J Prod Anal (2014) 42:305–325
DOI 10.1007/s11123-014-0390-2

A firm level perspective on migration: the role of extra-EU workers in Italian manufacturing

Giulia Bettin · Alessia Lo Turco · Daniela Maggioni

Published online: 3 April 2014

Abstract A production-theory approach to migration is adopted in this paper to address the role of migrant workers from extra-EU countries in Italian manufacturing firms. The adoption of flexible functional forms to model firm-level technology lets us directly derive different measures of elasticity from the coefficients of the estimated production and cost functions. The use of foreign labour is shown to affect the industry composition in favour of low skill intensive sectors and the estimated cross demand elasticities confirm the complementarity between migrant and native workers found in previous studies. However, the two labour inputs prove to be substitutes in terms of the Morishima elasticity of substitution: in general, firms tend to increase the foreign labour intensity of production in response to a decline in migrants' wage, while the migrant to domestic labour ratio responds to changes in the domestic workers' wage only for firms in low skill intensive sectors.

Keywords Migrant workers · Output elasticity · Morishima elasticity of substitution · Translog

JEL Classification F22 · D22 · J61 · L60

G. Bettin (✉) · A. Lo Turco · D. Maggioni
Department of Economics and Social Sciences, Università Politecnica delle Marche, P.le Martelli 8, 60121 Ancona, Italy
e-mail: g.bettin@univpm.it

A. Lo Turco
e-mail: a.loturco@univpm.it

D. Maggioni
e-mail: d.maggioni@univpm.it

G. Bettin
Department of Economics and Social Sciences and Mo.Fi.R., Università Politecnica delle Marche, P.le Martelli 8, 60121 Ancona, Italy

1 Introduction

Migration, and specifically workers' mobility, is a wide and complex phenomenon that has long since drawn the attention of economic literature. Large inflows of migrants, mainly from developing countries, have raised doubts on the absorbing capacity of richer economies: public opinion is often concerned that migrants take jobs away from native workers and burden on developed countries' welfare systems which are facing population ageing and birth rates decline.

The literature so far has focused on the impact of migrants on the labour market and in particular on the domestic wage. By means of Census or Labour Force survey data, most of the empirical studies have found evidence of complementarity between domestic and foreign labour and only modest evidence of detrimental effects deriving from immigration, or even no evidence at all (Card 2001; Ottaviano and Peri 2011; D'Amuri and Peri 2011). At the aggregate level, Docquier et al. (2010) compute long-run effects of both immigration and emigration flows on wages of native low-skilled and high-skilled workers in European countries between 1990 and 2000. While emigration negatively affects average wages and wage inequality, the effect of immigration is positive on both sides.

The mixed empirical evidence might depend on the fact that most studies disregard the occupational dimension and simply focus on workers' educational attainment. In this respect, Steinhardt (2011) shows that, by following the standard approach of classifying workers according to their education and work experience, no negative effects on native wages emerge. On the other hand, when taking immigrants' occupational clustering into account, a clear negative impact emerges on the wages of native workers, particularly those employed in basic occupations in the service sector, like cleaning or retail trade activities. Migrants specialise in manual and low-skill intensive jobs, while natives prefer high-skill intensive occupations or simply jobs requiring different levels of ability in terms of language and communication tasks (Peri and Sparber 2009). However, a further explanation of inconsistent empirical results might lie in the fact that the analyses based on Labour Force Survey and Census data are not able to capture the impact of migrants on the production structure of the economy. Across sectors, migrants could affect production techniques and, ceteris paribus, an increase in the availability of low-skilled workers might cause a Rybczynski effect and generate a reallocation of resources towards low skill intensive sectors. This implies that, even in the absence of any sizable labour market effect, the inflow of migrants may importantly affect the structure of the economy and its growth potential. In this respect, a recent strand of empirical literature developed with the specific aim of disclosing the within- and between-industry impact of foreign labour. Evidence in favour of within-industry instead of between-industry adjustments stemming from increased migration inflows has recently been found in empirical studies on Spain and Germany respectively by González and Ortega (2011) and Dustmann and Glitz (2008), in line with the previous findings for the US (Card and Lewis 2005). The inflow of migrants is associated with a reduction in the average skill intensity across sectors. By the same token, increased skill intensity is sorted out in Israel because of the high-skilled migrants coming from Russia (Gandal et al. 2004). At the firm level, Lewis (2011) shows that the increase in the supply of low-skilled workers in the US metropolitan areas due to immigration significantly induces firms to adopt less machinery per unit output. Opposite evidence is provided for Italy by Accetturo et al. (2012) who show that an increase in immigration of low-skilled workers from developing countries, measured at the provincial level, raises the capital intensity in small manufacturing firms. Kangasniemi et al. (2012) instead look at the impact of immigration on productivity performance at sectoral level in Spain and the UK. While in the UK the long term effect of foreign workers on total factor productivity is positive and their contribution to labour productivity growth is negligible (although negative) in size, both effects are negative and significant in the case of Spain.

All the different contributes mentioned above are crucially linked to the kind of relationship (complementarity/substitutability) that exists between migrant and native workforce in terms of skill levels. And despite factor complementarity and substitutability depict firms' decisions over production techniques, the mentioned studies investigate the effects of immigration on production by means of Census or Labour Force Survey data, with the only exception of Lewis (2011) and Accetturo et al. (2012) which rest on firm level datasets. However, the two studies estimate reduced form models where migration is measured at the province/metropolitan area level and is by no means observed at the firm level.

In this paper, we aim at assessing the contribution of migrants to an advanced economy's manufacturing sector by making use of firm level information on foreign-born workforce. In particular, we adopt a production theory approach at the firm level and shed light on the impact of extra-EU workers on Italian manufacturing output, on the skill intensity of the production techniques and on the native workers' demand.

The production-theory approach to migration was introduced by Grossman (1982) and has been further developed by Kohli (1993, 1999) in an analysis for Switzerland. His estimation results, derived from the GNP-function framework, show that nonresident and resident workers are substitutes for each other while imports and nonresident labour are found to be complements. This holds both in terms of Allen-Uzawa elasticities of substitution and in terms of Hicksian elasticities of complementarity.

Making use of the 9th wave of the Survey on Italian Manufacturing Firms carried out by Capitalia in 2004 (with information on the period 2001–2003), we first retrieve output elasticities from the parameter estimates of a translog production function, which allow us to assess the contribution of extra-EU migrants to manufacturing output. In a second step, we shed light on the substitutability/complementarity relationship between natives' and migrants' labour, and more in general among all production factors, by estimating a cost function and computing the demand elasticities. These measures may be informative of the linkages between domestic and migrant labour especially in a framework with rigid wages like the Italian labour market and in a short-term time horizon, where scale effects are less important in magnitude than changes in the choice of the production techniques.

Finally, to assess the impact of factor price changes on the foreign labour intensity of production for a given output level, we move from absolute—i.e. the demand elasticity measure—to relative measures of substitutability and calculate the Morishima elasticities of substitution (*MES*). To the best of our knowledge, it is the first time that a relative measure of substitutability is adopted to assess the relationship between native and foreign workers in production. Whereas the absolute demand elasticities inform us on the absolute change in the demand of a production factor with respect to the price of another factor, *MES* inform us on the change in the ratio between the quantities of the two inputs after one of the two prices changes. In particular, it can be interesting to analyse whether the firm responds to a rise in the domestic workers' wage with an increase in the ratio of foreign to domestic workers for a given output level. At the same time, *MES* may highlight whether the willingness of migrants to accept lower wages could foster a reduction in the ratio of domestic to migrant workers in production. Therefore, we consider *MES* as a more informative elasticity of substitution from which to draw implications for the manufacturing firm production techniques in terms of skill intensity.

Analysing the role of foreign labour in Italian manufacturing production is an interesting empirical issue since in recent years the country has experienced a rapidly increasing migration from developing countries. Despite the labour market evidence of complementarity between migrants and natives (Gavosto et al. 1999) and the fact that foreign workers are mostly employed in sectors that domestic workers usually try to avoid such as construction and services (Istat 2009), complaints about migrants stealing jobs from natives within the manufacturing sector are still frequent. In addition, the future prospects of Italian manufacturing firms may be closely linked to the consequences of an increasing presence of migrant workforce as well. To the extent that an inflow of low skilled migrants actually stimulates the adoption of less skill intensive techniques (Lewis 2011), this may further contract the technological upgrading whose lack and inadequacy have already been recognized as responsible for the decline of Italian manufacturing sector.

From our findings, the output elasticity of foreign labour is rather small and extra-EU migrants especially contribute to output in low skill intensive sectors thus favouring, ceteris paribus, an increasing weight of these activities in the Italian manufacturing output. Absolute demand elasticities confirm the complementarity found in previous studies between migrants and natives, regardless of workers' skill level, while the two labour inputs are substitutes in terms of the Morishima elasticity of substitution. This result needs some more qualifications: in general, firms only tend to increase the foreign labour intensity of production in response to a decline in its own wage, while the foreign to domestic labour ratio does not seem to vary when price changes concern domestic labour. This result, however, is not valid in the subsample of firms operating in low skill intensive sectors. All in all, an increase in the foreign workforce from non-EU countries slightly contributes to the decline of the skill ratio in Italian manufacturing firms.

The work is organized as follows: Sect. 2 and 3 respectively present the empirical model and the data in detail. Results from the estimates are discussed in Sect. 4, while Sect. 5 concludes.

2 The empirical model

The substitutability/complementarity among production factors and their contribution to the output can be assessed by the estimates of the technological parameters retrieved from a production function or its dual cost function. Our interest in the substitutability among factors and the availability of firm level information on production inputs and output led us to choose a translog production function (Christensen et al. 1973) which imposes no *a priori* restriction on the relationships among factor inputs. The function is specified as follows:

$$lnY_f = \alpha_0 + \sum_i \alpha_i lnX_{fi} + \frac{1}{2} * \sum_i \alpha_{ii} lnX_{fi} lnX_{fi} + \sum_i \sum_{j \neq i} \alpha_{ij} lnX_{fi} lnX_{fj} \quad (1)$$

For each firm f in our sample, lnY measures the logarithm of real output while lnX_i represents the log of the quantity of input i used in production. In the model i indexes the technology inputs, which, in the basic specification, are materials (IM), services (IS), capital (K), domestic labour (L_D) and foreign labour (L_M), respectively. We also explore a six-input production technology where we relax the assumption of homogeneity within the group of domestic workers L_D and split them into white, L_{DW}, and blue collars, L_{DB}. Foreign labour is kept as a unique factor of production which is assumed to be exclusively composed by workers employed in low skilled occupations as supported by evidence from different data sources (see Sect. 3).

