The cost of immigrants' occupational mismatch in Canada

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Abstract

Given the large sample at our disposal (20 percent sample of the 2006 Census), we create a continuous index that reflects the "relatedness" between 1375 fields of study and 520 occupations for native-born Canadian educated workers. Unlike studies that define the match between pre- and post-immigration (or intended) occupations, this study uses the clustering of native-born workers in each cell of the field of study-occupation matrix as a benchmark reflecting the "common" matching quality in Canadian labour markets that internationally educated immigrant workers could achieve in the long-run. This allows us to approximate the annual cost of underutilization of immigrants' human capital by estimating the change in immigrant earnings if they were distributed same as the native-born in terms of relatedness (field of study-occupation match). Although the results show a significant and persistent poor matching quality for foreign-educated immigrant workers, their relative underutilization cost is not as sizeable as envisioned in some policy circles. The results help us understand not only the magnitude of waste in human capital but also the importance of occupational mismatch in explaining the wage gap between immigrant and native-born workers.

JEL Classification: J6, J15, J61

Keywords: Occupational mismatch, relatedness, underutilization, immigration, wage gap

Recent studies in developed economies indicate a significant mismatch problem between workers' qualifications and what their jobs' require in the labour force, which is conceptually different from short-term cyclical underemployment.[1] In a study of Canadian university graduates between 1993 and 2001 Li et al. (2006) found that those who were chronically or always overqualified accounted for about 50 percent of the ever-overqualified population. Most studies measure the matching quality by the amount of surplus or deficit in schooling (Leuven and Oosterbeek 2011). Robst (2007) was the first major study to investigate the mismatch in terms of the extent to which workers' field of study and their occupation were related, and how the degree of "relatedness" between the two affects wage earnings in the U.S. There are 1375 fields of study and 520 occupations classified in the 2006 Canadian census. In a recent study, Boudarbat and Chernoff (2012) report that 35.1 percent of Canadian university graduates are in jobs that are not related to their education 5 years after graduation. Studies show that choice of a field of study is directly influenced by the relative pay of graduates in related occupations (Freeman and Hirsch 2008; Altonji et al. 2015).

Immigrants' inability to practice in their trained occupation has been also blamed for the substantial decline in new immigrants' earnings in the last decades and the general slower labour market integration of immigrants since the 1970s, which is well documented in the literature (Picot and Sweetman 2012; Borjas 2013; Dustmann and Fabbri 2005; Kaushal et al. 2015). As noted by Sweetman et al. (2015), there is a common perception that a deficiency in foreign qualification recognition and an excessive cost of re-entry to regulated (or self-regulated) occupations following migration hinders the labour market integration of new immigrants. This is a particular concern in Canada as it has a point system for selecting skilled immigrants who would be employed in occupations that arguable face long-term labour shortage. In a recent study, Uppal and LaRochelle-Cote (2014) report that, among internationally educated university graduate immigrants, 48 percent women and 37 percent men worked in occupations usually requiring a high school education or less in

[1] The latest research on skill mismatch can be found at a workshop's program recently organized by IZA and CEDEFOB in October 2015 (http://www.cedefop.europa.eu/en/events-and-projects/events/cedefopiza-workshop-skills-and-skill-mismatch-0)

2006.[2] The same rates are 15 and 17 percent for Canadian educated native-born university graduates, respectively. The poor matching quality is seen as a symptom of slower immigrant labour market integration that may result in a substantial underutilization of human capital in the whole economy. For instance, Reitz (2001) estimates the annual cost to be as high as 15 billion dollars. On the other hand, the Conference Board of Canada (2001) has estimated this cost to be much lower, somewhere between 4.1 billion – 5.9 billion dollars.

Although the non-recognition of foreign qualification is frequently blamed in public policy for declining returns to pre-migration labour market experience and for the immigrant-native born gap in the rate of return to education in Canada, the evidence shows that the differences in pre-immigration educational "quality" have substantial impacts on the Canadian labour market earnings of immigrants (Li and Sweetman 2014) and the individual-level test scores (as a proxy for pre-immigration educational quality) explain the entire immigration-native born gap (Ferrer and Riddell 2008). In addition, studies have also found that low literacy skills and language proficiency of immigrants have a direct effect on the poor post-immigration labour market outcomes (Warman et al. 2015; Ferrer at al. 2006). These findings raise the question of the portability of internationally-educated new immigrants' human capital, an issue that has been investigated in the literature in conjunction with immigrants' occupational attainment and mismatch in hosting countries (Green, 1999; Imai et al 2011; Warman et al. 2015). If it is the non-portability of their foreign credentials resulted from to the shifting source country composition (Warman and Worswick 2015) that penalizes their wage earnings in hosting labour markets, rather than the immigrants' transitory occupational mismatch, solutions to the poor economic integration of immigrants to Canadian labour markets should lie more in policies targeting new immigrants' source country human capital characteristics rather than policies designed for post-immigration improvements (Green and Worswick 2012).

In this study, given the large sample at our disposal (20 percent sample of 2006 census), we were able to create a continuous index that reflects the "relatedness" between 1375 fields of study and 520 occupations for native-born Canadian educated workers. Unlike studies that define the match between pre- and post-immigration (or intended) occupations, this study will use the clustering of native-born workers in each cell of the field of study-occupation matrix as a benchmark reflecting the "common" matching quality in Canadian labour markets that internationally-educated immigrant workers can attain in the long-run. This approach allows us to approximate the annual cost of underutilization of immigrants' human capital by estimating the change in immigrant earnings if they were distributed identically to the native-born in terms of relatedness (field of study-occupation match) in Canada. This type of application has some important advantages: first, it eliminates the difficult problem of determining an "ideal" matching ordering of 520 occupations for each of 1375 fields of study in labour markets, particularly for unregulated occupations. While some fields of study have strong connections with some specific, perhaps regulated occupations, many do not.[3] Most studies on the subject use surveys that contain questions explicitly aimed at extracting information on field of study-occupation matching. Since those surveys are usually limited in size, even producing descriptive analyses in order to understand the incidence of mismatch becomes a real challenge because of the level of aggregation in classifications. Moreover, its effect on labour market outcomes modeled through self-reported binary variables involves some arbitrariness in the classification of workers in two categories – related or not, especially since "relatedness" is perhaps more a matter of degree, than an all-or-none concept. Second, even if such an ordering could be found, the actual cost of immigrants' underutilization should be gauged relative to a comparison group, and millions of native-born workers in labour markets would appear to be a natural choice.

Although the results show a significant and persistent poor matching quality for foreign-educated immigrant workers, their relative underutilization cost is not as sizeable as envisioned in some policy circles. This finding implies that, if the immigrants' occupational mismatch is rather a symptom of underlying problems, namely poor (or nonequivalence of) foreign education quality, language proficiency and literacy skills, without a substantial progress in these specific human capital characteristics, the isolated effects of relative improvements in occupational match will not be so rewarding for immigrants. In other words, the immigrants' occupational mismatch is much more a

[2] The same rates slightly decline in 2011 to 43 percent and 35 percent, respectively.
[3] Sweetman et al. (2015) provide an excellent overview about occupational regulation and foreign qualification recognition.

"source-country problem" rather than being a "host-country problem" that can be efficiently dealt with by post-arrival policies. The rest of the paper is organized as follows: Section 1 summarizes previous research; Section 2 introduces the data and contains a descriptive analysis. Econometric results and a discussion of our findings are given in Section 3; Section 4 presents the cost calculations. We provide the concluding remarks in Section 5.

