422	155,422	152,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: see Table 3

Table 6. IV estimates of the percent change in firm outcomes with respect to changes in the local stock of immigrants interacted with a dummy for low tech and high tech industries

	Δ Real operating profits	Δ Real average labour cost	Δ Real capital stock	Δ TFP	Δ Real value added	Δ Real total labour cost
Percent change when M increases by 1 thousand units – small low tech firms	1.440*** (0.216)	-0.117** (0.058)	-0.099** (0.042)	-0.011 (0.007)	0.447*** (0.076)	0.150* (0.082)
Percent change when M increases by 1 thousand units – small medium and high tech firms	1.160*** (0.165)	-0.113*** (0.028)	-0.107 (0.080)	-0.008 (0.006)	0.257*** (0.052)	-0.018 (0.037)
Percent change when M increases by 1 thousand units – large low tech firms	0.362*** (0.035)	-0.080 (0.050)	0.052*** (0.007)	-0.002 (0.005)	0.092*** (0.010)	0.025 (0.022)
Percent change when M increases by 1 thousand units – large high and medium tech firms	0.264*** (0.027)	-0.078* (0.042)	0.014** (0.006)	0.000 (0.005)	0.064*** (0.014)	0.007 (0.015)
Observations	155,422	155,422	155,422	152,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: see Table 3

Table 7. IV estimates of the percent change in firm outcomes with respect to changes in the local stock of immigrants. Differences between areas with a higher than median share of low skilled labour (in 2001) and other areas.

	Δ Real operating profits	Δ Real average labour cost	Δ Real capital stock	Δ TFP	Δ Real value added	Δ Real total labour cost
Percent change when M increases by 1 thousand units – firms in LLM with a lower than median share of low skilled labour in 2001	0.444***	-0.137***	0.019	-0.010	0.116***	0.018
	(0.044)	(0.049)	(0.013)	(0.006)	(0.019)	(0.002)
Percent change when M increases by 1 thousand units – firms in LLM with a median or higher than median share of low skilled labour in 2001	5.260***	-5.330*	0.351	-0.550**	1.830***	0.575
	(1.630)	(2.720)	(0.578)	(0.271)	(0.526)	(0.363)
P-value test differences	0.003	0.056	0.553	0.041	0.001	0.128
Observations	155,422	155,422	155,422	152,141	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: see Table 3

Table 8. IV estimates of the percent change in firm operating profits with respect to changes in the local stock of immigrants. Differences between areas with higher than median bank loans or number of bank branches per capita (in 2001) and other areas.

	Bank loans	Bank branches
Percent change when M increases by 1 thousand units – firms in LLM with a lower than median share of bank loans or bank branches per capita in 2001	0.121 (0.041)	0.425*** (0.047)
Percent change when M increases by 1 thousand units – firms in LLM with a median or higher than median share of bank loans or bank branches per capita in 2001	0.358*** (0.041)	1.440*** (0.684)
P-value test differences	0.547	0.123
Observations	155,422	155,422
LLM dummies	Yes	Yes
Year dummies	Yes	Yes
Firm-level controls	Yes	Yes

Notes: see Table 3

Table A1. Value added of the firms in our baseline sample and total value added. Manufacturing 2015

Regions	Value added - 40,034 incorporated manufacturing firms. 2015	Total value added manufacturing 2015	Share (1)/(2)
Emilia-Romagna	14803.4	31791.2	0.465
Friuli-Venezia Giulia	2812.3	6700.3	0.419
Lazio	4057.8	9892.2	0.410
Liguria	1267.8	4256.4	0.297
Lombardia	37939.6	65485.2	0.579
Marche	2542.2	8289.6	0.306
Piemonte	12220.4	24046.2	0.508
Toscana	6739.4	17167.1	0.392
Trentino-Alto Adige	1675.5	4502.2	0.372
Umbria	1198.3	3165.1	0.378
Veneto	15027.3	32621.4	0.460
Total	100284.4	207916.9	0.482

Source: AIDA data and territorial accounts (ISTAT)

Table A2. IV estimates of the effects of changes in the local stock of immigrants (M) and the local share of immigrants (SM). Dependent variable: annual change in real operating profits

	Δ Real Operating Profits	Δ Real Operating Profits	Δ Real Operating Profits
ΔM	2. 288***		2.310***
	(0.241)		(0.279)
Δ SM		117.144**	-10.148
		(55.897)	(45.375)
Observations	155,422	155,422	155,422
LLM dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes

Notes: see Table 3. SM: share of immigrants

Table A3. OLS regressions of the change in the instrument during the period 2013-16 on the change of firm variables during the period 2008-2011.

