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The inventive performance of immigrants across multiple sectors: the importance of education and occupation

Yannu Zheng

Abstract

This is the first study on the distribution and inventive performance of immigrants across sectors based on individual-level data, which matches inventors with the general population in Sweden from 1985 to 2007. It also investigates the extent to which the match between education and occupation influences immigrants' inventive performance. The results clearly indicate that immigrants and natives have different probabilities of patenting in different sectors. In the high-tech knowledge-intensive service (KIS) sector, immigrants are more likely to patent than natives, which is mainly because immigrants have a higher educational level than natives; furthermore, immigrants' high and similar representation in high-skill occupations as natives enable them have as good patenting rate as natives after controlling for variance in all variables. In the high-tech manufacturing, low-tech and "other KIS" sectors, especially in the former two sectors, immigrants are less likely to patent than natives, largely because immigrants are over-represented in low-skill occupations. Overall, the lower match between education and occupation in immigrants reduces their chances of patenting in the above three sectors. Immigrant inventors perform as well as natives in terms of number of forward citations for the patents.

Keywords foreign-born, patent, innovation, high-tech, low-tech, industry, Sweden

JEL classification I21 . J24 . O14 . O31

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1 Introduction

Recently there has been a lot of interest in immigrants' contribution to technological innovation and economic growth in the host country, from both scholars and policymakers (e.g. Stephan & Levin, 2001; Hunt & Gauthier-Loiselle, 2010; No & Walsh, 2010; Hunt, 2011; Parrotta et al., 2014; Zheng & Ejermo, 2015). Studies have shown that immigrants, especially highly skilled immigrants working in high-tech industries such as software, computer science and engineering, have contributed significantly to technological advances and innovation (e.g. Kerr, 2010; Goldin et al., 2011; Hunt, 2011). It is important to emphasize, however, that innovation is not confined solely to high-tech sectors but can be expected occur to varying degrees across all sectors (Helmets & Rogers, 2011). Moreover, immigrants may be over-represented in innovation in certain high-tech sectors relative to natives (Kerr, 2010). It is also important to underscore that highly skilled immigrants in the high-tech sectors constitute a special group of immigrants who are usually more highly qualified than immigrants in general and so their level of innovation performance is unlikely to be representative of immigrants in other sectors. This paper argues that more attention needs to be paid to the heterogeneity of immigrants as focusing on one specific group may preclude generalizations about immigrants' innovativeness and restrict implementation of policies designed to ensure that immigrants fulfil their potential for innovation.

There has not been any previous research into the innovation of immigrants across multiple sectors, using individual-level data. This is the first study compares inventive performance of first-generation immigrants¹, hereafter immigrants, and natives (i.e. native-born with two native-born parents) in different sectors. It also looks at the combined effect of education and occupation on immigrants' inventive performance, which has not been done before. The rationale for this analysis was that both educational level and occupation were expected to influence innovation performance and previous research had shown that in several sectors immigrants tend to differ from natives with respect to education and occupation (Saxenian, 2002; Hunt & Gauthier-Loiselle, 2010; No & Walsh, 2010; Hunt, 2011; Bosetti et al., 2012; Singer, 2012). There is more likely to be a mismatch between actual and required education in the case of immigrants than natives. Immigrants tend to be employed in different roles from natives with similar education and experience (Battu & Sloane, 2002, 2004; Green et al., 2007; Ottaviano & Peri, 2012).

This research was possible because I had access to a specialised database, which matches inventors with the general population in Sweden between 1985 and 2007 (Jung & Ejermo, 2014; Zheng & Ejermo, 2015). I consider an inventor to be a

¹ Second-generation immigrants who have at least one foreign-born parent are excluded in this paper as they share characteristics with both natives and immigrants and perform differently from both these groups (Zheng and Ejermo, 2015; Zheng, 2016).

Swedish resident who has been listed as an inventor on a patent application filed with the European Patent Office (EPO). The innovativeness of immigrants and natives was compared using two indicators: (a) the patenting rate for the employed population; (b) the number of forward citations (NFC) received per patent.² The database makes it possible to measure the direct distribution and inventive performance of immigrants in the sector in which they are employed. Sectors are categorized into four groups based on the three-digit codes of the Swedish Standard Industrial Classification (SNI92) system: (a) high-tech manufacturing sector (e.g. chemicals); (b) high-tech KIS sector (e.g. telecommunications); (c) “other KIS” sector (e.g. health care and social services) and (d) low-tech sector (e.g. food industry).³ Work in the high-tech KIS sector is more likely to generate patents than work in the “other KIS” sector. The empirical research focused on employed individuals educated to at least secondary school level or the equivalent.⁴

This study provides clear evidence that immigrants and natives have different probabilities of patenting in most sectors. In the high-tech KIS sector, immigrants are more likely to patent than natives, which is mainly because immigrants are more highly educated than natives; moreover, immigrants’ high and similar representation in high-skill occupations as natives enables them have similar probabilities of patenting as natives when holding all variables constant. In the high-tech manufacturing, low-tech and “other KIS” sectors, especially in the former two sectors, however, immigrants are less likely to patent than natives. This is largely because immigrants are more concentrated in the low-skill occupations, despite their average educational level being higher than that of natives. Overall, possibly due to lack of country-specific human capital or discrimination, the match between the education and occupation is much lower for immigrants than for natives and this appears to be the main reason for the lower patenting rate for immigrants working

² Although patents have some shortcomings as indicators of innovation (they only apply to certain types of invention and do not necessarily have commercial value; see Giuri et al., 2007), they are still the most common output measure of innovation.

³ (a) *High-tech manufacturing sector* includes: manufacture of refined petroleum products and nuclear fuel (code 23x excluding 231); chemicals and chemical products (24x); machinery and equipment (29x); office machinery and computers (30x); electrical machinery and apparatus (31x); radio, television and communication equipment and apparatus (32x); medical, precision and optical instruments, watches and clocks (33x); motor vehicles, trailers and semi-trailers (34x); other transport equipment (35x excluding 351). (b) *High-tech KIS sector* includes: postal and telecommunication services (64x); computing and related activities (72x) and research and development (73x). (c) *Other KIS sector* includes such as water transport (61x); air transport (62x); real estate activities (70x); financial intermediation (65x, 66x); education (80x), health care and social services (85x). (d) *Low-tech sector* includes: primary sector (e.g. agriculture hunting and forestry); low- and medium-tech manufacturing sector (e.g. food industry) and low KIS sector (e.g. hotels and restaurants).

⁴ Because data on the explanatory variable ‘field of study’ was only available for this group. Overall, the empirical regressions represent 75% and 60% respectively of the 25-64-year-old native and immigrant populations during 2001 to 2007 (see Table 6). The corresponding figures for native and immigrant inventors are 86% and 55% respectively (see Table 7).

in the above three sectors. Immigrant inventors perform similar as native inventors in terms of NFC per patent.

The rest of the paper is structured as follows. Section 2 summarizes relevant previous research and section 3 provides the theoretical background. Section 4 describes the databases and sets out descriptive statistics. Section 5 discusses the methods employed. Section 6 reports the empirical results. The final section presents conclusions from the study.

2 Literature review

Innovation is considered one of the most important driving forces behind advanced economies for most developed countries, many of which are experiencing increasing immigration (OECD, 2007, 2016). It is little wonder, therefore, that increasing attention is being paid to the innovation performance and contribution of immigrants to their host countries. Previous researches, however, mainly focused on highly skilled immigrants working in special high-tech sectors (e.g. Stephan & Levin, 2001; Chellaraj et al., 2008; Kerr, 2008; Hunt & Gauthier-Loiselle, 2010; No & Walsh, 2010; Hunt, 2011). Although previous literature has provided valuable insight into the contribution of immigrants, most studies to date have been small-scale and based on case studies or survey data. The findings usually show highly skilled or highly educated immigrants positively influence the innovation outcomes in the host country, but it is not clear to what extent the results are generalizable to the general population of immigrant employees. This is because not all immigrant employees have a high level of education. It is important to bear in mind that immigrant populations are very heterogeneous in terms of skills and education and distributed across all economic sectors in host countries.