To improve the estimation efficiency, the production function is augmented, as usual in the literature, with the input share equations obtained as its first derivatives:

$$S_{fi} = \alpha_i + \alpha_{ii} lnX_{fi} + \sum_{j \neq i} \alpha_{ij} lnX_{fj} \quad (2)$$

Under the hypothesis of constant returns to scale and profit maximization, S_i represents the share of input i in total output:

$$\frac{\partial lnY}{\partial lnX_i} = \frac{\partial Y}{\partial X_i} * \frac{X_i}{Y} = S_i$$

To overcome the lack of information on the share of labour costs attributable to foreign workers, we follow Yasar and Morrison Paul (2008) and we express the share of the two labour inputs as a sum. We then include the share of overall labour which is something we actually observe:

$$S_{fL} = S_{fL_D} + S_{fL_M} = (\alpha_{L_D} + \alpha_{L_M}) + (\alpha_{L_D L_D} + \alpha_{L_{L_M} L_D}) * ln(L_D) + (\alpha_{L_M L_M} + \alpha_{L_M L_D}) * ln(L_M) + (\alpha_{L_D K} + \alpha_{L_M K}) * ln(K_f) + (\alpha_{L_D IM} + \alpha_{L_M IM}) * ln(IM_f) + (\alpha_{L_D IS} + \alpha_{L_M IS}) * ln(IS_f) \quad (3)$$

From the parameter estimates of the above system it is then possible to calculate the output elasticities for each factor as $\frac{\partial lnY_f}{\partial lnX_{if}}$.

The following step in our analysis is to investigate the response of the demand for foreign labour to an increase in the wage of domestic workers. In this respect, a null or positive response of the domestic wage to the increased availability of foreign workers could be observed, while an increase in the wage of domestic workers might actually foster their substitution with migrant workers. If an increase in the price of input *j* raises/lowers the demand of input *i*, the two factors are classified as *p-substitutes/complements*. This piece of information is contained in the partial demand elasticities which are based on the estimates of the Allen elasticities of substitution (AES), σ.

Despite indirect estimates could be retrieved also from the production function estimation, the dual approach represents in our opinion the most natural way to compute the AES, and consequently the partial demand elasticities. Therefore, we estimate a translog short-term cost function with log of prices substituting for the log of input quantities. and the log of the cost substituting for the log of output in Eq. 1 (Kohli 1999; Mundra and Russell 2001). We use sector level prices of material and services and average wages for domestic and foreign labour at the region-sector[1] level, keeping capital fixed. The cost function is estimated jointly with the cost shares of inputs and we adopt the strategy already mentioned to overcome the lack of information on the exact firm level measure of the shares of domestic and foreign labour.

The partial demand elasticity of factor *i* with respect to factor *j*'s price, $\eta_{x_ip_j}$, is calculated as follows:

$$\eta_{x_ip_j} = \sigma_{ij} * S_j = \frac{\beta_{ij} + S_i * S_j}{S_i} \tag{4}$$

with β_{ij} corresponding to the parameters retrieved from the cost function estimation. $\eta_{x_ip_j}$ therefore represents the percentage response of the demand of input *i* to an increase of 1 % in the price of input *j*.

Finally, we obtain the Morishima elasticity of substitution (*MES*) as:

$$MES_{ij} = \eta_{x_ip_j} - \eta_{x_jp_j} = \frac{\partial ln(X_i/X_j)}{\partial lnP_j} \tag{5}$$

Whereas cross-price elasticities are absolute measures of substitution, the *MES* represents a relative substitution elasticity and measures the percentage change in the ratio of input *i* to *j* when only p_j varies and all other prices are constant. Two factors *i* and *j* are termed *MES-substitutes* if $MES_{ij} > 0$ and *MES-complements* if $MES_{ij} < 0$ (Chambers 1988).

In other words, one might observe that although an increase in natives' wages decreases the demand for both native and foreign labour, the latter might decline less, thus causing production techniques to become more foreign labour intensive. In this sense two factors can be MES substitutes even if they have been classified as complements when dealing with absolute demand elasticities. The issue has been widely discussed in the literature (Blackorby and Russell 1989; Chambers 1988; Nguyen and Streitwieser 1997; Frondel 2004; Stern 2011) with many contributes pointing at *MES* as the right informative elasticities to assess the curvature of an isoquant when the production technology employs more than two factors, although other measures of substitutability may better capture the shape of the production technology in the multi-input case.[2] Since *MES* keeps the prices and not the quantities of the other inputs fixed, for a given level of output we can assess how and if changes in the price of the domestic or foreign labour affect their ratio within the firm. In this respect, the asymmetry of *MES* allows us to better explore the response of the relative position of foreign and domestic labour in production in terms of their relative cost shares after a change in one of the two wages and to isolate the effect of such a change on the firm's skill ratio.

2.1 Estimation issues

In the following, we employ the Maximum Likelihood Zellner-efficient estimator to estimate the system made up of the production function (cost function) displayed in Eq. 1 and the revenue (cost) share equations displayed in Eq. 2. Elasticities are obtained by combining the parameter estimates with the predicted factor shares and their respective standard errors are calculated by means of the delta method.

Homogeneity of degree one has been imposed both on the production and cost function[3] and all specifications include time, sector, area and firm size dummies together

[1] Sector variation is at the level of divisions of NACE Revision 1 while regions are defined at NUTS 2 level.

[2] As an example, Stern (2011) refers to the Symmetric Elasticity of Complementarity, *SEC*, as the "best overall statistic summarizing the production technology" since it "holds the quantity of the other inputs constant and hence measures the shape of the traditional production isoquant."

[3] Homogeneity and symmetry are imposed through the following restrictions: $\sum_i \alpha_i = \lambda$, $\sum_j \alpha_{ij} = 0$ and $\alpha_{ij} = \alpha_{ji}$ in the case of the production function and $\sum_i \beta_i = \lambda$, $\sum_j \beta_{ij} = 0$ and $\beta_{ij} = \beta_{ji}$ in the case of the cost function. For the linear homogeneity $\lambda = 1$. We estimated the production and cost function both for the λ homogeneity and linear homogeneity cases and results do not change substantially; therefore, we simply present the results for the constant returns to scale production technology. The remaining set of results is available from the authors upon request.

with the regional unemployment rate and the regional share of irregular workers in order to capture local economic conditions.[4]

Since taking the log of foreign labour leads to exclude those observations where this input is equal to zero, we restrict the sample to the firms using foreign labour. We control for sample selection by including the OLS residuals from the estimation[5] of the probability of hiring foreign workers (Rivers and Vuong 1988; Vella 1998).

Finally, most of the empirical contributions that estimate the elasticity among production factors (Berndt 1991; Nguyen and Streitwieser 1997; Kohli 1991, 1999, 2002; Yasar and Morrison Paul 2008) do not correct for the endogeneity of the right hand side variables in the production function. We have addressed this issue by implementing a 3 Stages Least Squares (3SLS) estimator where all the production factors, their squares and their interactions have been instrumented by means of their lagged value and of their current and past prices. The estimated production function coefficients and output elasticities are very close to the ones from baseline estimates, but the number of violations of the first and second order conditions is higher in some cases and the use of lagged values as instruments leads to the loss of one sample year.[6] Therefore, as no striking difference emerges in the estimates, we prefer to stick to baseline results which rest on a larger sample and bear a definitely lower number of violations.

3 Data and descriptive evidence

The data used in the following analysis are retrieved from the 9th wave of the Capitalia Survey, containing plenty of information on Italian manufacturing firms' characteristics and activities for the period 2001–2003. Unfortunately, we are not able to exploit either previous waves, which include no information concerning migrant workforce, or the following one where this piece of information—available just for 1 year—is coded differently.[7] The dataset includes all firms with more than 500 employees, while for firms with more than 10 and less than 500 employees a rotating sample is created stratifying by industry, size class and geographical area. Information concern firms' output, inputs, investments, innovation activities, internationalisation strategies and, more importantly for our aims, firms are asked about Extra European Community (EC)[8] employees hired each year. From now on, we will indifferently refer to these workers as migrants or foreign workers.

After a cleaning procedure,[9] we end up with a sample of 3,264 firms for a total of 9,314 firm-year observations in

[4] Firm fixed effects were not included as the time dimension of our data set is too short and time demeaning would result in poor coefficient and elasticities estimates. Nevertheless, in the light of the empirical and theoretical literature stressing the existence of important within sector firm heterogeneity, in order to account for it—apart from the inclusion of size dummies—we ran two checks adding firm innovation and trade status dummies to the basic system specification. These two firm activities are the most related to unobserved heterogeneous efficiency levels which are unobserved and unaccounted for in our empirical framework. Thus, we firstly added two dummy variables to account respectively for product and process innovation, and secondly we included two dummy variables to account for firm import and export status. Both sets of results did not show any relevant change compared to the basic specification and are not shown for the sake of brevity, but they are readily available from the authors upon request.

[5] The first-step model includes labour productivity, capital intensity, the firm's age and size with their squared value and several other firms' characteristics: dummies for investors, innovators, offshoring, import and export status and intensity, a dummy for the destination of offshoring and for the type of activity offshored, sector and area of activity. Results are not shown for the sake of brevity.

[6] It is worth mentioning that we tested for a number of alternative sets of instruments. First of all, we made use of different instruments under the hypothesis of inputs in the production function being subject to adjustment frictions (Bond and Söderbom 2005). So, we tested for the use of lagged inputs and output and the use of "gmm style" instruments in both the static and dynamic production function in levels, differences and system. Such attempts gave rather poor outcomes, especially in terms of first order conditions violations. This is consistent with some of the inputs—migrant labour, as well as materials and services—constituting flexible inputs, or at least inputs characterised by low adjustment costs in manufacturing production. We then exploited the cross-sector variation in prices of capital, services and materials and cross-region-sector variation in wages to instrument our production function inputs, under the assumption of price taking behaviour of firms. Again an extremely high number of violations of the first and second order conditions emerged, consistently with some of the inputs—e.g. domestic labour and capital—being actually subject to relevant adjustment costs. Then, to account for the existence of inputs with a different level of adjustment costs without an *a priori* assumption on the input nature as quasi-fixed or flexible, we instrumented all production factors, their squares and interactions by means of their lagged value and of their current and past prices. The latter choice led to the loss of a much lower number of observations due to the violation of the first order condition with respect to the other mentioned alternatives. Furthermore, the IV diagnostics were satisfactory, with the F-statistics in each first-stage equation highly significant and the Hansen J test not rejecting the null hypothesis of the validity of instruments. However, results stemming from the adoption of instrumental variables do not substantially differ. The 3SLS estimates making use of this set of instruments are not shown for the sake of brevity, but they are available from the authors upon request.

[7] While in the 9th wave of the Capitalia survey firms are asked about Extra European Community workers, in the 10th wave the question concerns all foreign born workers. The information therefore are not directly comparable.

[8] The period of the analysis is prior to the two rounds of Eastern EU enlargement so Extra European Community workers include also citizens from the new Member States.

[9] We drop observations with missing data for our variables of interest (output, value added, employment, capital, services materials, and

the period 2001–2003; 1,403 firms have employed migrant workers at least in 1 year of the period 2001–2003 (3,822 firm-year observations).

