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Abstract

Data on EU economies show no correlation between low-skilled immigration and the skill premium. We rationalise this evidence in a model where firms face search and screening costs. Low-skilled immigration diminishes the relative benefit of screening skilled workers, leading to a decline in their relative ability within the firm and an undetermined impact on the skill premium. On region-sector and firm level data from 2008 to 2013, we find that low-skilled immigration in Italian regions has reduced skill intensity without affecting the skill premium. Using proxies for workers' ability and screening activity, we provide supporting evidence for the theorised mechanisms.

KEYWORDS: Matching, screening, skill-intensity, factor relative ability

JEL CLASSIFICATION: F22; J61; F16; D24.

1 Introduction

Migration from low and middle income countries to high income economies has reached record highs in recent decades. Eurostat reports that 2.3 million foreign citizens, mainly from low and middle income countries, entered the EU in 2021 and on the first of January 2022 foreign-born citizens constituted about 8.5% of the European population.[1] The relevance of the phenomenon has stimulated a vast literature that investigated the consequences of immigration on wages and employment of the incumbents. The impact of immigration on the skill premium, instead, has received very little attention so far. Perhaps the reason is that the theoretical prediction seems straightforward: immigration of unskilled labour, by increasing the relative supply of unskilled labour, would result in an increase of the skill premium. However, this prediction is far from warranted. Theoretically, as we show in the paper, labour market frictions make the relationship between the relative supply of unskilled workers and the skill premium undetermined. Empirically, even a preliminary look at cross-country data shows no evidence of a clear relationship between immigration of unskilled workers and the skill premium (see Figure A2.1 in the appendix).

In this paper, we take up the challenge of investigating the link between immigration of unskilled workers, skill intensity, and the skill premium. In so doing, we discover new mechanisms that link immigration to local labour market outcomes. Our analysis is also interesting as it allows to examine the welfare consequences of immigration in three binary dimensions: between factors, between employed and unemployed, and between industries for the same factor.

We build a model that features search costs, screening costs, and firm-level wage determination in the spirit of Helpman et al. (2010a). We extend this model substantially by introducing a two-good and two-factor set up plus factor-biased heterogeneity among firms. In this model, immigration of low skilled workers causes a reduction in the relative cost of searching unskilled labour. As a consequence, firms will employ relatively less skilled workers, and the skill intensity declines. But there is more. Due to the reduction

[1] Sources, respectively: Eurostat and European Commission.

of the skill intensity, firms reduce the relative effort in screening skilled workers (screening may be interpreted also as training or as any type of activity that firms may undertake to increase factor productivity). The reason for such response is that the benefits of screening skilled workers become smaller as they accrue to a relatively smaller number of workers. The relative ability of skilled workers then declines and so does their productivity relative to that of unskilled workers. While the skill intensity unambiguously declines, the skill premium is subject to two forces: the increase in the relative supply of unskilled labour pushes the skill premium upward, but the decline in relative productivity of skilled workers pushes the skill premium downwards. The relationship is therefore theoretically undetermined.

For our empirical investigation, we use data on the Italian labour market focusing on workers in the manufacturing sector over the period 2008-2013. Italy is an interesting case for three reasons: the share of immigrants has risen dramatically in that period, almost all immigrants came from low and middle income countries, and, as reported by the Migration Observatory (Frattini, 2018), migrants are less educated than natives and are almost entirely employed as low skilled workers.[2] To asses the validity of the model, we dissect the mechanisms that drive the change in the skill premium by estimating the impact of immigration on a proxy for the relative ability of skilled workers. To retrieve the relative ability of the skilled in the Italian labour market, we estimate a wage equation on a matched employer-employee database where we account for worker and firm characteristics and we use individual fixed effects estimates as a proxy of a worker's ability that is not explained by observable factors (Abowd et al., 1999; Card et al., 2013). We find that immigration in a region reduces the skill intensity and the relative ability of the skilled within industries, while it has no significant effect on the skill premium. In

[2]The evidence of a large low-skill component of immigration emerges from the Italian Labour Force Surveys 2011-2018 where the share of workers with a tertiary degree is about 7% among immigrants and 11% among Italians, while the share of workers with a lower secondary degree or less is 48% among immigrants and 37% among Italians. This feature is stressed by several reports of the Migration Observatory. More specifically, Frattini (2018) reports that "Immigrants' education varies greatly across member states: Italy displays both the second highest share of immigrants with at most primary education (47%) and the lowest share of immigrants with tertiary education (13%)". The same document also points at an important role of the downgrading of immigrant skills. Indeed, higher percentages of the occupation–education mismatch for immigrant workers with respect to natives have been highlighted for Italy by existing evidence (Aleksynska and Tritah, 2013; Sparreboom and Tarvid, 2017).

line with the theoretical predictions of the model, we find that when individuals' wages are purged from their ability level, the positive effect of low skilled immigration on the skill premium is restored. Also, low skill immigration into a region reduces the relative screening of the skilled within industries.

This evidence is based on the traditional instrumental variable (IV) strategy used in migration studies that rests on the pre-existing immigrant enclaves from the same origin country (Altonji and Card, 1991; Card, 2001). The exogeneity of the source of identification of the IV is validated by the adoption of the tests suggested by Goldsmith-Pinkham et al. (2020). Robustness tests are conducted to explore the competing and potentially confounding role of emigration, capital investments and international trade.

Finally, based on the empirical evidence, we proceed to a structural verification from which we retrieve plausible values for the structural parameters of the model. The latter, together with parameters based on the literature, are used to perform welfare simulations. The simulations show a positive effect of immigration on aggregate welfare. Firm level wages increase for all factors equiproportionally but frictional unemployment increases for unskilled workers so much that the expected real wage declines. Thus, unskilled new entrants have worse opportunities. For skilled workers, the reduction in the screening effort by firms induces their wages not to increase as much as they otherwise would; however, the wage increase and the reduction in frictional unemployment makes them better off ex-ante and ex-post.

The remainder of the paper is structured as follows: Section 2 surveys and discusses the relevant literature and highlights our contribution; Section 3 presents the theoretical model and Section 4 sketches the theoretical predictions. Section 5 empirically validates the model. In Section 6 we carry out a welfare analysis. Section 7 concludes.

2 Literature review

The results emerging from the vast literature that studied the effect of immigration on wages are rather mixed. Many contributions show no significant effect on native wages or employment and when effects are statistically significant they are often small in magnitude. This is indeed one of the conclusions of the comprehensive review compiled by OECD (2016b), a synoptic table of which is reported in the appendix (Table O2.1). The sensitivity of results to different settings and methods appears already in the milestones works of Card (1990) and Card (2001). In the first paper, the author finds that the Mariel Boatlift had no significant effect on wages and employment of less-skilled native workers. In the second paper, using a different data set and an improved methodology, he finds a negative effect on employment. Later contributions point at a negative effect of immigrants on native wages. This is the case of Borjas (2003) and Aydemir and Borjas (2007) who consider nationwide labour markets and Malchow-Møller et al. (2012) who, instead, exploit firm level data. In other studies, results are more nuanced. Tumen (2016) uses immigration of Syrians in Turkey and finds no effect on wages of natives, a negative effect on employment of informal native workers and a positive but small effect on the employment of formal native workers. Brücker et al. (2014), by comparing the cases of Germany, UK, and Denmark, point at the role of labour market flexibility in shaping the immigration effect. The literature is further enriched by works that address the imperfect substitutability between immigrants and natives. Manacorda et al. (2012) find that immigration in the UK has primarily reduced the wages of immigrants with only little effect on the wages of the native-born. Similarly, Ottaviano and Peri (2012), find that immigration led to an average increase of six decimal percentage points in the wages of native workers and a decline in the wages of previous immigrants more than ten times larger. The substitutability issue is central also in Lewis (2011) and Lafortune et al. (2018). Dustmann et al. (2013) and Dustmann et al. (2016) argue that a possible explanation for the ambiguity in empirical results is the downgrading of immigrant education and experience. Addressing this problem, Dustmann et al. (2013) find that immigration in the UK during the period 1997-2005 depressed wages below the twentieth percentile, but it contributed to wage growth above the fortieth percentile. Although the ambiguity of the results mentioned above does not concern specifically the skill premium, it is consistent with our theoretical conclusion that the effect of immigration on wages is theoretically undetermined.

Two works that are largely immune from the problem of downgrading are Prantl and Spitz-Oener (2020) and Edo (2020) because in both papers immigrants and natives have been trained in equivalent educational systems. The first paper, uses data on German reunification. Although Germany was divided for long time, the educational and vocational systems remained very similar. The paper finds that immigration has a small negative effect on wages that vanishes for firms where workers participate to firm's decisions. The second paper uses the repatriation of French citizens residing in Algeria (part of France at that time) in the aftermath of the Algerian independence war of 1962. French repatriates were on average more skilled than the French residing in continental France. The paper finds that such increase in the relative supply of skilled labour resulted in a decrease of the skill premium. In our paper, labour market frictions make that such negative correlation between relative supply and relative price of skilled labour is not the only possible outcome.

A further strand of literature has presented compelling evidence regarding the impact of immigration on firms' performance. For instance, Olney (2013) finds that firms respond to immigration at the extensive margin and that this effect is particularly strong in low-skill intensive industries. Similarly, both Akgündüz et al. (2018) for Turkey and Casabianca et al. (2021) for Italy highlight an increase in the number of firms in low-skill intensive and labour intensive sectors following inflows of low-skill immigrants.[3] All these facts are consistent with the predictions of our model that immigration of low skilled workers lead to entry of low-skill intensive firms. Still in the Italian context, Bettin et al. (2014) find that, across firms, the influx of migrants leads to a decrease in the firm level skill intensity (an evidence consistent with our findings) and especially favours output expansion of firms in low skill intensive industries.[4] Further firm level outcomes have

[3]The impact of immigration in reshaping the industry structure of regions, particularly in favour of simple-task intensive sectors relative to other sectors, has been highlighted by De Arcangelis et al. (2015) in the context of Italy.

[4]Previous research has documented some of the forces affecting the skill premium in Italy. See, for example, Manasse et al. (2004) and, more recently, Iodice and Tomasi (2016). Turning to the exact role of migration in shaping the skill intensity and premium in the Italian labour market, the only evidence we are aware of is Venturini et al. (1999) who, for the period 1986-1995, show that the inflow of immigrants raises the wages of native manual workers, and this effect is larger in small firms and in the north of the

been explored by Mitaritonna et al. (2017), providing a thorough investigation into the effects of immigration on firm performance in France during the period 1995-2005. The immigration of skilled workers drives to an increase in total factor productivity and this effect is associated with faster capital growth, larger exports, and higher wages for native workers. Orefice and Peri (2020) study the effect of immigration on matching between firms and workers. They document that over the period 1995-2005 France observed a rise in high-skilled, white collar immigration in aggregate. This increase was associated with stronger positive assortative matching, higher average wages, higher average profits, and higher wage dispersion. These empirical conclusions are consistent with our theoretical framework but we take a different focus and propose different theoretical mechanisms. Most of the literature reviewed above does not question the positive relationship between immigration of low-skilled workers and the skill premium. Instead, we argue that this relationship is theoretically undetermined because immigration may induce changes in relative factor productivity that fully compensate for, or even exceed, the effect associated with the relative supply.

3 Theoretical background

In this section we sketch the model focusing on the economic mechanism and on the results. Section O.1 in the online appendix reports the complete description of the model and the proofs of results.

Demand. Consumers' preferences are represented by a Cobb-Douglas utility function defined over CES aggregates of two differentiated goods indexed by $i = Y, Z$. The expenditure shares on aggregates are $\varepsilon_i > 0$ and the elasticity of substitution between any two varieties of the same good is $\varsigma > 1$. The dual price index associated with each aggregate, denoted P_i, is also a CES aggregate defined over the prices of all varieties of the same industry. Firms, indexed with ξ, are heterogeneous in the way we explain below. The demand for the output of a firm ξ in industry i is $q_i^d(\xi) = (p_i(\xi))^{-\varsigma} (P_i)^{\varsigma-1} \varepsilon_i E$, where

country. However, over a 'crucial threshold' of the share of foreign work (7.7-12%), additional inflows in the labour market of foreign work have a negative effect on native wages.

$q_i^d(\xi)$ represents the quantity demanded and $p_i(\xi)$ is the price of the variety produced by firm ξ. Total expenditure equals national income and is denoted by E. Inverting the demand function and multiplying it by the price, we may write the sales of a firm in industry i as

$$s_i(\xi) = \left(q_i^d(\xi)\right)^{\frac{\varsigma-1}{\varsigma}} (P_i)^{\frac{\varsigma-1}{\varsigma}} (\varepsilon_i E)^{1/\varsigma} \tag{1}$$

Technology. Goods are produced by employing two factors, H and L whose endowments are $\overline{H}$ and $\overline{L}$. We shall refer to them as skilled and unskilled labour, respectively. Both factors are heterogeneous in terms of ability levels. Immigration of low skilled labour turns into an increase in $\overline{L}$. The production technology requires continuously fixed and variable inputs. The variable input technology takes the following CES form

$$q_i = \left[(1-\phi_i)\left\{\bar{a}_L\left[l\alpha(\xi)\right]^\gamma\right\}^{\frac{\sigma-1}{\sigma}} + \phi_i\left\{\bar{a}_H\left[h\beta(\xi)\right]^\gamma\right\}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1. \tag{2}$$

The elements of the production functions are the following: l, h are inputs of L and H; ξ is the realisation of a continuous random variable whose probability density function has support $(0,\infty)$; $\alpha(\xi)$ and $\beta(\xi)$ are non-decreasing and deterministic functions of ξ; as a result, $l\alpha(\xi)$ and $h\beta(\xi)$ are effective factor inputs; $\overline{a}_L$ and $\overline{a}_H$ are average factor abilities of workers employed by the firm; ϕ_i are industry-specific technological parameters; $\gamma > 0$ governs the degree of homogeneity of the production function and together with σ determines the elasticity of substitution between factors which is equal to $\sigma/(\gamma-(\gamma-1)\sigma)$. Convexity of the isoquant requires $\gamma < \sigma/(\sigma-1)$ which we henceforth assume. The presence of within firm average ability of each factor in the production function may be justified by the presence of human capital complementarity as in Helpman et al. (2010b), where the productivity of a worker depends on the average productivity of the team. Factor intensities differ between industries even for firms that draw the same ξ because $\phi_Y \neq \phi_Z$. In addition, even within the same industry, factor intensities differ between firms because of different draws of ξ. To fix ideas and without loss of generality, let $\phi_Y > \phi_Z$. Then, for any two firms that draw the same ξ, the skill-intensity is larger for the firm in Y than for the firm in Z.

Models that focus on Hicks-neutral heterogeneity assume $\alpha(\xi) = \beta(\xi)\ \forall\xi$. We, instead, allow for biased heterogeneity, that is: $\alpha(\xi) \neq \beta(\xi)$. By allowing for such bias, the model can explain the increase in the dispersion of skill premia observed in the data. Let $\flat(\xi) \equiv \beta(\xi)/\alpha(t)$. Then, heterogeneity is *H-biased* if $\flat'(\xi) > 0\ \forall t$; is *L-biased* if $\flat'(\xi) < 0\ \forall t$; is *neutral* if $\flat'(\xi) = 0\ \forall t$. This terminology is coherent with the fact that in the first case the relative marginal productivity of H increases with ξ, in the second case it decreases with ξ, and in the third case it remains constant. To simplify the prose we assume that heterogeneity is skill-biased but our results are independent of this assumption.

Firms continuously face a fixed production cost, F_i, and fixed entry cost, F_{ie} and a probability of death equal to $\eth$. Assuming homogeneous or heterogeneous fixed costs gives qualitatively the same results, but we assume homogeneous fixed costs since this assumption allows focusing on heterogeneity in the production process, which is the heart of the matter. This is also the assumption most commonly retained in the literature (Melitz (2003), Bernard et al. (2007) and many others). Specifically, we assume $F_i = \widetilde{mc}_i \digamma_i$ and $F_{ie} = \widetilde{mc}_i \digamma_{ie}$, where $\widetilde{mc}_i$ is the average marginal cost of production in industry i, while $\digamma_i$ and $\digamma_{ie}$ are positive real numbers. This assumption represents the fixed cost as a quantity of output ($\digamma_i$, $\digamma_{ie}$) that must be produced by the firm and that ultimately cannot be sold. This interpretation is proposed by Yeaple (2005) and is widely used in the literature. Here, the unsaleable output is produced by assembling all varieties of the industry-country output. Alternatively, but equivalently in terms of results, fixed costs may be interpreted as the input of a homogeneous composite good produced in a perfectly competitive market by assembling all the varieties of the industry output in a CES production function; this interpretation is in the spirit of Ethier (1982).

Profits. Firms are profit maximisers. In addition to fixed and variable production costs, they face search and screening costs. A firm seeking to hire workers first invites prospective workers for job interviews (searching) and then selects them according to the ability to perform the job (screening). Search and screening costs will be detailed below. Here, we just anticipate that to randomly invite n_j workers the firm pays a search cost equal to $b_j n_j$; furthermore, to detect whether abilities are above or below a threshold $\underline{a}_j$ the firm pays a screening cost equal to k_j times $\left(\underline{a}_j\right)^{\delta}/\delta$. Thus, firm profit is

$$\pi_i = s_i - \underbrace{\left[w_L(l)\,l + w_H(h)\,h\right]}_{Wage\ Bill} - \underbrace{\sum_j b_j n_j}_{Search\ Cost} - \underbrace{\frac{1}{\delta}\sum_j k_j \left(\underline{a}_j\right)^{\delta}}_{Screening\ Cost} - F_i \tag{3}$$

Firms optimize over employment, l and h, over the number of workers to search for, n_j, and over the threshold ability levels, $\underline{a}_j$. Firm-level wage negotiation gives endogenously the wages functions $w_L(l)$ and $w_H(h)$. We do not use industry indices on these variables but it should be clear that they depend on industry characteristics through general equilibrium.