1 Previous research

This study brings together two different but interrelated fields in the literature: education/skill mismatch in labour markets and immigrants' economic assimilation in hosting countries. Both fields are major research areas that have generated a fair amount of work. Following a study done by Duncan and Hoffman (1981) that defines a worker's attained education as the sum of schooling years in required education and overeducation or undereducation, there has been a growing body of research on how these separate measures of education affect wages using different datasets from different countries. Hartog (2000) and Leuven and Oosterbeek (2011) compared the results of a wide range of studies and concluded that although the effects of over- and undereducation mismatches on earnings are consistent across studies (a substantial wage penalty for surplus schooling, for example), the two main econometric challenges that make the underutilization cost questionable remain unsolved in this literature: estimator bias resulting from unobserved heterogeneity (e.g., ability) and possible measurement errors in required education. Most studies in this literature (sometimes called as the ORU literature) quantify the educational mismatch by the amount of surplus or deficit in schooling years. This approach assumes that more years of education is better and use the "quantity" of schooling rather than the "type" of education to identify the mismatch.

Robst (2007) was the first major study to investigate the relationship between workers' field of study and their occupation, and how the degree of "relatedness" between the two affects wages in the United States. He used a question in the 1993 National Survey of College Graduates that asks how the respondents' field of study is related to their current occupation. He controlled for relatedness by using the answer to construct a binary variable equal to one if the survey answer is either "related" or "somewhat related" and to zero if otherwise. The Robst paper, along with a number of recent studies such as Nordin et al. (2010) and Yuen (2010), shows that workers tend to earn higher wages when in an occupation that is closely related to their field of study. While most of the studies use self-reported answers to a survey question, Nordin et al. paper is the first study to use the distribution of Swedish workers across occupations to identify matching occupations for each major. They manually (not statistically) identify "crowded" occupations for each major and classify occupations in three categories: related, weakly related, and unrelated.

In a most recent paper, Lemieux (2015) identifies three channels through which education affects wage outcomes: first, a higher overall "quantity" of education makes workers more productive; second, a higher degree helps workers get into higher-paying occupations; and third, the skills acquired in a given field of study become more valuable in jobs that are a good match for their education program.[4] He uses the self-reported answers in 2005 National Graduate Survey with about 10 thousand university graduates to identify whether the person works in a related job and then calculates the average of these binary answers in each of 90 cells (10 fields of study and 9 occupations). These average measures reflect each major's relatedness to 9 occupations. By merging these relatedness measures with publicly available 2006 Canadian census file, he controls for the "relatedness" for each worker through both continuous and binary variables in wage regressions and finds that educational degrees and relatedness (job match) explain close to half of the conventionally measured return to education. This is important because it is the first decomposition that quantifies the match (relatedness) effect that accounts for 22.3 percent of university-high school wage gap in Canada.

Due to difficulties in measuring the matching quality between fields of study and occupations, studies looking at immigrants' occupational attainment in hosting labour markets have investigated the match between immigrants' pre- and post-migration occupations. Green's work (1999), for example,

[4] This was also the Presidential address delivered at the 2014 Annual Meeting of the Canadian Economic Association in Vancouver, BC.

is one of the first studies to compare occupational distribution of native-born and immigrant workers by using several Canadian censuses and files of immigrant landing records, which include information about the immigrants' pre-migration occupations and intended occupations in Canada. Although Green did not pursue this in his study, he pointed out that comparing the distribution of intended occupations with the actual occupational attainments would make it possible to approximate the level of mismatch in Canada. In a recent study, Jantzen (2015) applied this approach to determine whether economic principal applicants work in their intended regulated occupations by using the National Household Survey and Immigration Landing File Linkage Database. How (and to what extent) the cross-border transferability of occupational human capital affects earnings is investigated more explicitly in two analytical works (Imai et al. 2011; Warman et al. 2015). By using Longitudinal Survey of Immigrants to Canada (LSIC), in addition to detailed information on labour maker experience during the first four years after immigrating, both studies are able to access information on the last occupation held in the source country prior to migrating and the intended occupation identified during the selection process. Findings in both studies point out that after immigrating to Canada immigrants have difficulty finding jobs that utilize the occupational human capital that they obtained abroad. Imai et al. (2011) further calculate the potential loss in immigrants' earnings due to inability to work in an occupation that matches their source country occupational skill requirements. They find that predicted mean earnings might have been 21-23 percent higher at four years after arrival.

At the junction of education/skill mismatch and internationally educated immigrants' labour market integration, there are two recent studies published in Statistic Canada's research paper series (Plante 2010, 2011). Based on the 20 percent sample of 2006 Census, they are the first studies in Canada that use a concordance table, which was developed by the Centre for Education Statistics at Statistics Canada using the 2006 Census distribution of Canadian-educated individuals aged 25 to 65, to determine whether internationally educated immigrants are working in their field of study.[5] The table presents the best possible matches between an instructional program and a group of 68 occupations identified as "targeted occupations" by the Foreign Credential Recognition (FCR) Program at Human Resources and Skill Development Canada (HRSDC). These targeted occupations are further grouped into 26 regulated and 42 unregulated occupations. Moreover HRSDC has developed a matrix (National Occupational Classification Matrix) that shows the classification of occupations by 5 skill levels and 12 skill types.[6] In her second study (2011) Plante analyses the determinants of the immigrants' integration into the Canadian labour markets measured by two proxies: (1) working in an occupation corresponding to their field of study or in an occupation requiring similar or higher skill levels, and (2) having earnings at or above the national median earnings calculated for the occupation corresponding best to their filed of study. Plante's findings indicate that internationally educated immigrants are less likely than Canadian-educated counterparts to be employed in their field or occupations requiring similar or higher skill levels.[7]

While this study greatly benefits from the previous research outlined above, it contributes to the current understanding by developing a new approach that estimates the wage gain that immigrant workers would have had if their occupational matching had improved to what native-born workers experience in labour markets. This will help us understand not only the true magnitude of waste in human capital but also the importance of occupational mismatch in explaining the wage gap between immigrant and native-born workers. The rest of the paper explains the details.

2 Data, proxy for relatedness, and mismatches

2.1 *Data and relatedness*

This study uses the 20 percent sample of 2006 Canadian census available in Canadian Research Data Centers. We restricted the data to include only nonaboriginal, civilian, full-time wage earners living in

[5] Identifying the field of study – occupation match for internationally educated immigrants requires information on location of study, which was not available in previous censuses.

[6] All these tables and files are publicly available and presented at the end of the Plante's papers.

[7] By using the same concordance table, Xeu and Xu (2010) also report very detail information about educational characteristics, occupational outcomes, skill and field of study distributions of postsecondary educated immigrants based on the 2006 Canadian Census. Moreover Zietsma (2010) also uses the same table to compare immigrants working in regulated occupations with native-born workers.