	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour cost
Coefficient of lagged firm variables	0.0001	-0.0002	0.00003	0.0034	0.0001	0.0003
	(0.0001)	(0.0005)	(0.00002)	(0.015)	(0.001)	(0.0002)
Observations	69,552	69,552	69,552	68,048	69,552	69,552
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: see Table 3

Table A4. Oster (2017) test applied to the first stage and the reduced-form regressions associated with Eq. (6).

	First stage	Reduced Form					
	ΔM	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real Value added	Δ Real total labour cost
ΔZ	[0.246,0.478]	[0.562,0.574]	[-0.0094, -0.0093]	[0.371,0.380]	[-0.0003,-0.0003]	[0.645,0.649]	[0.054,0.055]
Observations	155,422	155,422	155,422	155,422	152,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Real operating profits, value added, wage bill, average labour cost and capital stock are measured in thousand euro. The sample includes only firms always present in the data during the period 2007-2016.

Table A5. Confidence intervals in the presence of small violations of the exclusion restriction, as in Conley et al., 2012.

	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real Value added	Δ Real total labour cost
ΔM	[1.258,3.296]	[-0.072,-0.005]	[-0.905, 3.934]	[-0.004, 0.001]	[1.229,4.010]	[-0.408,0.842]
Observations	155,422	155,422	155,422	152,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Real operating profits, value added, wage bill, average labour cost and capital stock are measured in thousand euro. The sample includes only firms always present in the data during the period 2007-2016. The hypothetical direct effect of DZ on firm outcomes is assumed to be normally distributed, with zero mean and standard deviation set at one twentieth of the effect of ΔM as reported in Table 3.

Table A6. IV Estimated percent changes when M increases by 1 thousand units. All immigrants and immigrants aged 15 to 64. Dependent variables: changes in firm outcomes.

	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour cost
Immigrants aged 15 to 64	0.583***	-0.138**	0.023	-0.007	0.147***	0.020
	(0.009)	(0.006)	(0.015)	(0.008)	(0.038)	(0.030)
Observations	155,422	155,422	155,422	152,132	155,422	155,422
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: see Table 3

Table A7. IV estimates of the effects of changes in the local stock of immigrants (M). Dependent variables: changes in firm outcomes. Including the South of Italy.

	First stage	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour cost
ΔZ	0.244***						
	(0.039)						
ΔM		2.325***	-0.037**	1.535	-0.001	2.561***	0.181
		(0.235)	(0.015)	(1.180)	(0.001)	(0.490)	(0.342)
Percent change when M increases by 1 thousand units		0.416***	-0.094**	0.016	-0.007	0.100***	0.011
		(0.042)	(0.037)	(0.012)	(0.006)	(0.019)	(0.021)
Observations	168,831	168,831	168,831	168,831	164,890	168,831	168,831
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F first stage	32.47						

Notes: see Table 3

Table A8. IV estimates of the effects of changes in the local stock of immigrants (M). Dependent variables: changes in firm outcomes. Firms with less than 50 employees in 2007.

	First stage	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour cost
ΔZ	0.247***						
	(0.042)						
ΔM		1.155***	-0.016*	1.083	-0.002	1.454***	0.134
		(0.254)	(0.009)	(0.913)	(0.002)	(0.352)	(0.200)
Percent change when M increases by 1 thousand units		0.366***	-0.040*	0.021	-0.008	0.117***	0.017
		(0.085)	(0.023)	(0.017)	(0.006)	(0.028)	(0.020)
Observations	121,142	121,142	121,142	121,142	118,323	121,142	121,142
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F first stage	34.37						

Notes: see Table 3

Table A9. IV estimates of the effects of changes in the local stock of immigrants (M). Dependent variables: changes in firm outcomes. Firms with at least seven records within the sample period

	First stage	Δ Real operating profits	Δ Real average labour cost	Δ Real Capital Stock	Δ TFP	Δ Real value added	Δ Real total labour cost
ΔZ	0.257*** (0.045)						
ΔM		1. 923*** (0.231)	-0.010 (0.009)	-0.151 (1.665)	0.000 (0.001)	2.098*** (0.457)	0.097 (0.249)
Percent change when M increases by 1 thousand units		0.407*** (0.049)	-0.026 (0.022)	-0.001 (0.019)	0.001 (0.004)	0.097** (0.021)	0.007 (0.018)
Observations	205,326	205,326	205,326	205,326	200,862	205, 326	205, 326
LLM dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F first stage	32.47						

Notes: see Table 3. Firms with at least seven records within the sample period.