Wage Determination. Search and screening costs are sunk when wages are negotiated. As the only information revealed by screening is whether a worker's ability is above or below $\underline{a}_j$, neither the firm nor workers can observe the match-specific productivity of a worker. The ability level of each worker is, therefore, considered equal to the average level $\overline{a}_j$. As a result, wage bargaining takes place under symmetric information and the equilibrium wage is one that obeys a differential equation where the workers marginal contribution to profits is equal to the workers wage. The solutions of these differential equations are denoted by $\omega_i^{\circ} \equiv \overset{\circ}{w}_H(h)$ and $\overset{\circ}{w}_L(l)$ and the firm-level skill premium $\omega_i^{\circ} \equiv \overset{\circ}{w}_H(h)/\overset{\circ}{w}_L(l)$ is:

$$\omega_i^{\circ} = \Phi_i \left(\frac{h}{l}\right)^{\gamma\mathfrak{s}-1} \left(\frac{\overline{a}_H}{\overline{a}L}\right)^{\mathfrak{s}} \flat(\xi)^{\mathfrak{s}\gamma}, \tag{4}$$

where $0 < \mathfrak{s} \equiv \frac{\sigma-1}{\sigma} < 1$ and $\Phi_i \equiv \phi_i/(1-\phi_i)$. Equation (4) is the traditional first order condition for profit maximization which requires the relative price of factors (ω_i°) to be equal to the marginal rate of technical substitution (the right hand side term of 4). The relative marginal productivity of H (i.e. the right hand side term 4) declines as *H-intensity* (h/l) increases since, as mentioned above, convexity of the isoquant implies $\gamma\mathfrak{s} < 1$. This standard mechanism reflects the change in the relative marginal productivity as we move along the isoquant. In addition to this standard mechanism, the relative marginal productivity of H increases with the relative average ability of *H-workers* employed in the firm ($\overline{a}_H/\overline{a}_L$). This effect reflects the change in the relative marginal productivity induced by a rotation of the isoquant. We now turn to the determination of h, l, $\overline{a}_H$, and $\overline{a}_L$.

Employment Determination. Since firm employment depends on the intensity of search and on the severity of screening, optimizing over employment is equivalent to optimising over searching and screening. Individuals, even within a factor type, are heterogeneous in abilities. To make things simple, we assume that the heterogeneity of abilities is distributed Pareto with shape parameter $\chi > 1$ and lower bound normalised to one for both factors. We therefore abstract from possible differences in the ability distributions between factors in order to gain mathematical tractability. Under this assumption, the relationship between employment, searching, and screening takes the simple functional form $l = n_L\left(\underline{a}_L\right)^{-\chi}$, $h = n_H\left(\underline{a}_H\right)^{-\chi}$, $\bar{a}_L = \frac{\chi \underline{a}_L}{\chi-1}$, $\bar{a}_H = \frac{\chi \underline{a}_H}{\chi-1}$. When deciding over employment, the firm cannot optimise over wages since the only information the firm has is how wages are determined. The firm anticipates the wage functions but knows neither the ability of each individual worker nor the average ability of the workers that will be employed by the firm. Thus, at the stage of employment determination the firm maximizes profits by choosing optimal searching ($n_L,\ n_H$) and optimal screening ($\underline{a}_L,\ \underline{a}_H$) given the wage functions.

Search. We follow the Diamond-Mortensen-Pissarides approach where the total number of prospective workers that receive an invitation to the job interview, N_j, is a Cobb-Douglas function of the total number of vacancies, V_j, and of the mass of workers looking for a job, $\underline{L}$ and $\underline{H}$:

$$N_L = \mu_1 V_L^{\mu_2} \underline{L}^{1-\mu_2}, \qquad N_H = \mu_1 V_H^{\mu_2} \underline{H}^{1-\mu_2}, \tag{5}$$

with $0 < \mu_1, \mu_2 < 1$. Let v_j denote the number of vacancies posted by a firm and assume that the number of workers randomly meeting with a firm, n_j, is proportional to the firm's share of total vacancies: $n_L = v_L N_L/V_L$, and $n_H = v_H N_H/V_H$. Then, a firm seeking to meet with n_j workers needs to post a number of vacancies, v_j, equal to $v_j = V_j n_j/N_j$, which, using the meeting technology (5), becomes $v_j = (1/\mu_1)^{1/\mu_2}(x_j)^{(1-\mu_2)/\mu_2} n_j$ where $x_L \equiv N_L/\underline{L}$ and $x_H \equiv N_H/\underline{H}$ denote the market tightness. The vacancy posting technology common to both factors is Cobb-Douglas with shares $0 \leq b \leq 1$ and searching is outsourced to perfectly competitive firms which pay the *ex-ante* expected wages w_{Le} and w_{He}. Then, the per-worker search cost, b_j, is equal to

$$b_j = (w_{He})^b (w_{Le})^{1-b} \left(\frac{1}{\mu_1}\right)^{\frac{1}{\mu_2}} (x_j)^{\frac{1-\mu_2}{\mu_2}}. \tag{6}$$

To determine the *ex-ante* expected wages we use the first order conditions for profit maximization detailed in online appendix O.1.1. Such condition implies that the expected wage conditional on meeting with a specific firm is equal to the unit search cost, that is: $\overset{\circ}{w}_L(l^\circ/\overset{\circ}{n}_L) = b_L$ and $\overset{\circ}{w}_H(h^\circ/\overset{\circ}{n}_H) = b_H$. A $^\circ$, as usual, indicates the optimal choice of the firm. The term in parenthesis represent the probability of being hired conditional to being invited to the job interview. The ex-ante expected wage is equal to the expected wage conditional on meeting with a firm times the probability of meeting with some firm. That is:

$$w_{Le} = \overset{\circ}{w}_L \frac{l^\circ}{\overset{\circ}{n}_L} \frac{N_L}{\underline{L}} = x_L b_L, \quad w_{He} = \overset{\circ}{w}_H \frac{h^\circ}{\overset{\circ}{n}_H} \frac{N_H}{\underline{H}} = x_H b_H \tag{7}$$

Given free entry and exit in the labour market, the ex-ante expected wages must equal the outside options w_{Lo} and w_{Ho}. Using (7) this condition is

$$w_{jo} = \underbrace{b_j x_j}_{w_{je}} \tag{8}$$

Equations (6) and (8) may be solved for b_j and x_j to yield

$$\frac{b_H}{b_L} = (\omega_o)^{1-\mu_2} \tag{9}$$

where $\omega_o \equiv w_{Ho}/w_{Lo}$.

Screening. We have seen already that the screening cost increases in $\underline{a}_j$. This assumption captures the idea common to the literature that more resources are needed to detect a higher level of ability. For the specification of k_j, we assume that the screening technology is Cobb-Douglas with cost shares k and $(1-k)$ for H and L. We assume that screening is done by the personnel of the firm at firm's wages. The corresponding cost functions are: $k_J = (w_H^\circ)^k (w_L^\circ)^{1-k}$ and the relative screening cost becomes simply $(\underline{a}_H^\circ/\underline{a}_L^\circ)^\delta$.

Alternative specifications of search and screening costs. We have assumed above that search is outsourced and screening is carried out in-house. These assumptions correspond to the most common practices, but alternative assumptions may be considered. A first alternative is that search is done in-house at firm's wages. Then, relative search cost would depend on firm wages in addition to ex-ante expected wages. A second alternative is that screening is outsourced to perfectly competitive firms which pay ex-ante expected wages. Under this assumption, the relative cost of screening would depend on the ex-ante expected wages. Yet, another assumption is that search and screening services are provided by non-production workers (personnel department) whose wages are the ex-ante expected wages. Under such assumption, search and screening would depend only on the ex-ante expected wages. All these alternatives give analytically identical results as long as the factor intensity in search and screening is the same across factors. Abandoning the latter assumption introduces feedback effects from the firm wages to the cost of search and screening. The crucial mechanism of the model, which links ex-ante expected wages to the relative cost of search and screening remains unchanged, however. Therefore, the theoretical results that immigration may have positive or negative effects on the skill premium remains valid if these alternative specifications are adopted.

4 Economic mechanisms and testable results

Optimal relative search ($\eta_i \equiv n_H^\circ/n_L^\circ$), optimal skill intensity ($\theta_i \equiv h^\circ/l^\circ$), optimal relative screening ($\psi_i \equiv \underline{a}_H^\circ/\underline{a}_L^\circ$), and optimal relative wage ($\omega_i \equiv w_H^\circ/w_L^\circ$) are interrelated through the four first order conditions displayed in the online appendix O.1.1. To understand the link among these variables we consider the impact stemming from immigration of unskilled workers. The increase in the relative scarcity of skilled workers caused by immigration pushes the outside option skill premium upward ($\omega_o \uparrow$). This would be the only consequence if we removed search and screening costs and firm-level wage determination from the model since market clearing wages would also represent firm wages. Then, we would observe an increase in the skill premium and a reduction in the skill intensity. In the data, instead, we observe a reduction in the skill intensity and no effect on the skill premium. This apparent inconsistency is resolved in our model by the effect that screening has on the skill premium. The rise in ω_o causes an increase in the relative cost of meeting with H (see equation 9) which, in turn, induces lower relative search for H. This triggers two opposite forces acting on the skill premium. First, lower relative search for H reduces firm *H-intensity* because, as discussed above, employment is proportional to search. The reduction in the skill intensity increases the relative marginal productivity of H and pushes the skill premium upward (see equation 4). This force is stronger the smaller is γ (strong convexity of the isoquant). This can be seen in equation (4) where the exponent $(\gamma s - 1)$ conveys the effect of changes in the skill intensity on the skill premium. The second force is that lower relative search for H induces less severe relative screening of H because the productivity gains obtained through screening accrue to a relatively smaller number of skilled workers. The consequence of less severe relative screening of H is a lower relative marginal productivity of H and thereby a lower skill premium (see equation 4). This force is stronger the smaller is δ because a low δ makes the relative screening cost to increase slowly with the severity of screening. The net effect of these two forces on the skill premium is then theoretically ambiguous. Formally, using (9) in the first order conditions (26) laid out in the online appendix and solving we obtain the following results:

$$\eta_i = (\Phi_i)^{\eta_1} (\omega_o)^{(1-\mu_2)\eta_2} [\flat(\xi)]^{\eta_4}, \qquad with \qquad (\eta_1, \eta_4) > 0, \ \eta_2 < 0, \tag{10}$$

$$\theta_i = (\Phi_i)^{\theta_1} (\omega_o)^{(1-\mu_2)\theta_2} [\flat(\xi)]^{\theta_4}, \qquad with \qquad (\theta_1, \theta_4) > 0, \ \theta_2 < 0, \tag{11}$$

$$\psi_i = (\Phi_i)^{\psi_1} (\omega_o)^{(1-\mu_2)\psi_2} [\flat(\xi)]^{\psi_4}, \qquad with \qquad (\psi_1, \psi_4) > 0, \ \psi_2 < 0, \tag{12}$$

$$\omega_i = (\Phi_i)^{\omega_1} (\omega_o)^{(1-\mu_2)\omega_2} [\flat(\xi)]^{\omega_4}, \qquad with \qquad (\omega_1, \omega_4) > 0. \tag{13}$$

The signs of the exponents are all unambiguously determined except for ω_2 (see online appendix section O.1.1). Immigration of unskilled labour reduces the skill-intensity ($\theta_2 < 0$), reduces the relative ability of skilled workers ($\psi_2 < 0$), but has an undetermined effect on the skill premium (sign of ω_2 undetermined). This is the first set of results that we subject to empirical scrutiny:

Result 1 *Immigration of unskilled labour reduces the skill intensity in all industries and firms (equation 11).*

Result 2 *Immigration of unskilled labour reduces the relative ability of skilled-labour in all industries and firms (equation 12).*

Result 3 *The effect of immigration of unskilled labour on the skill premium may be positive, negative, or nil (equations 13 and 14).*

The sign of ω_2 is positive or negative according to this condition :

$$\omega_2 \gtreqless 0 \qquad \Leftrightarrow \qquad \delta \gtreqless \frac{\mathfrak{s}}{1 - \gamma\mathfrak{s}}, \tag{14}$$

The positive effect on the skill premium prevails when δ is large and γ small, then ω_2 is positive and the skill premium increases with immigration (this is the conventional result). The second force prevail when δ is small and γ large, then ω_2 is negative and the skill premium declines with immigration (this is the unconventional result).

A fourth testable result concerns the dispersion of skill premia. The increased availability of unskilled labour favours firms that use them intensively. The firm that was making zero profit before immigration will make positive profits after immigration and a new -

even less skill-intensive firm - will be the new cut-off firm. In terms of the model, this effect is represented by a leftward shift of the entry cut-off ξ_i^*. While the leftward shift is independent of the form of the cumulative density function $G(\xi)$, its effect on the dispersion of skill intensities depends on the form of $G(\xi)$ and on the index of dispersion we use. To be concrete, we rely on the results of many empirical studies who find that the revenue distribution is well represented by a log-normal.[5] In line with these findings we assume that $G(\xi)$ is such that $\flat(\xi)$ is log-normal. As a result, firm revenues are also log-normal. Let the dispersion of the distribution be measured by the coefficient of variation, denoted CV_i:[6]

$$CV_i = \frac{\sqrt{\mu_{i,2} - (\mu_{i,1})^2}}{\mu_{i,1}} \tag{15}$$

where $\mu_{i,N}$ is the N^{th} moment of the truncated probability density function of the endogenous variable of interest, that is:

$$\mu_{i,N} = \frac{1}{1 - G(\xi_i^*)} \int_{\xi_i^*}^{\infty} [x_i(\xi)]^N \, dG(\xi), \qquad where \qquad x = \omega(\xi), \theta(\xi). \tag{16}$$

Immigration causes a decline in ξ_i^* because less productive and less skill intensive firms become viable (see equation 67 in the online appendix). Recalling that $CV_i(\omega)$ is decreasing in ξ_i^* leads to the following result.

Result 4 *Immigration of unskilled labour causes an increase in the dispersion of skill premia and skill intensity.*

5 Empirical analysis

In this section, we investigate the impact of immigration on the skill intensity and premium in Italian manufacturing by testing the empirical implications of the mechanisms highlighted in the theoretical model developed in Section 3. For our baseline analysis we rely on information on employment and wages at region-sector level mainly sourced

[5]See, e.g., Bee et al. (2017) and Growiec et al. (2008) for direct fit of firm revenue distribution; see Combes et al. (2012) and Bas et al. (2017) for fit of revenues implied by log-normal productivity distribution.

[6]Taking other measures - e.g., the Gini coefficient, Theil, Hoover, etc. - would leave the result qualitatively unchanged.

from the Italian Labour Force Surveys available from the Italian Institute of Statistics (Istat) merged with information on the share of resident foreign born population in Italian regions available from the Istat GeoDemo portal. Given the limited availability of information on wages, the baseline analysis covers the years 2008-2013. We further rest on the matched employer-employee dataset provided by the Italian national institute of social security (INPS) to obtain a proxy of workers' abilities and delve into the mechanisms highlighted by the model. The details on the sources of the data used in the remainder of the paper are described in Section A1 of the appendix.

5.1 Economic Context: Immigration, skill intensity, and skill premium in Italy

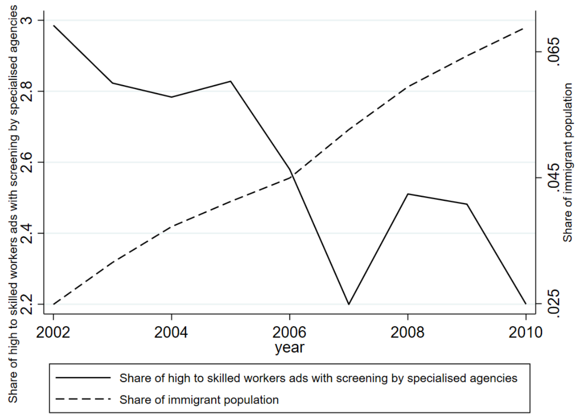
Italy represents an interesting case for studying the effect of migration on the skill premium for a number of reasons. First, the country has experienced growing inflows of migrants during the period examined. In 2014 immigrants stood at about 8% of the country's population from 2.7% in 2003. Second, in the same year nearly 95% of these migrants were from less developed economies and were usually employed as low-skilled workers. Italian Labour Force Surveys report for the first year of our sample - year 2008 - that 93% of foreign workers in Italian manufacturing were employed as blue collars against the 45% of natives, and more than 58% of immigrants either had no education (6%) or had achieved the primary or lower secondary education, against the 47% of natives of which only a tiny share (0.40%) reported no education. The peculiar low skill intensity of immigration in Italy compared to other European economies has been underscored by several reports of the Migration Observatory. This evidence is also confirmed in Figures A2.1a and A2.1b which show that Italy has experienced the largest growth in the share of immigrant population and the highest ratio of low to high skilled immigrants. Third, compared to other advanced countries, Italy's economy is characterised by poor capital accumulation and its manufacturing traditionally bends towards low skilled labour intensive goods (De Benedictis, 2005; Larch, 2005).

To explore to what extent the mechanism proposed in the paper is at work in the Italian labour market we first provide some descriptive evidence. From the *Demand for Qualified Labour* survey available from the Italian national institute for the analysis of public policies (INAPP), we extract data on advertisement for workers with no previous experience (see appendix A1.1). For these workers screening can be considered especially useful to assess workers' ability, as firms cannot infer it from previous work experience. We then compute the share of job advertisements for which skilled workers' selection is entrusted to specialised agencies relative to the same share for the low skilled and observe the evolution of this relative share over time. As shown in Figure 1, the relative share of advertisements for the skilled screened by specialised agencies declines over time. This evidence is in line with the hypothesised mechanism of a declining return from screening skilled workers relative to low skilled workers, during a period of increasing inflows of low-skilled immigrants.