10 provinces and between 19 and 65 years of age, who worked in 2005 and did not attend school at the time. We also dropped non-degree holders and those whose field of study contains less than 10 workers. After these restrictions, we obtained about 1.4 million observations. The 2006 census enables the classification of individuals' major field of study in which the highest postsecondary certificate, diploma or degree was granted to them. Statistics Canada classifies the major fields of study by using the Classification of Instructional Programs (CIP), which includes 1375 instructional program classes with finer breakdowns provided with up to six-digit codes.[8] The 2006 Census occupation data are classified according to the National Occupational Classification for Statistics 2006 (NOC–S 2006), which is composed of four levels of aggregation. At the first three levels there are 10 broad occupational categories containing 47 major groups that are further subdivided into 140 minor groups. In this study we use the most detailed level, in which there are 520 occupation unit groups. Statistics Canada defines this classification as occupation unit groups that are formed on the basis of the education, training, or skill level required to enter the job, as well as the kind of work performed, as determined by the tasks, duties and responsibilities of the occupation.[9]

In this study, given the large sample at our disposal, we use frequency distributions of each of 1375 fields of study and 520 occupations, which give us 715 thousands cells to calculate the following clustering index:

$$RI_{of} = \frac{L_{of} / L_f}{L_o / L_T},$$

where L is the number of workers, o is the occupation, f is the field of study and T denotes the whole workforce. This index (RI) measures the relatedness of occupation o in major f by calculating the percentage of workers in major f working in occupation o adjusted by the size of occupation o in the entire workforce. The index is an increasing function of the importance of an occupation in the economy, as measured by the denominator, and of the importance of a particular field of study in an occupation, as measured by the numerator. The index is greater or less than unity, depending upon which of these two components is relatively larger. The role of the denominator in the index is two-fold: first, it removes the directional differences in simple density calculations. Although relatedness is usually conceptualized (Nordin et al. 2010) by the distribution of a field of study across occupations (which occupation is most observed in major f), it is also reasonable to consider relatedness as the distribution of an occupation across fields of study (which field of study is most observed in occupation o).[10] Second, it adjusts the simple densities (nominator) by the size of occupation (or field of study). Hence RI reflects more accurate clustering in each cell free of the size effects and directional differences. Comparing the shares of each occupation in a field of study with the marginal distribution of each occupation is not new and a similar application is used by Lemieux (2015) showing the distribution of nine occupations by ten fields of study. In Table 2 (p.13), he identifies occupation-field of study cells (in bold) for which the proportion of workers in the occupation is more than the twice as high as the marginal distribution (the share of each occupation in the entire labour force). Lemieux (2015) and Ransom (2014) also use the Duncan index to quantify the occupational distinctiveness of a particular field of study.[11] Lemieux specifies the Duncan index, DI_f, in field of study f as follows:

$$DI_f = \frac{\sum_o \left|\theta_{of} - \theta_o\right|}{2},$$

[8] Details of coding can be found on the following web site of Statistics Canada: http://www23.statcan.gc.ca:81/imdb/p3VD.pl?Function=getVDPage1&db=imdb&dis=2&adm=8&TVD=127939

[9] https://www12.statcan.gc.ca/census-recensement/2006/ref/dict/pop102-eng.cfm

[10] $(L_{of}/L_f)/(L_o/L_T) = (L_{of}/L_o)/(L_f/L_T)$

[11] The Duncan index is commonly used in social sciences to see the level of occupational segregation between sexes.

where θ is the fraction of workers. *DI* and *RI* indices are similar in the sense that both measures are calculated by the distance between the share of the workers holding a degree in major *f* working in occupation *o* and the share of the same occupation in the entire labour force.[12] *DI*, as expressed above, is an aggregation showing the occupational distinctiveness of each field of study and gets bigger as workers cluster in few occupations for a given field of study. *RI*, on the other hand, reports the fraction of workers in each occupation-field of study cell relative to the marginal distribution of each occupation or field of study.

2.2 *Matching*

The findings in Lemieux (2015) work are consistent with those in Ransom's (2014) study for the U.S. and both indicate that STEM fields relative to those in humanities and social sciences have a higher occupational distinctiveness.[13] Instead of summarizing here the same evidence again, which is also found in our study, we restrict our descriptive tables to report how the matching quality for immigrants compares to that of native-born workers. We consider the occupational distribution of native-born workers as a benchmark reflecting the long-term matching quality in Canadian labour markets. To accomplish this, for each of 1375 fields of study, we first normalize *RI* calculated for native-born workers between 1 and 0 by using the highest *RI* index as numeraire. Classifying normalized *RI*s (*NRI*) in five class intervals (1.0-0.8, 0.8-0.6, 0.6-0.4, 0.4-0.2, and 0.2-0) allows us to rank each occupation based on the native-born workers' distribution.[14] Table 1 shows the current distribution of workers by *NRI*s and the highest education degree obtained.

Table 1: Distribution of native-born and immigrant workers by *NRI* and education degrees – 2006 (weighted)

	***NRI* –Normalized *RI* (for native-born)**								
	Native-born, Canadian educated			**Immigrant, Canadian educated**			**Immigrant, internationally-educated**		
Deg.	**1.0-0.2**	**0.2-0.0**	**Total**	**1.0-0.2**	**0.2-0.0**	**Total**	**1.0-0.2**	**0.2-0.0**	**Total**
3	38.1%	61.9%	883,215	36.3%	63.7%	104,895	23.9%	76.1%	47,865
4	46.8%	53.2%	449,475	41.8%	58.2%	66,635	26.2%	73.8%	30,210
5	38.8%	61.2%	301,460	38.1%	61.9%	51,700	23.5%	76.5%	11,375
6	41.5%	58.5%	1,199,525	39.7%	60.3%	173,530	22.6%	77.4%	52,470
7	49.5%	51.5%	916,480	44.3%	55.7%	147,055	23.6%	76.4%	78,770
8	44.2%	56.8%	430,945	37.9%	62.1%	115,940	20.1%	79.9%	105,135
9	47.3%	53.7%	1,504,535	42.2%	57.8%	279,505	24.3%	75.7%	270,605
10	57.2%	43.8%	220,400	51.1%	48.9%	44,485	26.0%	74.0%	51,915
11	77.6%	23.4%	20,605	70.0%	30.0%	6,360	26.8%	73.2%	13,355
Total	44.9%	55.1%	5,926,640	41.3%	58.7%	990,105	23.7%	76.3%	661,700

Notes: (i) The highest degrees which grants a major field of study earned by workers are classified by Statistics Canada in the 2006 Census as (3) Apprenticeship certificate or diploma; (4) Other trades certificate or diploma; (5) College, CEGEP or other non-university certificate or diploma from a program of 3 months to less than 1 year duration; (6) College, CEGEP or other non-university certificate or diploma from a program of 1 year to 2 years duration; (7) College, CEGEP or other non-university certificate or diploma from a program of more than 2 years duration; (8) University certificate or diploma below bachelor level; (9) Bachelor's degree; (10) University certificate or diploma above bachelor level; (11) Degree in medicine, dentistry, veterinary medicine or optometry. (ii) The middle 3 columns, "Immigrant, Canadian educated", also include immigrants whose location of study is the US or the UK.

Table 1 reveals a number of interesting features. Although the division may seem arbitrary, for any given field of study, if we consider the occupations with normalized *RI* between 1 and 0.2 as

[12] $L_{of}/L_f = \theta_{of}$ and $L_o/L_T = \theta_o$

[13] Ransom (2014) also uses an aggregate index, an adjusted version of the Herfindahl index, to measure the occupational variety of a major.