Some studies have, however, explored the link between the general immigrant population and innovation using data aggregated at regional or country level. For example, Bratti & Conti (2014) used regional data on Italian provinces to show that the overall stock of immigrants do not appear to have an effect on the number of patent applications. Their results did suggest that there is a difference between low-skilled and high-skilled immigrants; an increase in the share of low-skilled migrants in the population would reduce patent applications whereas, highly skilled immigrants have a positive effect on patent applications. Based on panel data in 170 European regions, Ozgen et al. (2012) showed that the proportion of immigrants in the population do not affect the number of patent applications. Based on the evidence available so far, the effect of immigrants on innovation appears to be different when including low-skilled immigrants in compared with when only considering highly skilled immigrants (No & Walsh, 2010; Hunt, 2011). This means that excluding low-skilled immigrants from analyses may produce a misleading picture of the overall impact of immigration on innovation. This issue is especially important for countries that attract large numbers of low-skilled immigrants. For

example, Sweden, the setting for this research, has a tradition of focusing on humanitarian migration and paying little attention to the economic impact of immigrants (Scott, 1999; Bevelander, 2000).⁵ In such cases, immigrants are expected to have a lower potential for innovation in the host country compared with countries that have immigration policies more geared towards economic development.

Considering immigrants in the aggregate does not, however, reveal anything about how the distribution and performance of immigrants varies across sectors. This is important because it is well-known that innovation activity varies significantly between sectors (Helmets & Rogers, 2011). If immigrants are concentrated in certain sectors, if they are just more likely to live in innovative regions like large cities but are not employed in innovative sectors, or if their skills do not match to their roles, looking at the aggregate effect of immigration on innovation can be misleading (i.e. ecological fallacy). Examining the distribution and innovation of immigrants across sectors would improve understanding of how and where immigrants actually contribute to the host society.

It is well-known that immigrant employment tends to be concentrated in particular sectors. Fertig & Schmidt (2001) found that first-generation immigrants to Germany are more likely than natives to work in the manufacturing sector. Constant (2005) showed that in France immigrants were concentrated in labour-intensive and low-skill industries. Singer (2012) revealed that in the USA immigrants were over-represented in both high- and low-skill sectors. In particular, immigrants are prominent in high-tech sectors such as information technology (IT) and high-tech manufacturing sector (see also Saxenian, 2002; Kerr, 2010), but they were also over-represented in low-tech sectors such as agriculture, construction, food service and accommodation. In addition, within a sector the educational level and occupation profile of immigrants and natives are different. In high-tech industries such as healthcare, high-tech manufacturing, IT and life sciences, immigrants were more likely than natives to have a high level of education and were clustered in high-skill occupations (e.g. professionals) (Saxenian, 2002; Singer, 2012). However, in low-tech industries, the proportion of low-skill workers (without a high school diploma) is typically higher amongst immigrants than natives and immigrants are also more likely to cluster in low-skill occupations (Singer, 2012). Dustmann & Frattini (2011) reported that in the UK immigrants tend to be over-represented in the most highly skilled occupations in the public sector, but in recent years the share of immigrants in low-skill sectors and occupations appears to have been growing rapidly (Rienzo, 2015).

⁵ Note, however that on 21 June, 2015, the Riksdag (the Swedish parliament) decided to tighten the criteria for obtaining asylum in Sweden because the large inflow of refugees had generated serious social and financial problems, but even with the new restrictions in place Sweden still attracts large numbers of refugees.

Very few studies have examined the relationship between immigrants' inventive activity and the sector in which they work. The knowledge required to innovate can vary dramatically between sectors, as does the skill level of immigrants (Breschi et al., 2000; Singer, 2012). To date only Fassio et al. (2015a, b) have explored this relationship. Using industry-level survey data from France, Germany and the UK, they showed that the effect of migrants on total factor productivity (TFP) growth varied across sectors. The effect of migrants on TFP growth is stronger in manufacturing than in the service sector, and much stronger in high-tech manufacturing. They also found immigrants with tertiary education had a positive effect on the rate of increase in productivity in high-tech manufacturing and to a lesser extent in service sector, whilst immigrants with a medium or low level of education have a small positive effect in the manufacturing sector (Fassio et al., 2015b). Within the manufacturing sector generally the effect of migrants on innovation varies across sub-sectors; highly skilled immigrants have a positive effect on innovation (indicated by the number of patents and patent citations per 1000 employees) that is specific to the high-tech manufacturing sector (Fassio et al., 2015a); whereas low-skill immigrants have a negative impact on innovation in both high- and low-tech manufacturing sectors, particularly in the latter sector.

In summary, immigrants are distributed differently from natives and there is quite a lot of variance in their skills, educational level and occupation. This is the first study to consider how all these factors affect immigrants' inventiveness across multiple sectors based on individual-level data. This provides a more accurate picture of the distribution and innovation contribution of immigrants than data aggregated at regional, country or even industry level.

3 Theoretical background

Sweden is an attractive country for both low-skilled and high-skilled immigrants. The relatively high payment to unskilled workers in Sweden makes it an attractive country for low-skilled immigrants, while its relative good economic performance, generous welfare system and high living standards make it attractive for both groups of immigrants (Eger 2010; Koopmans 2010; Giulietti & Wahba 2013).

The skills of immigrants can vary widely between sectors; educational level and occupation can be used as indicators of skill (Bosetti et al., 2012). Immigrants working in the high-tech sector are more likely to be highly skilled compared with those who work in the low-tech sector. Moreover, the recruitment process may also be more rigorous in the high-tech sector than in the low-tech sector. In the low-tech sector, recruitment is usually based on capacity for physical or manual work and there is a relatively low requirement for human capital such as education and communication skills; this means that often it does not make much difference whether a position is filled by a native or by an immigrant. It is different in the high-

tech sector; the cost of labour and the requirement for human capital is usually higher and this may make employers more cautious about employing immigrants.

It is usually more difficult for immigrants to obtain positions for which a particular level of education or country-specific human capital is required, even if they have similar education and experience to natives in these roles. Immigrants are more likely to face discrimination and lack language skills and relevant social networks. To compete successfully with their native counterparts immigrants must usually have a skill advantage, such as higher education, to compensate for their disadvantage in country-specific human capital (Green et al., 2007). This is more likely in the high-tech sector, where the requirement for knowledge is generally greater than in the low-tech sector. Educational level plays a very important role in innovation, which seems to explain why immigrants are more innovative than natives in some studies (Hunt & Gauthier-Loiselle, 2010; No & Walsh, 2010; Hunt, 2011). One might expect, therefore, that for a given role, Swedish immigrants are more highly educated than native employees and the education has a stronger effect on immigrants than on natives for inventive activity. This effect may be especially pronounced in the high-tech sector.

The effect of skills and education on knowledge creation and economic productivity is likely to be lower if an individual's role fails to utilize his or her skills (Green et al., 2007). Educational attainment is treated as independent from occupation in the case of the foreign labour force, because there is often a mismatch between immigrant employees' educational level and the level required for their roles such that immigrants are often overeducated for their roles (Battu & Sloane, 2002, 2004; Green et al., 2007). Ottaviano & Peri (2012) reported that there are differences in the occupational profile on immigrants and natives with similar levels of education and experience. Moreover, the mismatch between education and occupation for immigrants can also vary across sectors (Battu & Sloane, 2002). The mismatch tends to be higher in sectors where there is high variance in the skills required than in sectors where specialist skills are required. As Bosetti et al. (2012) have argued, immigrants' occupation may be a better indicator of their contribution to the creation of new knowledge than their educational level, because highly educated immigrants are not always employed in the high-skill occupations that generate patents at a higher rate. I therefore investigated the association between immigrants' occupation and inventiveness across sectors.

4 Data and descriptive analysis

4.1 Summary of data

This paper is based on a rich database which matches inventors with the general population in Sweden from 1985 to 2007 (Jung & Ejermo, 2014; Zheng & Ejermo, 2015). The data on inventors and inventions were extracted from the Worldwide

Patent Statistics (PATSTAT) database provided by the EPO. Inventors social security numbers (SSNs)⁶ were added by matching the names and addresses provided by the EPO to those offered by a commercial company or a 1990 Swedish population directory. Finally, inventors were merged into the entire population in terms of their SSNs. Detailed demographic information on inventors was obtained from Statistics Sweden, which has collected such information for all Swedish residents from 1985 onwards.

