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ABSTRACT

Skilled Immigrants' Contribution to Productive Efficiency*

This paper studies whether skilled migrants contribute to the host country's 'productive efficiency' (Farrell, 1957) using input-output and immigration sectoral data for seven industries in twelve countries during the period 1999-2001. We find that skilled migrants contribute positively to a country's productive efficiency with the exception of the finance sector. The results broadly support the adoption of skill-biased migration policies.

JEL Classification: D24, F2, F66, J6, J24

Keywords: highly skilled migration, human capital, productive efficiency

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1 Introduction

One of the current controversies surrounding immigration policy is the usefulness of skill-biased immigration programmes like those in force in Canada, Australia, and New Zealand, which select 'skilled' immigrants on the basis of a points system[1] (Borjas, 1991; Beach et al, 2007). In such programmes, 'skilled' includes a composite of formal education typically at or above Bachelor's degree, relevant work experience, minimum knowledge of the host country's language, and age. Skilled migration streams contrast with traditional family reunification programmes, which admit immigrants on the basis of kinship with the host country's residents, and humanitarian programmes of relocation of asylum seekers (Miller, 1999; Belot and Hatton, 2012).

The rationale for implementing a skill-biased immigration policy is that skilled migrants are more likely to find employment after admission to the host country, are more mobile, and contribute faster to the public finance than other types of immigrants.[2] Indeed, research on the labour market outcomes of recent immigrants to Canada, Australia, and New Zealand provides support for skill-biased migration (Green and Green, 1995; Winkelmann, 1999; Antecol et al 2003), fuelling the debate on its usefulness in countries that currently do not have one, like the United States, and where large unregulated immigration has occurred, or is feared, as in the European Union (Zimmermann et al, 2000).

One under-researched angle of existing analyses of skill-biased immigration policies is the extent to which skilled migrants contribute to the efficient use of productive

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[1] The point-based immigration system started in Canada in 1962 and later adopted in Australia and New Zealand and in a plethora of other destination countries in more recent times, including the UK, the Czech Republic, Denmark, Japan, Hong Kong, Singapore, and Germany amongst others.

[2] Studies that analyse the effect of migrants in general, as opposed to skilled migrants, often find a negative effect on productivity; see for example, Kangasniemi et al. (2012) for the UK and Spain, and Paserman (2013) for Israel.

inputs for the host country. Existing work tends to analyse the effects of migration on productivity resulting from the reallocation of human capital between places of origin and destination. By migrating, individuals unable to use their skills at home do so in the host country, leading to increased production there[3]. For example, the literature on skilled migration highlights the contribution of these migrants to innovation activity and the development of new technology in the United States (Hunt and Gauthier-Loiselle, 2008). Similar work for the European Union suggests that such contribution is evident only for non-EU skilled migrants, who are subjected to some form of screening unlike their EU counterparts (Huber et al, 2010).

The increased productivity resulting from migration however captures only part of migrants' overall contribution to the host country's economy. Migrants' skills are often under-utilised by host country employers, even in countries applying a selective immigration policy, as emerging from the study of immigrants' level of experience and formal education vis-à-vis the jobs they fill (Dolton and Vignoles, 2000; Kler, 2007). This implies a wastage of resources that is detrimental to the country of origin, which subsidises emigrants' formal education, and the host country where such human capital earns a lower rate of return than what is achieved by its native equivalents.

The total effect of skilled migration on the host country's economy can nevertheless be captured by a weighted measure of migrants' contribution to productivity and level of utilisation in the labour market known as 'productive efficiency'. Such approach measures how close an economy is to a benchmark production possibility frontier that uses all resources efficiently: namely when inputs are used in their lowest possible amounts for the production of an output.

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[3] Migration also improves conditions in the host country via higher capital/labour ratios and/or remittance inflows.

We apply the productive efficiency approach to a number of countries that differ in immigration policy towards skilled migration: some have established skill-biased migration policies, like Australia, Canada and New Zealand; others have a much narrower approach to skilled migration (e.g. the United States). Some have only recently introduced targeted programmes to attract specific skilled workers (eg. the Czech Republic and Denmark).

Our analysis covers seven industries in twelve countries for the period 1999-2001, and uses input and output data from the EU-KLEMS database and the single cross-sectional information on skilled migration data from the OECD Stan database. Given the limited availability of data over time we construct a single cross-sectional dataset, and measure relative productive efficiency at a given point in time[4].

Our results suggest that skilled migrants contribute positively to a country's productive efficiency in all sectors aside from Finance, for which we offer an interpretation, and they broadly support the introduction of skill-biased migration policies. They provide additional insights into the various dimensions in which skilled migration contributes to a country's economy and offers new information to policymakers debating the advantages and limitations of introducing skill-biased immigration policies.

The rest of the paper is organised as follows: Section 2 introduces the concept of productive efficiency and the methodology. Section 3 presents the data. Section 4 discusses the results. Section 5 concludes and highlights implications for policy.

[4] We only have one year of information about the proportions of skilled migrant workers. Constructing a single cross-sectional dataset prevents us from using panel data approaches measuring total productivity as the result of changes attributable to a change in the production technology as well as changes in productive efficiency, as occurring when there is a shift of the efficiency frontier, which usually occurs over time. A measure of total productivity such as the multi-factor productivity (MFP), which is based on the growth-accounting method, is inappropriate for a comparison of productivity levels across countries and industries at a given point in time (see for example Inklaar and Timmer, 2008).

2 Measurement of Productive Efficiency

Productive efficiency aims to measure the minimum amount of inputs required to produce a certain quantity of output. The literature on productive efficiency stems from the empirical work of Farrell (1957), who developed a method to estimate the productive efficiency of a country. Over time, the estimation of production function frontiers has been carried out using either deterministic methods or stochastic techniques. Deterministic methods, which include methodologies known as data envelopment analysis (DEA) of Charnes et al. (1978) and the free disposal hull (FDH) of Deprins et al. (1984), apply linear programming techniques to construct a frontier by using a piecewise linear envelope that connects the best performers (e.g. sector-country combinations that receive the highest efficiency scores). The main advantage of this approach is the small number of restrictions imposed on the properties of the production technology. Its main limitation is not disentangling white noise from inefficiency measures.