[14] Empty cells, if a cell has no Canadian educated native-born workers in it, are assigned zero.

relatively better matching occupations, 55 percent of native-born wage earners work in unrelated occupations. The mismatch ratio falls down to 53 percent at the bachelor's degree, which is the most populated degree with 1.5 million university graduates. As expected, for medical degree holders, the ratio becomes the lowest: 23 percent. When we use these normalized *RI*s as a benchmark for immigrants who are educated in Canada, the U.S., or the U.K., the distribution does not change significantly. However, when we identify the immigrants who are internationally educated the overall mismatch ratio rises up to 76 percent. Since this overall mismatch ratio would likely depend upon country or region of origin, we provide in Table 2 additional information on how relatedness varies across source country/region, again by the location of study. In line with what was observed in Table 1, it can be seen from Table 2 that whether immigrants work in jobs that match their training depends clearly upon where they obtain their education.

Table 2: Distribution of all immigrants by *NRI* and location of study – 2006 (weighted)

	NRI		
Location of Study	**1.0-0.2**	**0.2-0.0**	**Total**
Canada	42.8%	57.2%	824,970
USA	39.4%	60.5%	86,320
UK	38.0%	62.0%	76,660
Europe	24.8%	75.2%	158,580
South America	23.9%	76.1%	66,620
Africa	26.4%	73.6%	50,050
Middle-East	24.8%	75.2%	34,780
China	18.4%	81.6%	61,420
Asia	23.5%	76.5%	288,160

Notes: Since the numbers are rounded, the totals can be slightly different than those in Table 1.

A pertinent question that must be considered, however, is whether or not such mismatches among immigrants persist over time because, if those mismatches are transitory rather than structural, the underutilization cost would be a temporary phenomena and the issue would not be of much interest to either researchers or policymakers. Ideally, the issue of persistency can be examined by following the same immigrants across censuses. However, this is not possible with census data.[15] Hence, in this paper, this issue is examined by the distribution of immigrant workers in terms of their field of study-occupation match and years since migration to Canada (Table 3). It can be seen that the percentage of immigrants working in unrelated occupations remains high, in the 75 percent range, regardless of how long they have been in Canada. This is especially noteworthy since, while longer years in Canada translate into significant wage gains in both *NRI* categories, the percentage of internationally-educated immigrants who work in unrelated jobs and the associated wage penalty do not show improvement.

One would expect that, if the underlying reasons are transitory, the resulting mismatch would subsequently enhance occupational mobility (Green 1999) so that, similar to Canadian (or US and UK) educated immigrants, the field of study-occupation distribution of internationally-educated immigrants would shift towards that of native-born workers face in the long run. Yet, the persistency in mismatch suggests that the immigrants' occupational mobility does not translate into better occupational matching as measured by cross-cohort comparisons in Table 2. When this is combined with the evidence that earning returns to foreign credentials of non-English speaking, non-European immigrants are discounted to zero in Canadian labour markets (Green and Worswick 2012), the immigrants' occupational mismatch seems to be a source country problem rather than being a problem that can be solved in hosting labour markets by better occupational assignments of immigrants.

[15] It is possible to follow the same cohort across the 1996, 2001, and 2006 censuses, since that cohort would represent drawings from the same population, albeit at different points in time. However, incompatible classifications of fields of study and occupations across censuses require a substantial amount of time, and this is beyond the scope of this study.

For brevity, we present only three descriptive tables here and a few additional tables in Appendix, which provide greater detail on the incidence of matching. We turn next to the models we use to estimate the effects of mismatch, and the method employed to approximate the cost associated with this mismatch for immigrants in Canadian labour markets.

Table 3: Average weekly wages and distribution of internationally-educated immigrants by *NRI* and years in Canada – 2006 (weighted)

	***NRI* (for native-born)**		
Years in Canada	**1.0-0.2**	**0.2-0.0**	**Total**
Less than 5 years	21.8%	78.2%	239,775
	887	636	685
More than 5 years	24.7%	75.3%	421,900
	1,143	866	926
Increase in wage	28.9%	36.2%	35.2%
Less than 10 years	22.6%	77.4%	343,855
	911	683	737
More than 10 years	24.8%	75.2%	317,820
	1,195	889	948
Increase in wage	31.2%	30.2%	28.6%
Total	23.7%	76.3%	661,675
	1,098	781	839

Notes: (i) Weekly average wages are reported below percentages; (ii) Since the numbers are rounded, the totals can be slightly different than those in Table 1.

3 Statistical framework and estimation results

3.1 *Wage earnings and matching*

Although it is well documented that estimated returns to education are large, there are different reasons identified in the literature why education may have positive effects on earnings. When education provides specific skills, it helps individuals find more complex and better paying jobs (occupations). Regardless of occupation, however, more and better education also increases productivity through specialization. In other words, while more-educated workers are assigned to more complex jobs, education also increases a general productivity in a given job. Lemieux (2015) calls these channels as "occupation upgrading" and "pure education" effects. The third reason that the education affects earnings comes from the interaction between these two channels: assignments of skills obtained by education to jobs that are available in labour markets. Studies have been using different measures such as years of schooling, abilities, and field of study-job relatedness to quantify this matching quality. As outlined earlier, in general, the evidence confirms the positive effect of a good match on wage earnings. Although modeling these three channels with matching is a fairly complex process, in practice the first two channels (occupation upgrading and specialization) are controlled in in Mincer-type wage functions by binary variables that identify occupation and field of study fixed effects. The approach in this study employs the Mincer wage function used by Lemieux (2015), augmented to include controls for each of the three earnings impacts of education impacts noted above, including one that captures the effect of matching quality. This specification is as follows:

$$\ln w_{ifo} = \mathbf{X}_i\beta + b_f + c_o + \alpha.m(f,o) + \varepsilon_{ifo}, \tag{1}$$

where person i working in occupation o with field of study f earns wage w. Vector $\mathbf{X}$ includes a set of usual variables such as age, gender, location of work, etc. Binary variables b_f and c_o control for differences in field of study in f and occupation o, respectively. The term $m(f, o)$ controls the matching quality between occupation o and field of study f and yields a wage premium, α, to the extend to which field of study f is valuable in occupation o. This model could be useful, for example, to understand the wage premium of a university degree for each field of study when the base of b is set for high school graduates. Although the high level of disaggregation in field of study (1375) may reduce its possibility, some fields of study could be offered in multiple degrees (trades, college, bachelor, and graduate degrees, for example). For this reason we also add e_d to equation (1) that controls for differences across nine education degrees (see notes to Table 1).[16]

A concern in the literature, one that we fully recognize, has been the problem of unmeasured ability. The latest studies (Ashenfelter et al. 1999) using instrumental variables (IV) methods confirm that the ability bias in the casual effect of education on wage earnings is small; when ordinary least squares (OLS) methods are used. The ability bias in the effect of field of study on wages has not been tested yet by IV methods due to difficulties in finding credible instrumental variables. Similar to the choice of field of study, the match quality could be correlated with the person's ability. However, studies investigating wage differentials across fields of study (Altonji et al. 2012) and the effect of relatedness on earnings (Nordin et al. 2010) include some proxies to their estimations to control for unobserved ability and observe no significant changes in results. Lemieux (2015) explains it in a great detail why the OLS results of equation (1) should be valid especially when they are used in estimating average effects.[17]

Table 4: Average weekly wage earnings and distribution of workers by *NRI* – 2006 (weighted)