As the Capitalia database provides information on the total number of white (directors and clerical workers) and blue (manual workers) collars within the firm, with no distinction on the basis of their nationality, we assume that all extra-EU workers are employed in low-skilled manual occupations. Such assumption is checked by employing the "Work History Italian Panel" (WHIP) database which consists in a representative sample of the Italian employment based on the INPS (National Institute of Social Security) administrative archives. WHIP data show that 91 % of foreign-born workers is represented by extra-EU migrants. This confirms that the population of extra-EU migrants, which represents the focus of our analysis, is highly representative of the migration phenomenon in Italy. Moreover, the public's growing concern about immigration is mainly related to this group of foreign workers. In terms of skill level, on average, 94 % of extra-EU migrants was employed in blue collar jobs between 2001 and 2003. In addition, by exploiting Italian Labor Force Survey data, Bettin (2012) shows that in 2006 around 60 % of extra-EU workers were low educated (lower secondary school or less) and 95 % of them worked as blue collars. These figures are pretty stable, at least up to 2010. These pieces of evidence make us confident that our choice to consider migrant labour substantially as a unique type of low skilled labour and white collars as purely represented by native workers is not going to bias our estimates of the six-input production function.[10] Furthermore, as Steinhardt (2011) suggests, it allows to take into account the occupational segregation of immigrants irrespective of their actual level of education. Data from the Capitalia sample also show that the share of migrants employed by firms decreases with the white collars share on total employment, thus possibly confirming that migrants are mainly employed in low skilled jobs.

As discussed in the previous section, besides the firm's production function, we estimate its dual cost function which requires the use of input prices. Since we have no firm level prices for production factors at our disposal, we make use of sectoral level prices. Material and services price indices have been retrieved from EU-KLEMS Database[11] and are defined at 2 digit NACE Rev.1 level.

With reference to wages, the Capitalia database allows us to compute just an average wage—regardless of workers' nationality—as the ratio between the firm total labour cost, from balance sheet, and the number of employees. Therefore, in order to have distinct wages for native and migrant workers, we employ the individual-level administrative information from the WHIP database and compute the average wages for both native and migrant workers by region and NACE division. Due to the lack of firm level information on natives' and migrants' wages, we exploit these averages at region-sector level gathered from WHIP, so that all firms located in the same geographical area and operating in the same sector of activity face the same migrants' and natives' labour prices. The high representativeness of the WHIP information with respect to the employees' population in Italy makes us confident about the validity of our strategy.[12] The reliability of these proxies and the consistency of firm level wage bills re-computed on the basis of WHIP wages with total wage bills declared by firms in their balance sheet is further discussed in the Appendix 1.

Turning to our firm level sample, we report some statistics about the employment of foreign workers in Table 1. In particular, we focus on the distribution of firms

Table 1 Firms employing foreign labour by sector, size and area, %

	MIGR	shL^M	$shL^M{}_{MIGR=1}$
All sample	43	4.61	9.33
Area			
North	48.46	4.65	9.60
Center-South	25.59	2.12	8.27
Sector			
High skill intensive	40.98	3.72	9.07
Low skill intensive	41.16	3.97	9.66
Size			
SMEs	41.37	4.09	9.88
Large firms	38.21	1.48	3.88

All values are in percentage (%)

MIGR: share of firms employing foreign labour; shL^M: average share of foreign employees on total employment for the whole sample; $shL^M_{MIGR=1}$: average share of foreign employees on total employment for firms hiring migrant workforce

Footnote 9 continued
labour costs), or with implausible negative values. We also delete firms which are considered as outliers for at least 1 year in the sample period. Outliers have been defined as observations from bottom and top percentile of the distribution of the value-added/labour and capital/value-added ratios.

[10] In addition, if we look at the macro-level data for Italy displayed in Docquier et al. (2009) where the stock of immigrants by country of origin and educational level is provided for 1990 and 2000, we get evidence in favour of extra-EU immigrants as being most low educated. In 1990, 56 % of extra-EU immigrants had just completed primary education, 31 % of them also completed secondary education while only 13 % had a higher degree.

[11] The database can be accessed at http://www.euklems.net.

[12] It is fair to assume that wages for the same employee skill level and nationality are pretty homogeneous across firms within the same sector and geographical region. Also, the use of sector-region level wages helps to mitigate the endogeneity issue.

Table 2 Migrant versus only-natives employers

	y	*lp*	*l*	*sk*	*ky*	*c*	p_L	$\frac{p_{L_{DW}}}{p_{L_{DB}}}$
MIGR	−0.03**	−0.06***	0.25***	−0.06***	0.06***	−0.04**	−0.08***	−0.11***
	[0.02]	[0.01]	[0.02]	[0.00]	[0.02]	[0.02]	[0.01]	[0.02]
Obs	9,298	9,298	9,298	9,298	9,298	9,179	9,179	9,104
R^2	0.69	0.08	0.04	0.11	0.10	0.68	0.15	0.10

All regressions include sector, size, area dummies, the regional unemployment rate and the regional share of irregular workers

y: log of output; *lp*: log of labour productivity; *l*: log of number of employees; *sk*: skill ratio; *ky*: log of capital over output; *c*: log of total cost; p_L: log of average wage; $p_{L_{DW}}/p_{L_{DB}}$: log of native white to blue collars wage ratio. OLS regressions. S.E. are reported in brackets

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

employing migrants across sectors,[13] size classes[14] and geographical areas.[15] About 43 % of Italian manufacturing firms in the sample was employing migrant workers in 2003, even if the average share of migrants on the total employment of those firms was rather low (9.33 %). High skill intensive sectors seem to be less likely to employ foreign workers compared to low skill sectors even if we cannot detect any strong difference according to the technological level. The use of foreign labour is more widespread in Northern regions, where the presence of migrants has always been higher thanks to better job opportunities. Concerning firm's size, the smaller the firm, the higher the share of migrant workers in the total employment.

In order to enrich the above information, Table 2 shows that, once accounted for firms' sector, geographical area and size class, regional unemployment rate and the regional share of irregular workers,[16] firms employing foreigners have on average lower output, productivity, skill intensity and total costs. They also pay lower wages and display a lower wage ratio between high and low skilled workers. On the other hand, they are larger in terms of number of employees and more capital intensive. A higher capital intensity, together with a lower skill intensity for firms using migrant labour may be supportive of the evidence that extra-EU workers are mainly blue collars performing unskilled tasks that possibly complement the use of machineries, as suggested by Accetturo et al. (2012).

4 Results

We estimate production and cost functions for the whole sample of firms and for the two subsamples of high and low skill intensive sectors.[17] Henceforth, each Table will present the results concerning the five-input technology—native and foreign labour, L_D and L_M respectively, materials, *IM*, services, *IS* and capital, *K*—on the left hand side and the ones for the six-input technology—with domestic labour split into white collars, L_{DW}, and blue collars, L_{DB}—on the right hand side. Table 3 reports the production function coefficients gathered by estimating the system described by Eqs. 1–3 in the previous section. These coefficients are not readily interpretable given that, under the translog functional form, marginal product elasticities for each input vary from observation to observation. We then exploit these estimates in order to compute the output elasticities at the sample average of the variables. Table 4 shows instead the results of the translog cost function. The validity of our empirical models is confirmed by testing for the regularity conditions of monotonicity and quasi-concavity required by the theory for both the production and cost functions, that are displayed and discussed for both functions in Appendix 2 and 3 respectively.[18]

13 Sectors are classified as low skill intensive if they belong to the Traditional activities from the Pavitt's taxonomy. These activities are characterised by a lower skill ratio if compared with Non Traditional Sectors (Science-based, Scale-intensive and Specialised Suppliers) and their ratio is below the median value. Based on the 3 digit NACE Classification, low skill intensive sectors are 151–205, 212, 245, 246, 251, 286–287, 361–362, 364–366. High skill intensive sectors are 211, 221–244, 247, 252–285, 291–355, 363.

14 SMEs are firms with less than 250 employees and include 90 % of the sample.

15 Italy is divided into 20 NUTS 2 level administrative regions which are commonly grouped into four different areas characterised by similar geographic and economic conditions. The four areas are North-West, North-East, Center and South, even if for convenience here we group the Northern regions from the one part and the Central and Southern regions from the other. The latter also includes the two islands, Sardinia and Sicily. Firms in the Northern regions represent 68 % of our sample.

16 Both the regional unemployment rate and the regional share of irregular workers are from the National Institute of Statistics (Istat). The latter measure is computed as the percentage share of irregular workers on total workers in the region and its use in the estimation process allows us to account for the possible misreporting or underreporting of the number of foreign workers employed irregularly by the firms.

17 We also investigated heterogeneity across other dimensions—firms' size, location and international exposure—with no significant differences in estimation results.

18 For the sake of brevity, we just report the regularity conditions for estimations covering the whole sample of firms.

Table 3 Production function estimates

	$Y = F(L_D, L_M, K, IM, IS)$			$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$		
	All [1]	High skill intensive [2]	Low skill intensive [3]	All [4]	High skill intensive [5]	Low skill intensive [6]
α_{L_D}	0.529***	0.555***	0.515***			
	[0.006]	[0.009]	[0.009]			
$\alpha_{L_{DW}}$				0.262***	0.266***	0.245***
				[0.009]	[0.011]	[0.014]
$\alpha_{L_{DB}}$				0.315***	0.306***	0.314***
				[0.008]	[0.010]	[0.012]
α_{L_M}	0.056***	0.050***	0.055***	0.077***	0.067***	0.081***
	[0.004]	[0.005]	[0.007]	[0.005]	[0.007]	[0.008]
α_{IM}	0.122***	0.101***	0.125***	0.056***	0.043***	0.071***
	[0.004]	[0.006]	[0.006]	[0.006]	[0.008]	[0.008]
α_K	0.091***	0.093***	0.100***	0.114***	0.136***	0.108***
	[0.004]	[0.006]	[0.005]	[0.006]	[0.008]	[0.008]
α_{IS}	0.203***	0.201***	0.206***	0.176***	0.182***	0.180***
	[0.005]	[0.006]	[0.007]	[0.006]	[0.008]	[0.010]
$\alpha_{L_D L_D}$	0.080***	0.087***	0.076***			
	[0.002]	[0.002]	[0.002]			
$\alpha_{L_{DW} L_{DW}}$				0.022***	0.017***	0.032***
				[0.002]	[0.002]	[0.003]
$\alpha_{L_{DB} L_{DB}}$				0.020***	0.022***	0.024***
				[0.002]	[0.002]	[0.003]
$\alpha_{L_M L_M}$	0.002***	0.003***	0.001	0.002**	0.002**	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{IMIM}	0.193***	0.198***	0.191***	0.195***	0.200***	0.192***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{KK}	0.0121***	0.0137***	0.0124***	0.010***	0.011***	0.010***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{ISIS}	0.160***	0.165***	0.155***	0.160***	0.165***	0.155***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
α_{IML_D}	−0.058***	−0.063***	−0.056***			
	[0.001]	[0.001]	[0.001]			
$\alpha_{IML_{DW}}$				−0.028***	−0.031***	−0.024***
				[0.001]	[0.001]	[0.001]
$\alpha_{IML_{DB}}$				−0.030***	−0.029***	−0.031***
				[0.001]	[0.001]	[0.001]
α_{IML_M}	−0.007***	−0.006***	−0.008***	−0.008***	−0.007***	−0.009***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{IMK}	−0.013***	−0.013***	−0.014***	−0.014***	−0.015***	−0.015***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{IMIS}	−0.115***	−0.116***	−0.113***	−0.115***	−0.117***	−0.114***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{KL_D}	0.006***	0.007***	0.006***			
	[0.001]	[0.001]	[0.001]			
$\alpha_{KL_{DW}}$				0.002*	0.009***	−0.001
				[0.001]	[0.001]	[0.002]
$\alpha_{KL_{DB}}$				0.009***	0.006***	0.010***
				[0.001]	[0.001]	[0.002]