In the stochastic approach, random shocks are included to cater for deviations from the production frontier, and inputs for productions are distinguished from other conditions that nevertheless have an influence on the efficient use of resources, like environment and institutions.

To ascertain the contribution of skilled migrants to a country's productive efficiency we apply the DEA method, and define a measure of productive efficiency that is comparable across countries and sectors. The DEA method is preferred to the stochastic frontier method in the present case because the group of decision-making units (DMUs) comprises various industries in different countries with potentially different production technologies, making it inappropriate to specify them using a specific functional form. We consider a sector of a country as a single DMU that produces its gross output using various inputs. Some sectors may be more efficient in utilizing the available technology and produce more output than others using the same level of inputs. Some may be less efficient and produce less than others. In the spirit of Farrell (1957), we measure the productive efficiency of a sector of a country by comparing its actual gross output with the maximum gross output that can be produced using the same levels of inputs. This can be facilitated via the output distance, which represents the proportion by which the actual output of a country could be increased without changing the levels of inputs if the sector were fully efficient under the available technology.

The *output distance function* is defined as

$$D(x,y:T) = \max_{\delta} \{\delta: (x,\delta y) \in T\} \tag{1}$$

where $y \in R_+$ is gross output, $x \in R_+^N$ is an input vector, and $T \subset R_+^{N+1}$ is the set of input-output mixes that are feasible under the available technology, namely T = {(x,y): x can produce y}. Under regular conditions, D(x,y) is greater than or equal to one. For a sector that is efficient, the output distance will be one because the actual level of output is the maximum that can be produced without changing inputs. For an inefficient sector, on the other hand, the output distance will be larger than one implying that output can be inflated without increasing inputs. Therefore, a measure of *productive efficiency* can be defined as

$$PE(x,y:T) = 1/D(x,y:T) \tag{2}$$

which is bounded between zero and one. PE will be one for efficient sectors and less than one for inefficient sectors. For example, a PE of 0.8 implies that the sector is only 80% efficient compared with the best performing sector and hence output could be increased by up to 25% (=[1-0.8]/0.8) given the same levels of inputs.

We measure distances using the DEA method under the assumption of constant returns to scale (CRS).[5] The linear-programming (LP) model for a sector of a country (DMU k) can be written as:

$$\begin{aligned} &\text{Max.} \quad \delta \\ &\text{s.t.} \quad \delta y^k - Y\lambda \leq 0 \\ &\qquad\; - x^k + X\lambda \leq 0 \\ &\qquad\; \delta, \lambda \geq 0 \qquad \text{for } k = 1, ..., K \end{aligned} \tag{3}$$

where δ is the output distance, y^k is DMU k's output, x^k is an (N×1) vector of DMU k's inputs, Y and X are (1×K) and (N×K) matrices of outputs and inputs of all K DMUs respectively, and λ is a (K×1) vector of intensity coefficients. This LP problem involves finding by how much DMU k can increase its output without changing its inputs, subject to the constraint that it cannot produce more than the maximum level implied by the frontier formed by the best performers in the group of K DMUs.[6]

3 Data

The main source of data for measures of productivity by sector is the EU KLEMS database[7], while measures of the national stocks of skilled migrants by industry are drawn from the OECD Stan database.

Following Jorgenson and Timmer (2011), we group the 31 industries in the EU KLEMS's alternative aggregation scheme into seven sectors: Electrical Machinery, Post and Communication Services (ELECOM); Total Manufacturing, excluding Electrical (MexElec); Other Production (OtherG); Distribution (DISTRB); Finance

[5] The countries included in the present study are relatively homogenous in terms of the level of economic development, and hence they are expected to have similar scale elasticities.
[6] Under the assumption of CRS, both output-oriented and input-oriented approaches result in identical efficiency measures because the input distance is simply the reciprocal of the output distance; see Proposition (2.1.26) of Färe and Primont (1995).
[7] See the EU KLEMS website euklems.net for the database, and Timmer et al. (2007) for the definitions and descriptions of the series.

and Business, except Real Estate (FINBU); Personal Services (PERS); and Non-Market Services (NONMAR).

Each sector produces a single output using intermediate, labor, ICT capital, and Non-ICT capital inputs. The quantity of output is defined as the real gross output of the sector (GO), while the quantity of intermediate input is defined as real expenditure on intermediate inputs (II). Labor input is defined as the total number of hours worked by persons engaged (H_EMP), and ICT and Non-ICT capital inputs are defined as real fixed capital stocks (K_ICT and K_NonICT).

All these series except H_EMP in the EU KLEMS database are in local currency values. To convert the nominal values to volumes that are comparable across countries as well as over time, the GO is divided by the PPP exchange rate (PPP, local currency per US$) and then by the US gross output price index (US_GO_P), while the II is divided by the PPP and then by the US intermediate input price index (US_II_P). K_ICT and K_NonICT are presented in local currency's 1995 price in the EU KLEMS database. These series are reverted to current values first and then converted to real volumes by dividing by the PPP and the US GDP deflator (Table A.1 in the Appendix summarises additional details and the definitions of the variables).

The group of countries included in the analysis is constrained by the availability of data on the capital input variables and migrant workers (to be used in the regression analysis in the next section), leaving a group of 12 countries comprising of Australia (AUS), Austria (AUT), the Czech Republic (CZE), Denmark (DEN), Finland (FIN), Italy (ITA), the Netherlands (NET), Portugal (POR), Spain (SPA), Sweden (SWE), the United Kingdom (UK), and the United States (US). Our sample data set includes 3 yearly observations over 1999 – 2001 of the seven sectors of each of the 12 countries. Some descriptive statistics of the productivity variables used for the DEA analysis are presented in Table 1, while more detailed 3-year averages for individual sectors and countries are in Table A.2.