	***NRI* (for native-born)**							
	NB	**Imm - CE**	**Immigrants, internationally educated**					
Degrees	**1.0-0.8**	**1.0-0.8**	**1.0-0.8**	**0.8-0.6**	**0.6-0.4**	**0.4-0.2**	**0.2-0.0**	**Total**
3	26.5%	24.0%	14.7%	1.3%	2.2%	5.9%	76.1%	47865
	833	859	885	885	850	697	769	785
4	38.4%	32.3%	17.5%	1.2%	2.1%	5.4%	73.8%	30210
	1076	1033	978	931	918	811	858	879
5	18.3%	17.4%	6.9%	2.1%	4.8%	9.7%	76.5%	11375
	821	813	1128	833	887	711	693	737
6	21.4%	20.3%	8.7%	2.1%	4.0%	7.7%	77.4%	52470
	919	926	875	840	853	734	701	728
7	29.0%	24.3%	12.4%	2.3%	2.7%	6.1%	76.4%	78770
	1032	1099	1082	985	908	794	764	815
8	20.4%	16.6%	7.3%	2.0%	3.1%	7.8%	79.9%	105135
	1203	1203	1173	1124	874	814	766	811
9	24.8%	20.7%	10.6%	2.9%	2.9%	8.0%	75.7%	270605
	1325	1371	1212	1126	957	895	781	850
10	33.3%	28.2%	12.2%	3.0%	3.1%	7.7%	74.0%	51915
	1375	1535	1226	1232	1180	1091	904	976
11	57.8%	51.2%	18.5%	7.6%	0.2%	0.4%	73.2%	13355
	1691	1959	1733	1965	919	1390	818	1076
Total	**25.8%**	**22.2%**	**11.0%**	**2.5%**	**2.9%**	**7.3%**	**76.3%**	**661700**
	1083	**1145**	**1137**	**1134**	**935**	**855**	**781**	**839**

[16] It also helps us reduce unobserved ability. If the same field of study can be obtained at different degrees, the choice of an educational degree (a master's degree in accounting versus trades) may signal valuable information about ability.

[17] Lemieux uses equation (1) as a base wage determination to calculate for the decomposition of the total return to university education. We also use it in calculating the average wage penalty due to the mismatch in labour markets for immigrants. Lemieux's study is a valuable source for understanding the use of OLS in estimations of the causal effect of education on earnings.

Notes: (i) NB and Imm-CE denote "native-born" and "immigrants – Canadian, the US, and the UK educated". (ii) For educational degrees see notes to Table 1. (iii) Weekly average wages are reported under % distributions.

In light of this, we also estimate the model using OLS with standard errors clustered at each cell of the field of study – occupation matrix (1375 x 520) and use *RI* as a proxy for *m*(*f*, *o*), which is a continuous variable by calculation. Our empirical goal is to use the distribution of Canadian educated native-born workers reflecting the long-term matching quality in Canadian labour markets. We hope to gain an understanding of the comparative matching quality of internationally-educated immigrants, as was done in descriptive terms in Table 1. This approach allows us to estimate the wage penalty associated with immigrants clustering in occupations that are not "preferred" by Canadian-educated native-born workers in a given field of study. To accomplish this, we use normalized *RI*s classified into five groups as noted earlier, which we treat as categorical variables that rank each occupation based on the native-born workers' distribution. Thus, using this categorical variable as a proxy for *m*(*f*, *o*) in equation (1) for immigrants not only allows us to estimate the wage penalty that immigrant workers face, but also enables us to treat *m*(*f*, *o*) as exogenous, which has been, otherwise, a major challenge for many studies in the literature.

Before analyzing the effect of relatedness on earnings more systematically, we report *NRI* and average weekly wage earnings in Table 4. The first two columns show the distribution of native-born and Canadian-educated immigrant workers working in occupations with normalized *RI* between 1.0 and 0.8. Next to these, we show the relationship between average weekly wage earnings and the native-born normalized *RI* distributions used for internationally-educated immigrant workers. The table reveals two critical observations: first, there is a clear wage penalty for immigrants associated with working in occupations that are regarded as relatively less related by native-born workers; second, the wage differences between native-born and internationally-educated immigrants workers fade away when we compare workers only in the most related occupations, i.e. in occupations that have normalized *RI*s between 1.0 and 0.8. Monotonic declines in average wages particularly at higher degrees suggest a very strong and positive correlation between relatedness and wage earnings. When this effect of relatedness is removed by comparing immigrants with native-born workers who work in their trained occupations, the negative wage differentials that have been documented in the literature for internationally educated immigrants disappear.

3.2 *Estimation results*

Table 5 summarizes the estimation results for three specifications of the earnings function given by equation (1). The first specification shows the results for native-born workers. Last two specifications report the results for Canadian (including the US and the UK) and internationally educated immigrant full-time wage earners, respectively. All specifications include controls for age-square, marital status, disability, visible minority status, primary earner status, spoken language, regional fixed effects for 10 provinces, and industry fixed effects at 21 categories. Moreover, the sample size allows us to control for field of study fixed effects at 1375 categories and occupation fixed effects at 520 categories, which help us isolate the effect of relatedness from the wage differences across fields of study and occupations. Both the second and the third columns use dummies created using the normalized *RI*s for the native-born workers, and not those of immigrants.

Regardless of nativity or location of study, the results indicate a positive impact on wages of greater relatedness. Note that this relationship as structured in equation (1) appears to be correlational rather than causational, particularly when self-reported answers to survey questions (Robst 2007; Lemieux 2015) or the distributional aspects of workers are used (Nordin et al, 2010) as a proxy for *m*(*f*, *o*): workers might feel better matched in better paying jobs, or they might cluster more around occupations with higher wages. Hence, the results for native born workers should be interpreted in light of this fact. When it comes to immigrants, however, using *NRI* dummies in specifications (2) and (3) calculated for the native-born field of study–occupation distribution, and not that of immigrants, provides us with the desired erogeneity in relatedness. In particularly, as we saw in Table 1, internationally-educated immigrants are less likely to be assigned to occupations where native-born workers choose to work. In other words, more immigrants work in less paying occupations relative to native born-workers, and this breaks the simultaneity between higher wage earnings and crowded occupations

The results also show that, while the effect of relatedness on wage earnings are similar for native born and Canadian educated immigrant workers, greater relatedness does not translate into higher rewards for internationally-educated immigrants as much as it does for the native-born working in the least matching occupations (NRI = 0.2 - 0.0). Considering that more than 76 percent of foreign educated immigrants work in those least matching occupations, occupational mismatch would appear to be less punishing for immigrants. These results are in line with the evidence in the sense that, when immigrants' education obtained abroad is less rewarding in Canadian labour markets (Li and Sweetman 2014), a better occupational match becomes less rewarding as well. Two final observations are worth mentioning. First, the return to work experience proxied by age in specification (3) is half of that found in specifications (1) and (2). This is consistent with the evidence that source-country work experience for immigrants is discounted to zero in Canadian labour markets (Green and Worswick 2012). Our use of age instead of years in Canada and abroad separately in the estimates of (3) for immigrants, probably accounts for the positive return to experience (as measured by age). Second, as noted earlier, the return to foreign education is significantly lower than that of education in the host country, which is in line with the accumulated evidence in the North American immigration literature (Li and Sweetman 2014, Ferrer and Riddell 2008). Our results also verify this finding in that, in contrast with the first two specifications, there is no education effect on wage earnings of immigrants who obtained their degrees out of Canada, the US, and the UK.