This paper only deals with employees for whom information on work sector was available. The descriptive analyses shown in Table 1 and Figures 1 and 2 cover all employees, regardless of their educational level. Panel data were used in the statistical analyses presented in this paper as an individual's work sector can vary from year to year. The analyses were also restricted to people aged between 25 and 64 years (mean age 43.9 years), because this is the age range in which people are most likely to be working and patenting and so restricting the sample in this way makes it more homogeneous (inventors outside this age range made a negligible contribution to overall inventions). Overall, Table 1 and Figures 1 and 2 represent 68% and 88% respectively of Swedish immigrants and natives aged between 25 and 64 years (i.e. they exclude the unemployed population). The distribution of employees across sectors was roughly similar for natives and immigrants throughout the study period. A slightly higher proportion of immigrants were employed in the high-tech manufacturing sector (on average, 2.8% higher) and the "other KIS" sector (on average, 1.3% higher).

Table 1 shows that patenting activity varies considerably across sectors. Of the four sectors investigated, high-tech manufacturing was the most active in patenting. Employees in this sector constituted only 7.3% of the employee population, yet they accounted for 43.4% of inventors and 44.1% of inventions (fractional count for inventions⁷) in Sweden. It is hardly surprising that this sector had the highest proportion of inventors (0.25%; i.e. on average there are 25 inventors per 10,000 workers), followed by the high-tech KIS sector (0.16%), the "other KIS" sector (0.02%) and the low-tech sector (0.01%). On average there were 18.7, 11.0, 1.2 and 1.4 inventions per 10,000 employees (natives and immigrants) respectively in the above four sectors.

Table 1 also shows that within a given sector patenting activity differed between natives and immigrants; this was especially true in high-tech manufacturing and high-tech KIS. In the high-tech manufacturing sector, the proportion of inventors was higher amongst native employees (0.27%) than

⁶ The Swedish social security number is a unique identification number for each resident in Sweden, including foreigners with a valid residence permit for at least one year.

⁷ Fractional count means that each co-patent is counted as a fraction, depending on how many inventors contributed to one patent. Each patent is summed as one. For example, if one patent has three co-inventors, then the invention for each inventor is one third.

Table 1 Data by sector for proportion (%) of Swedish population aged 25–64 years identified as inventors (panel data), proportion of inventions (fractional count) they contributed to and employee population (panel data) grouped by immigration status, for 1985–2007.

	High-tech manufacturing			High-tech KIS			Other KIS			Low-tech sector			Share of natives and imm. in the Swedish pop.	Total no. of obs. ^a
	Nat	Imm	SuT	Nat	Imm	SuT	Nat	Imm	SuT	Nat.	Imm	SuT		
Percentage of the inventor pop.	38.6	4.8	43.4	12.2	2.1	14.3	13.9	2.0	15.9	16.4	1.6	18.0	91.6	37,548
Percentage of inventions	38.8	5.4	44.1	11.5	2.1	13.7	12.8	2.0	14.8	17.3	1.8	19.1	91.7	27,050
Percentage of the general employee pop.	6.2	1.1	7.3	3.5	0.4	3.9	33.6	4.6	38.2	38.9	4.8	43.6	93.1	87,841,866
Percentage of general pop. who are inventors	0.27	0.18	0.25	0.15	0.24	0.16	0.02	0.02	0.02	0.02	0.01	0.02		0.04

Sources (for all table and figures): Statistics Sweden and CIRCLE data on inventors.

Notes: (1) Nat=Natives; Imm=First-generation immigrants, same as in tables below; SuT=Sub-total; pop.=population

(2)^a Second-generation (2nd-gen) immigrants are included in the calculations.

immigrant employees (0.18%); the opposite applied in the high-tech KIS sector (0.15% vs. 0.24%). In the “other KIS” sector and the low-tech sector, neither natives nor immigrants were very active in patenting and the difference between the groups was very small.

4.2 Growing trends for immigrants by sector

I also compared the proportion of immigrant employees in the Swedish employee population, the proportion of immigrant inventors in the Swedish inventor population and their percentage contribution to inventions as a whole (Figure 1) and in each sector (Figure 2).

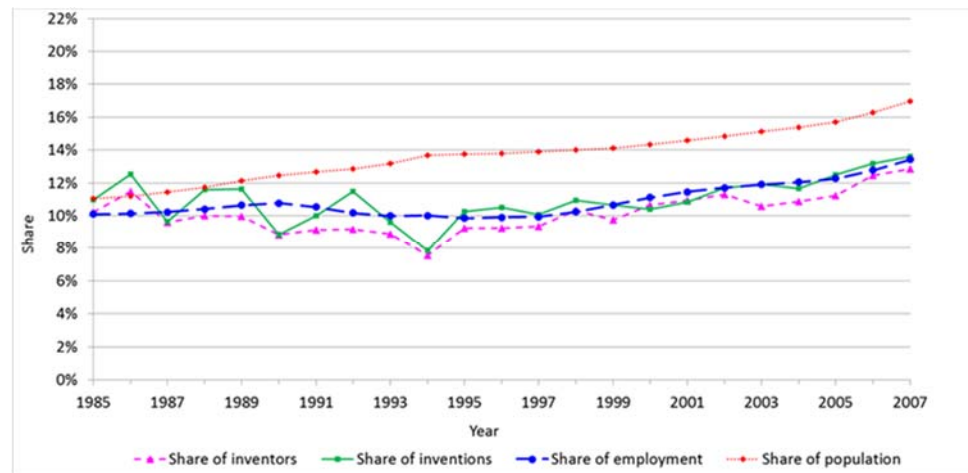


Figure 1 Immigrant inventors as a percentage of the Swedish inventor population (share of inventors) and their percentage contribution to inventions (share of inventions), immigrant employees as a percentage of the Swedish employee population (share of employment) for all sectors and immigrants as a percentage of the general Swedish population (share of population) aged 25–64 years; annual data for 1985–2007.