Table 1: Descriptive Statistics of the Data for DEA Analysis*

	ALL#	ELECOM	MexElec	OtherG	DISTRB	FINBU	PERS	NONMAR
Output								US$m (2000)
average	2,209,050	171,689	503,968	225,519	352,556	348,051	140,156	463,164
s.d.	4,448,395	378,242	923,286	378,302	640,181	783,188	275,501	1,070,561
c.v.	2.01	2.20	1.83	1.68	1.82	2.25	1.97	2.31
Intermediate Input								US$m (2000)
average	1,094,862	85,314	344,724	125,293	146,331	157,433	70,204	158,718
s.d.	2,065,207	177,936	608,808	192,444	233,465	337,324	139,037	378,188
c.v.	1.89	2.09	1.77	1.54	1.60	2.14	1.98	2.38
Labour								million hours
average	38,088	1,449	5,479	4,457	7,696	5,870	4,183	8,953
s.d.	74,288	3,077	9,553	6,985	14,392	12,690	7,968	19,812
c.v.	1.95	2.12	1.74	1.57	1.87	2.16	1.91	2.21
ICT Capital								US$m (2000)
average	255,727	59,381	25,213	11,084	44,495	76,283	7,619	31,652
s.d.	599,457	148,071	54,298	25,278	94,125	194,535	9,707	75,423
c.v.	2.34	2.49	2.15	2.28	2.12	2.55	1.27	2.38
NonICT Capital								US$m (2000)
average	3,321,193	105,247	258,833	354,330	283,481	321,231	100,247	1,901,339
s.d.	6,185,266	245,125	406,648	654,527	451,209	704,743	161,405	4,008,128
c.v.	1.86	2.33	1.57	1.85	1.59	2.19	1.61	2.11

*: Averages of 12 countries. Each country's figures are averages over 3 years, 1999, 2000, and 2001. The largest and the smallest sectors are highlighted.
#: The figures for ALL sectors are slightly different from the sum of sectoral figures because price indices (GO_P) used in the conversion of nominal values to real volumes are different from sector to sector. (Source of the raw data: EU KLEMS)

The relatively high coefficient of variation (c.v.) of real output for the whole economy, 2.01, reflects huge differences in the sizes of economies with the largest economy, that of the US, being more than 70 times that of Finland, the smallest in the group. With exceptions of Australia, Denmark and US, the largest sector of a country in terms of size of output is the Manufacturing (excluding Electrical) sector. For both Australia and Denmark, the largest sector is the Distribution sector, while for the US it is the Non-Market sector, which is not surprising as it includes defence (Table A.2). For all countries, the biggest user of intermediate input is the Manufacturing sector. When it comes to the use of labour, it is either the Distribution sector or the Non-Market sector for most countries. The input that has the highest variation in quantity across the countries is ICT-capital, with the coefficient of variation being greater than 2 for all sectors but the Personal Services sector. In most countries, the Finance &

Business and the Distribution sectors use the most ICT-capital, but in Austria, the Czech Republic and the UK it is the Electrical and Communications sector that does. Apart from the Non-Market services sector, the Other Production and the Distribution sectors have the largest Non-ICT capital stock in all countries but in Italy. In Italy, the Finance and Business Services sector has more Non-ICT capital stock than any other sectors including the Non-Market Services sector.[8]

Table 2 presents data on skilled migrant and native workers for each country. The observations were made only once in the year 2000. In the empirical analysis, to exploit the three-year span for which we have data, we will assume that the proportion of migrant workers during 1999-2001 remains unchanged relative to the 2000 level.

Table 2: Descriptive Statistics of the Immigrants Data

Country	Skilled Foreigners/ Total Foreigners	Skilled Natives/ Total Natives	Skilled Foreigners/ Total Skilled
AUS	35.7%	26.5%	29.8%
AUT	13.6%	15.4%	12.4%
CZE	22.8%	15.5%	5.7%
DEN	28.7%	24.5%	6.1%
FIN	24.9%	34.1%	1.6%
ITA	16.5%	15.0%	5.1%
NET	25.3%	24.7%	8.5%
POR	23.7%	12.0%	15.5%
SPA	22.8%	25.8%	6.0%
SWE	28.9%	27.1%	11.2%
UK	44.1%	24.9%	14.5%
US	31.9%	34.9%	12.3%

Source: STAN Database, OECD.

Skilled foreigners constitute about a quarter to a third of the stock of immigrant workers available in each of the twelve countries. The only exceptions are Austria, where they constitute 13.6% and Italy (16.5%). The highest proportions of skilled migrants are in English-speaking countries, topped by the UK, then Australia and the US, perhaps reflecting the language advantage of English, which is one of the most commonly spoken languages in the world, as these countries' official language. They are followed by the Nordic countries (Sweden, Finland, and Denmark), whose official

[8] The capital stock for the Finance and Business Services sector in Italy is certainly an outlier, which could be a result of mis-measurement due to the complexity of the classification and measurement of

languages are also similar and which have an established policy of openness to regional labour movements across them. The countries with the lowest proportion of skilled foreigners are traditional emigration countries, which have experienced net immigration flows only since the mid-1990s (Italy, Spain, Portugal, and the Czech Republic).

The proportion of skilled workers amongst immigrants tends to be higher than the corresponding proportion amongst natives, with the exception of Austria, Finland, Spain, and the US. Immigrants account for a third of the overall stock of skilled labour in the case of Australia – the only host country with an established skill-biased immigration policy. Austria, Sweden, Portugal, the UK, and the US have broadly similar skilled shares of immigrants in their skilled workforce (11%-15%). In contrast, immigrants account for only a relatively small fraction of the skilled workforce in Finland (the lowest, with only 1.6%), the Czech Republic, Italy, Spain, and Denmark (1%-5%). Table 3 presents the proportion of immigrants amongst skilled labour for each sector of the countries. The top left cell in the Table informs that immigrants account for 44.5% of skilled workers in Electrical Machinery, Post and Communication Services (Elecom) in Australia (AUS).