Table 5: OLS Estimates of weekly wage earnings - 2006

	1		**2**		**3**	
	Coef.	**sd.**	**Coef.**	**sd.**	**Coef.**	**sd.**
Male	0.1641	0.0040	0.1276	0.0059	0.1437	0.0073
Age	0.0796	0.0010	0.0802	0.0015	0.0455	0.0020
Dummies for *NRI*						
1.0-0.8	Base	n/a	Base	n/a	Base	n/a
0.8-0.6	-0.0187	0.0076	-0.0208	0.0102	-0.0259	0.0145
0.6-0.4	-0.0169	0.0071	-0.0293	0.0118	-0.0399	0.0175
0.4-0.2	-0.0382	0.0058	-0.0326	0.0091	-0.0526	0.0138
0.2-0.0	-0.1259	0.0040	-0.1276	0.0066	-0.1166	0.0105
Degrees						
Apprenticeship	Base	n/a	Base	n/a	Base	n/a
Trades	0.0418	0.0044	0.0195	0.0092	-0.0432	0.0137
College - less than 1 year	**-0.0035**	0.0042	-0.0265	0.0105	**-0.0196**	0.0198
College - 1 to 2 years	0.0355	0.0032	**0.0138**	0.0091	-0.0314	0.0122
College - more than 2 years	0.0752	0.0041	0.0583	0.0990	-0.0256	0.0115
University - below bachelor's	0.1040	0.0049	0.0509	0.0113	**0.0033**	0.0135
Bachelor's	0.1728	0.0051	0.1210	0.0118	**-0.0079**	0.0131
Above bachelor's less than Master's	0.2156	0.0074	0.1521	0.0153	0.0354	0.0154
Medicine & Veterinary medicine	0.0873	0.0411	0.1367	0.0626	**-0.0125**	0.0510
R2	0.358		0.314		0.244	
Observations	1150617		190624		127066	

Notes: (1) The dependent variable is log weekly wage. (2) Standard errors, next to the coefficients, are clustered at occupation-field of study cells. (3) Bold coefficients are statistically insignificant at the 5% level. (4) All estimations also control for age-square, marital status, disability, visible minority status, primary earner status, spoken language (only English, only French, bilingual, others), regional fixed effects for 10 provinces, field of study fixed effects at 1375 categories, occupation fixed effects at 520 categories, and industry fixed effects at 21 categories.

4 Underutilization cost and the wage gap

The literature on the return to education based on Mincer-type earnings function models has the common premise that a person's human capital translates into wages through productivity, regardless of the particular variant or extension of the model used. Evidence shows that individuals are more productive when they work in matching occupations, independently of whether matching is measured in terms of schooling variables, skill levels, or the training reflected in fields of study. These findings lead to a bigger question: how would one approximate the overall cost of labour force that is overeducated, overskilled, or working in unrelated jobs, each of which is associated with a substantial wage penalty at the individual level?

Isolating the mismatch effect from that of ability is a real concern in the literature. For example, when mismatch is measured by years of schooling as in the ORU literature, the underutilization cost is conceptualized in terms of surplus schooling that is not utilized in an occupation that requires less education. However, to view this as lost productivity from the viewpoint of the whole economy is valid only if surplus schooling reflects a pure occupational mismatch rather than the possibility that some workers might compensate for their lack of ability through over-education. In a recent paper, Leuven and Oosterbeek (2011) extensively review the ORU literature and conclude that, unless the ability bias is addressed in estimation, the wage penalty that has been consistently found in ORU studies cannot be interpreted as the cost of underutilization. Although it is a lesser concern, the same ability bias likely shadows the productivity loss when individuals work unrelated jobs: if workers' inherent lack of ability prevents them from finding better matching jobs in their field of study, the cost associated with working in "unrelated" jobs may not be characterized as underutilization because better matching cannot simply be achieved by an occupational reassignment in labour markets. Moreover, classifying occupations as "related" or "unrelated" in many fields of study, especially for unregulated occupations, is a major challenge and possible measurement errors in matching make the wage penalty unreliable for measuring the cost of underutilization. The approach adopted in this study in defining matching quality, and in estimating its effect on wage earnings helps us address some of these problems. By using *NRIs,* calculated for native-born workers in immigrants' wage equations, not only do we avoid possible measurement errors in defining what constitutes an "ideal" match between occupations and fields of study, but we also reduce a possible ability bias.

One conventional approach to measuring the cost of underutilization internationally-educated immigrants, given the wage penalty information in Table 5 and the incidence of mismatch in Table 4, would be to consider an alternative distribution where all immigrants work in their most matching occupations. This can be seen in the upper section of Table 5: if all immigrants working in "unrelated" jobs characterized by *NRI*s lower than 0.8 were reassigned to the most related occupations (with *NRI*s between 1.0 and 0.8), using the estimates from Table 4 (column 4), the total weekly wage gain would be 49.3 million dollars (2.5 billion dollars annually or 8.8 percent of the total weekly wage bill), which can be considered as the underutilization cost. Obviously, this is an unrealistic scenario because it is based on an assumption that immigrants' occupational match can be improved beyond what millions of native-born workers face in labour markets.

A more meaningful approach would be to quantify the wage gain if immigrants' occupational matching quality were to be identical to that currently experienced by native-born workers. As well, since the absolute wage gains for immigrants and native-born are also not meaningful given large differences in size and average wages across these groups, we use a measure of comparative wage gain that makes and adjustment for these differences. Our measure is as follows:

$$CG = \left(\sum_{c=2}^{5} WG_c(m) \right) - \left(\sum_{c=2}^{5} WG_c(n) \right) \left(\frac{TWB(m)}{TWB(n)} \right), \tag{2}$$

where *CG*, *TWB*, *WG*, *m, n*, and *c* denote, comparative gain, total wage bill, wage gain, immigrants, the native-born, and five categories of normalized *RI* (*NRI* - as shown in Table 5), respectively. Since the comparative gain is calculated by simultaneous improvements in the quality of occupational match for both native-born and immigrant workers, the result shows the wage gain that immigrant workers would achieve, if they had the same distribution as native-born workers. The ratio of the *TWB* terms serves the role of an adjustment rate for the native-born and makes both *WG*s comparable.[18] Table 6 reports the calculations based on (2), and explains the each term in detail.

The number of workers in Table 6 are taken from Table A1 in the Appendix, while the total weekly wage bill for the native-born and immigrants are the product of the number of workers and average weekly wages in each of the five classifications of the *NRI*. The weekly gain from a move to the highest level of relatedness (the 0.8-1 range of *NRI)* is given in the third and sixth rows of the table by the estimated coefficients of equation (1) reported in Table 5, for internationally-educated immigrants and the native-born respectively. The total weekly wage gain (*WG*) is then the product of these coefficients and the total weekly wage bill for the immigrants and native-born workers. The ratio of the *TWB* terms serves the role of an adjustment rate for the native-born and makes both *WG*s comparable.[19] Since this adjustment rate, which works out to 9.35 percent (as shown in Table 5), removes from the *WGs* differences in average wages and labour market sizes, the difference between *WG*s in (2) shows the wage gain of immigrant workers had their occupational matching improved to what native-born workers experience in labour markets. The calculations in Table 6 show that, when immigrants' occupational match is measured relative to native-born workers, the total weekly wage gain that immigrants would experience amounts than 2 percent of the total weekly wage bill (10.3/554.9), implying that the wage gain of 8.8 percent calculated earlier using conventional methods, largely overestimates the true underutilization cost. The important point is that, regardless of whether we use a narrower or broader *NRI* classification than the 5-category classification reported in this paper, the cost associated with immigrants' occupational mismatch should be calculated in relative terms and, when immigrants have the same occupational distribution as native born workers. That this would entail a smaller cost of underutilization is also evident from the fact that our estimate of the annual cost of underutilization of about 540 million dollars is substantially smaller than that suggested by Reitz (2001), as well as the 5 billion dollars cost estimated by Conference Board of Canada (2001).