Table 3 continued

	$Y = F(L_D, L_M, K, IM, IS)$			$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$		
	All [1]	High skill intensive [2]	Low skill intensive [3]	All [4]	High skill intensive [5]	Low skill intensive [6]
α_{KL_M}	0.002***	0.002***	0.003***	0.002***	0.002**	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{KIS}	−0.008***	−0.010***	−0.007***	−0.008***	−0.012***	−0.006***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
α_{ISL_D}	−0.034***	−0.036***	−0.033***			
	[0.001]	[0.001]	[0.001]			
$\alpha_{ISL_{DW}}$				−0.011***	−0.014***	−0.009***
				[0.001]	[0.001]	[0.001]
$\alpha_{ISL_{DB}}$				−0.021***	−0.019***	−0.021***
				[0.001]	[0.001]	[0.001]
α_{ISL_M}	−0.004***	−0.003***	−0.003***	−0.005***	−0.004***	−0.006***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$\alpha_{L_DL_M}$	0.006***	0.004***	0.007***			
	[0.001]	[0.001]	[0.001]			
$\alpha_{L_{DW}L_M}$				0.001	0.003***	−0.002*
				[0.001]	[0.001]	[0.001]
$\alpha_{L_{DB}L_M}$				0.008***	0.004***	0.012***
				[0.001]	[0.001]	[0.001]
$\alpha_{L_{DW}L_{DB}}$				0.014***	0.016***	0.005**
				[0.001]	[0.001]	[0.002]
Observations	3,391	1,865	1,526	3,368	1,850	1,518
R-squared	0.993	0.993	0.993	0.993	0.993	0.993

Robust S.E. in brackets. All specifications also include area, time and sector dummies together with controls for regional unemployment rate and regional share of irregular workers

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

4.1 Output elasticities

Output elasticities for each input are reported in Table 5. In the whole sample (column 1) the doubling of migrant labour would correspond to an increase of only 1 % in the output of Italian manufacturing, while the contribution of natives would be fifteen times larger. The output elasticities are in general pretty similar among the sub-groups of firms. However, it is worth noting that a slightly higher contribution of foreign labour is shown for low skill intensive sectors while the contribution of domestic labour is slightly higher for firms in high skill intensive sectors.[19] The lower contribution of migrants to output may be related to different reasons. Migrants may be employed in less skill intensive tasks or less value-added intensive tasks with respect to native blue collars. In addition, they might have lower productivity in the use of the firms' machinery and, more in general, of capital equipment due to lower levels of experience and familiarity with the use of all equipment and machinery employed by Italian manufacturing firms.[20]

From these elasticities it is possible to assess how, ceteris paribus, the observed change in the employment of migrant labour may affect the distribution of economic activity between high and low skill intensive sectors. The

[19] Output elasticities for domestic labour, capital and material are close to the ones found by Yasar and Morrison Paul (2008) for Turkey, even if their set of production inputs is slightly different from ours.

[20] The overall evidence of a low contribution of migrants to manufacturing output might stem from the high correlation between the domestic and foreign labour indicators. If this was the case, a spurious complementarity relationship between the two factor inputs might also display. In order to ascertain the strength of such a collinearity we have calculated the correlation coefficient between domestic—total, white and blue collar—labour and foreign labour and in each case the correlation coefficient was lower than 0.4. In addition, to assess multicollinearity among the factor inputs in our system of equations, we computed the Variance Inflation Factors, which all proved rather low. We are grateful to an anonymous referee for having raised this point.

Table 4 Cost function estimates

	$Y = F(L_D, L_M, K, IM, IS)$			$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$		
	All [1]	High skill intensive [2]	Low skill intensive [3]	All [4]	High skill intensive [5]	Low skill intensive [6]
β_{L_D}	0.758***	0.793***	0.773***			
	[0.028]	[0.041]	[0.039]			
$\beta_{L_{DW}}$				0.232***	0.237***	0.255***
				[0.021]	[0.027]	[0.033]
$\beta_{L_{DB}}$				0.553***	0.490***	0.612***
				[0.026]	[0.035]	[0.038]
β_{L_M}	0.148***	0.181***	0.082***	0.093***	0.134***	0.039
	[0.013]	[0.017]	[0.019]	[0.020]	[0.028]	[0.029]
β_{IM}	−0.519***	−0.598***	−0.509***	−0.429***	−0.441***	−0.470***
	[0.058]	[0.080]	[0.079]	[0.047]	[0.064]	[0.067]
β_{IS}	0.612***	0.624***	0.654***	0.551***	0.580***	0.564***
	[0.051]	[0.069]	[0.070]	[0.041]	[0.054]	[0.058]
$\beta_{L_D L_D}$	0.012*	0.004	0.019*			
	[0.007]	[0.011]	[0.010]			
$\beta_{L_{DW} L_{DW}}$				0.004	0.014**	−0.016**
				[0.004]	[0.005]	[0.006]
$\beta_{L_{DB} L_{DB}}$				0.006	0.021***	−0.015*
				[0.005]	[0.007]	[0.008]
$\beta_{L_M L_M}$	−0.004*	0.001	−0.008***	−0.003	0.001	−0.007**
	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]
$\beta_{L_D L_M}$	−0.009***	−0.019***	0.001			
	[0.002]	[0.003]	[0.003]			
$\beta_{L_{DW} L_M}$				−0.002	−0.006**	0.003
				[0.002]	[0.003]	[0.003]
$\beta_{L_{DW} L_{DB}}$				−0.006	−0.016***	0.013**
				[0.004]	[0.005]	[0.006]
$\beta_{L_{DB} L_M}$				−0.010***	−0.014***	−0.007**
				[0.002]	[0.003]	[0.003]
β_{IMIM}	−0.994***	−0.644***	−1.204***	−1.032***	−0.716***	−1.179***
	[0.075]	[0.122]	[0.099]	[0.074]	[0.122]	[0.098]
β_{ISIS}	−0.908***	−0.583***	−1.059***	−0.943***	−0.668***	−1.008***
	[0.078]	[0.126]	[0.104]	[0.0751]	[0.122]	[0.101]
β_{IML_D}	0.021	0.02	0.037*			
	[0.014]	[0.019]	[0.021]			
$\beta_{IML_{DW}}$				−0.009*	−0.002	−0.013*
				[0.005]	[0.007]	[0.007]
$\beta_{IML_{DB}}$				0.039***	0.018	0.073***
				[0.009]	[0.011]	[0.014]
β_{IML_M}	0.028***	0.027***	0.030***	0.029***	0.026***	0.035***
	[0.003]	[0.004]	[0.005]	[0.003]	[0.004]	[0.004]
β_{IMIS}	0.946***	0.597***	1.138***	0.973***	0.675***	1.084***
	[0.075]	[0.123]	[0.099]	[0.073]	[0.121]	[0.097]
β_{ISL_D}	−0.024*	−0.005	−0.056***			
	[0.012]	[0.017]	[0.018]			
$\beta_{ISL_{DW}}$				0.014***	0.010*	0.013**
				[0.004]	[0.006]	[0.006]

Table 4 continued

	$Y = F(L_D, L_M, K, IM, IS)$			$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$		
	All [1]	High skill intensive [2]	Low skill intensive [3]	All [4]	High skill intensive [5]	Low skill intensive [6]
$\beta_{ISL_{DB}}$				−0.030***	−0.009	−0.064***
				[0.007]	[0.009]	[0.012]
β_{ISL_M}	−0.014***	−0.009***	−0.022***	−0.014***	−0.00739**	−0.0243***
	[0.002]	[0.003]	[0.004]	[0.002]	[0.003]	[0.004]
γ_K	−0.099***	−0.099***	−0.097***	−0.066***	−0.075***	−0.062***
	[0.006]	[0.009]	[0.008]	[0.016]	[0.023]	[0.022]
γ_{KL_D}	0.023***	0.023***	0.024***			
	[0.002]	[0.003]	[0.003]			
$\gamma_{KL_{DW}}$				0.011***	0.014***	0.008**
				[0.002]	[0.003]	[0.003]
$\gamma_{KL_{DB}}$				0.013***	0.010***	0.017***
				[0.002]	[0.003]	[0.004]
γ_{KL_M}	0.002*	0.003	0.000	0.003*	0.003	0.002
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
γ_{KIS}	0.005**	0.001	0.012***	0.007***	0.004	0.012***
	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]
γ_{KIM}	−0.031***	−0.027***	−0.037***	−0.039***	−0.036***	−0.043***
	[0.003]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]
γ_Y	1.333***	1.335***	1.342***	1.163***	1.168***	1.185***
	[0.008]	[0.013]	[0.011]	[0.021]	[0.032]	[0.030]
γ_{YL_D}	−0.100***	−0.099***	−0.107***			
	[0.003]	[0.004]	[0.004]			
$\gamma_{YL_{DW}}$				−0.033***	−0.037***	−0.031***
				[0.003]	[0.004]	[0.004]
$\gamma_{YL_{DB}}$				−0.074***	−0.068***	−0.081***
				[0.004]	[0.005]	[0.005]
γ_{YL_M}	−0.014***	−0.014***	−0.009***	−0.011***	−0.009***	−0.009***
	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]
γ_{YIM}	0.150***	0.148***	0.152***	0.157***	0.149***	0.162***
	[0.004]	[0.005]	[0.006]	[0.004]	[0.006]	[0.006]
γ_{YIS}	−0.036***	−0.035***	−0.036***	−0.044***	−0.040***	−0.046***
	[0.003]	[0.005]	[0.005]	[0.003]	[0.005]	[0.005]
γ_{YK}	0.006***	0.005***	0.006***	0.005***	0.005***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
Observations	3,367	1,848	1,519	3,338	1,831	1,507
R-squared	0.995	0.995	0.995	0.993	0.994	0.993

Robust S.E. in brackets. All specifications also include area, time and sector dummies together with controls for regional unemployment rate and regional share of irregular workers

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

percentage growth in output explained by the hiring of foreign workers can be simply obtained by multiplying the estimated elasticities by the effective average growth in the use of migrant labour.