Table 3: Immigrants' Share of Skilled Labour in the Data Used

Country	ELECOM	MexElec	OtherG	DISTRB	FINBU	PERS	NONMAR
AUS	44.5%	38.0%	25.9%	36.6%	33.1%	31.3%	24.9%
AUT	15.5%	11.0%	6.9%	17.5%	14.5%	21.7%	9.7%
CZE	5.9%	5.8%	4.0%	10.7%	5.7%	9.2%	4.6%
DEN	8.1%	7.5%	5.4%	9.0%	7.2%	9.9%	4.7%
FIN	2.2%	1.5%	0.9%	1.8%	1.5%	2.1%	1.5%
ITA			7.7%	9.5%	2.8%	17.7%	3.6%
NET	12.1%	9.0%	6.1%	15.1%	8.0%	10.2%	7.3%
POR	15.7%	17.1%	25.0%	17.5%	14.7%	23.6%	13.8%
SPA	5.8%	5.4%	8.3%	6.3%	5.4%	15.5%	4.6%
SWE	15.2%	14.3%	8.5%	16.4%	11.1%	14.0%	9.8%
UK	15.6%	11.1%	9.1%	17.8%	17.0%	17.6%	13.1%
US			9.7%	14.2%	12.7%	14.6%	11.2%

Source: STAN Database, OECD.

capital stocks.

In general, skilled immigrant workers concentrate in Distribution services and Manufacturing, especially in countries that traditionally import immigrant labour (e.g. English-speaking countries). In countries where immigration is more recent, skilled immigrants seem to find employment particularly in Personal Services (Austria, Italy, Portugal, Spain).

4 Empirical Results

The empirical analysis consists of two stages. First, we estimate each country-sector's productive efficiency. For the measurement of productive efficiency, each sector of a country in each year is treated as a single DMU whose performance is measured against a common technological frontier consisting of all sectors of all countries in all three years. Hence, there are 252 DMUs (7 sectors x 12 countries x 3 years) to form a frontier in a 5-dimensional space (one output plus four inputs).

Table 4 presents productive efficiency scores, defined by (2), averaged over the three years. The best performer in terms of the overall average score is the U.S. (0.925), followed by Austria (0.911). The U.S. has the highest score for the Distribution sector and the second highest scores for the Electrical & Communication sector, the Finance & Business sector, and the Personal Services sector. Austria does not have the highest score for any sector, but it performs well consistently across all sectors. Finland has the highest scores for the Electrical & Communication sector and the Finance & Business sector, while the Netherlands, Portugal, Spain and Italy are the best performers in the Manufacturing, the Other Production, the Personal Services, and the Non-Market sectors respectively.

At the other end of the spectrum is the Czech Republic whose scores are the lowest for all sectors, ranging from 78% (NONMAR) to 95% (MexElec) of the next lowest scores within the corresponding sectors. These low efficiency scores are consistent with the input-output figures in Table A.2. In terms of output, the Czech Republic is the fourth smallest country after Finland, Denmark and Portugal. However, the country uses more intermediate, labour and ICT-capital inputs than five other countries, including Austria and Sweden who produce more outputs. This result is not surprising given that the Czech Republic is the only country in the group that is a former communist country, and hence might have had limited access to new technology and production systems. [9]

Across sectors, the most efficiently operated sector is the Manufacturing sector (0.933), while the least efficient sector is the Non-Market Services sector (0.792). It appears natural that the Non-Market sector is the least efficient, but that the Electrical & Communication sector and the Finance & Business sector perform less efficiently than the Manufacturing sector is somewhat surprising. In fact, for some countries the Finance & Business sector is more efficient than the Manufacturing sector. However, the poor performance of the former relative to the latter in the Czech Republic, Italy, the Netherlands, Portugal and the UK drives the lower average score.

Table 4: Productive Efficiency Scores (average over three years)

Country	ELECOM	MexElec	OtherG	DISTRB	FINBU	PERS	NONMAR	Average
AUS	0.909	0.933	0.767	0.818	0.878	0.743	0.776	0.832
AUT	0.944	0.986	0.945	0.926	0.949	0.799	0.830	0.911
CZE	0.739	0.814	0.641	0.648	0.644	0.609	0.528	0.660
DEN	0.858	0.858	0.842	0.832	0.901	0.705	0.739	0.819
FIN	0.984	0.986	0.754	0.833	1.000	0.705	0.676	0.848
ITA	0.885	0.968	0.862	0.848	0.754	0.910	0.998	0.889
NET	0.876	0.990	0.902	0.971	0.863	0.857	0.853	0.902
POR	0.877	0.973	0.959	0.908	0.888	0.717	0.768	0.870
SPA	0.927	0.904	0.950	0.790	0.959	0.988	0.796	0.902
SWE	0.818	0.881	0.779	0.880	0.944	0.881	0.974	0.879
UK	0.959	0.949	0.874	0.962	0.834	0.845	0.760	0.884
US	0.983	0.956	0.760	0.993	0.994	0.987	0.805	0.925
Average	0.897	0.933	0.836	0.867	0.884	0.812	0.792	0.860

* The highest and lowest scores are highlighted.

[9] Despite of the Czech Republic's short history as a capitalist country, it is one of the 34 IMF-defined 'Advanced Economies' like the others in the sample. The group of 34 Advanced Economies, classified by the IMF, includes Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan Province of China, United Kingdom, and United States. Source: http://www.imf.org/external/pubs/ft/weo/2011/02/weodata/weoselagr.aspx#a110 (22 September 2013)

In the second stage of the empirical analysis, we relate the estimate of productive efficiency to inputs, taking into account their qualities (this was not part of the measurement of productive efficiency, as the quality of an input is assumed to be the same for all sectors in all countries).

To analyze how the differences in the proportion of migrant workers in the labour force affect the productive efficiency given the other qualities of the inputs we apply the regression model formalized by:

$$ln PE_{it} = \alpha + \gamma_1 D1_{it} FL_{it} + \ldots + \gamma_7 D7_{it} FL_{it} + \beta_1 ln LW_{it} + \beta_2 ln KW_{it} + u_{it} \quad (4)$$

where:

Dk_{it} = 1 for sector k and 0 otherwise (k = 1,..7),

FL_{it} = the proportion of migrant workers out of all high-skilled (or medium-to-high skilled) workers (%),

LW_{it} = quality of all labour input measured by labour compensation per unit of labour,

KW_{it} = quality of all capital input measured by capital compensation per unit of capital stock,

ln(.) = the natural logarithm, and u_{it} is the random error term

for i = 1,..,84 (7 sectors for 12 countries), and t = 1999, 2000 and 2001.

Of our main interest are whether the γ coefficients are significantly different from zero or not, and if significant what their signs are. If the composition of the labour force, apart from different skill levels as are represented by unit labour compensation, is important for productivity, then the γ coefficients will be significant. The effect could be in either direction. The β coefficients are the productivity elasticity with respect to the quality of labour and capital inputs.