To present further descriptive evidence and provide a regional perspective we analyse fixed term training contracts.[7] Firms may use such contracts as a screening tool to assess workers on the job over a limited time period. These contracts may also contain training programmes aimed at developing abilities in the workplace. As such, they are particularly useful to provide a measure of a firm's efforts in screening and training workers. These efforts, indeed, can be proxied by the share of workers on a fixed-term training contract over the total of newly hired workers with less than two years of tenure. To assess the relative effort in screening/training skilled workers, we calculate these shares for both the group of skilled and unskilled workers and we take their ratio within each region. In Figure 2 we plot the relationship between the overall 5-year evolution of the relative screening measure and migration across Italian regions over the period 2008-2013. Although migration has increased in all regions, those experiencing a higher change in the immigrant population share have also experienced a stronger decline in the relative screening of the skilled.

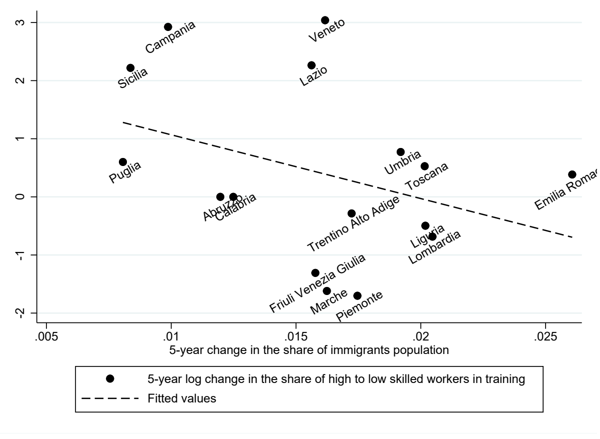
[7] Regional level information on job advertisements for which selection is entrusted to specialised agencies is not publicly available.

Figure 1: Relative screening of the skilled in the Italian labour market: a nation-wide perspective



Source: Author's own calculations on INAPP DLQ database and Istat GeoDemo. The Figure shows uniformly weighted moving average - by using two lagged terms and two forward terms, and including the current observation - of the share of migrants - foreign citizens - in total population, and of the relative share of job advertisements for inexperienced workers for which worker selection is entrusted to a specialised agency.

Figure 2: Relative screening of the skilled and immigration in Italy, 2008-2013: a regional perspective from short-term training contracts



Source: Istat GeoDemo and Labour Force Surveys.
The Figure show the nexus between the evolution of relative screening of the skilled workers and immigration across Italian region over the 2008-2013 period. The evolution of the relative screening of the skilled workers at the regional level is measured as the log change in the ratio between the share of skilled workers - managers, executives and clerks - on a fixed-term training contract over the total newly hired skilled workers with less than two years of tenure and the same share computed for unskilled workers.

5.1.1 Measuring the relative abilities of the skilled with respect to the unskilled

To further explore the mechanisms at work in the model, we matched employer-employee database provided by INPS to compute a proxy of the relative abilities of the skilled versus the low skilled at region-sector level. We estimate the following Mincerian wage equation:

$$w_{o\xi ri\ t} = \quad \delta + \eta' Z_{o,\ t} + \phi' Size_{\xi,\ t} + \varrho_{it} + \eta_o + \kappa_\xi + \nu_{o\xi ri\ t} \tag{17}$$

where $w_{o\xi ri\ t}$ is the log of individual o's daily wage working in firm ξ of industry i located in region r at time t and $Z_{o,\ t}$ is a bunch of worker level characteristics: age, squared age, a dummy for the skilled, a dummy for part-time workers and the log number of days worked in a year. The model also includes firm size dummies - i.e. the vector $Size_{\xi,\ t}$ refers to 14 different firm size classes - interacted by year, industry-year, ϱ_i, individual, η_o, and firm, κ_ξ, fixed effects. We follow Abowd et al. (1999) and Card et al. (2013) and interpret individual effect η_o as a combination of skills and other factors that are rewarded equally across all the jobs of an individual, while the remaining part of the specification in model 17 is aimed at capturing all other demographic and aggregate factors that affect a specific worker. The identification of the worker and firm fixed effects relies on the mobility of workers between firms. To account for the "limited mobility bias" (Andrews et al., 2008), we then retain workers moving at least twice across different employers and firms with more than 15 employees moving across different employers. After estimating equation (17), we use the exponential of the individual fixed effect estimates as a proxy of individuals' ability not caught by observable characteristics. We then average these individual abilities for the group of skilled and unskilled workers by region and sector. Eventually, we take the ratio of the average ability estimate of the skilled over the unskilled to get a proxy of the relative unobserved ability of the skilled in each sector and region.

5.2 Empirical model and estimation issues

To uncover the effect of immigration on the skill intensity and premium in the Italian context and explore the mechanisms highlighted by the theoretical model, we exploit variation across regions and industries and estimate the following empirical model:

$$y_{r,i\ t} = \alpha + \beta Migrants^{share}_{r,\ t-1} + \gamma' X_{r,\ t-1} + \lambda_{it} + \varpi_r + \epsilon_{rit} \tag{18}$$

where $y_{r,i\ t}$ alternatively measures the skill intensity, the skill premium and the relative ability of skilled workers in industry i[8] of NUTS2 region r at time t, $Migrants^{share}_{r,t-1}$ is the share of migrant residents in region r at time $t-1$, $X_{r,t-1}$ is a vector of region level time-varying control variables, λ_{it} represents industry-year fixed effects, ϖ_r are region fixed effects and ϵ_{rit} is the idiosyncratic error term.[9] Due to the region-year variation of our main right-hand-side variable, in the estimation below, standard errors are clustered at region level, unless otherwise specified.

The correct identification of the effect we are searching for is potentially subject to endogeneity of migration flows towards any particular region. More specifically, this issue stems from two forces pulling in opposite directions. On the one side, immigrants might reach low skill abundant regions where their labour endowment could easily match local labour demand. On the other side, immigrants might be attracted by high-wage, more skill abundant regions with better job opportunities. In both cases, OLS would deliver a biased estimate of the effect of migration, the direction of the bias is uncertain and endogeneity, and especially reverse causality and sorting, can prevent the correct identification of the effect. To address this issue, we implement an IV strategy. In particular, we rest on the use of the standard shift and share IV adopted by immigration studies based on the idea that the presence of immigrant enclaves from the same origin country represent a non-demand driven determinant of migration into a location (Altonji and Card, 1991; Card, 2001). Our baseline IV is built as follows:

[8]Industries are NACE sub-sections as listed in Table O2.1 in the online appendix.

[9]Baseline control variables include region level GDP, the share of manufacturing on total value added and the unemployment rate.

$$IVperm_{rt}^{94} = \sum_{k=1}^{N} w_{rk}^{1994} * \frac{Migrants_{kt}}{Population_r^{1994}} \quad (19)$$

where w_{rk}^{1994} is the share of residency permits granted to migrants from country k in region r in 1994 on total permits released to immigrants from country c and $Migrants_{kt}$ is the number of immigrants from country k residing in Italy in year t. The presence of immigrants from country k at time t is imputed to regions according to the (pre-sample) 1994 distribution of permits to immigrants from country k across Italian regions and is normalised by the 1994 region population.

In Section O.3 of the online appendix we analyse the sources and the validity of the identification based on shift-share instrumental variables (Adão et al., 2019; Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020) to corroborate the plausibility of the identification strategy.

5.3 Evidence

Table 1 presents 2SLS estimates of the impact of immigration on the skill intensity - Columns [1]-[3] - and premium - Columns [4]-[6] - in a region and industry.[10] As expected, the results reveal that an increase in the share of immigrants over population is associated to a reduction in the skill intensity. This evidence persists whether the presence of immigrants is measured as the share of immigrant population over total population or when it is measured as the share of immigrant labour force - immigrants aged 15-65 - over the total labour force. Also, the negative relation between immigration and the region-industry skill intensity is observed when we only focus on the share of immigrants from Low&Middle income economies, which, as previously stated, account for about 95% of immigrants in Italy and better capture variation in the availability of low skilled workers. In this case, the coefficient is bigger.[11] According to the specification of Column [1], a 1 percentage point increase in the regional migrant share leads to a contraction of the

[10] Corresponding First-Stage results are shown in Table O2.4 in the online appendix A2.

[11] This pattern is confirmed by the OLS estimates of Table O2.2 in the online appendix A2. Here, the estimated coefficients are systematically smaller in absolute terms implying an upward bias in OLS estimates. See online appendix Section O.3 for the analysis of the validity of the sources of the identification in the IV.

skill intensity by about 0.14. Considering that, on average, the share of immigrants in total population has increased by 1.7 percentage points between 2008 and 2013 across regions, this has caused a reduction of the skill intensity by 0.24, which, according to the descriptive statistics from Table A2.1 in the appendix, corresponds to about half of the average skill intensity observed across region-industry pairs in our sample period. Indeed, the coefficient estimate in Column [1] implies an elasticity of - 1.81: an increase by 1% in migration would then reduce the skill intensity by 1.81%.[12] Having the share of migration increased by about 32% between 2008 and 2013, this observed increase implies, according to our estimate, an overall reduction by about 50% in the skill intensity. We thus confirm *Result 1* of the model at industry-region level.

Turning to the evidence on the skill premium in Columns [4]-[6], we find non significant effect of migration on this variable.[13]

To corroborate *Result 1* and *3*, we run a parallel analysis of the impact of regional migration on the skill intensity and premium at firm level by exploiting the INPS LOSAI database. Results are shown in Table O2.6 in the appendix. The empirical evidence confirms the findings emerging from the region-industry analysis: an increase in a region's share of immigrants reduces the skill intensity of firms located in that region, while having no effect on their skill premia. There is a difference, however. The 2SLS coefficient estimates in the Table O2.6 are definitely smaller than those presented in Table 1 and, on the basis of the descriptive statistics in Table A2.1, imply an elasticity of 0.20 which is much lower than the one stemming from the region-industry sample.[14] This difference in magnitude is predicted by our model through the entry mechanism. When measured at firm level, the elasticity captures the response of firms existing both before and after the immigration shock. When measured at the regional level, the elasticity captures the response of all firms (including the entrants).[15] It is worth highlighting that the nil effect

[12]The elasticity is computed as $\varepsilon_\beta = \frac{\partial y}{\partial x}\frac{\hat{x}}{\hat{y}}$, where $\hat{x}$ and $\hat{y}$ are the sample average of the right and left hand side variables, respectively. Hence, taking as reference the descriptive statistics in Table A2.1, $\varepsilon_\beta = \beta * \frac{0.064}{0.591} = -16.728 * \frac{0.064}{0.591} = 1.811$.

[13]This pattern is confirmed by the OLS estimates of Table O2.2 in the online appendix.

[14]This elasticity is very close to the firm level estimate of the elasticity of the skill intensity with respect to migrant workers - 0.166 (0.206 for firms in the low skill intensive industries) - obtained by Bettin et al. (2014) on the sample of Italian firms in the 2001-2003 period.

[15]This distinction is well represented by the term $\widehat{\widehat{b}}_{ir.}(.)$ in equations (20) - (22) which captures precisely

Table 1: The impact of immigration on the skill intensity and premium - 2SLS

	Skill Intensity			Skill Premium		
	[1]	[2]	[3]	[4]	[5]	[6]
$\frac{Migrants}{Population}_{t-1}$	-16.728**			-1.968		
	[6.694]			[3.921]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		-13.028**			-1.532	
		[5.112]			[3.021]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			-17.961**			-2.090
			[6.500]			[3.720]
Observations	1,219	1,219	1,219	1,219	1,219	1,219
Shea-R2	0.431	0.455	0.444	0.431	0.455	0.444
First Stage F-test	17.06	20.55	19.72	17.06	20.55	19.72
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region. The dependent variable in Columns [1]-[3] is the ratio of the skilled - managers, executives and clerks - to the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. The dependent variable in Columns [4]-[6] is the ratio of the average wage of the skilled - managers, executives and clerks - to the average wage of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing_{t-1}^{Share}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$. Table O2.4 in the online appendix shows first-stage results.

of immigration on the skill premium emerging from both region-sector and firm level results is predicted by *Result 3* of the theoretical model and is expected to originate from the two counteracting forces that shape the relationship between migration and the skill premium. On the one hand, the increase of the relative supply of low skilled labour would drive to an increase in the local skill premia. On the other hand, the resulting reduction in the relative use of skilled labour reduce the severity of screening skilled workers, as the costs of the latter activities may now overcome their benefits that accrue to a relatively smaller number of skilled workers. It follows that the relative ability of workers is expected to drop and this will turn into a reduction in the skill premia.

Before delving into the mechanisms of the model, we empirically test *Result 4*, according to which, immigration of low skilled workers is expected to induce an increase in the dispersion of the skill intensity and premia across firms. By exploiting firm level information

the contribution of new entrants to the aggregate response.

Table 2: The impact of immigration on skill intensity and premium dispersion across firms - 2SLS

	Skill Intensity Dispersion			**Skill Premium Dispersion**		
	[1]	[2]	[3]	[4]	[5]	[6]
$\frac{Migrants}{Population}_{t-1}$	93.811*			161.023		
	[53.308]			[100.795]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		73.042*			125.373	
		[40.020]			[75.784]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			97.892*			168.452
			[53.813]			[100.912]
Observations	1,182	1,182	1,182	1,182	1,182	1,182
SheaR	0.435	0.463	0.445	0.435	0.463	0.445
Ftest	16.33	19.62	18.94	16.33	19.62	18.94
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region. The dependent variable is the standard deviation of the skill intensity, in columns [1]-[3], and skill premium, in columns [4]-[6], across firms within an industry-region pair between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

retrieved from the INPS LOSAI database, we measure the standard deviation of the skill intensity and premium across firms in the same region-industry and we use it as dependent variable in the empirical model in equation 18. Results from 2SLS are presented in Table 2. As predicted by the theoretical model, we do find that an increase in the share of immigrants increases the dispersion of the skill intensity across firms within an industry-region pair, while in the case of the skill premium the 2SLS migration coefficient is negative but not significant.

The mechanism of the model. According to *Result 2*, we expect a reduction of the relative ability of the skilled following an increase in the share of immigrants. We rest on the LOSAI matched employer-employee data set and on the procedure discussed in section 5.1.1 to retrieve the region-industry relative abilities of the skilled for our sample period and we estimate equation 18 with this measure as our dependent variable. The corresponding 2SLS results are shown in Columns [1]-[3] of Table 3. The set of estimates confirms the predictions of the model, by showing that the shock to the local low skilled labour supply brought about by immigration, leads to a reduction of the relative abilities of skilled workers compared to unskilled workers. This evidence is consistent with the reduction in the relative screening activities on skilled workers. To further corroborate the mechanics of the model, in columns [4]-[6] we show results for the relative wage of skilled compared to unskilled workers when the wage of both groups are predicted from equation (17) net of the individual ability η_o. When ability is removed from average individual wages, the increase of immigration of low skilled workers exerts a positive effect on the relative wage of the skilled. Theoretically, this can be seen in equation (4).

To further inspect the mechanism of the model we test the impact of immigration on the relative screening of skilled workers. To do so, we measure the relative screening as the difference between the share of skilled workers on a fixed-term training contract over the total newly hired skilled workers with less than two years of tenure and the same share computed for unskilled workers in a region-sector-year.[16] As explained above, fixed-term training contracts conveniently proxy for on-the-job screening since they are aimed at assessing (over two years) worker skills before moving to a permanent contract. As shown in Table 4 we find a significant and negative effect of immigration on the relative screening of the skilled which supports the main mechanism in our model. Taking as reference the coefficient in the first column of Table 4, a 1 percentage point increase in the regional migrant share leads to a contraction of the difference in the screening of the skilled and the unskilled by about 0.074. Again, considering that, on average, the share of immigrants in total population has increased by 1.7 percentage points between 2008 and 2013 across regions, this has caused a reduction of the difference in screening between the skilled and the low skilled of about 0.13 which is sizeable considering that the average difference in our data is -0.036 (see Table A2.1 in the appendix).

[16]OLS results are in Table O2.3 in the online appendix. Note that in Tables 4 and O2.3 the number of observations is reduced due to the presence of some missing values either in the share of skilled or low skilled workers on a fixed-term training contract for some region-sector pairs. The use of the ratio of the two shares rather than the difference was prevented by the presence of 0s in both shares which would leave us with a much lower number of observations (525 compared to 883).

Table 3: The impact of immigration on the relative ability of the skilled - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]
	Relative ability of the skilled			Relative wage of the skilled (net of the ability)		
$\frac{Migrants}{Population}_{t-1}$	-8.583*			7.608*		
	[4.148]			[3.993]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		-6.667*			5.909*	
		[3.194]			[3.091]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			-8.753*			7.713*
			[4.214]			[4.062]
Observations	1,093	1,093	1,093	1,093	1,093	1,093
Shea-R2	0.416	0.448	0.425	0.416	0.448	0.425
F-test	14.45	17.53	16.9	14.45	17.53	16.9
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable in Columns [1]-[3] is the ratio of the average ability of the skilled - managers, executives and clerks - to the average ability of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. The dependent variable in Columns [4]-[6] is the ratio of the average residual (net of the ability) wage of the skilled - managers, executives and clerks - to the average residual wage (net of the ability) of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$. Table O2.8 in the online appendix shows first-stage results.

Table 4: The impact of immigration on the relative screening of the skilled - 2SLS

	[1]	[2]	[3]
$\frac{Migrants}{Population}_{t-1}$	-7.482**		
	[3.492]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		-5.791**	
		[2.682]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			-7.584**
			[3.493]
Observations	883	883	883
Shea-R2	0.386	0.424	0.399
First Stage F-test	12.681	15.788	14.601
Fixed Effects			
region-sector	y	y	y
sector-year	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable is the difference between the share of skilled workers on a fixed-term training contract over the total newly hired skilled workers with less than two years of tenure and the same share computed for unskilled workers in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

5.4 Robustness checks

Although the IV strategy is expected to grant identification when the main variable of interest is endogenous, we further test the robustness of the above empirical findings by adding further controls to our baseline specification. Especially, we focus on the potential confounding effect of three main factors: emigration, capital investment and international trade.