Table 6: Comparative wage gain if the immigrants' matching improves to that of native-born workers – 2006 (weighted)

	Normalized Relatedness Index (*NRI* - for native-born)					
	1.0-0.80	**0.80-0.60**	**0.60-0.40**	**0.40-0.20**	**0.20-0.00**	**Total**
Number of Immigrants	72,490	16,745	19,065	48,260	505,115	661,675
Total weekly wage bill (x1000)	82,421	18,989	17,826	41,262	394,495	554,993
Wage gain if move to 1.0-0.8 (%)		2.59	3.99	5.26	11.66	
Total weekly gain (*WG)* (x1000)		492	711	2,170	45,998	49,372
Number of native-born workers	1,530,780	274,025	292,720	561,595	3,267,460	5,926,580
Total weekly wage bill (x1000)	1,657,837	345,544	317,310	563,839	3,051,809	5,936,339
Wage gain if move to 1.0-0.8 (%)		1.87	1.69	3.82	12.59	
Total weekly gain (*WG*) (x1000)		6,462	5,363	21,539	384,223	417,586
TWB(*m*)/*TWB*(*n*) = (554,993/5,936,339)						9.35%
Weekly *CG* (x1000)						10,331
Annual *CG* (x1000)						**537,220**

Notes: (i) Since the numbers are rounded, the totals can be slightly different than those in Table 1. (ii) Total weekly wage bills are represent predicted values.

[18] This can be seen better if we express the overall average weekly wage of immigrants and the number of immigrants as proportions of the average wage and number of native-born respectively: $w(m) = \beta w(n)$ and $M = \delta N$, where $w(m)$ and $w(n)$ are the average wages of immigrants and native-born respectively, and M and N are number of immigrants and native-born respectively. With this notation, we can that reduce $TWB(m)/TWB(n)$ to $\delta\beta$. It is possible to interpret our measure of comparative gain as one in which the *per-capita* gain to the native-born (that is, the dollar gain *per native-born)*, is expressed it as a percentage of their *average wage* (wage per person), and this percentage is then applied to a scaled down wage bill - the wage bill of immigrants.

[19] The difference between 19.42% and (1002-913)/913=9.7%, which is almost 50% of the gap, 19.42%.

It could be argued that averaging the wage gains can mask the differential wage rewards for different segments of the labour force. For example, the cost of mismatch for STEM workers or medical degree holders could be much higher than the average. As outlined above, the occupational distinctiveness of some specific fields of study could be more visible than others if they are regulated or self-regulated. In cases such as these, the cost calculation by equation (2) can be affected by two ways: first the number of mismatched workers could be higher for immigrants; second, the differences in total wage bills across *NRI* groups could be sharper. As an example, we calculated the same cost for medical degree holders and summarized the results in Table 7.

Without comparing their relative gain with native-born workers, the total weekly gain for immigrants holding a medical degree amounts to 6.8 percent of the total weekly wage bill. The comparative gain, on the other hand, is 585 thousand dollars, which is 4 percent of the weekly wage bill. Since the improvement in matching for immigrants would be much better among medical degree holders than for others, the comparative gain is twice as much as the average of 2 percent shown in Table 6. Although similar calculations can be done for different groups of workers to ascertain differential underutilization costs, the observed magnitude of the cost would likely be smaller. This is because jobs requiring medical degrees would likely be ones that display the highest degree of occupational distinctiveness among regulated or self-regulated professions. It is interesting to see that while medical degree holders (13,360) account for only 2 percent of all immigrant workers (661,675), their comparative weekly wage gain (30.4 million dollars) makes up more than 6 percent of the total weekly wage gain of all immigrant workers (537 million dollars).

Table 7: Comparative wage gain if the immigrants' matching improves to that of native-born workers – only for medical degree holders - 2006 (weighted)

	Normalized Relatedness Index (*NRI* - for native-born)					
	1.0-0.8	**0.8-0.6**	**0.6-0.4**	**0.4-0.2**	**0.2-0.0**	**Total**
Number of Immigrants	2,470	1,020	30	55	9,785	13,360
Total weekly wage bill (predicted)	4,282,243	2,008,230	53,732	75,060	8,001,676	14,420,941
Wage gain if move to 1.0-0.8 (%)		2.59	3.99	5.26	11.66	
Total weekly gain (*WG*)		52,013	2,144	3,948	932,995	991,101
Number of native-born workers	11,905	3,565	100	215	4,820	20,600
Total weekly wage bill (predicted)	20,127,973	6,921,288	124,047	210,657	6,453,980	33,837,945
Wage gain if move to 1.0-0.8 (%)		1.87	1.69	3.82	12.59	
Total weekly gain (*WG*)		129,428	2,096	8,047	812,556	952,128
TWB(*m*)/*TWB*(*n*) = (14,421/33,838)						42.62%
Weekly *CG*						585,326
Annual *CG*						**30,436,957**

Notes: Since the numbers are rounded, the totals can be slightly different than those in tables 1 and 3.

One may consider whether a complete equalization of immigrant and native-born distributions is desirable. This is because immigrants, especially those coming through the points system, are supposed to fill meet labour shortages. This argument goes back to the question of whether immigrants are substitutes or complements in host country labour markets (Green 1999). In this context, thus, the difference between pre- and post-immigration occupations may not constitute a mismatch. Our approach does not impose an identical occupational distribution on immigrant and native-born workers, but uses the native-born workers' field of study-occupation distribution to define immigrants' occupational match. We argue that the assessment of occupational mismatch for any segment of labour force should be made against a comparison group, particularly for immigrants, because, although the immigrants' distribution across occupations could be different than that of native born workers, the "ideal" occupational distribution of immigrants in each field of study should not be different than the one for the native-born, and further, any occupational reassignment of immigrants to achieve better matching is not likely to shift the occupational distribution of immigrants beyond what native-born workers can currently achieve in Canadian labour markets.

Our findings also help us approximate the part of the wage gap between native-born and immigrant workers than can be attributable to immigrants' occupational mismatch. As reported in the top portion ("Total") of Table 8, if all foreign educated immigrants had worked in the most matching occupations, the wage gap would have been narrower by only about 2 percentage points (19.42-17.38), which implies that roughly 10 percent of the wage gap (19.42%) may result from the occupational mismatch. The same gap would be 9.7 percentage points narrower (i.e. corresponding to about 50 percent of the gap) if only improvements in the immigrants' occupational matching were taken into account,[20] which shows the importance of calculating wage gains in relative terms.