Table 6 reports the observed percentage increase in the employment of migrant workers ($dlnL_M$) for the estimation sample, which turns into a contribution of around 0.03 % to the average growth in manufacturing output (0.03 and

Table 5 Output elasticities

	$Y = F(L_D, L_M, K, IM, IS)$			$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$		
	All [1]	High skill intensive [2]	Low skill intensive [3]	All [4]	High skill intensive [5]	Low skill intensive [6]
K	0.039***	0.038***	0.045***	0.043***	0.043***	0.046***
	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
L_D	0.144***	0.160***	0.137***			
	[0.002]	[0.003]	[0.003]			
L_{DW}				0.062***	0.070***	0.054***
				[0.002]	[0.003]	[0.003]
L_{DB}				0.081***	0.080***	0.081***
				[0.002]	[0.003]	[0.003]
L_M	0.014***	0.012***	0.015***	0.019***	0.015***	0.022***
	[0.001]	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]
IM	0.520***	0.502***	0.533***	0.515***	0.504***	0.523***
	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
IS	0.282***	0.288***	0.269***	0.280***	0.288***	0.275***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]

S.E. in brackets. Output elasticities are computed at the sample average of the variables

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

Table 6 Observed growth in labour input quantities and prices

	All (%)	High skill intensive (%)	Low skill intensive (%)
$dln\bar{L}_D$	0.59	1.05	0.01
$dln\bar{P}_D$	3.28	3.19	3.40
$dln\bar{L}_M$	3.34	2.95	3.84
$dln\bar{P}_M$	4.67	4.32	5.11
$dln\bar{L}_{DW}$	2.13	2.13	2.12
$dln\bar{P}_{DW}$	4.52	2.82	6.88
$dln\bar{L}_{DB}$	0.34	0.97	−0.45
$dln\bar{P}_{DB}$	2.15	2.52	1.67

Authors' calculation on the Capitalia sample

Changes in the sample period are reported

0.05 % for high and low skill intensive sectors, respectively). This implies that the observed growth in migrant labour could explain 0.02 % of the output increase of a low skill intensive firm with respect to the average manufacturing firm, and the relative decrease in the output of a high skill intensive firm by the same percentage. If the estimated elasticities are applied to each firm in our sample according to the sector she belongs to, the overall effect would approximately correspond to an increase of 2 % of the weight of low skill intensive sectors in the aggregate of manufacturing. In other words, ceteris paribus, the observed increase in the foreign-born workforce could explain by itself a rise by approximately 2 % in the weight of low skill intensive sectors.

When domestic labour is split into white and blue collars, the right side of Table 5 confirms the above results of a lower contribution of foreign labour to production—when compared to both native skilled and unskilled labour—and its relatively higher importance in low skill intensive sectors. As expected, the contribution of white collars is instead higher in high skill intensive sectors.

4.2 Demand elasticities

Table 7 shows partial demand elasticities which refer to the degree of *p-substitutability*[21] between each pair of inputs.

The general message is that domestic and foreign labour are p-complements in Italian manufacturing production.

Domestic and foreign workers in fact are likely to perform different tasks in the firm production process without competing against each other. Even when natives are employed as blue collars, they may be involved in more specialised tasks, while firms may hire migrant workers for manual and routine jobs with the lowest skill content (Peri and Sparber 2009; Ottaviano and Peri 2011). This would also explain the higher contribution of native workers to output compared to migrants that we have highlighted in the previous paragraph.

[21] We only show the estimated elasticities for the domestic and foreign labour with respect to each other and to the remaining inputs; by symmetry, their signs also tell the kind of relationship of the remaining inputs with respect to domestic and foreign labour.

Table 7 Partial demand elasticities: direct estimates from the cost function

	All	High skill intensive	Low skill intensive
	$C = F(p_{L_D}, p_{L_M}, K, p_{IM}, p_{IS})$		
$\eta_{x_{L_D}p_{L_D}}$	−0.738***	−0.765***	−0.707***
	[0.035]	[0.049]	[0.051]
$\eta_{x_{L_D}p_{L_M}}$	−0.032***	−0.070***	0.013
	[0.012]	[0.016]	[0.017]
$\gamma_{x_{L_D}K}$	0.114***	0.107***	0.124***
	[0.009]	[0.013]	[0.013]
$\eta_{x_{L_D}p_{IM}}$	0.598***	0.573***	0.690***
	[0.069]	[0.090]	[0.105]
$\eta_{x_{L_D}p_{IS}}$	0.171***	0.262***	0.003
	[0.060]	[0.077]	[0.093]
$\eta_{x_{L_M}p_{L_M}}$	−1.279***	−0.932***	−1.827***
	[0.150]	[0.176]	[0.280]
$\eta_{x_{L_M}p_{L_D}}$	−0.485***	−0.899***	0.267
	[0.177]	[0.206]	[0.342]
$\gamma_{x_{L_M}K}$	0.176*	0.173	0.037
	[0.104]	[0.123]	[0.198]
$\eta_{x_{L_M}p_{IM}}$	2.540***	2.088***	3.616***
	[0.214]	[0.223]	[0.474]
$\eta_{x_{L_M}p_{IS}}$	−0.777***	−0.256	−2.055***
	[0.183]	[0.187]	[0.407]
	$C = F(p_{L_{DW}}, p_{L_{DB}}, p_{L_M}, K, p_{IM}, p_{IS})$		
$\eta_{x_{L_{DW}}p_{L_{DW}}}$	−0.835***	−0.600***	−1.385***
	[0.136]	[0.141]	[0.165]
$\eta_{x_{L_{DW}}p_{L_{DB}}}$	−0.13	−0.327**	0.413***
	[0.128]	[0.132]	[0.157]
$\eta_{x_{L_{DW}}p_{L_M}}$	−0.06	−0.137*	0.080
	[0.071]	[0.075]	[0.084]
$\gamma_{x_{L_{DW}}p_K}$	0.373***	0.364***	0.207**
	[0.073]	[0.079]	[0.083]
$\eta_{x_{L_{DW}}p_{IM}}$	0.18	0.439**	0.180
	[0.172]	[0.180]	[0.194]
$\eta_{x_{L_{DW}}p_{IS}}$	0.745***	0.533***	0.626***
	[0.145]	[0.150]	[0.163]
$\eta_{x_{L_{DB}}p_{L_{DB}}}$	−0.839***	−0.660***	−1.155***
	[0.069]	[0.088]	[0.120]
$\eta_{x_{L_{DB}}p_{L_{DW}}}$	−0.05	−0.156**	0.231***
	[0.049]	[0.063]	[0.088]
$\eta_{x_{L_{DB}}p_{L_M}}$	−0.117***	−0.162***	−0.095*
	[0.031]	[0.040]	[0.051]
$\gamma_{x_{L_{DB}}K}$	0.167***	0.120***	0.246***
	[0.033]	[0.043]	[0.054]
$\eta_{x_{L_{DB}}p_{IM}}$	1.019***	0.713***	1.599***
	[0.113]	[0.137]	[0.207]
$\eta_{x_{L_{DB}}p_{IS}}$	−0.11	0.17	−0.667***
	[0.096]	[0.113]	[0.180]
$\eta_{x_{L_M}p_{L_M}}$	−1.260***	−0.887***	−1.724***
	[0.200]	[0.241]	[0.363]

Table 7 continued

	All	High skill intensive	Low skill intensive
$\eta_{x_{L_M}p_{L_{DW}}}$	−0.16	−0.373*	0.340
	[0.175]	[0.204]	[0.355]
$\eta_{x_{L_M}p_{L_{DB}}}$	−0.753***	−0.927***	−0.713*
	[0.199]	[0.229]	[0.385]
$\gamma_{x_{L_M}K}$	0.303*	0.29	0.200
	[0.169]	[0.248]	[0.232]
$\eta_{x_{L_M}p_{IM}}$	2.955***	2.334***	4.446***
	[0.237]	[0.255]	[0.497]
$\eta_{x_{L_M}p_{IS}}$	−0.878***	−0.24	−2.433***
	[0.198]	[0.210]	[0.423]

S.E. in brackets. $\gamma_{x_{L_M}K}$, $\gamma_{x_{L_D}K}$, $\gamma_{x_{L_{DW}}K}$, and $\gamma_{x_{L_{DB}}K}$, actually represents the demand elasticity of L_M, L_D, L_{DW} and L_{DB}, respectively, when the fixed factor increases

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

The elasticity of the demand of migrant workers with respect to domestic wages is shown to be higher than the elasticity of domestic labour with respect to the wage of foreign workers. From this, the observed change in the price of native labour accounts for 48 % of the total variation in foreign employment while the variation in migrants' wages accounts only for 25 % of the change in the use of domestic labour.[22]

The own elasticities are shown to be generally higher in absolute value for the "weaker" group—i.e. foreign workers—and this supports the evidence on segmented labour markets provided by Hamermesh (1993) which also corroborates the estimates of the own elasticity of natives around 0.23 in absolute value.

Domestic white and blue collars seem to be *p-substitutes* in low skill intensive sectors. The same relationship, although not significant, concerns foreign labour and domestic white collars, thus generally hinting at substitutability between high and low skilled labour in the most traditional sectors of Italian manufacturing.

Turning to the relationship with the other inputs, foreign labour results *p-substitute* with respect to materials. Since *p-substitutability* with respect to materials concerns also domestic blue collars, we could read such results as evidence of potential vertical integration/disintegration processes in response to increasing/decreasing costs for materials. This finding recalls the evidence provided by Barba Navaretti et al. (2008) on Italian offshorers as less likely to employ foreign-born workforce.

[22] From Table 6 $dln\hat{L}_D = |\eta_{x_{L_D}p_{L_M}}| * dln\bar{P}_{L_M}/dln\bar{L}_D = 0.032 * 4.67/0.59 = 0.253$ and $dln\hat{L}_M = |\eta_{x_{L_M}p_{L_D}}| * dln\bar{P}_{L_D}/dln\bar{L}_M = 0.485 * 3.28/3.34 = 0.476$.