Concerning the first factor, Bütikofer and Peri (2021) show that higher adaptability - the capacity to adjust to new environments and situations - and higher cognitive ability are significant predictors of the probability to migrate. The issue of brain drain and, more generally, the loss of human capital and skilled labour has long been a concern for developing economies. However, the recent evolution of the labour market in some advanced economies suggests that they may be experiencing the same phenomenon, especially in the aftermath of the 2008-2010 Great Recession. In this respect, Anelli et al. (2023) study the case of Italy to inspect the impact of emigration on entrepreneurship in the country. They report from administrative data a loss of almost 1 percent of the Italian population over the 2008-2015 period, stemming from the cumulative emigration flows. In addition, they show that the rate of emigration was particularly high among individuals aged 25-44 and college graduates. If the mechanism of our model is at work, the effects of emigration of skilled workers should be observationally equivalent to those of the immigration of low skilled workers. Furthermore, the effect of international emigration could be reinforced by the flows of internal emigration which, in Italy, especially involves the movement of educated workers from one region to another (ISTAT, 2023).

A second potential concurring explanation to patterns observed in the data is the evolution of capital investment. The complementarity/substitutability issue has been analysed in Lewis (2011) in a three factor model where machines (such as automation machinery) are substitutes with unskilled workers and complement with skilled workers. In a similar model, Lafortune et al. (2018) examine the effect of the high immigration in the U.S. that occurred between 1860-1930 on the skill mix and find that capital initially complemented both high- and low-skill labour. Despite of the large evidence of capital-skill complementarity in modern production systems (Griliches, 1969; Duffy et al., 2004), we cannot neglect the possibility that, if any form of complementarity between capital and low skilled labour is at work in our data, this could work as a confounding factor within our framework and could by itself account for the absence of an impact on the skill premium following an increase in the low skilled relative labour supply.[17]

As a final confounding factor, we inspect the role of imports in the region. In principle, there is no particular reason to expect that trade might have influenced the skill premium. The reason is that in the period covered by our data the European Union (and therefore Italian) tariff rate has remained remarkably flat. Nonetheless, we cannot completely rule out the possibility that the growth and capital accumulation in some trading partners (China, especially) might have indirectly impacted the Italian labour markets through imports.

Tables O2.9 - O2.15 in the online appendix report the results of these robustness checks.[18] The additional controls are not significantly related to the evolution of the skill intensity, while capital investments seem to be negatively related to the skill premium and the relative ability of the skilled.[19]

In all cases our baseline results are confirmed.

[17]In this respect, for Italian manufacturing firms Bettin et al. (2014) estimate a positive elasticity of both high and low skilled labour demand to growth in the capital stock. The estimated elasticity for skilled workers is double compared to that estimated for the low skilled. However, when splitting the sample between advanced and traditional industries, the elasticity's difference for the last group of sectors is reversed.

[18]The emigration rate is measured as the share of emigrants from a region to a foreign country or to another region in total region population, and is obtained from the Istat data on cancellations from the population register due to a change of residence abroad or in another region. The regional import share is obtained as the total regional imports - from Istat COE dataset - normalised by region GDP. Finally, to measure the role of investments we exploit the Istat dataset on Economic Accounts of Firms at region level and we compute the total investments on capital goods per output for each region-sector pair.

[19]This evidence suggests a potential relative deskilling of the skilled associated with new capital equipment which goes hand in hand with a decline of the relative abilities needed by skilled workers to perform their jobs. In this direction, Autor (2019) discusses how automation, together with international trade, has dramatically and negatively affected not only the bulk of non-college blue collar production jobs, but also white collar administrative support, and clerical jobs. Furthermore, Seamus McGuinness and Redmond (2023) show that skill-displacing technological change predominantly affects higher-skilled workers.

6 Welfare simulations

In appendix A3 we proceed to a structural verification of our theoretical model by subjecting it to external and internal consistency checks. These checks lend support to the mechanisms of the model and provide plausible values for the structural parameters of the model. Using such model consistent parameters and parameters retrieved from the literature, we perform a simulation exercise to investigate the welfare consequences of immigration of low skilled workers.[20] The richness of the model makes possible to explore welfare changes in three binary dimensions: between skilled and unskilled workers, between employed and unemployed, and between industries for any factor.

First, we compute the welfare changes measured by the ex-ante expected real wage for each category of workers. These are expected *ex-ante*, that is, before sampling and screening take place. They also represent the mean wage (by type of worker) computed across employed and unemployed. In sum, these are the wages that prospective workers can expect by participating to the labour market. They are market clearing in the sense that they assure that all individuals participate to the labour market and that such labour supply (by type) equals expected labour demand. Of course, there is frictional unemployment. In the simulations, the increase in the share of unskilled worker in the labour force gives rise to an increase in the expected real wage of skilled workers of about 7.3% over the period of interest and to a reduction of expected real wage of unskilled workers of about 0.5%. Total per capita welfare (utilitarian weights) increases by 2.1%. Thus, immigration of unskilled workers gives rise to welfare losses and welfare gains, but the gains of those who gain are larger than the losses of those who lose.

Second, we compute the changes in ex-post real wages; these are firm level wages actually paid. Firm-level wages increase for all workers equiproportionally within any industry (because $\omega_2 = 0$) but with different magnitude between industries: by 2.9% in the skill intensive industry and by by 0.97% in the low-skill intensive industry. These changes

[20]For the simulations we use the following parameter values: $\sigma = 4$, $\chi = 11/10$, $\phi_Y = 1 - \phi_Z = 0.6$, $F_i = F_{ie} = 10\ \forall i$, $\eth = 0.05$, $\mu_2 = 1/2, \epsilon_i = 1/2$ and we assume that ξ is extracted from a Pareto with shape parameter equal to 4. δ obtains from $\omega_2 = 0$ and γ stems from equation (24) using $R_{\theta\psi} = 1.279$. Lastly, $L/(H + L)$ - the share of low skilled workforce recorded from the LFS - equals 0.67 at the beginning of the period (2008) and 0.69 at the end (2013).

widen the welfare gap between the employed and the unemployed and between workers employed in different industries.

The third dimension of welfare analysis is employment. Unemployment rates evolve differently for different factors. Frictional unemployment rate declines by 3.8% for skilled workers while increases by 2.4% for unskilled workers. A worker may be unemployed either because did not fall in the random sample of search or because, while being sampled, did not pass the screening test. The first source of unemployment is proportional to the market tightness and is factor specific. In the simulations, about 58% of the increase in unemployment of unskilled workers is due to the change in market tightness, while the remaining part is due to more severe screening. For skilled workers the change in the market tightness account for 37% of the unemployment decrease, while the rest is due to less severe screening.

In conclusion, skilled workers gain for two reasons: first because (if employed) get higher wages and, second, because (if not employed) they have a higher probability of finding a job. Employed unskilled workers gain, while prospective unskilled workers lose because the higher probability of remaining unemployed more than compensate for the higher wage if employed. Programmes aimed at enhancing worker skills only mitigate the welfare losses experienced by prospective unskilled workers. While these programs may increase the fraction of sampled workers passing the test, they would not affect the increase in frictional unemployment. Lastly, workers in skill intensive industries gain more or lose less compared to workers in low-skill intensive industry.

7 Conclusion

This paper contributes to the literature on the effect of immigration on labour market outcomes by focusing on the skill premium. The theoretical highlight is that immigration of unskilled workers while reducing the skill intensity has undetermined effects on the skill premium. The empirical highlight is that, in the Italian case, immigration of low skilled workers, by reducing the relative ability of employed skilled workers, resulted in a nil effect on the skill premium.

To explain this puzzling evidence, we build a model where immigration of unskilled labour sets in motion two mechanisms that push the skill premium in opposite directions. On the one hand, the increase in the relative supply of low skilled labour pushes towards an increase of the skill premium. On the other hand, firms respond to the scarcity of skilled workers by decreasing the screening and training effort. This response reduces the relative productivity of skilled workers thereby pushing the skill premium downward. According to the relative importance of these two forces, the skill premium may increase, decrease, or stay unchanged. The skill intensity is instead predicted to decline while the dispersion of skill premium is predicted to increase.

By exploiting the variation of immigration rates across Italian regions, we find no significant effect of immigration on the skill premium at region-industry level over the period 2008-2013. Immigration of low-skilled worker is found, instead, to have a significant and negative impact on the skill intensity. Consistently with the model predictions, the elasticity of the skill intensity to immigration of unskilled workers is weaker when estimated at firm level than at regional level. We explain these findings by testing for the mechanism theorised in the model. We estimate a proxy for individual ability and we find evidence that low skilled migration flows have caused a reduction in the relative ability of skilled workers within Italian regions and sectors over the period of our analysis. Evidence also corroborates a negative impact of immigration on a proxy for the relative screening of the skilled. The mechanism highlighted in the model is then pivotal in order to explain the non significant nexus between migration and skill premium. Furthermore, as predicted by the model, we find that immigration of unskilled labour increases the dispersion of skill premia and skill intensity. Finally, simulations support welfare gains brought about by inflows of low skilled migrants, but the effects are heterogeneous between factors (ex-ante), between industries (for any sector) and between employed and unemployed.

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A1 Data Sources

A1.1 Demand for qualified labour survey in Italy

The survey on the Demand for qualified labour (Dlq) in Italy concerns job advertisements in the main Italian newspapers. We use the annual databases for the period 2000-2010. They present classification uniformity within a thirty-year series (ended in 2010). The data was materially collected by the CSA-Company Statistics Center of Florence. The subject of the Dlq survey are the so-called "form" advertisements, which pass through special spaces (forms, in fact) on the pages and on the fixed days that the newspapers dedicate to them. Each record represents a job position in an advertisement: the record therefore corresponds to an advertisement, if only one professional profile is sought through this. For each of the latter, the corresponding number of work units required is always indicated.

A1.2 Immigration

The Italian Statistical Institute (ISTAT) keeps record of the resident population at January 1 of each year and makes it available through the GeoDemo portal. We use this source to collect information on foreign residents by nationality at region level for each year between 2008 and 2013 included. Data on the stock of migrants is also available for previous and subsequent years. The exclusion of previous years is due to the lack of available data on workers' labour earnings for the corresponding years needed to compute the skill premium at the local level. The exclusion of subsequent years, instead, depends on the policy change in economic migrant admissions: starting from the end of 2013, the Italian government only allowed the legal entry of mostly seasonal workers and a very tiny share of legal workers. Consequently, more recent data on foreign residents could be an unreliable measure of the true presence of immigrants in the Italian regional labour markets, especially for those areas that are more exposed to the arrival of refugees.

A1.3 Labour Force Surveys and Administrative Sources for Measuring Skill Intensity, Premium and relative Ability

The main data source in this work is the Labour Force Survey (LFS) collected by the Italian National Statistical Office (ISTAT). Every year over 250,000 families resident in Italy are interviewed (for a total of 600,000 individuals) distributed in approximately 1,400 Italian municipalities. The families to be interviewed are randomly extracted from the municipal registry lists according to a sampling strategy aimed at building a statistically representative sample of the resident population in Italy in relation to the variables under investigation. Since January 2004, the survey has been continuous, i.e. the information is collected with reference to all the weeks of each quarter, by means of a uniform distribution of the sample over the weeks. The survey is carried out during all weeks of the year. The families included in the sample are interviewed 4 times over a 15-month period. Each family is interviewed for two consecutive quarters; an interruption follows for the next two quarters, after which she is interviewed again for another two quarters. Considering that the transitions from inactivity to employment of individuals over the age of 74 are almost nil, from 1 January 2011, families consisting of only people aged 75 or more inactive are not re-interviewed. The two stages of sampling are municipalities and families respectively. Municipalities are stratified with respect to the demographic dimension on a provincial basis. The estimate procedure is bound to the totals of population by age classes, gender, region and territory.

The survey reports for each individual the position in her profession from which we define managers, executives and clerks as the skilled and blue collars and apprentices as the unskilled.[21]

[21] As an alternative, one could define skills according to the education level of workers, nevertheless the existing evidence on the Italian stresses the importance of over-education and mis-match (OECD, 2016a). As an example, Mandrone et al. (2017) estimated that in 2014 the share of undereducated was only 5.7%, whereas that of vertical over educated - that is share of workers whose level of education is more than required - amounted to 18%. For this group of workers the estimated wage penalty is about 13.6% of the median wage (Caroleo and Pastore, 2018). Hence, defining the skilled as the group of graduated workers would cause including a large share of low wage workers in this category and would largely reduce the difference of the two groups. Also, being the focus of our study the impact of immigrants on the regional labour markets, it is worth mentioning that the ISTAT labour force survey reports that in 2011 about 84% of immigrants were employed as blue collars, as opposed to 51% of native workers. Immigrants' presence was higher in manufacturing (36% compared to 33% in other industries) and, in line with

Starting from 2008, for these two groups of workers, we observe monthly earnings and weekly working hours from which we retrieve the hourly wage. Hence, on the basis of sampling weights, we aggregate employment and wages at the NUTS2 region-sector level for each year and for each skill group, in order to get a measure of skill intensity and skill premia varying by geographical unit and industry. Sectors correspond to NACE Rev. 2 Subsections.[22]

In order to estimate the relative unobserved abilities of the skilled and unskilled we use the LOSAI administrative data set available from the Italian Social Security Institute (INPS) for the years 2002-2016. This database allows to merge information on a sample of privately employed individuals born in two given dates of every month (thus potentially covering about 6.6% of the universe) with information on the corresponding employer firm. The data set provides information on individuals' birth date, region of residence, gender, number of days worked in a year and yearly wages, as well as the occupation according to five categories: managers, executives, clerks, blue collars and apprentice. For each job spell it is also provided a unique identifying code for the employer which allows for the matching to another data set provided by INPS and which contains information on firm characteristics, such as industry at the 2-digit level and average number of employees. In order to retrieve the firm location region, we identify the mode of the residence region across all observed workers employed by the firm. It is worth highlighting that the matched employer-employee LOSAI database is designed to follow workers' job histories and as a consequence it is not designed to be representative at firm level. Nevertheless, on our sample period we find a correlation of 0.73 between the logs of region level ISTAT-LFS skill intensity and of the regional average of the skill intensity across LOSAI firms and a correlation of 0.42 between the logs of the region level ISTAT-LFS skill premium and of

the evidence by Peri and Sparber (2009), within finely defined manufacturing sectors and occupation categories immigrants especially performed less interactive and more manual task intensive jobs. From this follows that the definition of the blue collar workers as the low skilled and, in general, of the skilled/low skilled according to the work activity rather than to the education level is more appropriate in our context.

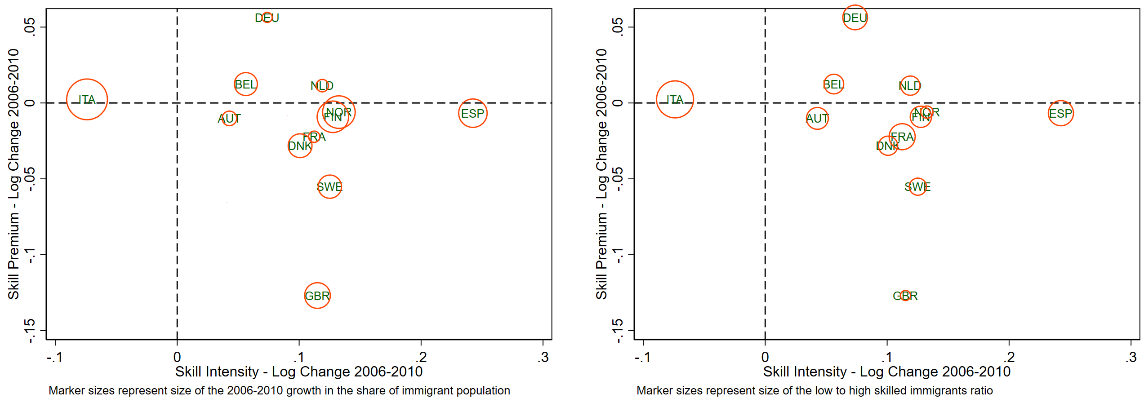
[22]This procedure required us to convert the NACE Revision 1 industries into Nace Revision 2 subsections, the result of which led us to a total of 11 different industries, as shown in Table O2.1 in the Appendix. It is worth highlighting that we exclude the subsection "Manufacturing of Coke and Refined Petroleum products" from the sample. Also, we retain in the sample workers whose working hours exceed 20 hours in a week.

the regional average of the skill premium across LOSAI firms.[23] Also, Figure O2.2 shows the quantile-quantile plots of the distributions of the region-industry skill intensity and premia from the two sources: although some differences of course do exist, we find that the two data sources do convey very similar information on the skill intensity distribution while the region-industry distributions of the skill premia diverge for the highest quantiles. It is worth reminding, however, that while skill premia from the LFS are computed on the bases of hourly wages, skill premia from LOSAI are based on daily wages and, as such, some differences might emerge.

[23] Corresponding correlations in levels are 0.65 and 0.38, respectively.

A2 Additional Descriptive Evidence

Figure A2.1: Immigration, skill intensity, skill premium.



(a) (b)

Source: Eurostat Population and migration statistics and European Labour Force Surveys. The two panels show the log-change in the skill intensity and premium in selected European economies between 2006-2010. Workers' skill is measured in terms of occupational status. The size of red circles represents the growth in the weight of immigrant population (panel A2.1a) and the relative size of low to high skilled immigrants (panel A2.1b). The latter information is based on educational attainments of foreign workers available from the European Labour Force Surveys in year 2012.