A complication with the PE variable in a regression analysis is that it is censored at 1, and hence its log at 0, from above. To overcome this problem, the PE scores of 1 are recomputed after excluding the inputs and output of the corresponding DMU from the X and Y matrices in the DEA problem (3). This allows the PE scores for the DMU to be higher than 1 implying that the DMU is 'super-efficient'. This approach has a useful advantage over the popular Tobit-model approach in that the former enables discrimination of super-efficient DMUs while the latter does not, resulting in the estimates based on the former approach being more efficient.[10]

The model was firstly estimated with sector dummy variables as well as their interaction with FL. However, their coefficients turned out to be jointly insignificant leading to the above model with their interactions with FL only.

Two versions of the model are estimated with two alternative definitions of FL – one as the proportion of migrant workers out of all high-skilled workers (Model 1) and the other as the proportion of migrant workers out of all medium-to-high skilled workers (Model 2). Both models had significant evidence of heteroscedasticity with the p-values of the Breusch-Pagan tests being close to zero. Hence, the models are estimated with the feasible generalised least-squares (FGLS) method while assuming the following variance function.

$$\mathit{ln}V(u_{it}) = \alpha_0 + \alpha_1 D1_{it}FL_{it} + \ldots + \alpha_7 D7_{it}FL_{it} + \alpha_8 \mathit{ln}LW_{it} + \alpha_9 \mathit{ln}KW_{it} + v_{it} \qquad (5)$$

Table 5 reports the FGLS estimation results with the standard errors and asymptotic p-values provided in parentheses and square brackets respectively.

The two sets of results are almost the same. The only significant differences are that the coefficients for FL_{OtherG} and FL_{NONMAR} become significant at 5% when the proportion of medium-to-high skilled migrant workers is used, and that the order of the sizes of the coefficients for FL_{OtherG} and $FL_{DISTRIB}$ reverses. All the coefficients

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[10] This approach was introduced by Andersen and Petersen (1993).

except those for FL_{OtherG} and FL_{NONMAR} in Model 1 are significant at 5%. The null hypothesis that all γ coefficients are jointly equal to zero is strongly rejected by both models, implying that the proportion of skilled migrant workers is an important factor in determining productivity. The null hypothesis that all the γ coefficients are the same has also been strongly rejected, implying that the effect of migrant skilled workers on the productivity varies across sectors.

Table 5: FGLS Estimation Results

	Model 1: High-Skilled	Model 2: Medium-to-High Skilled
FL		
ELECOM	0.0011	0.0015
	(0.0004)	(0.0006)
	[0.012]#	[0.009]
MexElec	0.0042	0.0054
	(0.0016)	(0.0019)
	[0.012]	[0.005]
OtherG	0.0050	0.0060
	(0.0026)	(0.0026)
	[0.052]	[0.021]
DISTRB	0.0048	0.0088
	(0.0010)	(0.0016)
	[0.000]	[0.000]
FINBU	−0.0048	−0.0056
	(0.0010)	(0.0011)
	[0.000]	[0.000]
PERS	0.0040	0.0054
	(0.0009)	(0.0011)
	[0.000]	[0.000]
NONMAR	0.0032	0.0049
	(0.0017)	(0.0020)
	[0.063]	[0.014]
***ln*LW**	0.2239	0.2299
	(0.0190)	(0.0187)
	[0.000]	[0.000]
***ln*KW**	0.1336	0.1356
	(0.0079)	(0.0074)
	[0.000]	[0.000]
Sample Size	240*	240
Buse R^2	0.696	0.722
Chi-square (7) statistic for all γ coefficients = 0	78.11 [0.000]	97.50 [0.000]
Chi-square (6) statistic for identical γ coefficients	71.74 [0.000]	93.44 [0.000]

#: Standard errors are in parentheses and asymptotic p-values are in square brackets.
*: The 12 observations for ELECOM and MexElec of Italy and U.S. are excluded as data on migrant workers for those sectors are not available.

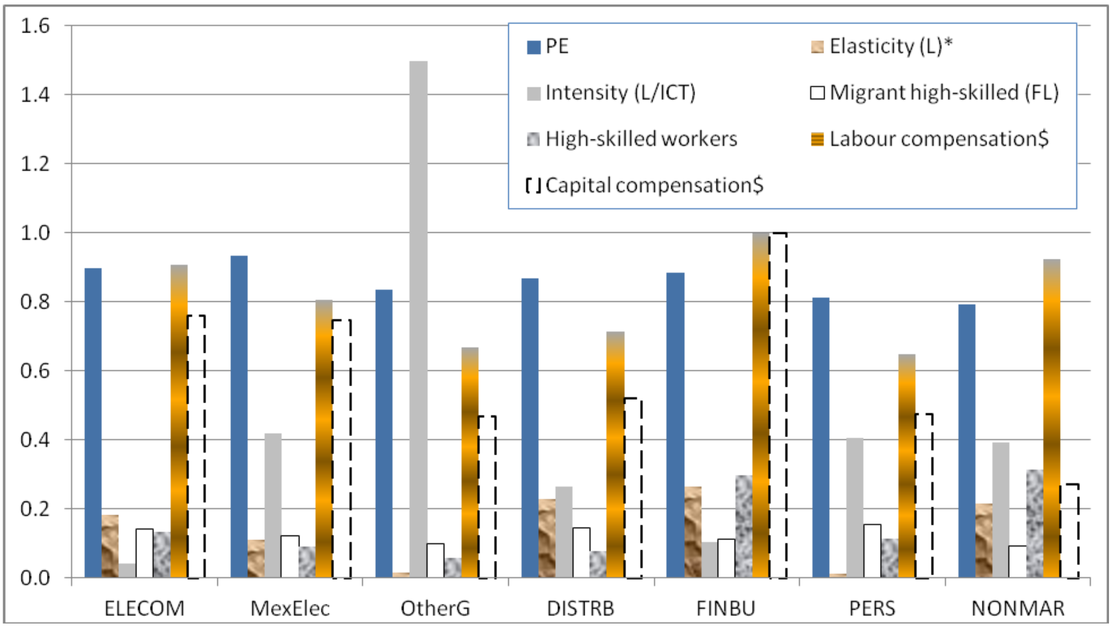
The proportion of skilled migrant workers has a positive effect on the productive efficiency for all sectors except the Finance & Business sector, where the effect is negative. This outcome reveals that skilled migrants contribute positively to their host countries' productive efficiency. The effect on the productivity of a one percentage point change in the proportion of medium-to-high skilled migrant workers (Model 2) is by far the largest for the Distribution sector (0.88%), while the effect of a change in the proportion of high-skilled migrant workers (Model 1) is the largest for the Other Production sector only by a small margin (0.50% versus 0.48%).