Figure 1.

Standardized stock of immigrants in LLMs. 2016

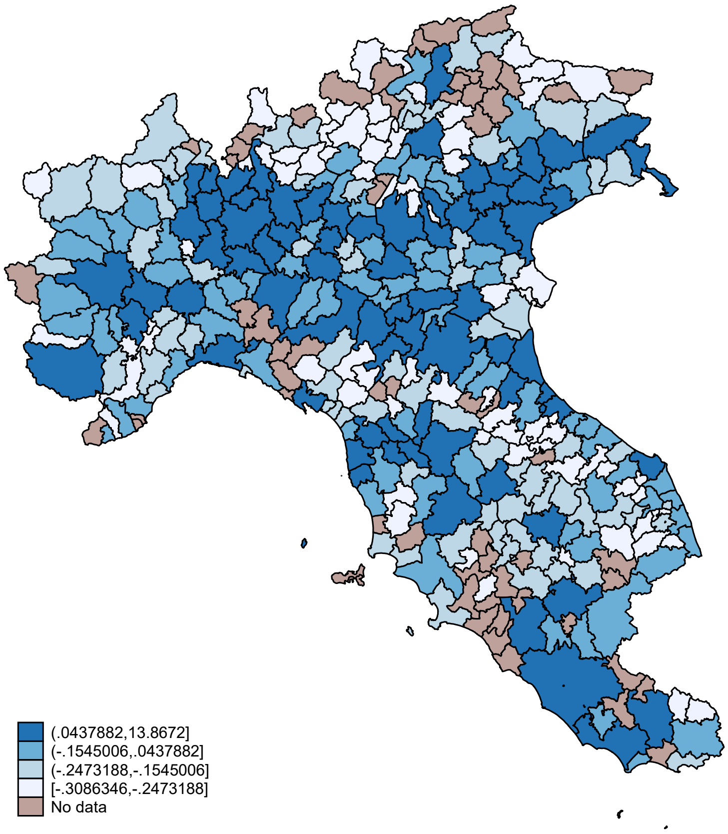


Figure 2.

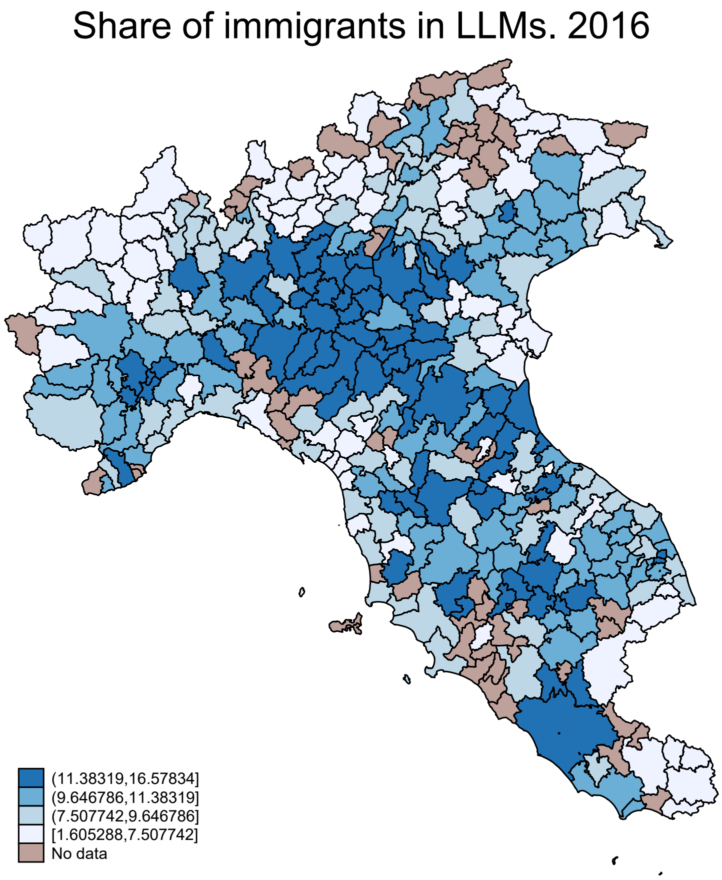

Share of immigrants in LLMs. 2016
(11.38319,16.57834]
(9.646786,11.38319]
(7.507742,9.646786]
[1.605288,7.507742]
No data

Figure 3.