Table A2.1: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
$Skill\_Intensity$	1,219	0.591	0.753	0.018	9.954
$Skill\_Premium$	1,219	1.240	0.190	0.284	2.802
Rel_Skill_Screen	883	-0.036	0.217	-1	1
$\frac{Migrants}{Population}_{t-1}$	1,219	0.064	0.031	0.015	0.113
$\frac{Migrants}{Labour\ Force}_{t-1}$	1,219	0.078	0.037	0.018	0.137
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$	1,219	0.059	0.029	0.012	0.108
GDP_{t-1}	1,219	10.882	1.051	8.364	12.774
$Manufacturing^{Share}_{t-1}$	1,219	0.147	0.062	0.038	0.253
$Unemployment\ Rate_{t-1}$	1,219	8.184	3.842	2.700	19.400

Skill Intensity is the ratio of the skilled workers - managers, executives and clerks - to the unskilled workers - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013; *Skill Premium* is the ratio of the average wage of the skilled workers - managers, executives and clerks - to the average wage of the unskilled workers - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. *Rel_Skill_Screen* is the relative screening of the skilled workers. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. All shares of migrants are measured at time $t-1$. GDP_{t-1} is the log of the region GDP in $t-1$. $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded in $t-1$. $Unemployment\ Rate_{t-1}$ is a region's unemployment rate in $t-1$.

A3 Structural verification

We subject the model mechanisms to structural verification as follows. First, we recover the model parameter values consistent with the empirical estimations of the previous section. Second, we check that the recovered parameter values comply with the theoretical restrictions imposed by the model (internal consistency). Third, we check that the model predicted elasticity of substitution between factors is close estimates found in the empirical literature (external validity).

Let $\widehat{x} \equiv dx/x$ for any variable x, let $\overline{x}$ be the mean of the truncated distribution of the variable: $\overline{x} = 1/(1-G(\xi_i^*)) \int_{\xi_i^*}^{\infty} xdG$, let $\tilde{\ }$ indicate the powered mean of the truncated distribution analogous to $\overline{x}$. Then, from equations (11)-(13) we have

$$\widehat{\overline{\theta}}_{ir} = (1-\mu_2)\theta_2\, \widehat{\omega}_{or} + \theta_4 \widehat{\tilde{b}}_{ir\theta}(\widehat{\omega}_{or}) \quad (20)$$

$$\widehat{\overline{\psi}}_{ir} = (1-\mu_2)\psi_2\, \widehat{\omega}_{or} + \psi_4 \widehat{\tilde{b}}_{ir\psi}(\widehat{\omega}_{or}) \quad (21)$$

$$\widehat{\overline{\omega}}_{ir} = (1-\mu_2)\omega_2\, \widehat{\omega}_{or} + \omega_4 \widehat{\tilde{b}}_{ir\omega}(\widehat{\omega}_{or}) \quad (22)$$

The first addendum on the right hand side of each of equations (20)-(22) represents the intensive margin of mean changes (the effect that changes at the level of existing firms have on the industry-region mean changes). The second addendum in each equation represents the extensive margin of mean changes (the effects that the entry of new firms has on industry-region mean changes). All the $\widehat{\cdot}$ terms depend negatively on ω_{ir}. The coefficients ψ_4 and ω_4 are both positive. Therefore the second addenda in equations (21) and (22) are negative.

Let $\widehat{\theta}_{ir}^f$, $\widehat{\psi}_{ir}^f$, and $\widehat{\omega}_{ir}^f$ be the values estimated using firm-level data (LOSAI data set). Their respective theoretical counterpart is the first addendum in each respective equation because the LOSAI data contains firms that are present both before and after the shock. The extensive margin is therefore not captured by estimations based on this dataset. Equating $\widehat{\theta}_{ir}^f$ and $\widehat{\omega}_{ir}^f$ to their respective theoretical counterpart and taking the ratio we obtain

$$\frac{\widehat{\theta}_{ir}^f}{\widehat{\psi}_{ir}^f} = \frac{\theta_2}{\psi_2} = \frac{\delta - \mathfrak{s}}{\gamma \mathfrak{s}} > 0 \tag{23}$$

where we have made use of equations (44) and (42) in the appendix for the expressions of θ_2 and ψ_2. In our empirical analysis, we have found that the estimate of $\widehat{\omega}_{ir}^f$ is zero, which implies $\omega_2 = 0$. From $\omega_2 = 0$, using equation (46) in the appendix, we obtain $\delta = \mathfrak{s}/(1 - \gamma\mathfrak{s})$ which we then use in (23) to obtain $\frac{\widehat{\theta}_{ir}^f}{\widehat{\psi}_{ir}^f} = \frac{\mathfrak{s}}{1-\gamma\mathfrak{s}} > 0$; which is positive given the convexity of the isoquant. Solving this equation, we obtain

$$\gamma = \frac{\sigma(R_{\theta\psi} - 1) + 1}{R_{\theta\psi}(\sigma - 1)} \tag{24}$$

where to compact notation $R_{\theta\psi} \equiv \frac{\widehat{\theta}_{ir}^f}{\widehat{\psi}_{ir}^f}$.

We can now proceed to the internal consistency check. We recall from the model that the consistency constraints are the following: (1) $\gamma\mathfrak{s} < 1$ which is necessary and sufficient for convexity of the isoquant; (2) $0 < \gamma < \chi^{-1} < 1$, which is necessary and sufficient for positive search. Note that restriction (2) implies (1) since $\mathfrak{s} \equiv (\sigma - 1)/\sigma < 1$. Therefore, the challenge for the empirical estimation is to satisfy $0 < \gamma < 1$ by using equation (24). This restriction requires the estimated value $R_{\theta\psi}$ to satisfy $(\sigma - 1)/\sigma < R_{\theta\psi} < \sigma - 1$. In our empirical analysis we have found $R_{\theta\psi} = 1.279$, which satisfies the constraint for any $\sigma > 2.279$. As the values of σ usually found in the literature range between 2 and 10, we can conclude that the internal consistency between model and data is satisfied.

For external consistency we check that, after imposing internal consistency, the model predicts values of the elasticity of substitution between factors consistent with those found by the literature. Such elasticity is on average 1.93, but it greatly varies across empirical papers according to the study characteristics. As an example, it varies between 0.97 and 1.34 for studies on manufacturing, while varying in a much higher range for other industries. It varies between 1.99 and 2.38 for studies on developed economies while varies on a lower range for studies on developing economies (see Havranek et al., 2020 and Havranek et al., 2022).[24] We take the range 0.97-2.38 as the reference for the elasticity of substitution between the skilled and the unskilled in the Italian manufacturing. The elasticity of substitution between skilled and unskilled labour in the model is $\sigma/(\gamma-(\gamma-1)\sigma)$. Replacing γ from equation (24) in this expression, we obtain the elasticity in terms of the estimation of $R_{\theta\psi}$:

$$\frac{\sigma}{\sigma-1}R_{\theta\psi} \tag{25}$$

External consistency requires expression (25) to give values comparable to those in the literature. We have seen above that to satisfy the internal consistency we have to impose $\sigma > 2.279$. This is consistent with the findings of the empirical literature, e.g. Li (2021), Broda and Weinstein (2006b), Soderbery (2015). In particular, Broda and Weinstein (2006a) find a median value of about 4 for manufacturing varieties imported into Italy. Applying $\sigma = 4$ and our estimate of $R_{\theta\psi}$ to expression (25) we obtain an elasticity of substitution between factors equal to 1.705, which is very close to the literature average of 1.93. Allowing σ to range between 2.8 and 5 gives values of the elasticity between 1.6 and 2, which are contained in the range of values found in the empirical literature. In conclusion, the model satisfies both internal and external consistency.

[24]The difference between developed and developing economies is possibly related to the relatively higher weight of services in high income economies which pushes the elasticities of substitution towards higher values.

Online Appendix

O.1 Theoretical appendix

Section O.1.1 describes the mathematical passages to obtain employment, screening, skill intensity and the skill premium at firm level, Section O.1.2 describes the general equilibrium, Section O.1.3 proves the ranking of cut-off values of entry, Section O.1.4 computes the coefficient of variation and obtains the sign of its derivative.

O.1.1 Employment determination, factor intensity, skill premium.

First order conditions The four first-order conditions for profit maximisation are

$$\left.\frac{d\pi_i}{dn_j}\right|_{w_L^\circ, w_H^\circ} = 0, \qquad \left.\frac{d\pi_i}{d\underline{a}_j}\right|_{w_L^\circ, w_H^\circ} = 0, \quad i = Y, Z, \quad j = L, H. \tag{26}$$

which may be written as

$$\begin{aligned} A_{iL}\left(\underline{a}_L\right)^{\mathfrak{s}(1-\gamma\chi)}\left(n_L\right)^{\gamma\mathfrak{s}-1}(\alpha)^{\gamma\mathfrak{s}} &= b_L && (27)\\ A_{iH}\left(\underline{a}_H\right)^{\mathfrak{s}(1-\gamma\chi)}\left(n_H\right)^{\gamma\mathfrak{s}-1}(\beta)^{\gamma\mathfrak{s}} &= b_H && (28)\\ B_{iL}\left(n_L\right)^{\gamma\mathfrak{s}}\left(\underline{a}_L\right)^{\mathfrak{s}(1-\chi\gamma)-\delta}\alpha^{\gamma\mathfrak{s}} &= -\text{ß} && (29)\\ B_{iH}\left(n_H\right)^{\gamma\mathfrak{s}}\left(\underline{a}_H\right)^{\mathfrak{s}(1-\chi\gamma)-\delta}\beta^{\gamma\mathfrak{s}} &= -\text{ß} && (30) \end{aligned}$$

where we recall that $\mathfrak{s} = \frac{\sigma-1}{\sigma} \in (0,1)$ and

$$\begin{aligned} A_{iH} &= \left(\frac{\chi}{1-\chi}\right)^{\mathfrak{s}} \frac{\mathfrak{s}\gamma\phi}{1+\mathfrak{s}\gamma}(P_i)^{\frac{\varsigma-1}{\varsigma}}(\epsilon_i E)^{1/\varsigma}, && (31)\\ A_{iL} &= \left(\frac{\chi}{1-\chi}\right)^{\mathfrak{s}} \frac{\mathfrak{s}\gamma(1-\phi)}{1+\mathfrak{s}\gamma}(P_i)^{\frac{\varsigma-1}{\varsigma}}(\epsilon_i E)^{1/\varsigma}, && (32)\\ B_{iH} &= \frac{\phi\mathfrak{s}(1+\gamma)\chi^{2-\mathfrak{s}}}{(1+\mathfrak{s}\gamma)(\chi-1)^{\mathfrak{s}}}(P_i)^{\frac{\varsigma-1}{\varsigma}}(\epsilon_i E)^{1/\varsigma}, && (33)\\ B_{iL} &= \frac{(1-\phi)\mathfrak{s}(1+\gamma)\chi^{2-\mathfrak{s}}}{(1+\mathfrak{s}\gamma)(\chi-1)^{\mathfrak{s}}}(P_i)^{\frac{\varsigma-1}{\varsigma}}(\epsilon_i E)^{1/\varsigma}, && (34)\\ \text{ß} &= \frac{\chi^{1-\delta}}{(\chi-1)^{\mathfrak{s}}}, && (35) \end{aligned}$$

The four first-order conditions (27)-(30) may be solved explicitly for the four endogenous variables $\overset{\circ}{n}_j, \overset{\circ}{\underline{a}}_j$. Dividing (28) by (27) and (30) by (29) and then rearranging we obtain the explicit solutions for the four ratios of interest, namely, the relative number of workers sampled, the relative severity of screening, the skill intensity and the skill premium:

$$\eta_i \equiv \frac{\overset{\circ}{n}_H}{\overset{\circ}{n}_L} = (\Phi_i)^{\eta_1} \left(\frac{b_H}{b_L}\right)^{\eta_2} \left(\frac{k_H}{k_L}\right)^{\eta_3} [\flat(\xi)]^{\eta_4} \tag{36}$$

$$\psi_i \equiv \frac{\overset{\circ}{\underline{a}}_H}{\overset{\circ}{\underline{a}}_L} = (\Phi_i)^{\psi_1} \left(\frac{b_H}{b_L}\right)^{\psi_2} \left(\frac{k_H}{k_L}\right)^{\psi_3} [\flat(\xi)]^{\psi_4} \tag{37}$$

$$\theta_i \equiv \frac{\overset{\circ}{h}}{l^{\circ}} = (\Phi_i)^{\theta_1} \left(\frac{b_H}{b_L}\right)^{\theta_2} \left(\frac{k_H}{k_L}\right)^{\theta_3} [\flat(\xi)]^{\theta_4} \tag{38}$$

$$\omega_i \equiv \frac{\overset{\circ}{w}_H}{\overset{\circ}{w}_L} = (\Phi_i)^{\omega_1} \left(\frac{b_H}{b_L}\right)^{\omega_2} \left(\frac{k_H}{k_L}\right)^{\omega_3} [\flat(\xi)]^{\omega_4} \tag{39}$$

where:

$$\eta_1 = -\frac{\delta}{\Delta} > 0; \ \eta_2 = \frac{\delta - \mathfrak{s}(1-\gamma\chi)}{\Delta} < 0; \ \eta_3 = \frac{\mathfrak{s}(1-\gamma\chi)}{\Delta} < 0 \tag{40}$$

$$\eta_4 = -\frac{\mathfrak{s}\gamma\delta}{\Delta} > 0. \tag{41}$$

$$\psi_1 = -\frac{1}{\Delta} > 0; \ \psi_2 = \frac{\gamma\mathfrak{s}}{\Delta} < 0; \ \psi_3 = \frac{1-\gamma\mathfrak{s}}{\Delta} < 0; \tag{42}$$

$$\psi_4 = -\frac{\gamma\mathfrak{s}}{\Delta} > 0. \tag{43}$$

$$\theta_1 = \frac{\chi - \delta}{\Delta} > 0; \ \theta_2 = \frac{\delta - \mathfrak{s}}{\Delta} < 0; \ \theta_3 = \frac{\mathfrak{s} - \chi}{\Delta} > 0; \tag{44}$$

$$\theta_4 = -\frac{\gamma\mathfrak{s}(\delta-\chi)}{\Delta} \gtreqless 0 \Leftrightarrow \delta \gtreqless \chi. \tag{45}$$

$$\omega_1 = -\frac{\chi}{\Delta} > 0; \ \omega_2 = \frac{\delta\gamma\mathfrak{s} + \mathfrak{s} - \delta}{\Delta} \gtreqless 0 \Leftrightarrow \delta \gtreqless \frac{\mathfrak{s}}{1-\gamma\mathfrak{s}} \tag{46}$$

$$\omega_3 = -\frac{(\gamma\mathfrak{s}-1)\chi}{\Delta} < 0; \ \omega_4 = -\frac{\chi\gamma\mathfrak{s}}{\Delta} > 0. \tag{47}$$

$$\Delta = \gamma\mathfrak{s}(\delta-\chi) + \mathfrak{s} - \delta < 0 \tag{48}$$

The signs of the exponents reported in equations (40)-(48) derive from two conditions. First, parameters must allow for positive search, $\overset{\circ}{n}_j > 0$, otherwise employment would be zero and production would not take place. Whenever search is positive, no matter how severe screening is, employment is positive and production takes place. The condition for positive search is $(1-\gamma\chi) > 0$, which we satisfy by assuming $0 < \gamma < \chi^{-1}$. If we require that to a higher $\flat(\xi)$ correspond a higher skill intensity we may set $\delta > \chi$. This would also automatically satisfy $\Delta < 0$. If this assumption is not taken on board, then we need $\delta > 1$ as sufficient but not necessary condition for $\Delta < 0$. In the paper, we have only assumed the latter. Consistently with our empirical results, $\omega_2 = 0 \implies \Delta < 0$ without any further condition.

O.1.2 General Equilibrium

To go from firm equilibrium to general equilibrium we have to go through three steps: sectorial equilibrium, aggregation, and general equilibrium.

Sectorial Equilibrium. Using (1) it is apparent that the sales ratio for two firms in the same industry and country depends only on relative output which, ultimately, depends only on the values of ξ drawn by the firms. Thus, for any ξ' and ξ'':

$$\frac{s_i(\xi')}{s_i(\xi'')} = \left[\frac{q_i(\xi')}{q_i(\xi'')}\right]^{\frac{\varsigma-1}{\varsigma}} \tag{49}$$

Let ξ_i^* denote the cut-off value of ξ in industry i such that profit is zero, $\pi_i(\xi_i^*) = 0$. Using this zero cut-off profit condition we obtain the sales of the cut-off firms

$$s_i(\xi_i^*) = \frac{\gamma(\sigma-1)+\sigma}{\sigma} F_i \tag{50}$$

Using (50) into (49) we obtain the sales of any firm as function of ξ and ξ_i^*:

$$s_i(\xi) = \left[\frac{q_i(\xi)}{q_i(\xi_i^*)}\right]^{\frac{\varsigma-1}{\varsigma}} \frac{\gamma(\sigma-1)+\sigma}{\sigma} F_i. \tag{51}$$

At this point of the analysis, all firm variables depend only on cut-off values. These values are determined in general equilibrium.