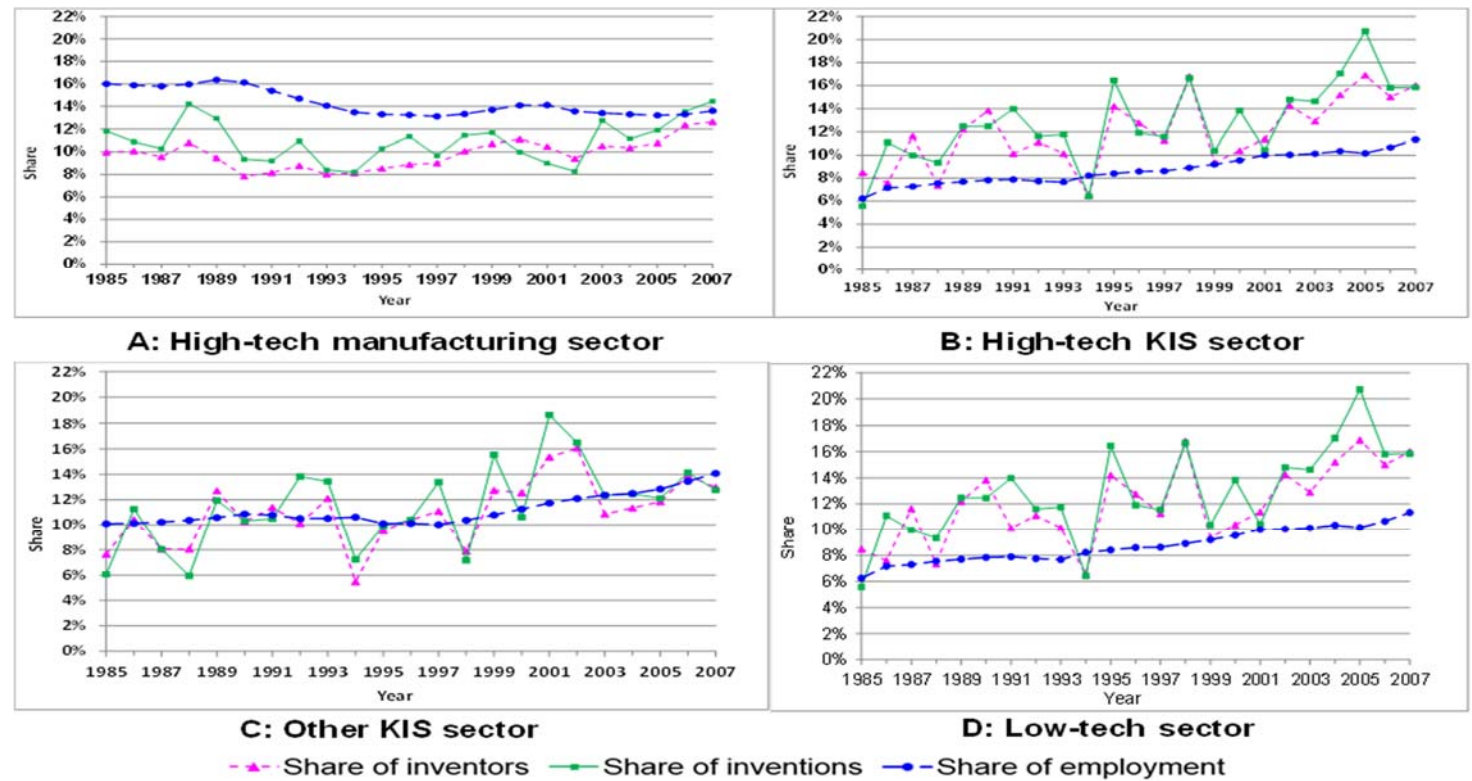


Figure 2 Immigrant inventors as a percentage of the Swedish inventor population (share of inventors) and their percentage contribution to inventions (share of inventions) and immigrant employees as a percentage of the Swedish employee population (share of employment) in each sectors aged 25–64 years; annual data for 1985–2007.

Figure 1 shows that, in general, immigrants were under-represented in the employee population. The proportion of jobs taken by immigrants decreased rapidly during the financial crisis of the early 1990s. Although it improved a little after the crisis (from 1997 onwards), as the Swedish economy recovered (Helgertz, 2010), it has not yet returned to the pre-crisis level when compared with the proportion of immigrant population in general Swedish population.⁸ Throughout the study period, immigrants were under-represented in the inventor population relative to their representation in the employee population, with the exception of the years 1986 and 1998. Immigrants accounted for a greater proportion of inventions than one would expect given their proportion of inventors.

Moreover, the proportions of inventors, inventions and employment attributable to immigrants varied considerably across sectors (see Figure 2, graphs A–D). In the high-tech manufacturing sector (graph A), immigrants accounted for smaller proportions of both inventors and inventions than one would expect given their representation in the workforce; however throughout the study period immigrant inventors were generally more productive (no. of patents per inventor) than their native counterparts. The growing trends in the low-tech sector were similar to those in the high-tech manufacturing sector, except during part of the early period (graph D). In the high-tech KIS sector, however, immigrants accounted for higher proportions of inventors and inventions than one would expect from their representation in the workforce (graph B). In the “other KIS” sector, immigrant representation in the inventor population and inventions varied across its proportion of workforce over the study period (graph C).

4.3 Educational level and occupational profiles amongst natives and immigrants

As expected that Sweden is attractive for both low- and high-skilled immigrants, immigrants were over-represented in the groups educated to primary school level and university education, regardless of whether the analysis was limited to employees (see Table 2). Table 2 also shows that individuals with only primary

⁸ Immigrants were struck harder than natives because, first, immigrants were overrepresented in the primary and manufacturing sectors which were most negatively affected by the recession. This put immigrants at a higher risk of unemployment during the recession (Arai and Vilhelmsson, 2004; Ekberg, 2011). Second, there was large inflow of refugees from the early 1990s, for instance, refugees from former Yugoslavia, Iran and Iraq. These newly arrived immigrants usually have problems to enter into labor market due to lack of human capital in some areas. Third, discrimination and the barriers to immigrants, especially those from non-European countries, can also increase when jobs are scarce in a recession (Ekberg, 2011). Finally, Sweden’s economic structural transition into post-industrial society (Schön, 2010) increases the demand of Sweden-specific knowledge (e.g. proficiency in Swedish) for labor market success, which puts immigrants at a disadvantage.

education were more likely to be unemployed than those with higher education, regardless of immigration status. Table 3 shows that amongst employees with the equivalent of at least secondary education, the proportion with a university education⁹ was higher amongst immigrants than natives in all sectors, especially high-tech KIS, regardless of whether the analysis is limited to inventors or includes the entire employee population. In all sectors, inventors tended to be more educated than employees generally.

Four occupation categories based on the Swedish Standard Classification of Occupations (SSYK 96), which is based on the International Classification of Occupations (ISCO-88), were used in the analysis. The following occupations are considered highly skilled as they usually require a high level of education or experience (Bosetti, 2012; International Labour Organization, 2012): legislators, senior officials and managers (code 1); professionals (code 2); technicians and associate professionals (code 3). All other occupations (codes 0, 4–8) are considered low-skill occupations. Table 4 shows that in three sectors immigrants were much less likely to work in high-skill roles than natives; the exception is the high-tech KIS sector, where the proportion of immigrants working in a professional role (48.0%) was higher than the corresponding proportion of natives (42.6%). When the analysis is limited to inventors, immigrants were more likely to be employed in professional roles than natives in all sectors except the “other KIS” sector. Moreover, in the “other KIS” sector, the proportion of immigrants employed as legislators, senior officials and managers (18.1%) was higher than the corresponding proportion of natives (14.3%), which is the opposite pattern to the other three sectors. The proportion of inventors employed in a professional role (52.6–86.9%) was around 1–5 times higher than for the employee population as a whole.

Table 5 shows the correlations between educational level and occupation for the general employee population and for inventors specifically. In the case of employees in general the correlation between educational level and occupation was lower for immigrants than for natives in all sectors. The discrepancy between immigrants and natives was highest in the low-tech sector, followed by “other KIS”, high-tech manufacturing and finally high-tech KIS. In the case of inventors the picture is slightly different. In high-tech manufacturing and high-tech KIS the education-occupation correlation was slightly higher for immigrant inventors than for native inventors. In the “other KIS” and low-tech sectors the correlation was still slightly lower for immigrant inventors than for native inventors, but the discrepancy of education-occupation correlation between immigrant and native inventors is smaller than for that of the general immigrant and native employee population.

⁹ Around 30% of inventors in this sample had a PhD education, so for the purposes of the regression analyses, individuals with a university education were divided into those with long education (i.e. ≥ 3 years of post-secondary education but below PhD level) and those with a PhD as this makes it clear how important PhD education is for invention.

Table 2 Percentage (%) distribution of educational level for the general population aged 25–64 years for 1985–2007, grouped by immigration status (panel data).

	General population		Employee population		Employee population educated to at least secondary level		Unemployed population	
	Natives	Imm	Natives	Imm	Natives	Imm	Natives	Imm
Primary education	26.5	30.7	23.8	26.3	–	–	44.9	40.6
Secondary education	46.1	42.5	46.8	44.6	61.4	60.5	41.3	37.9
<3 years of post-secondary education	12.7	11.3	13.5	12.1	17.7	16.4	7.4	9.6
University education ^a	14.7	15.5	16.0	17.1	20.9	23.1	6.4	12.0
Total	100	100	100	100	100	100	100	100

Note: ^a University education is defined as ≥ 3 years of post-secondary education, i.e. a bachelor's degree, master's degree, doctorate or equivalent.

Table 3 Educational profile of immigrants and natives, expressed as percentages (%) of the employee population and inventor populations aged 25–64 years for 1985–2007 and grouped by sector.

	All sectors		High-tech manufacturing		High-tech KIS		Other KIS		Low-tech sector	
Population	Natives	Imm.	Natives	Imm.	Natives	Imm.	Natives	Imm.	Natives	Imm.
Short	78.6	75.9	83.4	82.9	74.0	58.5	70.3	68.7	87.4	84.8
Long	20.3	21.8	15.4	15.0	22.1	30.7	28.3	28.5	12.3	14.5
PhD	1.1	2.3	1.2	2.1	3.8	10.8	1.4	2.7	0.3	0.7
Total	100	100	100	100	100	100	100	100	100	100
No. of obs.	50,762,634	5,345,282	3,847,847	546,771	2,685,012	239,870	23,132,544	2,492,074	21,097,231	2,066,567
Inventors										
Medium	30.6	20.1	30.7	22.0	15.9	11.4	26.6	12.2	48.6	38.0
Long	42.8	33.2	46.7	35.4	43.9	25.2	32.0	33.3	39.6	37.9
PhD	26.6	46.7	22.6	42.6	40.2	63.4	41.4	54.5	11.8	24.1
Total	100	100	100	100	100	100	100	100	100	100
No. of obs.	40,178	5,314	20,444	2,660	6,899	1,115	5,969	892	6,866	647

Notes: (1) Medium=Medium education (secondary or <3 years of post-secondary education); Long=Long education (≥ 3 years of post-secondary education but below PhD level)

(2) The data on number of observations are the data used in the regressions reported in Tables A3 and A4. The educational profiles of natives and immigrants are similar to those based on data from 2001–2007.