The γ-coefficient estimates for the Distribution sector in the two models imply that an increase in the proportion of high-skilled migrant workers by one percentage point leads to a 0.5% increase in the productivity, while an increase in the proportion of medium-to-high skilled migrant workers leads to a 0.88% increase, *ceteris paribus*.

The smallest positive effect occurs for the Electrical & Communication sector, where one percentage point increases in the proportions of high-skilled and medium-to-high skilled migrant workers lead to increases in productivity by 0.11% and 0.15% respectively. In contrast, an increase in the proportion of migrant workers out of skilled workers has a negative effect for the Finance & Business sector, where a one percentage point increase leads to 0.48% and 0.56% decreases in the productivity for Model 1 and Model 2 respectively.

To help understand the reasons for this opposite effect of migrant workers on productivity, Figure 1 presents the average values of some key figures about labour input in each sector.

Figure 1: Key Figures about Labour Input (sectoral averages)



*: The elasticity of output with respect to labour input, which is estimated as the coefficient for the log of labour input in a Cobb-Douglas production function. The eight production functions, one for each sector plus one for the whole economy, are estimated as an SUR model.
$: Scaled.

What makes the Finance & Business sector unique is that the elasticity of output with respect to (quality-unadjusted) labour input is the highest (0.263), implying that its labour force is the most productive among the sectors. This fact is reinforced by that it has the second highest proportion of high-skilled workers (0.297), only next to the Non-Market sector (0.315). It also has the second lowest labour intensity relative to ICT capital (0.105), suggesting high substitution elasticity of labour for capital and hence high productivity of labour. All these are consistent with labour compensation per unit that is the highest among sectors as it reflects the quality of labour input. The highest quality of capital input in the same sector, represented by its capital compensation, further enhances the productivity of its labour input.

On the other hand, the two sectors that have the largest γ coefficients, the Other-Production and Distribution sectors, do not seem to have many features in common. The Other Production sector has the highest labour intensity (1.498), but the Distribution sector has relatively low labour intensity (0.263). The Other Production sector has the second lowest labour elasticity (0.015), while the Distribution sector has the second highest (0.230). The only conspicuous features common in both sectors are that the proportions of high-skilled workers out of all workers are the lowest (0.057 and 0.079 for OtherG and DISTRB respectively) and consequently the lowest labour compensation levels except for the Personal Service sector.

A clear picture emerging from these analyses is that skilled migrant workers are more productive than average skilled workers in most sectors, where the lower the level of skill of general workers in the sector the higher the contribution of additional skilled migrant workers to improving the productivity. However, in the Finance & Business sector, where the skill level of average worker is the highest among sectors, the skill level of average skilled migrant worker is lower than that of general average skilled worker, and hence the higher the proportion of migrant workers the lower the productivity.

There could be many reasons why migrant workers' skill level is not as high as the general skill level in the Finance & Business sector. One of the obvious reasons is that it includes industries where entrance is most competitive, resulting in the best workers ending up working in the industries. Another possible reason is that migrant workers' knowledge about the business environment and rules, including the language, may fall short of that of native skilled workers in a sector that is often characterised by cut-throat competition (e.g. Peri and Sparber, 2008; Chiswick and Taengnoi, 2007).

Finally, the elasticity of productivity with respect to labour compensation is almost twice that with respect to capital compensation (0.22% versus 0.13%). It implies that, on average, enhancing the quality of labour input is much more effective than enhancing the quality of capital input in improving productive efficiency.

5 Conclusions and Implications for Policymakers

The empirical results suggest that skilled migrants are both desirable and valuable in enhancing a host country's productive efficiency. Introducing a skill-biased immigration policy appears therefore justified on the basis that skilled migrants make a positive contribution to efficiency, and the result is statistically robust to changes in model specification.

It is however important to highlight that Australia, the only country with an explicit labour-market driven approach to migration, does not stand out as the host country where skilled immigrants make the largest contribution to efficiency, as the interaction variables combining skilled migrants with county dummies yield coefficients that are seldom statistically significant. Other relevant forces are therefore at play, first and foremost institutional differences amongst host countries.

Recent research has pointed out that the emphasis on skilled migration may contribute to the higher incidence of over-education in the host country's labour market. It has been estimated that about 40% of immigrants to Australia perform jobs that require a lower level of education than that possessed. Similar figures exist for domestic labour markets in Canada and New Zealand as well as the European Union. Immigration policy matters in selecting applicants but it is the labour market that determines the success of the immigration policy in place.

Our results support the side of the debate calling for a skill-biased approach to immigration policy, especially for countries where income inequalities do not act as a natural screening device (Roy, 1951; Borjas, 1987). However, issues about immigrants' social inclusion, participation, and success ultimately depend on how efficient a country's labour market is in granting access to opportunities and in rewarding the human capital supplied. A skill-biased immigration policy may contribute to the well-functioning of the domestic labour market, but it cannot per se solve issues connected with the most efficient utilisation of skilled labour and the resources available.