Aggregation Let $G(\xi)$ be a cumulative density function. Average sales and profit are:

$$\overline{s}_i(\xi_i^*) = \frac{[\gamma(\sigma-1)+\sigma] F_i}{\sigma[1-G(\xi_i^*)]} \int_{\xi_i^*}^{\infty} \left[\frac{q_i(\xi)}{q_i(\xi_i^*)}\right]^{\frac{\varsigma-1}{\varsigma}} dG, \tag{52}$$

$$\overline{\pi}_i(\xi_i^*) = \frac{\sigma}{\gamma(\sigma-1)+\sigma}\overline{s}_i - F_i. \tag{53}$$

Note that $\overline{s}_i$ and $\overline{\pi}_i$ are also the expected sale and profit of a firm prior to entry. Average factor demand in production is

$$\bar{l}_{i,pr}(\xi_i^*) = \int_{\xi_i^*}^{\infty} \frac{l_i^{\circ}(\xi)}{1-G(\xi_i^*)} dG, \qquad \overline{h}_{i,pr}(\xi_i^*) = \int_{\xi_i^*}^{\infty} \frac{h_i^{\circ}(\xi)\, dG}{1-G(\xi_i^*)}. \tag{54}$$

Average factor demand for fixed inputs, $\bar{l}_{i,F}$ and $\overline{h}_{i,F}$ takes the same functional forms as (54) except that the $(\digamma_i + \digamma_{ie})$ replaces the term $(P_i)^{\frac{\varsigma-1}{\varsigma}}(\epsilon_i E)^{1/\varsigma}$ we find in $l_i^{\circ}(\xi)$ and $h_i^{\circ}(\xi)$. Average factor demand for vacancy posting is

$$\bar{l}_{i,v}(\xi_i^*) = \int_{\xi_i^*}^{\infty} \frac{\overset{\circ}{n}_L(\xi)}{[1-G(\xi_i^*)]} dG, \qquad \overline{h}_{i,scr}(\xi_i^*) = \int_{\xi_i^*}^{\infty} \frac{\overset{\circ}{n}_H(\xi)}{[1-G(\xi_i^*)]} dG. \tag{55}$$

Average factor demand for the screening activity is

$$\bar{l}_{i,scr}(\xi_i^*) = \int_{\xi_i^*}^{\infty} \frac{\left[\underline{\overset{\circ}{a}}_L(\xi)\right]^{\delta}}{[1-G(\xi_i^*)]\,\delta} dG, \quad \overline{h}_{i,scr}(\xi_i^*) = \int_{\xi_i^*}^{\infty} \frac{\left[\underline{\overset{\circ}{a}}_H(\xi)\right]^{\delta}}{[1-G(\xi_i^*)]\,\delta} dG. \tag{56}$$

Total average factor demands are $\bar{l}_i(\xi_i^*) = \sum_{d\in D} \bar{l}_{i,d}(\xi_i^*)$ and $\overline{h}_i(\xi_i^*) = \sum_{d\in D} \overline{h}_{i,d}(\xi_i^*)$ where $D = \{pr, F, v, scr\}$.

General Equilibrium There are four sets of equilibrium equations that apply to every industry.

First, stationarity of the equilibrium requires the mass of potential entrants, M_{ei}, to be such that at any instant the mass of successful entrants, $[1-G(\xi_i^*)]\, M_{ei}$, equals the mass of incumbent firms that die, $\eth M_i$:

$$[1 - G(\xi_i^*)] M_{ei} = \eth M_i \tag{57}$$

Second, the free entry condition equates the entry cost, F_{ei}, to the expected profit prior to entry, $\overline{\pi}_i$, discounted by the probability of death and multiplied by the probability of successful entry:

$$[1 - G(\xi_i^*)] \overline{\pi}_i / \eth = F_{ei} \tag{58}$$

Third, goods market clearing requires

$$M_Y \overline{s}_Y = \varepsilon_Y E \tag{59}$$

$$M_Z \overline{s}_Z = \varepsilon_Z E \tag{60}$$

Fourth, factor market clearing requires

$$\bar{l}_Y(\xi_Y^*) M_Y + \bar{l}_Z(\xi_Z^*) M_Z = \overline{L} \tag{61}$$

$$\overline{h}_Y(\xi_Y^*) M_Y + \overline{h}_Z(\xi_Z^*) M_Z = \overline{H} \tag{62}$$

In writing the factor market equilibrium equations, we have taken into account that the stationarity condition implies that the quantity of each factor released by firms that die is equal to the quantity of each factor demanded by successful entrants. After replacing average profit, average sales, average factor demands, and cut-off output in (58)-(62) the general equilibrium system counts five independent equations and six endogenous variables. The equations are the two free entry conditions (58), one out of two goods market equilibrium conditions (59)-(60), the two factor market equilibrium conditions (61)-(62). The endogenous are the two masses $\{M_i\}$, the two outside options $\{w_{jo}\}$ and the two cut-off values $\{\xi_i^*\}$. The choice of a numéraire makes the system determined.

O.1.3 Ranking of cut-off values

Using (52) and (53) we may write the free entry condition (58) as

$$\int_{\xi_i^*}^{\infty} \left[\left(\frac{q_i(\xi)}{q_i(\xi_i^*)} \right)^{\frac{\varsigma-1}{\varsigma}} - 1 \right] dG = \frac{\digamma_{ie}\eth}{\digamma_i}. \tag{63}$$

After replacing the optimal search, screening, and factor inputs into equation (63) we obtain

$$\underbrace{\int_{\xi_i^*}^{\infty} \left[\left(\frac{(\Phi_i)^{\frac{-\delta}{\Delta}} (\omega_o)^{\omega_5} (\beta)^{\flat_0} + (\alpha)^{\flat_0}}{(\Phi_i)^{\frac{-\delta}{\Delta}} (\omega_o)^{\omega_5} (\beta_i^*)^{\flat_0} + (\alpha_i^*)^{\flat_0}} \right)^{\frac{(\varsigma-1)\sigma}{\varsigma(\sigma-1)}} - 1 \right] dG}_{\Upsilon\left(\Phi_i,\omega_o,\xi_i^*\right)} = \frac{\digamma_{ei}\eth}{\digamma_i} \tag{64}$$

where $\flat_0 = \frac{-\mathfrak{s}\delta\gamma}{\Delta} > 0$, $\omega_5 = \frac{(\gamma(\delta-\chi)+1)\mathfrak{s}}{\Delta} < 0$. The latter inequality is assured by the condition for positive search that requires $\gamma < 1/\chi$ and by $\Delta < 0$. Differentiating totally equation (64) we see that

$$\begin{aligned} \Upsilon'_{\omega_o}\left(\Phi_i, \omega_o, \xi_i^*\right) &\lesseqqgtr 0 \Leftrightarrow \flat(\xi) \gtreqqless \flat(\xi_i^*) && (65) \\ \Upsilon'_{\xi_i^*}\left(\Phi_i, \omega_o, \xi_i^*\right) &< 0 && (66) \end{aligned}$$

Therefore

$$\frac{d\xi_i^*}{d\omega_o} = -\frac{\Upsilon'_{\omega_o}\left(\Phi_i, \omega_o, \xi_i^*\right)}{\Upsilon'_{\xi_i^*}\left(\Phi_i, \omega_o, \xi_i^*\right)} \lesseqqgtr 0 \Leftrightarrow \flat(\xi) \gtreqqless \flat(\xi_i^*) \tag{67}$$

Recall that heterogeneity is *H-biased* if $\flat'(\xi) > 0$, neutral if $\flat'(\xi) = 0$, and *L-biased* if $\flat'(\xi) < 0$ for any t. Equivalently, we may say that heterogeneity is *H-biased* if $\flat(\xi) > \flat(\xi_i^*)$, neutral if $\flat(\xi) = \flat(\xi_i^*)$, and *L-biased* if $\flat(\xi) < \flat(\xi_i^*)$ for any $\xi > \xi_i^*$. Thus, equation (67) shows that immigration of low skilled labour reduces the cut-off value via the increase in ω_o.

O.1.4 Ranking the coefficients of variations

O.1.4.1 The probability density function of ω

We succinctly rewrite the expression (13) as $\omega_i(\xi) = \breve{A}_i [\flat(\xi)]^{\omega_4}$ where $\breve{A}_i$ represents the multiplicands of $[\flat(\xi)]^{\omega_4}$ in expression (13). Let $\omega_i^{(-1)}(\omega)$ be the inverse of $\omega_i(\xi)$, that is: $\xi = \flat^{-1}\left(\left(\omega/\breve{A}_i\right)^{1/\omega_4}\right)$ where $\flat^{-1}$ is the inverse of $\flat$. Then, the probability density function of ω - denoted $f_i(\omega)$ - is

$$f_i(\omega) = g\left(\xi = \omega_i^{(-1)}(\omega)\right)\left|\frac{d\omega_i^{(-1)}(\omega)}{d\omega}\right|, \tag{68}$$

where $g(\xi) = dG/d\xi$. This function may be used to compute the preferred index of inequality.

O.1.4.2 Coefficients of variation.

If $g(\xi)$ is such that $\flat(\xi)$ is log-normally distributed, we can compute the coefficient of variation of ω directly using the distribution of $\flat$. Furthermore, since $\omega_i(\xi)$ may be inverted in $\flat$ we may compute the N^{th}-moments directly as in (16) and obtain

$$\mu_{i,N} = \frac{2\left(\breve{A}_i\right)^N e^{N\omega_4\mu+(N\omega_4)^2 v_\flat}\left[1-\mathrm{erf}_N\right]}{1-\mathrm{erf}_0} \tag{69}$$

where $v_\flat$ and μ are, respectively, the variance and mean of the normal distribution associated with the log-normal $\flat$ and where

$$\mathrm{erf}_N \equiv \mathrm{erf}\left(\frac{-N\omega_4 v_\flat + \ln\left(\flat(\xi_i^*)\right)-\mu}{\sqrt{2v_\flat}}\right). \tag{70}$$

Replacing (69) into (15) and taking the derivative, we see that the condition for the coefficient of variation of ω to be decreasing in ξ_i^* is

$$\frac{e_0}{2} - \frac{e_1(1-\mathrm{erf}_0)}{1-\mathrm{erf}_1} + \frac{e_2(1-\mathrm{erf}_0)}{2\left(1-\mathrm{erf}_2\right)} < 0 \tag{71}$$

where

$$e_N \equiv e^{-\frac{1}{2}\frac{\left(-N\omega_4 v_\flat+\ln\left(\flat(\xi_i^*)\right)-\mu\right)}{v_\flat}} \tag{72}$$

Condition (71) is satisfied since the expression has no roots and its limit for $\flat_i^* \to 0$ and for $\flat_i^* \to \infty$ are both zero from below. Expressions (69) and (71) prove Result 4.

O.2 Additional Descriptive Evidence and Empirical Results

Figure O2.1: Empirical studies on the impact of migration on wages, employment and unemployment. Source OECD (2016b)

Overview of studies on the labour market impact of migration using national and sub-national data

A. Impact on wages of native-born

Country	Reference Period	Author(s)	Year of publication	Spatial level	Impact of a 1 percentage point increase in the immigrant share of the labour force
Australia	1982-96	Addison and Worswick	2002	States (6)	No significant impact
Austria	1988-91	Winter-Ebmer and Zweir	1996	Regions (93)	+2.1% to +3.7% (for young native blue collar workers)
France	1962, 1968	Hunt	1992	National; Major Regions (9); Regions (21)	No significant impact
France	1976-2007	Ortega and Verdugo	2015	Commuting zones (297 *zones d'emploi*)	-0.36% (for low-educated natives in non-tradable sectors)
Israel	1990-1994	Friedberg	2001	National	No significant impact
Italy	1986-95	Gavosto et al.	1999	Regions (20)	+0.1%
Netherlands	1997-98	Zorlu and Hartog	2005	Municipalities (548)	-0.4% to +0.6%
Norway	1989, 1996	Zorlu and Hartog	2005	Counties (19)	+0.2% to + 0.9%
Portugal	1974-76	Carrington and de Lima	1996	Districts (18)	No significant impact
Spain	1989-92	Dolado et al.	1996	Provinces (50)	+0.03% to +0.05%
Spain	1991-2002	Carrasco et al.	2008	National; Regions (17)	No significant impact
Switzerland	1999-2007	Beerli and Peri	2015	Regions	No significant impact
United Kingdom	1992-2000	Dustmann et al.	2005	Regions (17)	No significant impact
United Kingdom	1997-98	Zorlu and Hartog	2005	Counties (66)	No significant impact
United Kingdom	1997-2005	Dustmann et al.	2013	Regions (17)	-0.5% in 1st wage decile. +0.6% for wages at the median. +0.4% in 9th wage decile.
United States	1979-85	Card	1990	City (Miami)	No significant impact
United States	1960-90	Borjas et al.	1997	Cities (Metropolitan Statistical Areas)	No significant impact
United States	1989	Card	2001	Cities (175 largest Metropolitan Statistical Areas)	-0.04% to 0.6%
United States	1960-2000	Borjas	2003	National	-0.4% to -0.3%
United States	1990-2006	Ottaviano and Peri	2012	National	+0.6% to +1.7% (for low educated natives)
United States	1972-1983	Peri and Yasenov	2015	City (Miami)	No effect
United States	1960-2000	Peri and Sparber	2009	States	+0.03%
Western Germany	1996-2001	Glitz	2012	Labour market regions (112)	No significant impact
Meta-analysis (multiple studies)					
18 studies for various OECD countries		Longhi et al.	2005	Various	No significant impact
22 studies for various OECD countries		Kerr and Kerr	2011	Various	9 studies: no significant impact; 6 studies: positive impact, but less than 0.1%; 7 studies: negative impact, near zero.

Figure O2.2: Quantile-Quantile plot of the region-industry skill intensity and premium from LFS and LOSAI

Source: Author's own calculations on Istat Labour Force Surveys and INPS LOSAI databases.

O.3 Validity of the shift-share instrumental variables

Goldsmith-Pinkham et al. (2020) show that the 2SLS estimator with the shift-share IV is numerically equivalent to a GMM estimator with the local country shares as IV and a weight matrix constructed by national immigration flows. In this respect, using the shift-share IV is equivalent as using the shares as IV and, then, the exogeneity condition should be interpreted in terms of the shares.[25] The Bartik estimator is then unpacked into a weighted sum of the just-identified IV estimators that use each country share as a separate instrument. The weights - referred to Rotemberg weights - depend on the

[25] A complementary view is the one by Borusyak et al. (2021) who claim that under the assumption of independent common shocks, the 2SLS estimator consistency can also come from the shocks. In our framework this would require to have random and sufficiently independent push factors in migration evolution.

Table O2.1: List of Nace Revision 2 Sub-sections

Sub-section	Title
CA	Manufacture of food products, beverages and tobacco products
CB	Manufacture of textiles, apparel, leather and related products
CC	Manufacture of wood and paper products, and printing
CE+CF	Manufacture of chemicals and chemical products +
	Manufacture of pharmaceuticals, medicinal chemical and botanical products
CG	Manufacture of rubber and plastics products, and other non-metallic mineral products
CH	Manufacture of basic metals and fabricated metal products, except machinery and equipment
CI	Manufacture of computer, electronic and optical products
CJ	Manufacture of electrical equipment
CK	Manufacture of machinery and equipment n.e.c
CL	Manufacture of transport equipment
CM	Other manufacturing, and repair and installation of machinery and equipment

The table includes the list of Nace Revision 2 Sub-sections. All of them are included in the analysis with the exclusion of Sub-section CD.

covariance between the kth instrument's fitted value of the endogenous variable and the endogenous variable itself and give an indication on how sensitive is the estimate of the parameter of interest to misspecification (endogeneity) in any instrument. They also give a direction on which exposure design gets more weight and which of the identifying assumptions is worth testing. Our study represents a typical setting where migration origin country shares across locations measure differential exposure to common shocks and identification is based on the share exogeneity. We therefore compute Rotemberg weights which turn all positive and in Table O3.4 we show that the top five origin countries are Romania, Albania, Morocco, China and Ukraine. These account for over 50% of the positive weights. The composition of the top 5 countries is not surprising and this is in accordance with the fact that the shares are almost totally explained by the shocks, as from the correlation in Panel A of Table O3.4. From this part of the Table we also learn that the Rotemberg weights are negatively correlated to the variation in country shares across locations ($var(z_{lk})$) which means that the presence of countries with a high weight tends not to vary a lot across locations. This is consistent with the existence of large enclaves in the country.

The identifying assumption of our empirical strategy is that initial country shares do not predict innovations in our main outcome variables. Although this assumption is not directly testable, we can assess its plausibility in a number of ways (Goldsmith-Pinkham et al., 2020). First, in Table O3.1 we explore the relationship between initial

Table O2.2: The impact of immigration on the skill intensity and premium - OLS

	[1]	[2]	[3]	[4]	[5]	[6]
	Skill Intensity			Skill Premium		
$\frac{Migrants}{Population}_{t-1}$	-10.323**			0.076		
	[4.875]			[2.279]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		-8.768**			-0.158	
		[3.957]			[1.846]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			-11.927**			0.06
			[4.901]			[2.307]
GDP_{t-1}	-0.133	-0.177	-0.115	-0.846**	-0.842**	-0.845**
	[0.812]	[0.812]	[0.804]	[0.331]	[0.331]	[0.331]
$Manufacturing^{Share}_{t-1}$	-1.13	-1.102	-1.075	2.267**	2.260**	2.266**
	[2.792]	[2.774]	[2.777]	[0.954]	[0.951]	[0.952]
$Unemployment\ Rate_{t-1}$	0.002	0.001	0.002	-0.001	-0.001	-0.001
	[0.020]	[0.019]	[0.020]	[0.009]	[0.009]	[0.009]
Constant	2.854	3.35	2.684	10.112**	10.088**	10.110**
	[8.905]	[8.924]	[8.818]	[3.644]	[3.653]	[3.648]
Observations	1,219	1,219	1,219	1,219	1,219	1,219
R-squared	0.644	0.644	0.644	0.322	0.322	0.322

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region. The dependent variable in Columns [1]-[3] is the ratio of the skilled workers - managers, executives and clerks - to the unskilled workers - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. The dependent variable in Columns [4]-[6] is the ratio of the average wage of the skilled - managers, executives and clerks - to the average wage of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. GDP_{t-1} is the log of the region GDP . $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded. $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

Table O2.3: The impact of immigration on the relative screening of the skilled - OLS

	[1]	[2]	[3]
$\frac{Migrants}{Population}_{t-1}$	-6.497*		
	[3.581]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		-5.392*	
		[2.783]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			-6.621*
			[3.793]
GDP_{t-1}	0.07	0.022	0.063
	[0.612]	[0.611]	[0.618]
$Manufacturing_{t-1}^{Share}$	0.228	0.25	0.289
	[1.178]	[1.168]	[1.176]
$Unemployment\ Rate_{t-1}$	0.014	0.014	0.015
	[0.013]	[0.014]	[0.013]
Constant	-0.517	0.026	-0.481
	[6.816]	[6.814]	[6.890]
Observations	883	883	883
R-squared	0.334	0.334	0.334
Fixed Effects			
region-sector	y	y	y
sector-year	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable is the difference between the share of skilled workers on a fixed-term training contract over the total newly hired skilled workers with less than two years of tenure and the same share computed for unskilled workers in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. GDP_{t-1} is the log of the region GDP. $Manufacturing_{t-1}^{Share}$ measures the share of manufacturing value added in the total region's value added recorded. $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

Table O2.4: First Stage Results

	[1]	[2]	[3]	[4]	[5]	[6]
	First stage of Table 1			First stage of Table 3		
	$\frac{Migrants}{Population}$	$\frac{Migrants}{Labour\ Force}$	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$	$\frac{Migrants}{Population}$	$\frac{Migrants}{Labour\ Force}$	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$
IV_perm^{94}	0.409***	0.526***		0.399***	0.513***	
	[0.099]	[0.116]		[0.105]	[0.123]	
$IV\_perm^{94\ Low\&Middle\ Income}$			0.408***			0.396***
			[0.092]			[0.096]
Observations	1,219	1,219	1,219	1,093	1,093	1,093
Controls	y	y	y	y	y	y
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y
	[1]	[2]	[3]	[4]	[5]	[6]
	First stage of Table 2			First stage of Table 4		
	$\frac{Migrants}{Population}$	$\frac{Migrants}{Labour\ Force}$	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$	$\frac{Migrants}{Population}$	$\frac{Migrants}{Labour\ Force}$	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$
IV_perm^{94}	0.410***	0.526***		0.395***	0.510***	
	[0.101]	[0.119]		[0.111]	[0.128]	
$IV\_perm^{94\ Low\&Middle\ Income}$			0.407***			0.394***
			[0.094]			[0.103]
Observations	1,182	1,182	1,182	883	883	883
Controls	y	y	y	y	y	y
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
$IVperm^{94}_{rt}$ is computed as follows

$$IVperm^{94}_{rt} = \sum_{k=1}^{N} w^{1994}_{rk} * \frac{Migrants_{kt}}{Population^{1994}_{r}}$$

where w^{1994}_{rk} is the share of residency permits granted to migrants from country k in region r in 1994 on total permits released to immigrants from country c and $Migrants_{kt}$ is the number of immigrants from country k residing in Italy in year t. The presence of immigrants from country k in region r at time t is imputed to regions according to the (pre-sample) 1994 distribution of permits to immigrants from country k across Italian regions and is normalised over the 1994 region population. $Low\&MiddleIncomecountries$ refers to the IV computed only over the group of low and middle income countries as from the 2018 World Bank Classification of Countries by income.
$\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population.