Table 4 Occupational profile of immigrants and natives, expressed as percentages (%) of the employee population and inventor populations aged 25–64 years for 1985–2007 and grouped by sector.

	All sectors		High-tech manufacturing		High-tech KIS		Other KIS		Low-tech sector	
Population	Natives	Imm	Natives	Imm	Natives	Imm	Natives	Imm	Natives	Imm
Low-skill occupations	48.0	59.0	49.0	64.4 ^a	27.3	28.4	40.9	51.9 ^b	58.4	70.8 ^c
Legislators, senior officials & managers	6.9	3.9	8.3	4.0	7.1	4.8	4.6	2.4	9.1	5.6
Technicians & associate professionals	22.6	16.3	27.2	18.9	23.0	18.8	24.2	18.1	19.9	13.0
Professionals	22.6	20.9	15.4	12.7	42.6	48.0	30.3	27.7	12.7	10.5
Total	100	100	100	100	100	100	100	100	100	100
No. of obs.	16,581,136	1,971,968	1,208,341	174,608	924,455	96,323	7,576,495	957,429	6,871,845	743,608
Inventors										
Low-skill occupations	1.8	2.6	1.2	2.2	0.4	0.8	2.0	2.5	5.4	8.7
Legislators senior officials & managers	15.4	11.5	13.8	9.8	16.6	9.3	14.3	18.1	20.2	12.5
Technicians & associate professionals	17.0	11.7	21.8	15.9	5.2	3.0	12.0	8.1	21.8	21.2
Professionals	65.8	74.2	63.2	72.1	77.8	86.9	71.7	71.3	52.6	57.7
Total	100	100	100	100	100	100	100	100	100	100
No. of obs.	18,596	1,938	9,351	874	3,930	497	2,497	359	2,818	208

Notes. (1) The data for number of observations are the data used in the regressions reported in Tables 6 and 7.

(2) ^a Compared with natives, the over-representation of immigrants in low-skill occupations in the high-tech manufacturing sector is mainly attributable to their over-representation in the following roles: craft and related trade roles (13.9% vs. 14.5%), plant and machine operators and assemblers (8.3% vs. 24.5%) and elementary occupations (2.7% vs. 4.5%). In the “other KIS” sector ^b and low-tech sector ^c their over-representation in low-skill occupations is attributable to their over-representation in the following roles: service workers and shop sales workers, plant and machine operators and assemblers and elementary occupations.

5 Methods

Two indicators were used to compare the patenting performance of immigrants and natives. First, I examined patenting rate, based on unbalanced panel data for the general Swedish population between 1985 and 2007. The dependent variable was the number of patent applications per individual in year t . Random-effects negative binomial regressions with observed information matrix (oim) standard errors were applied in the regressions. Second, for inventors, I examined NFC for their patents in order to compare the quality of patents contributed by immigrants and natives. NFC is positively correlated with patent value (e.g. Harhoff et al., 2003; Hall et al., 2005; Gambardella et al., 2008) and it is the mostly commonly used indicator of patent value and is considered by some to be the best predictor of patent value (Lanjouw & Schankerman, 1999). NFC was calculated for the five-year period following the filing of the patent. Negative binomial models were used because NFC is both a count variable and highly over dispersed (zero citations: 49.3 %, standard deviation: 2.8, mean: 1.5). Since 46.4 % of inventors had been listed in more than one invention, I controlled for intra-inventor correlation using clustered robust standard errors for inventors (Zheng & Ejermo, 2015). Table A2 presents the descriptive statistics for both dependent variables. The unit of analysis for patenting rate was the individual whereas for NFC it was the patent–inventor combination¹⁰ since the NFC varies within inventors.

Four models were used to examine the inventiveness of immigrants in all sectors on the basis of 2001–2007 data, as this is the period for which occupation data were available. Model 1 compares immigrants with natives whilst controlling for variance in *field of study*; *age*; *age*²; *gender*; *firm size*; *industry of work*; *region of work*.¹¹ The analyses of NFC also controlled for variance in *technology field*; *application year*; *number of inventors per patent*; *number of co-inventors in a patent who are natives* /*second-generation immigrants with one native-born parent and one foreign-born parent* (henceforth *mixed second-generation immigrants*) /*second-generation immigrants with two foreign-born parents*/*first-generation immigrants*. Models 2 and 3 also included the variable *highest educational level* and *highest occupation*, which were expected to have especially strong effects on patenting and can vary considerably between natives and immigrants and across sectors (Battu & Sloane, 2002; Hunt, 2011). Model 4 was the full model, controlling for variance in educational level, occupation and all other control variables. Table A1 provides

¹⁰ For example, a patent filed jointly by three inventors generates three patent–inventor observations. An inventor who contributed to four patents generates four patent–inventor observations.

¹¹ I also examined the effect of *years of residence* (data only available from 1961 onwards) on immigrants' probability of patenting in the various sectors (see Table A5). Overall, immigrants' probability of patenting increased with years of residence in Sweden.

Table 5 Correlation of educational level and skill level of occupation.

	All			High-tech manufacturing			High-tech KIS			Other KIS			Low-tech sector		
Kendall's tau-b	All	Natives	Imm	All	Natives	Imm	All	Natives	Imm	All	Natives	Imm	All	Natives	Imm
Population	0.55	0.56	0.48	0.54	0.55	0.49	0.49	0.50	0.47	0.61	0.62	0.55	0.43	0.44	0.34
Inventors	0.36	0.36	0.37	0.39	0.39	0.41	0.21	0.21	0.25	0.38	0.39	0.34	0.28	0.28	0.26

Notes: (1) Kendall's tau-b, which can be used to measure the correlation between ordinal variables, is applied here (Gadermann, 2012).

Data on number of observations are the data used in the regressions reported in Tables 6 and 7.

(2) The four skill levels of **occupation** (ordinal variable) are derived from the ten major ISCO-88 occupation groups. *Level 1* covers elementary occupations (code 9). *Level 2* covers basic administrative roles (code 4), service workers and shop and market sales workers (code 5), skilled agricultural and fishery workers (code 6), craft and related trades workers (code 7), plant and machine operators and assemblers (code 8) and armed forces (code 0). *Level 3* covers technicians and associate professionals (code 3). *Level 4* covers legislators, senior officials and managers (code 1) and professionals (code 2).

(3) **Educational level** (ordinal variable) is divided into four levels here: *level 1* represents completion of secondary school; *level 2* represents < 3 years of post-secondary education; *level 3* represents ≥ 3 years of post-secondary education but below PhD level; *level 4* represents PhD education (also unfinished).

brief rationales for the inclusion of each control variable and an explanation of their structures. To check the robustness of the analysis I carried out a parallel analysis of data from the 1985–2007 period using the same models 1 and 2 as above but without including occupation (occupational data were not available for the period before 2001).