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Table A.1: Definitions of the Variables and Sources of Data

Variables for Productivity Measurement

Variable	Unit of Variable	Raw Series				Comment
		Code	Description	Unit	Source[1]	
Output	volumn in millions	**GO**	Gross output at current basic prices	$M	output_09I_alt	Converted to the real volumn by dividing by **US_GO_P** & **PPP**.
Intermediate Input	volumn in millions	**II**	Intermediate inputs at current purchasers' prices	$M	output_09I_alt	Converted to the real volumn by dividing by **US_II_P** & **PPP**
Labour	million hours	**H_EMP**	Total hours worked by persons engaged	million hours	output_09I_alt	
ICT Capital	volumn in millions	**K_ICT**	ICT assets (real fixed capital stock)	millions in 1995 price	capital_09I	As for the above case, it should be divided by PPP to make it comparable across countries. However, PPP is based on the current price not on real price. Hence, it should be reverted to the current value before dividing it by **PPP** and **US_GDP deflator**. Note that K_ICT[t] is the current value of ICT assets, CV[t], divided by the 1995-base price index in period t, 95P[t]. Let P[t] be the available price index with a base period 0, namely P[t] = 95P[t]/95P[0]. Then, CV[t] = {CV[t]/95[t]}*95[t] = K_ICT[t]*95P[t] = **K_ICT[t]*P[t]*95P[0] = K_ICT[t]*P[t]*(P[0]/P[95]) = K_ICT[t]*P[t]/P[95]**. This would be necessary only if 95 ≠ 0, and if the 1995-base price index is still used for a country, simply K_ICT[t]*P[t]*95P[0] = K_ICT[t]*95P[t]*95P[95] = K_ICT[t]*95P[t]*1 = **K_ICT[t]*95P[t]**.
NonICT Capital	volumn in millions	**K_NonICT**	Non-ICT assets (real fixed capital stock)	millions in 1995 price	capital_09I	as above

Variables for Regression Analysis

Variable	Unit of Variable	Raw Series				Comment
		Code	Description	Unit	Source[1]	
Proportion of Migrant Workers in MS & HS	%	**ISCED 3/4 & 5/6**	ISCED 3/4 (secondary level), ISCED 5/6 (tertiary level); Native and Foreign Born	Persons employed	OECD Migration Statistics, Immigrants by Sector[2]	Foreign-born MS & HS employees / (All MS & HS employees)
Share of MS & HS Labour Input	%	**H_MS, H_HS**	Share of Total Hours Worked by Medium & High Skilled Persons Engaged[4]	%	output_alt_08I	H_MS + H_HS
Quality of Capital Inputs	real price per 1000 units of capital input	**CAP**	Capital compensation	$M	output_09I_alt	Converted to the real price per 1000 units of capital input as 1000*CAP/(ICT capital + NonICT capital) and then divided by **PPP & US_GDPdeflator**.
R&D Expenditure	PPP 2005 $b	**GB.XPD.RSDV.GD.ZS**	R & D Expenditure as % of GDP[5]	% of GDP	The World Bank - World Development Indicators (5 May 2011)[3]	

Variables Used for Conversion of Raw Series

Variable	Unit of Variable	Raw Series				Comment
		Code	Description	Unit	Source[1]	
Sectoral Output Price Index	index	**GO_P**	Gross output, price indices	1995 = 100	output_09I	Used to make gross output comparable over time (US_GO_P)
Sectoral Intermediate Input Price Index	index	**II_P**	Intermediate inputs, price indices	1995 = 100	output_09I	Used to make intermediate input comparable over time (US_II_P)
PPP	Price of US$1 in local currency	**PPP**	PPP exchange rate	Local currency per $US	The World Bank - World Development Indicators (5 May 2011)[3]	Used to make variables comparable across countries
GDP Deflator	index	**NY.GDP.DEFL.ZS**	GDP deflator[6]	different base for different countries	The World Bank - World Development Indicators (5 May 2011)[3]	Used to convert K_ICT & K_NonICT to current values (see note for K_ICT)
US GDP Deflator	index	**NY.GDP.DEFL.ZS**	US GDP deflator[6]	2000 = 100	The World Bank - World Development Indicators (5 May 2011)[3]	Used to make quantities expressed in PPP ($US) comparable over time
GDP	PPP 2005 $b	**NY.GDP.MKTP.PP.KD**	PPP GDP	real PPP 2005 billion dollars	The World Bank - World Development Indicators (5 May 2011)[3]	

Reference Variables

Variable	Unit of Variable	Raw Series				Comment
		Code	Description	Unit	Source[1]	
DTFP		**VAConTFP**	Contirbution of TFP to VA change	%	output_09I_alt	Contribution of TFP to value added growth (percentage points)
TFP	index	**TFPva_I**	TFP growth index	1995=100	output_09I_alt	TFP (value added based) growth, 1995=100

1. EU KLEMS database (euklems.net) unless stated otherwise.

For US, **naics_output_09I_alt_rev** & **usa-naics_capital_09Irev**. Also, used **sic_labour_input_08I** for H_MS and H_HS.

For POR(tugal), **ouput_alt_08I** for DTFP, TFP and **captial_08I** for KICT & KNICT.

2. stats.oecd.org
3. data.worldbank.org
4. Definitions slightly vary across countries. See Table 5.3 of Timmer et al. (2007) for detailed definitions.
5. Interpolated (AUS 99, 01, 03; DEN 00, SWE 98, 00, 02)
6. All countries' deflators are converted to a 1995-based series by P[t]/P[95]

Table A.2: Data for DEA Analysis (3-year average: 1999,2000, and 2001)