Table 8 Morishima elasticities of substitution, $\frac{\partial ln(X_i/X_j)}{\partial lnp_j}$

	All [1]	High skill intensive [2]	Low skill intensive [3]		All [4]	High skill intensive [5]	Low skill intensive [6]
		$C = F(p_{L_D}, p_{L_M}, K, p_{IM}, p_{IS})$				$C = F(p_{L_DW}, p_{L_DB}, p_{L_M}, K, p_{IM}, p_{IS})$	
		$\frac{\partial ln(L_D/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_{DW}/X_j)}{\partial lnp_j}$	
$mes_{L_DL_M}$	1.247***	0.862***	1.840***	$mes_{L_{DW}L_{DB}}$	0.714***	0.332*	1.568***
	[0.159]	[0.189]	[0.292]		[0.171]	[0.189]	[0.241]
mes_{L_DIM}	3.106***	2.424***	3.580***	$mes_{L_{DW}L_M}$	1.196***	0.750***	1.804***
	[0.171]	[0.274]	[0.233]		[0.242]	[0.286]	[0.410]
mes_{L_DIS}	4.056***	3.020***	4.335***	$mes_{L_{DW}IM}$	2.711***	2.402***	2.982***
	[0.298]	[0.468]	[0.398]		[0.237]	[0.318]	[0.291]
				$mes_{L_{DW}IS}$	4.819***	3.627***	4.822***
					[0.325]	[0.479]	[0.411]
						$\frac{\partial ln(L_{DB}/X_j)}{\partial lnp_j}$	
				$mes_{L_{DB}L_{DW}}$	0.787***	0.444**	1.616***
					[0.172]	[0.187]	[0.234]
				$mes_{L_{DB}L_M}$	1.143***	0.725***	1.629***
					[0.217]	[0.265]	[0.387]
				$mes_{L_{DB}IM}$	3.546***	2.676***	4.402***
					[0.195]	[0.301]	[0.294]
				$mes_{L_{DB}IS}$	3.964***	3.267***	3.529***
					[0.301]	[0.457]	[0.440]
		$\frac{\partial ln(L_M/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_M/X_j)}{\partial lnp_j}$	
$mes_{L_ML_D}$	0.250	−0.130	0.973***	$mes_{L_ML_{DW}}$	0.677***	0.230	1.721***
	[0.178]	[0.209]	[0.340]		[0.263]	[0.292]	[0.450]
				$mes_{L_ML_{DB}}$	0.090	−0.270	0.440
					[0.234]	[0.278]	[0.429]
mes_{L_MIM}	5.048***	3.938***	6.506***	mes_{L_MIM}	5.482***	4.298***	7.250***
	[0.270]	[0.354]	[0.522]		[0.287]	[0.377]	[0.540]
mes_{L_MIS}	3.108***	2.503***	2.277***	mes_{L_MIS}	3.196***	2.854***	1.764***
	[0.357]	[0.496]	[0.603]		[0.354]	[0.485]	[0.607]
		$\frac{\partial ln(L_{IM}/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_{IM}/X_j)}{\partial lnp_j}$	
mes_{IML_D}	0.984***	1.021***	0.974***	$mes_{IML_{DW}}$	0.845***	0.635***	1.398***
	[0.0544]	[0.0770]	[0.0783]		[0.138]	[0.145]	[0.167]
				$mes_{IML_{DB}}$	0.993***	0.777***	1.366***
					[0.0759]	[0.0972]	[0.132]
mes_{IML_M}	1.348***	1.005***	1.895***	mes_{IML_M}	1.329***	0.954***	1.802***
	[0.150]	[0.177]	[0.281]		[0.200]	[0.242]	[0.364]
		$\frac{\partial ln(L_{IS}/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_{IS}/X_j)}{\partial lnp_j}$	
mes_{ISL_D}	0.860***	0.963***	0.709***	$mes_{ISL_{DW}}$	0.912***	0.673***	1.466***
	[0.0570]	[0.0785]	[0.0825]		[0.136]	[0.142]	[0.165]
				$mes_{ISL_{DB}}$	0.809***	0.709***	1.000***
					[0.0731]	[0.0928]	[0.127]
mes_{ISL_M}	1.242***	0.917***	1.760***	mes_{ISL_M}	1.223***	0.875***	1.649***
	[0.150]	[0.176]	[0.280]		[0.200]	[0.242]	[0.363]

S.E. in brackets. MES are computed according to formula 5

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

P-complementarity holds between foreign labour and services in the overall sample and in low skill intensive sectors. Anyway, it is difficult to deepen this finding without any description of the kind of services entering the firms' production processes.

4.3 Morishima elasticities of substitution

Although domestic and foreign labour appear to be complements according to the traditional absolute definition of complementarity that has usually been addressed in the literature, it may well happen that factor price variations—through changes in the absolute demands—induce significant changes in the relative use of inputs and hence in the production techniques adopted at the firm level.

Table 8 shows that domestic and foreign labour are indeed *MES-substitutes* since an increase in the wage of migrants increases the natives/migrants ratio: a 1 % increase in the price of migrant labour causes the demand of migrants to decrease more than the demand of natives. Anyway, it is interesting to highlight that an increase in the wage of natives is followed by a change in the migrants/natives ratio only in low skill intensive sectors, where the positive sign suggests that production techniques may become more migrant labour intensive as domestic wages increase.

Turning to the remaining elasticities, they all show a positive sign. A 1 % increase in the price of materials is followed by an increase of 5.05 % in the migrants/materials ratio. The finding might point again at the vertical integration/disintegration process that firms undertake as a cost-saving strategy when material suppliers apply higher/lower prices. In general, the *MES* elasticities with respect to materials are higher for foreign than for domestic labour. The reverse holds true as far as elasticities with respect to services are taken into account.

4.4 Skill ratio

Finally, an interesting point is to assess how the white-collar/blue-collar ratio, $SR = \frac{L_{DW}}{(L_{DB}+L_M)}$, changes in response to a 1 % change in the availability of migrants. From the derivation of the skill ratio with respect to the price of foreign labour we have:

$$\frac{dlnSR}{dlnP_{L_M}} = \eta_{L_{DW}L_M} - \eta_{L_{DB}L_M} * \frac{L_{DB}}{(L_{DB}+L_M)} - \eta_{L_M L_M} * \frac{L_M}{(L_{DB}+L_M)}$$

from which follows

$$\frac{dlnSR}{dlnL_M} = \frac{\eta_{L_{DW}L_M}}{\eta_{L_M L_M}} - \frac{\eta_{L_{DB}L_M}}{\eta_{L_M L_M}} * \frac{L_{DB}}{(L_{DB}+L_M)} - \frac{L_M}{(L_{DB}+L_M)} \quad (6)$$

Table 9 Changes in the skill ratio explained by observed migration changes

	All	High skill int. sectors	Low skill int. sectors
$\frac{dlnSR}{dlnL_M}$	−0.166**	−0.147	−0.206***
	[0.065]	[0.101]	[0.062]
$\frac{dlnSR}{dlnL_M} * dln\bar{L}_M$	−0.553**	−0.433	−0.790***
	[0.216]	[0.297]	[0.239]

S.E. in brackets. $\frac{dlnSR}{dlnL_M}$ is computed according to Eq. 6

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

Table 9 shows that an increase by 1 % in foreign labour causes a reduction of 0.17 % in the skill ratio for the overall sample, and of 0.21 % for low skill intensive sectors (the coefficient turns to be non significant for high skill intensive sectors). When we take into account the observed average annual growth in the availability of migrant blue collars in the second row of the Table, migrant labour growth is associated, ceteris paribus, with a decline in the skill ratio around 0.55 %, mainly driven by the result on low skill intensive sectors (−0.79 %). Had the availability of migrants not increased in these sectors, the growth in the skill ratio could have been higher (4 % instead of the actual 3.2 %).

4.5 Robustness checks

We test the robustness of our results to the change of the proxy of the natives' and migrants' wages. Due to confidentiality reasons, Italian firm-level wages by worker nationality are not publicly available to researchers. Nevertheless, to test the robustness of our results to a more detailed definition of wages than the region-sector one adopted in the baseline cost function specification, we further take into account the possibility that firms may face different wages according to their size. We then exploit a more disaggregated wage measure, for both natives and migrants, which varies across region, sector and firm's size.[23]

All results previously discussed remain qualitatively unchanged; for the sake of brevity,[24] we show here in Table 10 only the Morishima elasticities of substitution and the results regarding the skill ratio. Our findings seems to

[23] We consider five size classes: less than 20 employees, 20–49 employees, 50–249 employees, 250–499 employees and more than 500 employees. This proxy has been kindly provided by Laboratorio Revelli, a research center that elaborates for INPS all administrative data on workers.

[24] The complete set of results is available upon request.

Table 10 Robustness: Morishima elasticities of substitution and skill ratio

	All	High skill intensive	Low skill intensive		All	High skill	Low skill
	[1]	[2]	[3]		[4]	[5]	[6]
		$C = F(p_{L_D}, p_{L_M}, K, p_{IM}, p_{IS})$				$C = F(p_{L_DW}, p_{L_DB}, p_{L_M}, K, p_{IM}, p_{IS})$	
		$\frac{\partial ln(L_D/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_{DW}/X_j)}{\partial lnp_j}$	
$mes_{L_D L_M}$	1.060***	0.628***	1.698***	$mes_{x_{L_{DW}} p_{L_{DB}}}$	0.718***	0.274	1.373***
	[0.186]	[0.181]	[0.395]		[0.181]	[0.187]	[0.279]
$mes_{L_D IM}$	2.870***	2.193***	3.349***	$mes_{x_{L_{DW}} p_{L_M}}$	1.265***	0.700***	1.813***
	[0.180]	[0.301]	[0.240]		[0.241]	[0.266]	[0.385]
$mes_{L_D IS}$	4.293***	3.077***	4.732***	$mes_{x_{L_{DW}} p_{IM}}$	2.454***	2.112***	2.688***
	[0.307]	[0.513]	[0.389]		[0.243]	[0.331]	[0.330]
				$mes_{x_{L_{DW}} p_{IS}}$	5.163***	3.854***	5.321***
					[0.329]	[0.504]	[0.436]
						$\frac{\partial ln(L_{DB}/X_j)}{\partial lnp_j}$	
				$mes_{x_{L_{DB}} p_{L_{DW}}}$	0.743***	0.347*	1.464***
					[0.179]	[0.180]	[0.279]
				$mes_{x_{L_{DB}} p_{L_M}}$	1.258***	0.690***	1.735***
					[0.218]	[0.251]	[0.347]
				$mes_{x_{L_{DB}} p_{IM}}$	3.313***	2.391***	3.983***
					[0.205]	[0.321]	[0.289]
				$mes_{x_{L_{DB}} p_{IS}}$	4.287***	3.510***	4.011***
					[0.305]	[0.487]	[0.430]
		$\frac{\partial ln(L_M/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_M/X_j)}{\partial lnp_j}$	
$mes_{L_M L_D}$	0.25	−0.144	0.979**	$mes_{L_M L_{DW}}$	0.626**	0.145	1.525***
	[0.209]	[0.200]	[0.455]		[0.266]	[0.275]	[0.451]
				$mes_{L_M L_{DB}}$	0.377	−0.171	0.954**
					[0.243]	[0.278]	[0.391]
$mes_{L_M IM}$	4.725***	3.427***	6.469***	$mes_{L_M IM}$	5.024***	3.838***	6.117***
	[0.309]	[0.369]	[0.677]		[0.291]	[0.385]	[0.491]
$mes_{L_M IS}$	3.248***	2.614***	2.332***	$mes_{L_M IS}$	3.573***	3.127***	2.599***
	[0.384]	[0.531]	[0.707]		[0.352]	[0.506]	[0.561]
		$\frac{\partial ln(L_{IM}/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_{IM}/X_j)}{\partial lnp_j}$	
mes_{IML_D}	0.715***	0.682***	0.789***	$mes_{IML_{DW}}$	0.738***	0.483***	1.282***
	[0.0577]	[0.0889]	[0.0767]		[0.143]	[0.136]	[0.217]
				$mes_{IML_{DB}}$	0.837***	0.588***	1.124***
					[0.0804]	[0.0979]	[0.126]
mes_{IML_M}	1.129***	0.745***	1.738***	mes_{IML_M}	1.372***	0.872***	1.802***
	[0.178]	[0.169]	[0.385]		[0.200]	[0.228]	[0.325]
		$\frac{\partial ln(L_{IS}/X_j)}{\partial lnp_j}$				$\frac{\partial ln(L_{IS}/X_j)}{\partial lnp_j}$	
mes_{ISL_D}	0.718***	0.677***	0.759***	$mes_{ISL_{DW}}$	0.838***	0.562***	1.388***
	[0.0604]	[0.0909]	[0.0795]		[0.142]	[0.134]	[0.215]
				$mes_{ISL_{DB}}$	0.729***	0.590***	0.852***
					[0.0773]	[0.0937]	[0.121]
mes_{ISL_M}	1.044***	0.669***	1.633***	mes_{ISL_M}	1.284***	0.807***	1.672***
	[0.178]	[0.168]	[0.384]		[0.199]	[0.227]	[0.324]