6 Empirical results

Table 6 compares the patenting rates of immigrants and natives. An incidence-rate ratio (IRR) greater than 1 indicates that immigrants were more likely to patent than natives; IRRs less than 1 that natives were more likely to patent than immigrants. The results show that when variance in other variables was controlled, immigrants were less likely to patent than natives, but patenting varied considerably across sectors (see models 1 for all-sector and per sector). Immigrants' lower patenting rate is mainly attributed to data from the high-tech manufacturing sector and the low-tech sector, where immigrants were respectively 24.8% ($p < 0.01$, model 2.1) and 33.1% ($p < 0.01$, model 5.1) less likely to patent than natives. In the "other KIS" sector, the patenting rate for immigrants was 6.3% lower than that of natives, although this result was not significant at 10% level (model 4.1). Controlling for variance in occupation resulted in reversal of the direction of the discrepancy, which indicates that immigrants' occupational disadvantage was the main reason for their lower patenting rate (models 2.3, 4.3 and 5.3). This is because immigrants were concentrated in low-skill occupations where they were less likely to be involved patenting (Table 4); this is especially true for those working in the high-tech manufacturing sector.¹² In all three sectors, controlling for variance in educational level increased the discrepancy between immigrants' and natives' IRRs by 9.9–15.2% (models 2.2, 4.2 and 5.2), which indicates that without an advantage in educational level, immigrants were even less likely to patent than natives. The full models, in which all control variables were held constant, show that immigrants working in the high-tech manufacturing and low-tech sectors had patenting rates that were respectively 10.7% ($p < 0.1$, model 2.4) and 18.3% ($p < 0.05$, model 5.4) lower than those of natives. The patenting rate for immigrants working in the "other

¹² The robustness of this finding was checked by analyzing data from individuals only in high-skill occupations in the high-tech manufacturing, other "other KIS" and low-tech sectors (results are available upon request). The results showed that, when holding other variables constant, the patenting rates for immigrants in the above three sectors were respectively 13.9% ($p < 0.05$), 19.2% ($p < 0.05$) and 15.4% (not significant at the 10% level) higher than that of natives. When controlling for variance in educational level, however, immigrants in the high-tech manufacturing and "other KIS" sectors become as likely to patent as natives, whereas immigrants in the low-tech sector had a patenting rate that was 18.2% ($p < 0.05$) lower than that of natives.

KIS” is 3.6% lower than natives, but the difference is not significant at 10% level (model 4.4).

However, when holding other variables constant, the patenting rate for immigrants in the high-tech KIS sector was 16.7% ($p < 0.05$) higher than that of natives (model 3.1). Controlling for variance in educational level reversed the direction of the discrepancy and decreased the IRR by 21.1% and the significant difference between natives and immigrants disappeared (model 3.2). This strongly indicates that immigrants had a better patenting rate than that of natives was mainly due to their superior educational level. Occupation does not appear to have had strong impact on the patenting activity of immigrants working in the high-tech KIS sector (model 3.3) since immigrants were highly concentrated in high-skill occupations as natives (Table 4) and the discrepancy in education-occupation match between immigrants and natives was fairly low in this sector (Table 5). This may be because the scientific and engineering knowledge required for working in the high-tech KIS sector is very professional, which needs high match between education and occupation. Nevertheless, it is easy to be transferred across countries as it is not dependent on institutional or cultural knowledge and or on good language skills (Hunt & Gauthier-Loiselle, 2010). For example, Ericsson needs employees who were highly educated in engineering to work as technicians or professionals, but it does not matter much whether the employee is a native or an immigrant. With all control variables held constant, immigrants in the high-tech KIS were as likely to patent as their native counterparts (models 3.4).

The robustness of the analyses of patenting rate was checked using data from a longer period, 1985–2007 (see Table A3). The results were very similar to those obtained for 2001–2007, which only examined the effect of education (compare to models 1 and 2 in Table 6). This implies that the results for comparison of the patenting rate of immigrants and natives are robust both in short and long periods. Table 7 shows that in most sectors, the NFC was similar for patents filed by immigrants and natives; the exception was the “other KIS” sector (models 4.1–4.5) where immigrants’ patents had a higher mean NFC ($p < 0.1$). These results were the same regardless of whether or not the control variables were included in the models and indicate that neither educational level nor occupation accounts for differences between natives and immigrants with respect to NFC per patent.

The robustness of the results was checked by analysing data from 1985–2007. The results were similar to those for the 2001–2007 data when using the same models (Table A4). In the high-tech manufacturing and low-tech sectors, immigrants and natives had similar NFCs. The only difference was in the case of the “other KIS” sector, where over the longer time period the difference in favour of immigrants was no longer significant (compare models 4.1–4.2 in Table A4 and Table 6). In the high-tech KIS sector the mean NFC was lower for immigrants’

Table 6 Random-effects negative binomial regressions on the patenting rate of immigrants (omit: natives) among the general employee population aged 25–64 years, 2001–2007.

	All				High-tech manufacturing				High-tech KIS			
	1.1	1.2	1.3	1.4	2.1	2.2	2.3	2.4	3.1	3.2	3.3	3.4
	All_sim	All_edu	All_occ	All_full	HM_sim	HM_edu	HM_occ	HM_full	HK_sim	HK_edu	HK_occ	HK_full
Immigrants	0.863*** (0.032)	0.710*** (0.026)	1.165*** (0.043)	0.933* (0.036)	0.752*** (0.045)	0.653*** (0.039)	1.093 (0.066)	0.893* (0.055)	1.167** (0.088)	0.956 (0.074)	1.198** (0.090)	1.000 (0.077)
Educational level	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.006*** (0.001)	0.007*** (0.002)	0.018*** (0.004)	0.017*** (0.004)	0.004*** (0.002)	0.017*** (0.005)	0.017*** (0.006)	0.042*** (0.014)	0.005*** (0.002)	0.001*** (0.000)	0.011*** (0.005)	0.002*** (0.001)
Wald χ^2	16,610	22,765	20,363	23,003	2,717	5,297	4,165	5,086	3,246	3,800	3,253	3,672
Log likelihood	−96,583	−91,751	−91,252	−88,917	−35,969	−34,398	−33,828	−33,204	−17,440	−16,998	−17,180	−16,878
No. of observations.	18,553,104				1,382,949				1,020,778			
No. of individuals	3,337,267				318,908				261,054			

Table 6 continued.

	Other KIS				Low-tech sector			
	4.1	4.2	4.3	4.4	5.1	5.2	5.3	5.4
	OK_sim	OK_edu	OK_occ	OK_full	LT_sim	LT_edu	LT_occ	LT_full
Immigrants	0.947 (0.077)	0.831** (0.068)	1.159* (0.095)	0.964 (0.080)	0.669*** (0.059)	0.517*** (0.043)	1.052 (0.086)	0.817** (0.070)
Educational level	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	No	Yes	Yes	No	No	Yes	Yes
Other Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.000*** (0.000)	0.003*** (0.002)	0.002*** (0.001)	0.009*** (0.005)	0.000*** (0.000)	0.003*** (0.001)	0.001*** (0.001)	0.013*** (0.006)
Wald χ^2	3,635	4,978	3,827	4,819	3,170	5,470	5,482	6,342
Log likelihood	-17,257	-16,231	-16,741	-16,062	-25,212	-23,671	-23,253	-22,558
No. of observations	8,533,924				7,615,453			
No. of individuals	1,805,230				1,654,857			

Robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Notes: (1) incidence-rate ratios are reported.

(2) There are three dummies for educational level and four dummies for occupation, the same in Tables 7, A3 and A4.

(3) The other control variables included here are: age; age²; gender; dummies for field of study, firm size, region of work, and industry of work and sector of work

Table 7 Negative binomial regressions on NFC for immigrant inventors (omit: natives) aged 25–64 years, 2001–2007.

	All				High-tech manufacturing				High-tech KIS			
	1.1	1.2	1.3	1.4	2.1	2.2	2.3	2.4	3.1	3.2	3.3	3.4
	All_sim	All_edu	All_occ	All_full	HM_sim	HM_edu	HM_occ	HM_full	HK_sim	HK_edu	HK_occ	HK_full
Immigrants	0.022 (0.073)	0.013 (0.070)	0.021 (0.073)	0.011 (0.070)	−0.048 (0.070)	−0.050 (0.070)	−0.050 (0.070)	−0.053 (0.070)	−0.100 (0.113)	−0.104 (0.110)	−0.095 (0.114)	−0.095 (0.111)
Educational level	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.979*** (0.346)	0.934*** (0.336)	0.978*** (0.356)	0.887*** (0.344)	0.908* (0.468)	0.894* (0.469)	0.810* (0.471)	0.713 (0.471)	−0.157 (0.551)	−0.292 (0.559)	−0.074 (0.548)	−0.212 (0.557)
Wald χ^2	3,390	3,381	3,403	3,398	2,215	2,205	2,233	2,215	713	711	715	713
Log pseudolikelihood	−27,872	−27,862	−27,871	−27,859	−13,349	−13,348	−13,347	−13,343	−6,491	−6,488	−6,485	−6,483
Pseudo R ²	0.050	0.050	0.050	0.050	0.053	0.053	0.053	0.053	0.067	0.067	0.068	0.068
No. of observations	20,532				10,223				4,427			
No. of inventors	8,348				3,910				1,833			

Table 7 continued.