Table O2.5: The impact of immigration on skill intensity and premium dispersion across firms - OLS

	Skill Intensity Dispersion			**Skill Premium Dispersion**		
	[1]	[2]	[3]	[4]	[5]	[6]
$\frac{Migrants}{Population}_{t-1}$	30.364**			107.549*		
	[12.721]			[54.497]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		26.847***			82.966**	
		[9.370]			[37.117]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			38.070***			142.387*
			[12.533]			[75.745]
GDP_{t-1}	-3.971*	-3.805*	-4.047*	-13.567	-12.842	-13.944
	[2.092]	[2.061]	[2.033]	[8.758]	[8.515]	[8.861]
$Manufacturing^{Share}_{t-1}$	14.152	14.04	13.996	44.359	43.695	43.917
	[9.515]	[9.453]	[9.359]	[27.629]	[27.271]	[27.376]
$Unemployment\ Rate_{t-1}$	-0.071*	-0.067*	-0.072*	-0.241**	-0.229**	-0.245**
	[0.039]	[0.038]	[0.038]	[0.110]	[0.108]	[0.115]
Constant	41.265*	39.286*	41.825*	139.567	132.046	142.275
	[22.209]	[21.837]	[21.462]	[90.962]	[88.855]	[91.099]
Observations	1,182	1,182	1,182	1,182	1,182	1,182
R-squared	0.674	0.674	0.674	0.335	0.335	0.335
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region. The dependent variable is the standard deviation of the skill intensity, in columns [1]-[3], and skill premium, in columns [4]-[6], across firms within an industry-region pair between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. GDP_{t-1} is the log of the region GDP. $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded. $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

Table O2.6: The impact of immigration on the skill intensity and premium - Firm level evidence

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Skill Intensity						Skill Premium					
	2SLS			OLS			2SLS			OLS		
$\frac{Migrants}{Population}_{t-1}$	-1.868*			-1.070**			11.765			5.107		
	[0.958]			[0.407]			[14.563]			[11.614]		
$\frac{Migrants}{Labour\ Force}_{t-1}$		-1.487*			-0.933**			9.337			2.529	
		[0.725]			[0.350]			[11.387]			[9.594]	
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$			-1.941*			-1.087**			9.421			3.011
			[0.956]			[0.413]			[14.999]			[11.430]
GDP_{t-1}	0.008	-0.009	0.01	-0.014	-0.022	-0.013	4.983**	5.097**	5.047**	5.178**	5.265**	5.238**
	[0.068]	[0.065]	[0.068]	[0.066]	[0.066]	[0.065]	[2.190]	[2.123]	[2.224]	[2.118]	[2.117]	[2.157]
$Manufacturing^{Share}_{t-1}$	0.207	0.213	0.221	0.206	0.21	0.213	-1.777	-1.814	-1.823	-1.722	-1.717	-1.726
	[0.173]	[0.171]	[0.169]	[0.170]	[0.169]	[0.167]	[2.798]	[2.825]	[2.767]	[2.807]	[2.816]	[2.815]
$Unemployment\ Rate_{t-1}$	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*	0.041	0.043	0.041	0.042	0.043	0.042
	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.028]	[0.028]	[0.029]	[0.028]	[0.028]	[0.028]
Observations	84,328	84,328	84,328	84,328	84,328	84,328	31,691	31,691	31,691	31,691	31,691	31,691
R-squared				0.917	0.917	0.917				0.667	0.667	0.667
Shea-R2	0.393	0.426	0.381				0.347	0.379	0.335			
First-Stage F-test	9.912	12.34	10.35				8.255	10.41	8.605			
Fixed Effects												
firm	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y
size-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable in Columns [1]-[3] is the ratio of the skilled - managers, executives and clerks - to the unskilled - blue collars and apprentices - employed in a firm between 2008 and 2013. The dependent variable in columns [7]-[12] is the ratio of the average wage of the skilled - managers, executives and clerks - to the average wage of the unskilled - blue collars and apprentices - employed in a firm between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. GDP_{t-1} is the log of the region GDP. $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded. $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

Columns [1]-[3] and [7]-[9] show 2 Stage-Least-Squares results, while Columns [4]-[6] and [10]-[12] show OLS results. The instrument variable adopted in the first stage of regressions reported in columns [1]-[3] and [7]-[9] is built as in equation 18 in the text. Table O2.7 in the Appendix shows the corresponding first-stage results.

Table O2.7: First Stage Results - Firm level evidence

	[1]	[2]	[3]	[4]	[5]	[6]
	First stage of Table O2.6, columns 1-3			First stage of Table O2.6, columns 7-9		
	$\frac{Migrants}{Population}$	$\frac{Migrants}{Labour\ Force}$	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$	$\frac{Migrants}{Population}$	$\frac{Migrants}{Labour\ Force}$	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$
IV_perm	0.465***	0.585***		0.449***	0.566***	
	[0.148]	[0.166]		[0.156]	[0.175]	
$IV\_perm^{Low\&Middle\ Income}$			0.463***			0.447***
			[0.144]			[0.152]
GDP_{t-1}	0.021*	0.016	0.021	0.021*	0.015	0.021
	[0.013]	[0.014]	[0.014]	[0.012]	[0.013]	[0.014]
$Manufacturing^{Share}_{t-1}$	0.015	0.023	0.022	0.015	0.023	0.022
	[0.035]	[0.039]	[0.033]	[0.033]	[0.036]	[0.031]
$Unemployment\ Rate_{t-1}$	0.000**	0	0.001**	0.001**	0	0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	84,328	84,328	84,328	31,691	31,691	31,691
Fixed Effects						
firm	y	y	y	y	y	y
sector-year	y	y	y	y	y	y
size-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
$IVperm^{94}_{rt}$ is computed as follows

$$IVperm^{94}_{rt} = \sum_{k=1}^{N} w^{1994}_{rk} * \frac{Migrants_{kt}}{Population^{1994}_{r}}$$

where w^{1994}_{rk} is the share of residency permits granted to migrants from country k in region r in 1994 on total permits released to immigrants from country c and $Migrants_{kt}$ is the number of immigrants from country k residing in Italy in year t. The presence of immigrants from country k in region r at time t is imputed to regions according to the (pre-sample) 1994 distribution of permits to immigrants from country k across Italian regions and is normalised over the 1994 region population. $Low\&MiddleIncomecountries$ refers to the IV computed only over the group of low and middle income countries as from the 2018 World Bank Classification of Countries by income.
$\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population.

Table O2.8: First Stage Results - Relative Abilities

	$\frac{Migrants}{Population}$ [1]	$\frac{Migrants}{Population}$ [2]	$\frac{Migrants}{Labour\ Force}$ [3]	$\frac{Migrants}{Labour\ Force}$ [4]	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$ [5]	$\frac{Migrants^{Low\&Middle\ Income}}{Population}$ [6]
IV_perm	0.411***	0.412***	0.528***	0.530***		
	[0.096]	[0.101]	[0.112]	[0.118]		
$IV\_perm^{Low\&Middle\ Income}$					0.406***	0.409***
					[0.087]	[0.093]
GDP_{t-1}		0.014		0.009		0.012
		[0.013]		[0.018]		[0.013]
$Manufacturing^{Share}_{t-1}$		-0.001		0.006		0.007
		[0.042]		[0.050]		[0.037]
$Unemployment\ Rate_{t-1}$		0		0		0
		[0.000]		[0.000]		[0.000]
Observations	1,198	1,198	1,198	1,198	1,198	1,198
Fixed Effects						
region-sector	y	y	y	y	y	y
sector-year	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
$IVperm^{94}_{rt}$ is computed as follows

$$IVperm^{94}_{rt} = \sum_{k=1}^{N} w^{1994}_{rk} * \frac{Migrants_{kt}}{Population^{1994}_{r}}$$

where w^{1994}_{rk} is the share of residency permits granted to migrants from country k in region r in 1994 on total permits released to immigrants from country c and $Migrants_{kt}$ is the number of immigrants from country k residing in Italy in year t. The presence of immigrants from country k in region r at time t is imputed to regions according to the (pre-sample) 1994 distribution of permits to immigrants from country k across Italian regions and is normalised over the 1994 region population. $Low\&MiddleIncomecountries$ refers to the IV computed only over the group of low and middle income countries as from the 2018 World Bank Classification of Countries by income.
$\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population.

Table O2.9: The impact of immigration on skill intensity - Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	-14.006*	-16.653**	-16.721**	-13.928**								
	[6.894]	[6.670]	[6.443]	[6.577]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					-10.804*	-12.969**	-13.004**	-10.732**				
					[5.234]	[5.097]	[4.914]	[4.989]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									-15.427**	-17.887**	-17.944***	-15.348**
									[6.732]	[6.470]	[6.201]	[6.354]
$\frac{Emigrants}{Population}_{t-1}$	-0.085			-0.085	-0.089			-0.089	-0.086			-0.085
	[0.052]			[0.053]	[0.052]			[0.053]	[0.052]			[0.053]
$Investment\ Inten_{t-1}$		0.125		0.122		0.125		0.122		0.125		0.119
		[0.370]		[0.357]		[0.371]		[0.358]		[0.370]		[0.358]
$Import^{Share}_{t-1}$			0.000	0.000			0.000	0.000			0.000	0.000
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219
R-squared	0.006	0.002	0.002	0.006	0.007	0.003	0.003	0.007	0.007	0.003	0.003	0.007
Shea-R2	0.428	0.43	0.437	0.434	0.458	0.454	0.46	0.464	0.442	0.443	0.448	0.446
F-test	16.15	17.13	19.14	18.28	19.35	20.65	22.84	21.72	18.81	19.8	21.94	21.11

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
The dependent variable is the ratio of the skilled workers - managers, executives and clerks - to the unskilled workers - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population.The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.
$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP. All regressors are measured at time $t-1$.

Table O2.10: The impact of immigration on skill premium - Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	-2.169	-2.403	-2.022	-2.65								
	[4.007]	[3.813]	[3.936]	[3.846]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					-1.673	-1.872	-1.573	-2.042				
					[3.056]	[2.930]	[3.030]	[2.925]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									-2.271	-2.523	-2.147	-2.754
									[3.796]	[3.613]	[3.730]	[3.637]
$\frac{Emigrants}{Population}_{t-1}$	0.006			0.005	0.006			0.004	0.006			0.005
	[0.022]			[0.023]	[0.021]			[0.023]	[0.022]			[0.023]
$Investment\ Inten_{t-1}$		-0.727***		-0.732***		-0.727***		-0.732***		-0.727***		-0.731***
		[0.199]		[0.201]		[0.199]		[0.201]		[0.199]		[0.201]
$Import^{Share}_{t-1}$			0.000	0.000			0.000	0.000			0.000	0.000
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219	1,219
Shea-R2	0.428	0.43	0.437	0.434	0.458	0.454	0.46	0.464	0.442	0.443	0.448	0.446
F-test	16.15	17.13	19.14	18.28	19.35	20.65	22.84	21.72	18.81	19.8	21.94	21.11
Fixed Effects												
region-sector	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable in Columns [4]-[6] is the ratio of the average wage of the skilled - managers, executives and clerks - to the average wage of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP. All regressors are measured at time $t-1$.

Table O2.11: The impact of immigration on skill intensity dispersion- Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	95.32	94.056*	94.186*	98.376*								
	[57.348]	[53.441]	[51.328]	[56.051]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					73.497	73.221*	73.320*	75.648*				
					[42.595]	[40.115]	[38.547]	[41.610]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									99.175	98.112*	98.373*	102.130*
									[57.368]	[53.935]	[51.882]	[55.948]
$\frac{Emigrants}{Population}_{t-1}$	-0.037			-0.094	-0.014			-0.065	-0.033			-0.087
	[0.139]			[0.148]	[0.126]			[0.130]	[0.133]			[0.140]
$Investment\ Inten_{t-1}$		0.464		0.567		0.436		0.553		0.442		0.542
		[0.723]		[0.764]		[0.700]		[0.754]		[0.714]		[0.756]
$Import^{Share}_{t-1}$			0.000***	0.000**			0.000***	0.000**			0.000***	0.000**
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182
Shea-R2	0.421	0.435	0.437	0.418	0.452	0.463	0.465	0.449	0.432	0.445	0.446	0.429
F-test	15.15	16.34	17.1	15.92	18.23	19.63	20.47	18.92	17.79	18.95	19.71	18.63
Fixed Effects												
region-sector	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
The dependent variable is the standard deviation of the skill intensity, in columns [1]-[3], and skill premium, in columns [4]-[6], across firms within an industry-region pair between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.
$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP. All regressors are measured at time $t-1$.

Table O2.12: The impact of immigration on skill premium dispersion- Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	174.695	158.874	161.927	181.556								
	[109.902]	[101.664]	[96.176]	[107.013]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					134.7	123.68	126.054*	139.612*				
					[81.709]	[76.473]	[72.289]	[79.479]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									181.223	166.404	169.626*	188.037*
									[109.019]	[101.720]	[96.335]	[105.815]
$\frac{Emigrants}{Population}_{t-1}$	-0.338			-0.53	-0.296			-0.477	-0.33			-0.517
	[0.372]			[0.471]	[0.352]			[0.445]	[0.366]			[0.462]
$Investment\ Inten_{t-1}$		-4.079		-4.112		-4.126		-4.138		-4.114		-4.159
		[3.687]		[3.741]		[3.688]		[3.745]		[3.680]		[3.746]
$Import^{Share}_{t-1}$			0.000*	0			0.000*	0			0.000*	0
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182	1,182
Shea-R2	0.421	0.435	0.437	0.418	0.452	0.463	0.465	0.449	0.432	0.445	0.446	0.429
F-test	15.15	16.34	17.1	15.92	18.23	19.63	20.47	18.92	17.79	18.95	19.71	18.63
Fixed Effects												
region-sector	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
The dependent variable is the standard deviation of the skill intensity, in columns [1]-[3], and skill premium, in columns [4]-[6], across firms within an industry-region pair between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.
$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP. All regressors are measured at time $t-1$.

Table O2.13: The impact of immigration on the relative ability of the skilled - Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	-8.669**	-8.759*	-8.618**	-9.163**								
	[4.025]	[4.320]	[4.010]	[4.214]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					-6.666**	-6.803*	-6.693**	-7.027**				
					[3.033]	[3.331]	[3.106]	[3.204]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									-8.810**	-8.923*	-8.810**	-9.299**
									[4.078]	[4.376]	[4.124]	[4.298]
$\frac{Emigrants}{Population}_{t-1}$	0.002			0.009	0			0.006	0.002			0.008
	[0.029]			[0.030]	[0.029]			[0.030]	[0.029]			[0.030]
$Investment\ Inten_{t-1}$		-0.618**		-0.649**		-0.615**		-0.649**		-0.615**		-0.646**
		[0.255]		[0.238]		[0.255]		[0.237]		[0.256]		[0.240]
$Import^{Share}_{t-1}$			0.000	0.000			0.000	0.000			0.000	0.000
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093
Shea-R2	0.399	0.416	0.417	0.397	0.434	0.448	0.449	0.432	0.41	0.425	0.426	0.407
F-test	13.28	14.47	15.11	14.09	16.14	17.55	18.24	16.85	15.78	16.92	17.54	16.65
Fixed Effects												
region-sector	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable is the ratio of the average ability the skilled - managers, executives and clerks - to the average ability of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP.