	ALL*	ELECOM	MexElec	OtherG	DISTR	FINBU	PERS	NONMAR
OUTPUT								US$m (2000)
AUS	957,182	45,079	180,694	169,846	184,743	145,020	55,502	167,146
AUT	367,830	27,465	95,348	45,262	68,280	41,959	24,740	65,240
CZE	354,761	33,230	122,249	59,495	57,546	30,437	15,659	39,171
DEN	237,699	15,720	49,886	29,811	51,567	27,366	12,237	50,864
FIN	227,034	31,822	68,567	25,123	35,526	17,834	10,026	41,928
ITA	2,638,923	156,849	825,189	263,740	551,597	301,944	169,372	382,108
NET	826,513	52,230	196,100	110,349	143,923	137,547	43,590	140,375
POR	305,746	19,137	82,342	48,719	50,545	32,215	20,080	51,224
SPA	1,516,754	84,067	449,054	235,717	235,634	139,466	139,693	222,815
SWE	419,784	42,966	116,387	30,582	68,772	52,923	19,849	91,689
UK	2,594,081	191,974	523,272	303,419	470,771	449,838	179,499	472,138
US	16,062,295	1,359,724	3,338,528	1,384,168	2,311,766	2,800,066	991,628	3,833,274
average	2,209,050	171,689	503,968	225,519	352,556	348,051	140,156	463,164
s.d.	4,448,395	378,242	923,286	378,302	640,181	783,188	275,501	1,070,561
c.v.	2.01	2.20	1.83	1.68	1.82	2.25	1.97	2.31
INTERMEDIATE INPUT								US$m (2000)
AUS	518,765	21,262	129,420	101,326	96,423	74,669	31,277	56,185
AUT	179,529	14,346	62,960	23,720	28,503	17,316	10,570	21,025
CZE	227,976	20,997	93,414	42,584	26,500	18,466	9,538	16,041
DEN	118,794	8,276	33,300	16,429	25,813	13,080	5,756	14,900
FIN	122,764	17,392	48,478	14,799	14,526	7,523	5,245	15,312
ITA	1,447,239	85,076	608,101	153,049	289,506	137,273	83,376	84,290
NET	450,565	31,429	145,348	70,853	61,199	68,838	23,667	46,217
POR	167,685	10,536	60,988	31,499	22,529	14,988	11,124	14,449
SPA	807,715	44,802	330,803	140,825	101,176	61,408	60,350	61,178
SWE	227,061	28,502	80,277	14,933	32,062	25,043	10,537	36,315
UK	1,389,816	98,236	343,145	187,929	223,823	244,496	89,937	189,280
US	7,480,431	642,915	2,200,448	705,565	833,906	1,206,091	501,067	1,349,419
average	1,094,862	85,314	344,724	125,293	146,331	157,433	70,204	158,718
s.d.	2,065,207	177,936	608,808	192,444	233,465	337,324	139,037	378,188
c.v.	1.89	2.09	1.77	1.54	1.60	2.14	1.98	2.38
LABOUR INPUT								million hours
AUS	16,423	461	2,063	2,653	3,808	2,399	1,698	3,341
AUT	6,725	241	1,002	1,016	1,437	823	762	1,445
CZE	10,031	473	2,386	1,761	2,138	929	702	1,641
DEN	4,289	165	649	471	892	499	341	1,271
FIN	4,008	188	632	717	749	366	304	1,053
ITA	42,714	1,355	8,106	5,930	9,480	5,011	6,121	6,711
NET	11,614	345	1,471	1,438	2,549	2,285	1,091	2,435
POR	9,286	181	1,777	2,397	1,885	581	1,072	1,392
SPA	28,253	704	4,789	5,419	5,899	2,657	3,823	4,961
SWE	7,052	291	1,206	760	1,284	834	561	2,116
UK	47,345	1,918	6,891	5,159	9,980	8,625	5,003	9,769
US	269,310	11,070	34,776	25,761	52,256	45,435	28,713	71,298
average	38,088	1,449	5,479	4,457	7,696	5,870	4,183	8,953
s.d.	74,288	3,077	9,553	6,985	14,392	12,690	7,968	19,812
c.v.	1.95	2.12	1.74	1.57	1.87	2.16	1.91	2.21
ICT CAPITAL INPUT								US$m (2000)
AUS	91,351	11,681	9,038	10,194	15,913	20,307	6,094	18,122
AUT	30,036	10,719	3,032	802	4,571	6,860	1,451	2,601
CZE	37,774	10,835	4,289	3,219	7,020	6,980	1,221	4,211
DEN	28,366	2,203	3,116	1,236	6,158	8,970	2,563	4,120
FIN	17,453	2,917	2,558	958	3,857	3,215	1,435	2,514
ITA	188,822	26,207	26,598	6,166	66,543	37,634	8,629	17,045
NET	78,055	13,279	7,847	3,798	12,548	23,635	3,622	13,326
POR	26,575	4,871	855	222	2,336	6,243	3,693	8,356
SPA	116,408	16,045	16,412	4,971	34,252	21,087	11,149	12,493
SWE	33,332	6,469	7,253	1,042	6,186	8,827	1,551	2,004
UK	277,762	82,895	26,232	9,780	37,468	81,464	14,887	25,039
US	2,142,787	524,451	195,331	90,619	337,091	690,173	35,129	269,994
average	255,727	59,381	25,213	11,084	44,495	76,283	7,619	31,652
s.d.	599,457	148,071	54,298	25,278	94,125	194,535	9,707	75,423
c.v.	2.34	2.49	2.15	2.28	2.12	2.55	1.27	2.38

	ALL	ELECOM	MexElec	OtherG	DISTR	FINBU	PERS	NONMAR
NonICT CAPITAL INPUT								US$m (2000)
AUS	1,455,679	48,689	85,214	265,922	194,165	74,477	55,308	774,061
AUT	770,661	11,755	58,033	90,075	80,069	25,785	42,196	462,749
CZE	703,895	19,609	91,980	101,160	124,635	27,301	30,775	308,435
DEN	543,712	13,219	30,638	55,607	47,848	9,830	17,226	369,344
FIN	373,217	10,262	35,132	40,561	50,024	3,631	12,786	220,822
ITA	4,947,324	103,839	628,058	494,222	384,765	2,377,484	142,658	816,298
NET	1,495,420	35,867	94,531	139,156	123,757	79,633	30,133	992,343
POR	422,530	10,541	50,895	37,056	58,077	18,879	14,928	232,155
SPA	2,849,714	40,082	286,458	230,134	300,809	58,152	92,251	1,841,826
SWE	492,645	23,631	59,280	66,707	69,902	18,862	12,489	241,774
UK	3,373,708	66,900	255,864	347,665	297,809	157,299	166,526	2,081,646
US	22,425,811	878,566	1,429,909	2,383,689	1,669,908	1,003,434	585,693	14,474,613
average	3,321,193	105,247	258,833	354,330	283,481	321,231	100,247	1,901,339
s.d.	6,185,266	245,125	406,648	654,527	451,209	704,743	161,405	4,008,128
c.v.	1.86	2.33	1.57	1.85	1.59	2.19	1.61	2.11

*: The figures for ALL sectors are slightly different from the sum of sectoral figures because price indices (GO_P) used in the conversion of nominal values to real volumes are different from sector to sector. (Source of the raw data: EU KLEMS)