	Other KIS				Low-tech sector			
	4.1	4.2	4.3	4.4	5.1	5.2	5.3	5.4
	OK_sim	OK_edu	OK_occ	OK_full	LT_sim	LT_edu	LT_occ	LT_full
Immigrants	0.213*	0.203*	0.211*	0.207*	-0.165	-0.190	-0.163	-0.190
	(0.128)	(0.121)	(0.125)	(0.119)	(0.139)	(0.137)	(0.139)	(0.137)
Educational level	No	Yes	No	Yes	No	Yes	No	Yes
Occupation	No	No	Yes	Yes	No	No	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.267*	1.067	1.304*	1.093	0.622	0.797	0.642	0.786
	(0.681)	(0.684)	(0.673)	(0.677)	(0.777)	(0.766)	(0.782)	(0.778)
Wald χ^2	1,190	1,056	1,057	1,046	241	249	265	268
Log pseudolikelihood	-4,083	-4,081	-4,079	-4,077	-3,760	-3,754	-3,755	-3,751
Pseudo R ²	0.041	0.041	0.042	0.042	0.035	0.036	0.036	0.037
No. of observations			2,856				3,026	
No. of inventors			1,565				1,490	

Robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Notes: (1) Coefficient results of clustered robust standard errors on inventors are reported. (2) The other control variables are: age; age²; gender; dummies for field of study, firm size, industry of work, region of work, technology field and application years; the total number of inventors in a patent; number of co-inventors in a patent who are natives /mixed second-generation immigrants/second-generation immigrants with two foreign-born parents/first-generation immigrants (3) Pseudo R² = 1 - log pseudolikelihood (full model) / log pseudolikelihood (constant-only model)

patents than for those of natives¹³ (models 3.1–3.2 in Table A4). Over the longer period educational level still did not contribute to differences between natives and immigrants.

The results relating to the control variables largely conformed to expectations (detailed results are available upon request). Both educational level and occupation have a significantly positive effect on patenting performance, but the effect is much stronger on the patenting rate than that on the NFC per patent. Educational level was positively associated with both patenting rate and NFC per patent. However, patents filed by inventors with PhD education and inventors with only a first stage of tertiary education (i.e. long education) had similar NFCs in all sectors. In the high-tech manufacturing and low-tech sectors, the patenting rate was higher for professional roles than other roles. However, in the high-tech KIS sector, legislators, senior officials and managers had a higher patenting rate than professionals, whereas in the “other KIS” sector, no significant difference is found from the above two roles. When the analysis was limited to inventors, however, in each sector, occupation had small effect on NFC for patents and the difference between professionals and other occupations was not large.

7 Conclusion

This study provides an overall picture of the distribution and inventiveness of immigrant employees as well as looking at the effects of educational level and occupation on inventive performance across multiple sectors. The results show that in general immigrants were less likely to patent than natives. This is mainly due to the contribution of immigrants working in the high-tech manufacturing and low-tech sectors, where their patenting rates were respectively 24.8% and 33.1% lower than that of natives. The patenting rate for immigrants working in the “other KIS” sector is 5.3% lower than natives, but the difference is not significant. The main reason that immigrants in the above three sectors, especially in the former two, are less likely to patent than natives because immigrants were concentrated in low-skill roles where involvement in patenting activity is less likely, despite their average educational level being higher than that of natives, which had a positive effect on decrease the discrepancy of patenting rate between natives and immigrants. However, the patenting rate for immigrants working in the high-tech KIS sector was 16.7% higher than natives and this is largely attributable to the fact that they tended

¹³ Further exploration showed that this was mainly due to data from the post and telecommunication and research and development sectors (results are available upon request). Immigrants only filed 32 patents in the post and telecommunication industry. This suggests that in this sector immigrant inventors are disadvantaged by the lack of a co-ethnic network, as such networks can be an important channel for knowledge dissemination, such as patent citations (Agrawal et al., 2006; Agrawal et al., 2008; Kerr, 2008).

to be more highly educated than their native counterparts. Moreover, in the high-KIS sector, immigrants' high and similar concentration in high-skill occupations as natives enable them have as good patenting rate as natives after controlling for variance in all variables. Overall, immigrants' higher educational level increased their patenting rates by 11.6–21.1% relative to that of natives in each sector, but immigrants' high representation in low-skill roles decreased their patenting rates by 21.2–38.3% in each sector except in the high-tech KIS sector. In general, however, immigrants' and natives' patents were of similar quality in terms of NFC – although there was a small difference in the KIS sectors. This is because both native and immigrant inventors tended to be highly educated and employed in high-skill roles. Therefore, there was only a small discrepancy between native and immigrant inventors with respect to education-occupation match. Compared with the general immigrant employee population, immigrant inventors were more highly educated and tended to be employed in roles requiring a higher level of skill.

The study indicates that the average educational level for immigrants working in the high-tech KIS sector is higher than immigrants working in other sectors (see Table 3) and the discrepancy between immigrants' and natives' education-occupation match was lower in the high-tech KIS sector than in other sectors (see Tables 4 and 5). This may be because working in the high-tech KIS sector usually requires special knowledge and skills, which are easier to be transferred across national boundaries than those in other sectors as they have lower requirement on country-specific human capital.

The lower patenting rate of immigrants (after controlling for variance in educational level) in all sectors except the high-tech KIS sector implies that immigrants were disadvantaged in terms of some unobserved form of human capital or that discrimination reduced their inventive productivity. It indicates even relatively high-educated immigrant employees (i.e. with at least secondary education or equivalent) had problems finding opportunities to make full use of their education and skills, which reduced their productivity in the host country. This conclusion is corroborated by the observed mismatch between educational attainment and occupation in the immigrant population. It is important to emphasise that failing to realise the full potential of immigrants damages the competitiveness of Swedish companies: they are not getting the most out of the human capital their employees represent. Improving the match between immigrants' education and occupation would be a good way of ensuring that their skills are used more effectively. One way of doing this would be for governments, companies and immigrants to place more emphasis on increasing immigrants' country-specific human capital, such as language skills, especially in the case of those working in sectors that place a premium on such skills; another would be to reduce discrimination.

Appendix

Table A1 Control variables: rationale for inclusion and categorization.

Control variable	Rationale	Categories
Highest education level	Studies indicate that educational level has a positive effect on patenting performance (Hunt & Gauthier-Loiselle, 2010; No & Walsh, 2010; Hunt, 2011).	Three category variables : (a) Secondary or <3 years of post-secondary education (medium education); (b) ≥ 3 years of post-secondary education but below PhD level (long education, reference); (c) Any PhD education (also unfinished).
Occupation	Individuals in roles requiring a high level of skill are usually more knowledgeable and skilled than those in low-skill occupations and are therefore expected to show better patenting performance (Bosetti et al., 2012)	Four category variables : (a) Low-skill occupations; (b) Legislators, senior officials and managers; (c) Technicians and associate professionals; (d) Professionals (reference).
Field of study	Patenting activity can vary according to field of study (Hunt & Gauthier-Loiselle, 2010; Hunt, 2011), e.g. those who have studied science and engineering (S&E) are more likely to patent than those who have studied business.	Four category variables : (a) Engineering, manufacturing and construction (reference); (b) Science, mathematics and computing; (c) Health and welfare; (d) Other fields.
Age and age ²	Inventive productivity has a curvilinear relationship with age (Simonton, 2000; Jones, 2010; Jung & Ejermo, 2014).	Discrete data.
Gender	There are gender differences in patenting performance (e.g. Ding et al., 2006; Azoulay et al., 2007).	Dummy variable: (a) Male (reference); (b) Female.
Firm size	Small firms may be more constrained in their propensity to patent and may therefore focus on the most valuable inventions (No & Walsh, 2010). Large firms are more likely to apply for patents and are expected to produce higher-quality patents as they usually devote more resources to invention and can afford to hire employees with greater innovation skills.	Three category variables: (a) Small firms, coded 1 for 1–99 employees, 0 otherwise; (b) Medium firms, coded 1 for 100–499 employees, 0 otherwise (reference); (c) Large firms, coded 1 for 500 employees or more, 0 otherwise.
Industry of work	Inventive activity varies by industry (Helmets & Rogers, 2011). I include	38 categories following SNI92