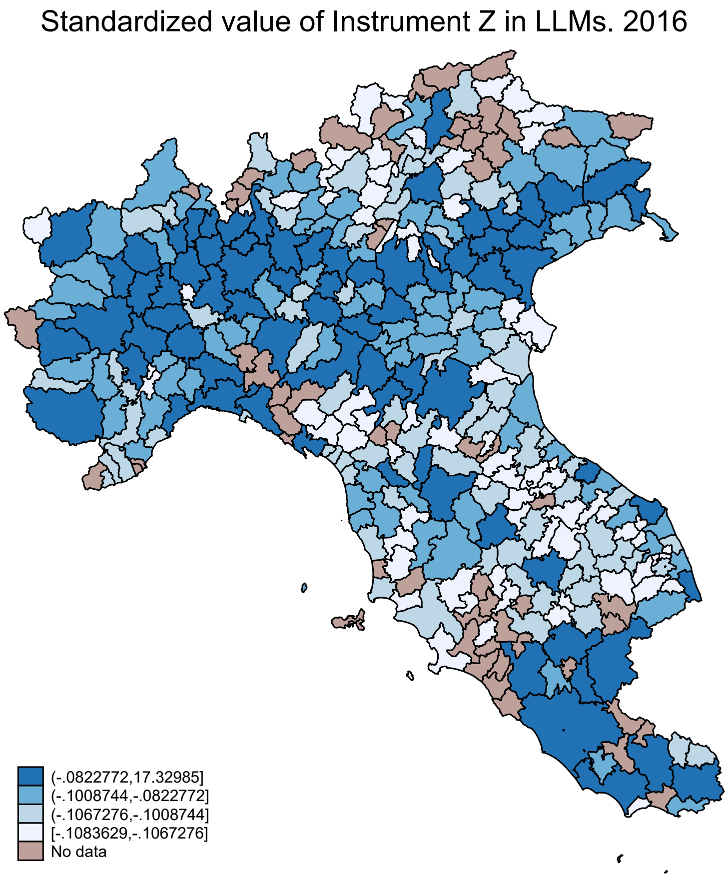
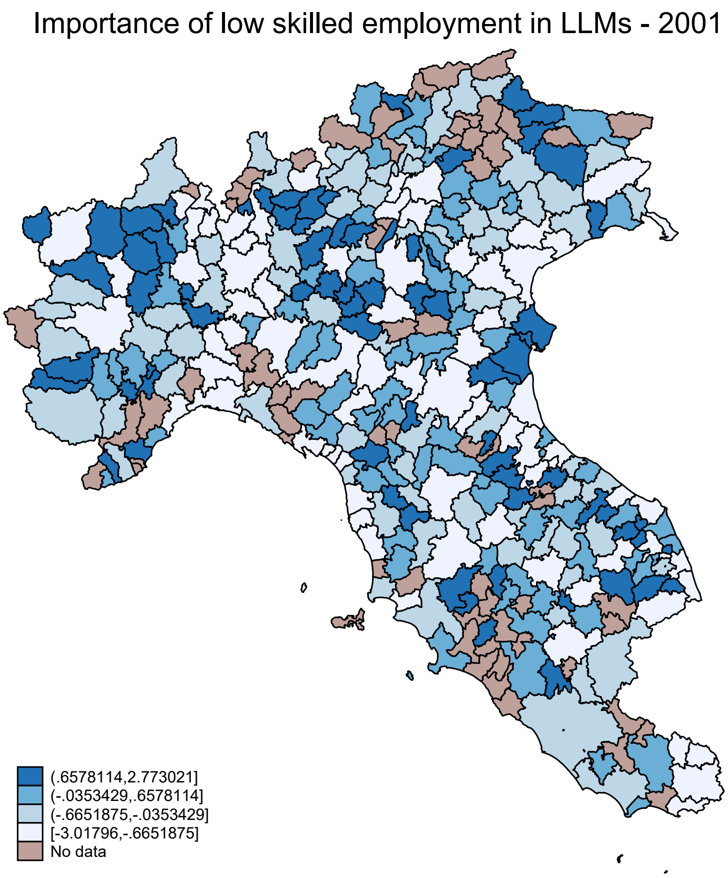

Standardized value of Instrument Z in LLMs. 2016
(-.0822772,17.32985]
(-.1008744,-.0822772]
(-.1067276,-.1008744]
[-.1083629,-.1067276]
No data

Figure 4.


Importance of low skilled employment in LLMs - 2001
(.6578114,2.773021]
(-.0353429,.6578114]
(-.6651875,-.0353429]
[-3.01796,-.6651875]
No data