Table 10 continued

All	High skill intensive	Low skill intensive		All	High skill	Low skill
[1]	[2]	[3]		[4]	[5]	[6]
				Skill ratio		
			$\frac{dlnSR}{dlnL_M}$	−0.131**	−0.135	−0.143*
				[0.065]	[0.105]	[0.073]
			$\frac{dlnSR}{dlnL_M} * dln\bar{L}_M$	−0.439**	−0.398	−0.550*
				[0.219]	[0.310]	[0.281]

S.E. in brackets. MES are computed according to formula 5

Elasticities are obtained by exploiting sector-region-firm size level averages of natives' and migrants' wages

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

be confirmed, when we take into account heterogeneous wages by firm size. In other words, even if we are prevented from controlling for wages computed at firm level, results in Table 10 show that moving to a finer definition of unit labour costs does not affect our main findings. In addition, the advantage of using aggregate information on input costs in this context might be relevant to mitigate endogeneity issues.

5 Conclusion

With this paper we contribute to the existing firm level evidence on the role of foreign labour to manufacturing production. By exploiting the information on the extra-EU workforce hired by Italian manufacturing firms, we model a flexible functional form for the firm level technology with five inputs: domestic labour, foreign labour, materials, services and capital. In a second stance, native labour is further split according to the skill contents of the job into white and blue collars. From the coefficients of the estimated production and cost functions we retrieve the output, partial demand elasticities and the Morishima elasticity of substitution among the inputs, in order to highlight the role of foreign labour in the Italian manufacturing production. The focus is on both its contribution to the overall production and its interaction with respect to the remaining inputs, especially native labour.

Our results show that the estimated elasticity of output with respect to extra-EU migrant labour is generally very small compared to the elasticity to native labour. Differently from previous empirical studies, but in line with the standard trade theory predictions, we find that, ceteris paribus, an increase in the adoption of foreign labour may change the manufacturing output mix in favour of low skill intensive sectors.

When turning to the evidence on the complementarity/substitutability nexus between foreign and domestic labour, foreign workers are *p-complements* with respect to blue collar natives and, in high skill intensive sectors, they are also complements with respect to high skilled native labour.

In general, foreign labour seems to represent an element of flexibility in the firm technology: its own and cross estimated elasticities are much higher than the ones estimated for native labour and it is also more responsive to what happens to non-labour variable factors such as materials and services.

When we investigate the Morishima elasticities of substitution, the foreign/domestic labour ratio in production only increases if migrants are ready to accept lower wages, while it never changes in response to an increase in the wage of native workers. However, when splitting domestic labour into high and low skilled workers, white collars are *MES-substitutes* for blue collars (both native and foreign) and vice-versa. This may suggest that when the price of skilled labour increases, firms tend to downgrade their production techniques towards less skill intensive ones. Turning to the effect of an increased availability of blue collar migrants on the ratio of white to blue collar workers, we find that ceteris paribus the presence of migrants modestly reduces the ratio in low skill intensive sectors only.

From the above evidence it emerges that, although in our sample period extra-EU migrants explain a small fraction of Italian manufacturing production and they do not seem to represent a direct threat for native employment in manufacturing, a sharp increase in their availability might foster production of firms in less skill intensive sectors and push them towards the use of low skill intensive production techniques. National data indeed show that in 2006 only 9 % of the whole foreign employment was represented by skilled workers, and in 2008 this share decreased to 8 %.

Unfortunately, our firm level data have a short time coverage and this fact represents a serious limit to the analysis of structural issues. Were detailed information available, further work could investigate the relationship between innovative activity and the increased availability of low skilled foreign workers and evaluate their contribution to the growth of the total factor productivity. If innovation activity goes hand in hand with production skill intensity, our results would suggest that innovation might be discouraged by the availability of cheap low skilled migrant labour; in addition, the specialisation of firms may move, within the same sector, towards less sophisticated and skill intensive goods.

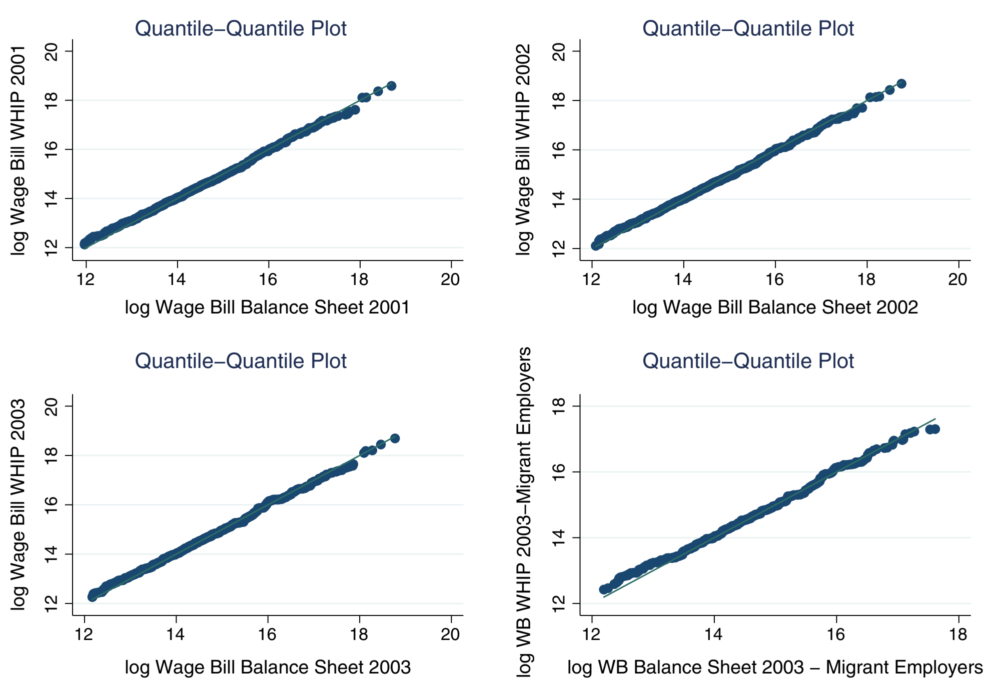
Acknowledgments The financial support received from the Italian Ministry of Education, University and Research (Scientific Research Programs of National Relevance 2007 on European Union Policies, Economic and Trade Integration Processes and WTO negotiation-PUE&PIEC) is gratefully acknowledged. Daniela Maggioni also acknowledges financial support from the Fondazione CRT—Progetto Alfieri in the framework of the Centro Studi Luca d'Agliano research project on "Migration and Mobility of Tasks: the Internationalisation of the Firm". We are grateful to three anonymous referees, the editors of the Journal of Productivity Analysis, Frank Barry, Roberto Esposti, Stefanie Haller, Jack Lucchetti, Claudia Pigini, Alberto Russo and Stefano Staffolani for useful comments and suggestions. We are also grateful to Stefano Staffolani and Enzo Valentini for providing us respectively with the WHIP database and the shadow economy indicator. We thank Roberto Leombruni and Michele Mosca for kindly providing us with region-sector-size wages from the comprehensive WHIP database version available at Laboratorio Revelli. We thank the participants of the Unicredit Workshop "I cambiamenti della manifattura italiana" at University of Milan, the Etta Chiuri's conference in Bari, the TOM Conference in Venice and the ESRI seminar in Dublin for their comments.

Appendix 1: Wage bill—comparison WHIP balance sheet

In order to check the consistency of information on wages at region-sector level sourced from WHIP with firm level evidence on total expenditure on wages and salaries (wage bill) from balance sheet data, for each firm we re-compute the total wage bill on the basis of region-sector level average wages for domestic and extra-EU workers. Thus for each firm we compute:

$$WageBill\_WHIP_{iRSt} = wage_{RSt}^{Natives\ \mathrm{WHIP}} * L_{D\ it} + wage_{RSt}^{Extra-\mathrm{EU\ WHIP}} * L_{M\ it} \quad (7)$$

We thus compare the wage bill in Eq. 7 to the total wage bill from balance sheet directly retrieved from balance sheet data available in Capitalia for each firm i located in region R and operating in sector S at time t . First, we compute the correlation coefficient which is extremely high, 96 %. Second, for each year of our sample and for the sub-sample of firms employing migrants in 2003, we compare the whole distribution of the two variables in logs. Quantile–quantile plots in Figure A, thus, confirm that when combining the region-sector level information on wages by worker nationality from WHIP with firm level information on domestic and extra-EU labour units we get a firm level total wage bill that is highly consistent with the one firms declare in their balance sheet.