Control variable	Rationale	Categories
	industry fixed effects to account for unobserved industry-specific effects.	
Region of work	Larger cities often offer economies of consolidation and hence more developed markets and more resources and opportunities for innovation than smaller cities (Orlando & Verba, 2005).	Three category variables: (a) Metro regions; (b) Urban areas; (c) Rural regions (reference).
Technology fields	Patents in technological fields in which many patents exist are likely to have a higher mean NFC than patents filed in sparsely patented fields (No & Walsh, 2010; Ejermo & Kander, 2011).	Five categories (Schmoch, 2008) ^a : (a) Electrical engineering (reference); (b) Instruments; (c) Chemistry; (d) Mechanical engineering; (e) Other fields.
Application year	Used to control for differences in citation behaviour over time and possible differences in the accumulation of citations over time (Sapsalis et al., 2006), although this is largely dealt with by counting citations over the five-year period immediately after filing.	Time dummy variables.
Total number of inventors in a patent	Used to control for the level of resources devoted to the research project which generates the patent, which is expected to be related to the quality of the patent (Sapsalis et al., 2006).	Discrete data.
number of co-inventors in a patent who are natives /mixed second-generation immigrants /second-generation immigrants with two foreign-born parents/first-generation immigrants ^a	Used to measure the cognitive diversity of inventors in a patent. Cognitive diversity may benefit a group if it is associated with greater diversity in ideas and perspectives and thus offers benefits in terms of problem-solving, generation of idea and patent quality (Nathan, 2014). Ethnic or cultural diversity may be a good proxy for cognitive diversity (Hong & Page, 2004).	Discrete data.

Note: ^a Only inventors identified in the patent are included in these figures. Zheng & Ejermo (2015) suggested that it is unlikely that there is any large sample selection issue in the data for unidentified inventors.

Table A2 Descriptive statistics for the dependent variables, 2001–2007.

Patenting rate	All		High-tech manufacturing		High-tech KIS		Other KIS		Low-tech sector	
	Natives	Imm	Natives	Imm	Natives	Imm	Natives	Imm	Natives	Imm
Mean	0.0012	0.0015	0.0067	0.0060	0.0044	0.0078	0.0004	0.0005	0.0008	0.0008
Standard deviation	0.5358	0.0636	0.1225	0.1196	0.1074	0.1480	0.0253	0.0345	0.0450	0.0546
Maximum	21	17	17	13	20	12	8	11	21	17
No. of obs.	16,581,136	1,971,968	1,208,341	174,608	924,455	96,323	7,576,495	957,429	6,871,845	743,608
NFC										
Mean	1.10	1.19	1.06	1.09	1.33	1.31	1.12	1.54	0.88	0.72
Standard deviation	2.11	2.33	2.19	2.12	2.45	2.78	1.79	2.59	1.46	1.17
Maximum	44	44	26	20	44	44	21	21	14	7
No. of obs.	18,596	1,938	9,351	874	3,930	497	2,497	359	2,818	208

Note: Minimum=0 for each indicator and sector

Table A3 Random-effects negative binomial regressions on patenting rate for immigrants (omit: natives) among the general employee population aged 25–64 years, 1985–2007.

	All		High-tech manufacturing		High-tech KIS		Other KIS		Low-tech sector	
	1.1	1.2	2.1	2.2	3.1	3.2	4.1	4.2	5.1	5.2
Immigrants	0.844*** (0.023)	0.733*** (0.020)	0.660*** (0.027)	0.612*** (0.025)	1.133** (0.070)	0.975 (0.061)	0.944 (0.056)	0.848*** (0.051)	0.683*** (0.044)	0.588*** (0.036)
Educational level	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.001*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.002*** (0.001)	0.000*** (0.000)	0.001*** (0.000)
Wald χ^2	30,621	39,233	5,952	10,364	5,413	6,305	7,770	9,811	5,397	8,471
Log likelihood	−205,634	−198,616	−84,975	−82,194	−30,920	−30,197	−38,883	−37,252	−51,522	−49,311
No. of observations	56,107,916		4,394,618		2,924,882		25,620,558		23,167,858	
No. of individuals	4,412,723		591,04		435,772		2,721,420		2,670,918	

Robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Notes: (1) incidence-rate ratios are reported.

(2) The other control variables included here are the same as in Table 6

Table A4 Negative binomial regressions on NFC for immigrant inventors (omit: natives) aged 25–64 years, 1985–2007.

	All		High-tech manufacturing		High-tech KIS		Other KIS		Low-tech sector	
	1.1	1.2	2.1	2.2	3.1	3.2	4.1	4.2	5.1	5.2
	All sim	All edu	HM sim	HM edu	HK sim	HK edu	OK sim	OK edu	LT sim	LT edu
Immigrants	–0.003 (0.050)	–0.013 (0.047)	0.019 (0.048)	0.018 (0.048)	–0.199*** (0.072)	–0.205*** (0.071)	0.163 (0.117)	0.144 (0.108)	–0.119 (0.098)	–0.139 (0.093)
Educational level	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.015*** (0.259)	1.108*** (0.259)	1.451*** (0.365)	1.509*** (0.367)	–0.360 (0.502)	–0.363 (0.505)	1.166** (0.557)	1.278** (0.565)	–0.169 (0.529)	0.058 (0.526)
Wald χ^2	3,980	4,005	2,247	2,272	1,154	1,161	617	609	537	544
Log pseudolikelihood	–70,383	–70,333	–35,494	–35,478	–13,642	–13,634	–10,563	–10,557	–10,377	–10,361
Pseudo R ²	0.044	0.045	0.049	0.050	0.051	0.052	0.032	0.032	0.034	0.035
No. of observations	45,492		23,104		8,014		6,861		7,513	
No. of inventors	15,262		7,663		2,994		3,214		3,316	

Robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Notes: (1) Coefficient results of clustered robust standard errors on inventors are reported.

(2) The other control variables included here are the same as in Table 7.

(3) Pseudo R² = 1 – log pseudolikelihood (full model) / log pseudolikelihood (constant-only model).

(4) The results for immigrant inventors are robust, based on comparisons with analyses of data from 1985 to 2004, 1985 to 2005 and 1985 to 2006. The exception is model 5.2.

Table A5 Odds ratios for the probability of patenting for the *general employee* immigrants (omit: natives) aged 25–64 years, grouped according to the duration of their residence in Sweden and by sector, 1985–2007.

Years of residence for immigrants	All	High-tech manufacturing	High-tech KIS	Other KIS	Low-tech sector
0–4 years	0.557*** (0.036)	0.564*** (0.057)	0.633*** (0.081)	0.475*** (0.077)	0.459*** (0.071)
5–9 years	0.742*** (0.034)	0.632*** (0.048)	1.012 (0.089)	0.839* (0.087)	0.551*** (0.062)
10–14 years	0.767*** (0.034)	0.631*** (0.045)	0.930 (0.089)	1.125 (0.102)	0.618*** (0.062)
14–19 years	0.743*** (0.034)	0.632*** (0.047)	1.071 (0.107)	0.784** (0.087)	0.691*** (0.069)
20–24 years	0.771*** (0.038)	0.749*** (0.054)	1.038 (0.122)	0.809* (0.095)	0.636*** (0.072)
25+ years	0.859*** (0.025)	0.825*** (0.035)	1.106 (0.083)	0.997 (0.063)	0.700*** (0.045)
No. of observations	56,095,149	4,388,676	2,924,469	25,617,134	23,164,870
No. of individuals	4,410,826	353,932	204,857	1,949,620	1,902,417
Wald χ^2	139,030	31,172	17,362	27,489	26,707
Log likelihood	–205,619	–81,849	–29,264	–39,129	–52,406
Pseudo R ²	0.253	0.160	0.229	0.260	0.203

Robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Notes: (1) odds ratios are reported.

(2) The other control variables included here are the same as in Table 6.

(3) Probability of patenting is set up as a dummy variable, coded as 1 if an individual has been listed as an inventor on at least one patent in year t and as 0 otherwise

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