Table 8: Wage gap if immigrants' matching improves to that of native-born workers – 2006 (weighted)

		Before			After	
	Number of workers	Total weekly wage bill	Average wage	Wage gain	Total weekly wage bill	Average wage
Total						
Native-born	5,926,581	5,936,339	1,002	417,586	6,353,924	1,072
Immigrant	661,675	554,993	839	49,372	604,364	913
Wage gap %			**19.42**			**17.38**
***NRI*=0.2-0.0**						
Native-born	3,267,461	3,051,809	934	384,223	3,436,031	1,052
Immigrant	505,113	303,573	601	45,998	349,571	692
Wage gap %			**55.41**			**51.95**

These findings contradict with a common view in public circles that impediments in entering hosting labour markets, especially problems in foreign qualification recognition, are one of the major factors for the poor performance of recent immigrants to Canada. The question of why the wage gain from improvements in occupational match is small despite the fact that internationally educated immigrants face a significant and persistent mismatch problem can be answered if we put these findings in perspective in line with the literature. Green and Worswick (2012) find that, between the early 1980s and the 1990s, the return to foreign experience went to zero particularly for non-English speaking, non-European immigrants resulting from the shifting in the source country composition. As outlined earlier, the evidence also suggests that the return to foreign education is drastically lower than to education obtained in Canada and the low literacy and language proficiency of immigrants have a significant effect on the poor post-immigration labour market outcomes. These findings imply that, if the occupational mismatch results from a combination of immigrants' poor (or nonequivalence) foreign education quality, language proficiency and literacy skills, without a substantial progress in these specific human capital characteristics, the isolated effects of relative improvements in occupational match will not be so rewarding for immigrants. This can be seen, for example, in the bottom portion of Table 6. Despite the large wage gap (55.4%) in the lowest matching category (*NRI* 0.2-0.0), which contains 76.3 percent of immigrants and 55.1 percent of native-born worker, the reassignment of the workers to the best matching occupations makes the gap only slightly lower (52%). In other words, the occupational mismatch can explain only 6.2 percent of the initial wage gap for workers who work in the least related occupations.[21] This is partly because occupational mismatch is less punishing for immigrants (11.66%) than for native-born workers (12.59%), as reported in Table 5.

[20] The difference between 19.42% and (1002-913)/913=9.7%, which is almost 50% of the gap, 19.42%.

[21] (55.41-51.95)/55.41 = 6.2%.

5 Concluding remarks

Given the large sample at our disposal, we developed a continuous index that reflects the "relatedness" between 1375 fields of study and 520 occupations for native-born Canadian educated workers. We used this clustering index in each cell of the field of study-occupation matrix calculated for native-born workers as a benchmark reflecting the "common" matching quality in Canadian labour markets that internationally educated immigrant workers could achieve in the long run. This allowed us to approximate the annual cost of underutilization of immigrants' human capital by estimating the change in immigrant earnings if they were distributed same as the native-born in terms of relatedness (field of study-occupation match). Although the results show a significant and persistent poor matching quality for foreign-educated immigrant workers, their relative underutilization cost is not as sizeable as envisioned in some policy circles.

The results also helped us understand the importance of occupational mismatch in explaining the wage gap between immigrant and native-born workers. The persistency in mismatch together with very low returns to foreign credentials implies that it may not be the immigrants' occupational mismatch that penalizes their wage earnings in hosting labour markets, but rather the non-portability of their foreign credentials, which appears to be the root cause of the mismatch and is largely attributable to the shifting source country composition (Green and Worswick 2012). In other words, the immigrants' occupational mismatch is much more a "source-country problem" rather than being a "host-country problem" that can be efficiently dealt with by post-arrival policies. As our findings point out, since it is a symptom of the underlying problems, even if the immigrants' occupational match is improved to that of the native-born, it does not translate into a sizable gain in human capital. Therefore, solutions to the poor economic integration of immigrants to Canadian labour markets should lie more in policies targeting new immigrants' source country human capital characteristics rather than policies designed for post-immigration improvements alone.

Acknowledgements

The analysis presented in this paper was conducted at the Atlantic Research Data Centre, which is part of the Canadian Research Data Centre Network (CRDCN). The services and activities provided by the Atlantic Research Data Centre are made possible by the financial or in-kind support of the SSHRC, the CIHR, the CFI, Statistics Canada, and Dalhousie University. The views expressed in this paper do not necessarily represent those of the CRDCN or those of its partners. We thank Heather Hobson at Atlantic Research Data Centre of Statistics Canada for her help during our work at the center. Responsibility for any shortcomings remains with us.

Appendix:

Table A1: Distribution of native-born and immigrant workers by *NRI* and education degrees – 2006 (weighted)

NRI	1-0.80	0.80-0.60	0.60-0.40	0.40-0.20	0.20-0.00	Total
Native-born						
3	26.5%	1.5%	3.4%	6.6%	61.9%	883,215
4	38.4%	1.6%	2.5%	4.2%	53.2%	449,475
5	18.3%	3.0%	5.9%	11.6%	61.2%	301,460
6	21.4%	3.1%	5.8%	11.1%	58.5%	1,199,525
7	29.0%	4.8%	6.0%	9.6%	50.5%	916,480
8	20.4%	6.3%	6.1%	11.5%	55.8%	430,945
9	24.8%	7.2%	4.9%	10.5%	52.7%	1,504,535
10	33.3%	11.1%	3.8%	9.0%	42.8%	220,400
11	57.8%	17.3%	0.5%	1.0%	23.4%	20,605
Total	**25.8%**	**4.6%**	**4.9%**	**9.5%**	**55.1%**	**5,926,640**
Immigrants - Canadian, the US, or the UK educated						
3	24.0%	1.2%	3.8%	7.4%	63.7%	104,895
4	32.3%	1.4%	3.0%	5.1%	58.2%	66,635
5	17.4%	2.6%	6.6%	11.5%	61.9%	51,700
6	20.3%	3.3%	5.6%	10.5%	60.3%	173,530
7	24.3%	4.9%	5.6%	9.6%	55.7%	147,055
8	16.6%	4.2%	5.4%	11.7%	62.1%	115,940
9	20.7%	6.7%	4.5%	10.3%	57.8%	279,505
10	28.2%	9.5%	4.1%	9.3%	48.9%	44,485
11	51.2%	18.0%	0.2%	0.6%	30.0%	6,360
Total	**22.2%**	**4.6%**	**4.9%**	**9.7%**	**58.7%**	**990,105**
Immigrants - internationally educated						
3	14.7%	1.3%	2.2%	5.9%	76.1%	47,865
4	17.5%	1.2%	2.1%	5.4%	73.8%	30,210
5	6.9%	2.1%	4.8%	9.7%	76.5%	11,375
6	8.7%	2.1%	4.0%	7.7%	77.4%	52,470
7	12.4%	2.3%	2.7%	6.1%	76.4%	78,770
8	7.3%	2.0%	3.1%	7.8%	79.9%	105,135
9	10.6%	2.9%	2.9%	8.0%	75.7%	270,605
10	12.2%	3.0%	3.1%	7.7%	74.0%	51,915
11	18.5%	7.6%	0.2%	0.4%	73.2%	13,355
Total	**11.0%**	**2.5%**	**2.9%**	**7.3%**	**76.3%**	**661,700**

Notes: (i) The highest degrees which grants a major field of study earned by workers are classified by Statistics Canada in the 2006 Census as (3) Apprenticeship certificate or diploma; (4) Other trades certificate or diploma; (5) College, CEGEP or other non-university certificate or diploma from a program of 3 months to less than 1 year duration; (6) College, CEGEP or other non-university certificate or diploma from a program of 1 year to 2 years duration; (7) College, CEGEP or other non-university certificate or diploma from a program of more than 2 years duration; (8) University certificate or diploma below bachelor level; (9) Bachelor's degree; (10) University certificate or diploma above bachelor level; (11) Degree in medicine, dentistry, veterinary medicine or optometry.

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