Appendix 2: Regularity conditions—monotonicity

Share	Production function				Cost function			
	$Y = F(L_D, L_M, K, IM, IS)$		$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$		$Y = F(L_D, L_M, K, IM, IS)$		$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$	
	Mean	%Viol.	Mean	%Viol.	Mean	%Viol.	Mean	%Viol.
S_L	0.198		0.19		0.216		0.210	
$\hat{S}_L$	0.186		0.19		0.218		0.212	
S_{L_D}	0.131				0.165			
$\hat{S}_{L_D}$	0.144	1.4			0.204	4.16		
$S_{L_{DW}}$			0.05				0.052	
$\hat{S}_{L_{DW}}$			0.06	2.10			0.029	0.00
$S_{L_{DB}}$			0.08				0.087	
$\hat{S}_{L_{DB}}$			0.08	1.00			0.076	1.20
S_{L_M}	0.010		0.01		0.013		0.012	
$\hat{S}_{L_M}$	0.014	2.7	0.02	3.41	0.013	25.75	0.012	12.55
S_{IM}	0.468		0.47		0.496		0.509	
$\hat{S}_{IM}$	0.520	0.5	0.51	0.00	0.496	0.00	0.507	0.00
S_{IS}	0.249		0.25		0.288		0.281	
$\hat{S}_{IS}$	0.282	0.7	0.28	1.00	0.286	0.00	0.281	0.00
S_K	0.033		0.03					
$\hat{S}_K$	0.039	1.6	0.04	1.00				

The columns "Mean" contain the computed (S) and estimated ($\hat{S}$) revenue share of inputs. The columns "%Viol." contain the percentage of observations violating the monotonicity condition

Monotonicity entails non-negative estimated revenue/cost shares. The Table above shows the shares computed from balance sheet data, S_i, and their predicted values, $\hat{S}_i$, as obtained from the estimation of the production function and cost function, respectively with five and six inputs. The two sets are pretty similar thus confirming the goodness of the estimation. To verify the reliability of our predicted shares, we make use of the average wages from WHIP, calculate the shares of migrant and domestic workers in total output and total cost and compare them to the average of their prediction from the estimates of the empirical model. The total % of violation of monotonicity, i.e. the number of negative predictions, is fairly low in general and slightly higher for the predicted share of migrants from the cost function. However, comparing the predicted and "actual" shares of foreign and domestic workers in total output and in total cost we find that, although not exactly equal, the prediction reflects our calculations (a slightly worse performance is shown for domestic labour shares, especially white collar, from the cost function). Sample averages and the average predictions for material, services and capital are very similar too. The estimations reported in the test have been obtained by dropping from the sample the observations that violate monotonicity.

Appendix 3: Regularity conditions on own partial price and demand elasticities—quasi-concavity

	Production function						Cost function				
	$\varepsilon_{p_i x_j}$ based on:						$\eta_{x_i p_j}$ based on:				
	Mean ε_{ij} across i	Median ε_{ij} across i	Estimated shares	Calculated shares	Violations (%)		Mean η_{ij} across i	Median η_{ij} across i	Estimated shares	Calculated shares	Violations (%)
	$Y = F(L_D, L_M, K, IM, IS)$						$Y = F(L_D, L_M, K, IM, IS)$				
$\varepsilon_{p_{L_D} x_{L_D}}$	−0.01	−0.30	−0.23	−0.18	14.39	$\eta_{x_{L_D} p_{L_D}}$	−0.70	−0.73	−0.74	−0.77	0.00
$\varepsilon_{p_{L_M} x_{L_M}}$	−0.74	−0.83	−0.90	−0.87	0.06	$\eta_{x_{L_M} p_{L_M}}$	−2.49	−1.31	−1.28	−1.46	0.00
$\varepsilon_{p_{IM} x_{IM}}$	−0.04	−0.10	−0.09	−0.10	9.17	$\eta_{x_{IM} p_{IM}}$	−2.58	−2.54	−2.51	−2.52	0.00
$\varepsilon_{p_{IS} x_{IS}}$	0.10	−0.15	−0.12	−0.07	17.19	$\eta_{x_{IS} p_{IS}}$	−3.96	−3.87	−3.89	−3.82	0.00
$\varepsilon_{p_K x_K}$	−0.53	−0.65	−0.62	−0.57	2.39						
	$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$						$Y = F(L_{DW}, L_{DB}, L_M, K, IM, IS)$				
$\varepsilon_{p_{L_{DW}} x_{L_{DW}}}$	−0.41	−0.59	−0.59	−0.49	3.55	$\eta_{x_{L_{DW}} p_{L_{DW}}}$	−0.44	−0.82	−0.83	−0.87	0.00
$\varepsilon_{p_{L_{DB}} x_{L_{DB}}}$	−0.62	−0.67	−0.54	−0.52	0.50	$\eta_{x_{L_{DB}} p_{L_{DB}}}$	−0.23	−0.81	−0.84	−0.84	1.21
$\varepsilon_{p_{L_M} x_{L_M}}$	−0.83	−0.89	−0.92	−0.86	0.00	$\eta_{x_{L_M} p_{L_M}}$	−1.71	−1.27	−1.26	−1.26	0.00
$\varepsilon_{p_{IM} x_{IM}}$	−0.01	−0.1	−0.09	−0.09	9.65	$\eta_{x_{IM} p_{IM}}$	−2.61	−2.56	−2.53	−2.51	0.00
$\varepsilon_{p_{IS} x_{IS}}$	0.4	−0.15	−0.11	−0.07	17.56	$\eta_{x_{IS} p_{IS}}$	−4.16	−4.05	−4.07	−4.07	0.00
$\varepsilon_{p_K x_K}$	−0.68	−0.73	−0.73	−0.67	0.56						

ε is the partial price elasticity computed according to the following formula: $\varepsilon_{p_i x_j} = c_{ij} * S_j = \frac{\alpha_{ij} + S_i * S_j}{S_i}$

Sufficient condition for quasi-concavity is that the bordered Hessian is negative semi-definite and this is validated both at the mean and the median of the sample. The elements on the main diagonal of the matrix, i.e. the own partial price and demand elasticities f_{ii}, need therefore to be non positive and the table above shows that this is the case for our sample. The columns respectively report the sample mean and median elasticities computed according to formulas $\varepsilon_{p_i x_j} = c_{ij} * S_j = \frac{\alpha_{ij} + S_i * S_j}{S_i}$ and $\eta_{x_i p_j} = \sigma_{ij} * S_j = \frac{\beta_{ij} + S_i * S_j}{S_i}$, and the elasticities evaluated at the mean of the prediction of the (revenue/cost) shares and at the mean of the shares calculated using WHIP wages. In the former case, we calculate the elasticity for each observation in the sample and then take respectively the average and the median together with the average and the median significance level. The four sets of elasticities are negative and bear consistent insights, in particular the own price and demand elasticities are often very similar to the shares computed on the sample data.

The average of the predicted own price elasticity is surprisingly positive for services, but since we are going to work with elasticities calculated at the mean of the predicted shares this will not represent a problem in the analysis. Finally, the last column displays the share of observations with positive estimated elasticities: a few violations occur for some observations, especially in the case of the production function, however they do not affect the results shown in the text (Wales 1977).

References

Accetturo A, Bugamelli M, Lamorgese AR (2012) Welcome to the machine: firms' reaction to low-skilled immigration. Bank of Italy, Temi di Discussione 846

Barba Navaretti G, Bertola G, Sembenelli A (2008) Offshoring and immigrant employment: firm-level theory and evidence. CEPR Discussion Papers 6743, C.E.P.R. Discussion Papers

Berndt E (1991) The practice of econometrics. Addison-Wesley, Reading

Bettin G (2012) Migration from the accession countries to the United Kingdom and Italy: socio-economic characteristics, skills composition and labour market outcomes. In: Béla G, Janine L, Andrew W (eds) EU labour migration in troubled times, Ashgate, Farnham, pp 47–79

Blackorby C, Russell RR (1989) Will the real elasticity of substitution please stand up? (A comparison of the Allen/Uzawa and Morishima elasticities). Am Econ Rev 79(4):882–888

Bond S, Söderbom M (2005) Adjustment costs and the identification of Cobb Douglas production functions. IFS Working Papers W05/04, Institute for Fiscal Studies

Card D (2001) Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. J Labor Econ 19(1):22–64

Card D, Lewis EG (2005) The diffusion of mexican immigrants during the 1990s: explanations and impacts. NBER Working Papers 11552, National Bureau of Economic Research Inc

Chambers RG (1988) Applied production analysis. A dual approach. Cambridge University Press, Cambridge
Christensen L, Jorgenson D, Lau L (1973) Trascendental logarithmic production frontiers. Rev Econ Stat 55:28–45
D'Amuri F, Peri G (2011) Immigration, jobs and employment protection: evidence from europe. NBER Working Papers 17139, National Bureau of Economic Research Inc
Docquier F, Lowell BL, Marfouk A (2009) A gendered assessment of highly skilled emigration. Popul Dev Rev 35(2):297–321
Docquier F, Çağlar Özden, Peri G (2010) The wage effects of immigration and emigration. NBER Working Papers 16646, National Bureau of Economic Research Inc
Dustmann C, Glitz A (2008) How do industries and firms respond to changes in local labour supply. Working paper, Centro Studi Luca d'Agliano
Frondel M (2004) Empirical assessment of energy-price policies: the case for cross-price elasticities. Energy Policy 32(8):989–1000
Gandal N, Hanson GH, Slaughter MJ (2004) Technology, trade, and adjustment to immigration in israel. Eur Econ Rev 48(2):403–428
Gavosto A, Venturini A, Villosio C (1999) Do immigrants compete with natives? Labour 13(3):603–621
González L, Ortega F (2011) How do very open economies adjust to large immigration flows? Evidence from spanish regions. Labour Econ 18(1):57–70
Grossman JB (1982) The substitutability of natives and immigrants in production. Rev Econ Stat 64(4):596–603
Hamermesh DS (1993) Labor demand. Princeton University Press, Princeton
Istat (2009) L'integrazione nel lavoro degli stranieri e dei naturalizzati italiani. Approfondimenti lavoro, Istat, Roma
Kangasniemi M, Mas M, Robinson C, Serrano L (2012) The economic impact of migration: productivity analysis for Spain and the UK. J Product Anal 38(3):333–343
Kohli U (1991) Technology, duality and foreign trade. Harvester Wheatsheaf and Ann Arbor, London
Kohli U (1993) International labor mobility and the demand for imports. Swiss J Econ Stat 129(III):547–561
Kohli U (1999) Trade and migration: a production theory approach. In: Faini R, de Melo J, Zimmermann KF (eds) Migration: the controversies and the evidence. Cambridge University Press, Cambridge
Kohli U (2002) Migration and foreign trade: further results. J Popul Econ 15(2):381–387
Lewis EG (2011) Immigration, skill mix, and capital-skill complementarity. Q J Econ 126(2):1029–1069
Mundra K, Russell R (2001) Dual elasticities of substitution: application to the Swiss labor market. Working paper in economics, Department of Economics, University of California, Riverside
Nguyen SV, Streitwieser ML (1997) Capital-energy substitution revisted: new evidence from micro data. Working Papers 97–4, Center for Economic Studies, U.S. Census Bureau
Ottaviano GI, Peri G (2011) Rethinking the effects of immigration on wages. J Eur Econ Assoc 10(1):152–197
Peri G, Sparber C (2009) Task specialization, immigration, and wages. Am Econ J Appl Econ 1(3):135–169
Rivers D, Vuong QH (1988) Limited information estimators and exogeneity tests for simultaneous probit models. J Econom 39:347–366
Steinhardt MF (2011) The wage impact of immigration in Germany–new evidence for skill groups and occupations. BE J Econ Anal Policy 11(1):31
Stern DI (2011) Elasticities of substitution and complementarity. J Product Anal 36:79–89
Vella F (1998) Estimating models with sample selection bias: a survey. J Hum Resour 33(1):127–169
Wales TJ (1977) On the flexibility of flexible functional forms. J Econom 5:183–193
Yasar M, Morrison Paul CJ (2008) Capital-skill complementarity, productivity and wages: evidence from plant-level data for a developing country. Labour Econ 15(1):1–17