Table O2.14: The impact of immigration on the relative wage net of the ability - Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	8.181*	7.661*	7.616*	8.387**								
	[4.054]	[4.055]	[3.972]	[3.949]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					6.291*	5.950*	5.915*	6.431**				
					[3.110]	[3.141]	[3.079]	[3.029]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									8.232*	7.764*	7.726*	8.427**
									[4.090]	[4.127]	[4.043]	[4.003]
$\frac{Emigrants}{Population}_{t-1}$	-0.015			-0.018	-0.013			-0.015	-0.014			-0.017
	[0.019]			[0.023]	[0.019]			[0.023]	[0.019]			[0.023]
$Investment\ Inten_{t-1}$		0.186		0.175		0.185		0.175		0.184		0.173
		[0.325]		[0.341]		[0.322]		[0.339]		[0.324]		[0.340]
$Import^{Share}_{t-1}$			0.000	0.000			0.000	0.000			0	0
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093	1,093
Shea-R2	0.399	0.416	0.417	0.397	0.434	0.448	0.449	0.432	0.41	0.425	0.426	0.407
F-test	13.28	14.47	15.11	14.09	16.14	17.55	18.24	16.85	15.78	16.92	17.54	16.65
Fixed Effects												
region-sector	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.

The dependent variable is the ratio the average residual (net of the ability) wage of the skilled - managers, executives and clerks - to the average residual wage (net of the ability) of the unskilled - blue collars and apprentices - employed in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the 2018 World Bank Classification of Countries by income - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.

$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP. All regressors are measured at time $t-1$.

Table O2.15: The impact of immigration on the relative screening of the skilled - Robustness - 2SLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$\frac{Migrants}{Population}_{t-1}$	-7.384*	-7.092*	-7.412*	-7.056*								
	[3.741]	[3.566]	[3.579]	[3.845]								
$\frac{Migrants}{Labour\ Force}_{t-1}$					-5.653*	-5.487*	-5.732**	-5.404*				
					[2.861]	[2.736]	[2.732]	[2.921]				
$\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$									-7.446*	-7.183*	-7.473**	-7.070*
									[3.747]	[3.552]	[3.537]	[3.780]
$\frac{Emigrants}{Population}_{t-1}$	-0.003			0.001	-0.005			-0.001	-0.004			-0.001
	[0.035]			[0.036]	[0.035]			[0.036]	[0.035]			[0.036]
$Investment\ Inten_{t-1}$		0.247		0.238		0.249		0.239		0.251		0.242
		[0.311]		[0.313]		[0.311]		[0.314]		[0.311]		[0.314]
$Import^{Share}_{t-1}$			0.000	0.000			0.000	0.000			0.000	0.000
			[0.000]	[0.000]			[0.000]	[0.000]			[0.000]	[0.000]
Observations	883	883	883	883	883	883	883	883	883	883	883	883
Shea-R2	0.362	0.381	0.398	0.372	0.403	0.418	0.434	0.411	0.378	0.394	0.407	0.385
F-test	11.675	12.76	15.69	14.818	14.476	15.941	19.31	18.191	13.637	14.686	17.931	17.095
Fixed Effects												
region-sector	y	y	y	y	y	y	y	y	y	y	y	y
sector-year	y	y	y	y	y	y	y	y	y	y	y	y

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are displayed in brackets and are clustered by region.
The dependent variable is the difference between the share of skilled workers on a fixed-term training contract over the total newly hired skilled workers with less than two years of tenure and the same share computed for unskilled workers in a region-sector-year between 2008 and 2013. $\frac{Migrants}{Population}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population. $\frac{Migrants}{Labour\ Force}_{t-1}$ measures the ratio between the stock of foreign residents in a region and the total resident population aged 15-65. $\frac{Migrants^{Low\&Middle\ Income}}{Population}_{t-1}$ measures the ratio between the stock of foreign residents originating from Low&Middle Income countries - as from the WBDI 2018 - in a region and the total resident population. The following controls are included in the specification and partialled out in the estimation: GDP_{t-1} is the log of the region GDP; $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded; $Unemployment\ Rate_{t-1}$ is a region's unemployment rate. All regressors are measured at time $t-1$.
$\frac{Emigrants}{Population}_{t-1}$ measure the share of emigrants from a region to a foreign country in total region population. $Investment\ Inten_{t-1}$ measures the ratio of total investments over output of a region-sector pair. $Import^{Share}_{t-1}$ is the share of a region's imports from abroad in total GDP. All regressors are measured at time $t-1$.

country shares and initial location characteristics for the top 5 migration origins in our data to inspect whether these shares are correlated with factors that predict changes of our dependent variables. Given the paucity of observations, we use the randomisation inference procedure proposed by Young (2018) to test the statistical significance of the initial conditions. Estimation results from the randomisation procedure are reported in Table O3.1, while Table O3.2 reports for each equation and coefficient the minimum, maximum and randomised c- and t- p-values stemming from 1000 iterations.[26] The Table also reports randomisation-c and -t p-values for the joint-test of the significance of treatment measures in each equation and in the experiment as a whole.

In all cases, the share of the top 5 countries of origin is not significantly correlated with any of the relevant initial conditions which may predict innovations in the skill intensity or the skill premium.

To further test the validity of our IV strategy and account for the potential finite sample bias of the 2SLS using all the shares as instruments, we present in Table O3.3 three alternative estimators which supposedly have better properties with many instruments: the modified bias corrected 2SLS (MBTSLS), the Limited Information Maximum Likelihood (LIML) estimator and the estimator proposed by Hausman et al. (2012). Apart from the HFUL estimator, results are quite similar and the overidentification test of the 2SLS with all the shares as instruments fails to reject the null. Figure O3.1 further confirms the view emerging from the overidentified 2SLS as the estimated beta are quite similar across countries.

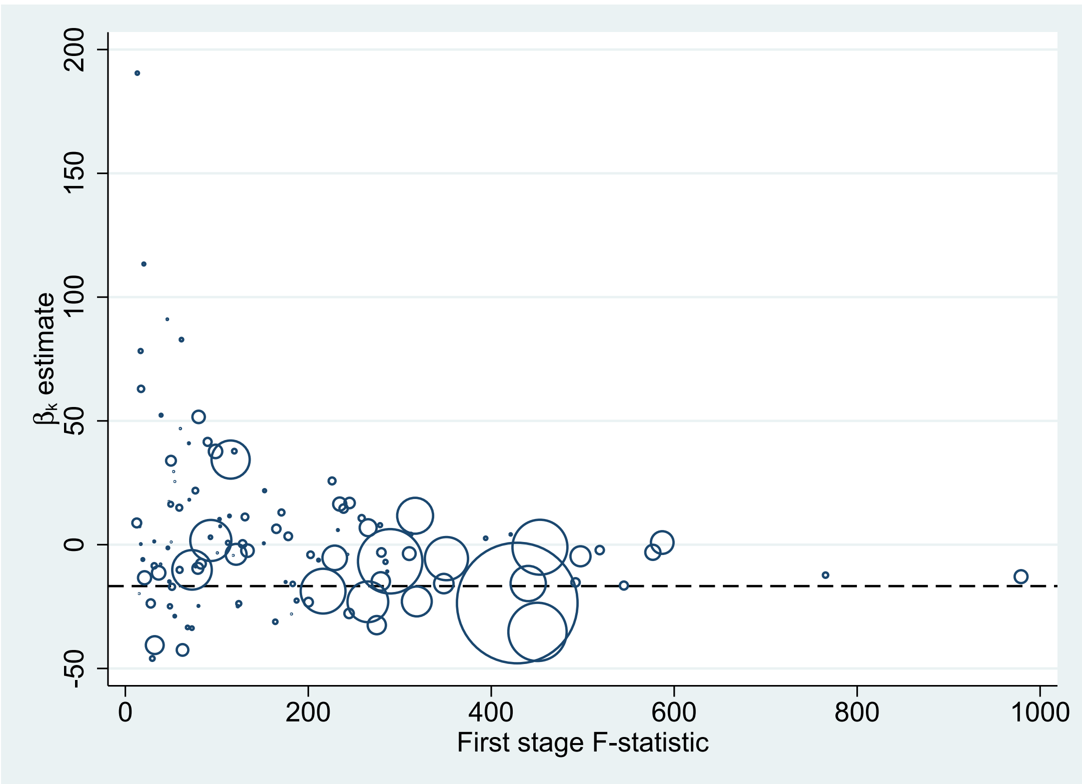
[26] As reported by Young (2018) , randomisation-c corresponds to bootstrap tests which use the distribution of bootstrapped coefficients to calculate the covariance matrix.

Table O3.1: Relationship between origin country shares and local characteristics

	[1] Romania	[2] Albania	[3] China	[4] Morocco	[5] Ukraine
Unemployment Rate	0.009*	0.004	0.008	0.007	0.007
	[0.005]	[0.004]	[0.007]	[0.005]	[0.005]
Per Capita Income	-0.002	-0.010	-0.074	0.051	0.002
	[0.115]	[0.099]	[0.164]	[0.118]	[0.102]
Share of Manufacturing Value Added	0.012	-0.037	-0.563	-0.249	0.325
	[0.560]	[0.474]	[0.848]	[0.587]	[0.361]
Secondary School Enrollment Rate	0.000	0.000	0.002	0.003	-0.001
	[0.002]	[0.002]	[0.004]	[0.002]	[0.001]
Labour Productivity in Manufacturing	0.001	0.001	0.002	0.000	0.001
	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]
Trade Openness	0.001	0.002	0.002	0.002	0.001
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
Patents per 1000 Inhab.	0.000	0.000	0.001	0.000	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Constant	-0.157	-0.136	-0.569	-0.044	-0.063
	[0.596]	[0.510]	[0.843]	[0.580]	[0.523]
Observations	20	20	20	20	20
R-squared	0.423	0.165	0.276	0.241	0.406

Notes: Each column reports results of a single regression of a 1994 origin country share on 1994 region characteristics. The data source of local initial condition is Istat. Standard errors in brackets.

Figure O3.1: Heterogeneity of β_k



Notes: This figure plots the relationship between each instruments' β_k, first-stage F-statistics, and the Rotemberg weights. Each point is a separate instrument's estimates (country share). The figure plots the estimated β^k for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights. The horizontal dashed line is plotted at the value of the overall β^k reported in the second column in the 2SLS (Bartik) row in Table O3.3. The figure excludes instruments with first-stage F-statistics below 10.

Table O3.2: Relationship between origin country shares and local characteristics

	min-c pvalue	max-c pvalue	rand-c pvalue	min-t pvalue	max-t pvalue	rand-t pvalue	iterations
				Romania			
Unemployment Rate	0.253	0.254	0.254	0.33	0.331	0.331	1000
Per Capita Income	0.19	0.191	0.191	0.426	0.427	0.426	1000
Share of Manufacturing Value Added	0.641	0.642	0.642	0.678	0.679	0.679	1000
Secondary School Enrollment Rate	0.555	0.556	0.556	0.636	0.637	0.637	1000
Labour Productivity in Manufacturing	0.311	0.312	0.311	0.241	0.242	0.242	1000
Trade Openness	0.501	0.502	0.502	0.286	0.287	0.286	1000
Patents per 1000 Inhab	0.789	0.79	0.789	0.742	0.743	0.742	1000
Joint Tests	0.651	0.652	0.652	0.588	0.589	0.589	1000
Westfall-Young multiple testing	0.678	0.679	0.679	0.691	0.692	0.692	1000
				Albania			
Unemployment Rate	0.679	0.68	0.68	0.651	0.652	0.652	1000
Per Capita Income	0.572	0.573	0.573	0.597	0.598	0.598	1000
Share of Manufacturing Value Added	0.913	0.914	0.914	0.899	0.9	0.9	1000
Secondary School Enrollment Rate	0.587	0.588	0.588	0.624	0.625	0.625	1000
Labour Productivity in Manufacturing	0.364	0.365	0.364	0.266	0.267	0.267	1000
Trade Openness	0.573	0.574	0.574	0.285	0.286	0.285	1000
Patents per 1000 Inhab	0.517	0.518	0.518	0.302	0.303	0.302	1000
Joint Tests	0.413	0.414	0.413	0.336	0.337	0.336	1000
Westfall-Young multiple testing	0.923	0.924	0.924	0.772	0.773	0.773	1000
				Cina			
Unemployment Rate	0.617	0.618	0.618	0.501	0.502	0.502	1000
Per Capita Income	0.371	0.372	0.372	0.38	0.381	0.381	1000
Share of Manufacturing Value Added	0.622	0.623	0.623	0.503	0.504	0.504	1000
Secondary School Enrollment Rate	0.683	0.684	0.684	0.688	0.689	0.689	1000
Labour Productivity in Manufacturing	0.43	0.431	0.43	0.264	0.265	0.265	1000
Trade Openness	0.365	0.366	0.365	0.27	0.271	0.27	1000
Patents per 1000 Inhab	0.82	0.821	0.82	0.828	0.829	0.828	1000
Joint Tests	0.292	0.293	0.292	0.458	0.459	0.458	1000
Westfall-Young multiple testing	0.909	0.91	0.91	0.735	0.736	0.736	1000
				Morocco			
Unemployment Rate	0.506	0.507	0.507	0.243	0.244	0.244	1000
Per Capita Income	0.573	0.574	0.574	0.472	0.473	0.472	1000
Share of Manufacturing Value Added	0.922	0.923	0.923	0.852	0.853	0.853	1000
Secondary School Enrollment Rate	0.389	0.39	0.389	0.191	0.192	0.191	1000
Labour Productivity in Manufacturing	0.375	0.376	0.375	0.205	0.206	0.206	1000
Trade Openness	0.767	0.768	0.768	0.48	0.481	0.48	1000
Patents per 1000 Inhab	0.096	0.097	0.096	0.013	0.014	0.013	1000
Joint Tests	0.018	0.019	0.018	0.11	0.111	0.11	1000
Westfall-Young multiple testing	0.429	0.43	0.429	0.072	0.073	0.073	1000
				Ukraine			
Unemployment Rate	0.295	0.296	0.296	0.464	0.465	0.465	1000
Per Capita Income	0.202	0.203	0.203	0.461	0.462	0.461	1000
Share of Manufacturing Value Added	0.593	0.594	0.594	0.593	0.594	0.594	1000
Secondary School Enrollment Rate	0.092	0.093	0.093	0.105	0.106	0.106	1000
Labour Productivity in Manufacturing	0.36	0.361	0.36	0.378	0.379	0.378	1000
Trade Openness	0.872	0.873	0.872	0.827	0.828	0.827	1000
Patents per 1000 Inhab	0.433	0.434	0.433	0.259	0.26	0.259	1000
Joint Tests	0.323	0.324	0.323	0.264	0.265	0.264	1000
Westfall-Young multiple testing	0.42	0.421	0.42	0.419	0.42	0.419	1000

Notes: the data source of local initial condition is Istat. Standard errors in brackets.
This set of results is obtained through the use of the Stata command *randcmd*

Table O3.3: OLS and IV Estimates

	[1]	[2]	[3]	[4]
OLS	1.491	-10.323	[0.022]	
	(1.203)	(6.051)		
2SLS (Bartik)	1.636	-16.728	[0.056]	
	[1.048]	[9.603]		
2SLS	1.494	-10.324	[0.019]	92.260
	[1.030]	[5.027]		[0.385]
MBTSLS	1.495	-10.324	[0.019]	
	[1.031]	[5.017]		
LIML	1.495	-10.324	[0.023]	87.766
	(1.317)	(5.273)		[0.517]
HFUL	-9.804	7.828	[0.931]	142.351
	(203.820)	(0.553)		[0.000]

Notes: This table reports a variety of estimates of the coefficient on immigrants share. The regressions are at the region-industry-year level for the 2008-2013 period. Column [1] does not contain controls, while column [2] does and in this case OLS and 2SLS rows refer to the first column of Tables O2.2 and 1, respectively. The controls are the following contemporaneous characteristics included in each specification: GDP_{t-1} is the log of the region GDP in $t-1$. $Manufacturing^{Share}_{t-1}$ measures the share of manufacturing value added in the total region's value added recorded in $t-1$. $Unemployment\ Rate_{t-1}$ is a region's unemployment rate in $t-1$. The 2SLS (Bartik) row uses the shift-share instrument of equation 19. The 2SLS row uses each origin country share separately as instruments. The MBTSLS row uses the estimator of Anatolyev (2013) and Kolesár et al. (2015) with the same set of instruments. The LIML row shows estimates using the limited information maximum likelihood estimator with the same set of instruments. Finally, the HFUL row uses the HFUL estimator of Hausman et al. (2012) with the same set of instruments. The J-statistic for HFUL comes from Chao et al. (2014). Standard errors are in parentheses and are constructed by bootstrap over regions. In Column [3] is the p-value for the equality of coefficients that compares the adjacent columns with and without controls. Column [4] displays the test for the over-identifying restrictions. P-values are in brackets.

Table O3.4: Summary of Rotemberg Weights

Panel A: Correlations of Country Aggregates					
	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	0.910	1			
β_k	-0.023	-0.011	1		
F_k	0.274	0.257	-0.049	1	
Var(z_k)	-0.054	-0.085	-0.348	-0.145	1

Panel B: Variation across years in α_k		
	Sum	Mean
2008	-2.833	-0.016
2009	-0.376	-0.002
2010	1.557	0.009
2011	3.256	0.019
2012	-1.048	-0.006
2013	0.444	0.003

Panel C: Top 5 Rotemberg weight countries			
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$
ROU	0.293	1600629	-23.558
MAR	0.061	808238.6	-1.021
ALB	0.040	880503	-18.754
CHN	0.064	371416.1	-35.223
UKR	0.083	327855.9	-6.703

Notes: This table reports statistics about the Rotemberg weights, which are all positive in this application. Panel A reports correlations between the weights (α^k), the national component of growth (g_k), the just-identified coefficient estimates (β^k), the first- stage F- statistics (F^k), and the variation in the origin country shares across locations ($var(z_k)$). Panel B shows the variation of Rotemberg weights across years. Panel C reports the top five origin countries according to the Rotemberg weights. The g_k is the immigration share from 2008 to 2013, β^k is the coefficient from the just-identified regression.