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The cost of immigrants' occupational mismatch and the effectiveness of postarrival policies in Canada

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Abstract

Using the 2006 Census, we create a continuous index that quantifies the relatedness between 1375 fields of study and 520 occupations for native-born workers and use it as the benchmark reflecting the "common" matching quality in Canadian labor markets that internationally educated immigrant workers could achieve in the long run. This allows us to approximate the cost of the occupational mismatch of immigrants by estimating the change in their earnings had they been distributed identically to the native born in terms of relatedness. Although the results show a significant and persistent poor matching quality for foreign-educated immigrants, their relative underutilization cost is negligible.

Jel codes: J6, J15, J61

Keywords: Occupational mismatch, Relatedness, Underutilization, Immigration, Wage gap

1 Introduction

Recent studies in developed economies indicate a significant mismatch problem between workers' qualifications and what their jobs require in the labor force, one that 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 % of the ever-overqualified population. Most studies measure the matching quality by the amount of surplus or deficit in schooling, relative to some "required" level of schooling (Leuven and Ooesterberg 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 USA. While studies show that choice of a field of study is directly influenced by the relative pay of graduates in related occupations (Altonji et al. 2012), in a recent study, Boudarbat and Chernoff (2012) reported that 35.1 % of Canadian university graduates are in jobs that are not related to their education 5 years after graduation.

The inability of immigrants to practice in their trained occupation has also been blamed for the substantial decline in new immigrants' earnings in the last decades and the generally slower labor market integration of immigrants since the 1970s, which has been 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 the excessive cost of reentry in regulated (or self-regulated) occupations following migration hinders the labor 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 arguably face long-term labor shortages. In a recent study, Uppal and LaRochelle-Cote (2014) reported that, among internationally educated immigrants who are university graduates, 48 % of women and 37 % of men worked in occupations that usually required a high school education or less in 2006.[2] The corresponding rates are 15 and 17 % for Canadian-educated native-born university graduates, respectively. The poor matching quality of immigrants is seen as a symptom of slower labor market integration that may result in a substantial underutilization of human capital in the whole economy. For instance, Reitz (2001) estimated 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 and 5.9 billion dollars.

Although the nonrecognition of foreign qualifications is frequently blamed in public policy discussions for declining returns to premigration labor market experience and for the immigrant–native-born gap in the rate of return to education in Canada, the evidence shows that differences in preimmigration educational quality have substantial impacts on the Canadian labor market earnings of immigrants (Li and Sweetman 2014) and individual-level test scores (as a proxy for preimmigration 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 postimmigration labor market outcomes (Warman et al. 2015; Ferrer et 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 their occupational attainment and mismatch in hosting countries (Green 1999; Imai et al 2011; Warman et al. 2015). If it is the nonportability of their foreign credentials resulting from shifting source-country composition (Warman and Worswick 2015) that penalizes their wage earnings in hosting labor markets, rather than their transitory occupational mismatch, solutions to the poor economic integration of immigrants should lie more in policies targeting source-country human capital characteristics of new immigrants rather than policies designed for postimmigration improvements (Green and Worswick 2012).

In this study, given the large sample at our disposal (20 % sample of the 2006 Census), we are able to create a continuous index that reflects the "relatedness" between 1375 fields of study and 520 occupations for native-born Canadian-educated workers. The index is calculated for the highest degree attained by each worker and the major field of study associated with that degree. The degrees are based on Statistics Canada's 11-level classification, and range from an apprenticeship certificate and a college certificate or diploma, to a degree in medicine. Unlike studies that define the match between pre- and postimmigration (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 labor markets that internationally educated immigrant workers can attain in the long run. This approach allows us to approximate the annual cost of underutilizing the human capital of immigrants by estimating the change in immigrant earnings that would occur 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 the 1375 fields of study in labor 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 labor market outcomes modeled through self-reported binary variables involves some arbitrariness in the classification of workers into 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 labor 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 occupational mismatch of immigrants is rather a symptom of underlying problems, namely poor (or nonequivalence of) foreign education quality, language proficiency, and literacy skills, without 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 occupational mismatch of immigrants is much more a "source-country problem" rather than being a "host-country problem" that can be efficiently dealt with by postarrival 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 concluding remarks in Section 5.

2 Previous research

This study brings together two different but interrelated fields in the literature: education/skill mismatch in labor markets and the economic assimilation of immigrants 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 defined 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 Ooesterberg (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 the ORU **O**ver-**R**equired-**U**ndereducation literature) quantify the educational mismatch by the amount of surplus or deficit in schooling years. This approach assumes that having more years of education is better and uses 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 USA. 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), showed 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, the Nordin et al. paper was the first study to use the distribution of Swedish workers across occupations to identify matching occupations for each major. They manually (not statistically) identified "crowded" occupations for each major and classified occupations in three categories: related, weakly related, and unrelated.

In a more recent paper, Lemieux (2014) identified 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. He used the self-reported answers in 2005 National Graduate Survey of about 10,000 university graduates to identify whether the person works in a related job and then calculated 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 the publicly available 2006 Canadian Census file, he controlled for the relatedness for each worker through both continuous and binary variables in wage regressions and found 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 % of the university–high school wage gap in Canada.

Due to difficulties in measuring the matching quality between fields of study and occupations, studies looking at the occupational attainment of immigrants in host-country labor markets have investigated the match between immigrants' pre- and postmigration occupations. Green's work (1999), for example, was one of the first studies to compare the occupational distribution of native-born and immigrant workers by using several Canadian censuses and files of immigrant landing records, which include information on premigration occupations as well as intended occupations of immigrants to 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 by using the National Household Survey and Immigration Landing File Linkage Database to determine whether economic principal applicants work in their intended regulated occupations. How (and to what extent) the cross-border transferability of occupational human capital affects earnings was investigated more explicitly in two analytical works (Imai et al 2011; Warman et al. 2015). By using the Longitudinal Survey of Immigrants to Canada (LSIC), in addition to detailed information on labor market experience during the first 4 years after immigrating, both studies were 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. Both studies found 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 calculated the potential loss in immigrants' earnings resulting from the inability to work in an occupation that matches their source-country occupational skill requirements. They found that predicted mean earnings might have been 21–23 % higher at 4 years after arrival.

At the junction of the literature on education and skill mismatch and the labor market integration of new immigrants are two recent studies published in Statistic Canada's research paper series (Plante 2010, 2011). Based on the 20 % sample of the 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.[4] 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.[5] In her second study, Plante (2011) analyzed the determinants of immigrant integration in Canadian labor 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 field of study. Plante's findings indicated that internationally educated immigrants are less likely than their Canadian-educated counterparts to be employed in their field or in occupations requiring similar or higher skill levels.[6]

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 improved to what native-born workers experience in labor 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.

3 Data, relatedness, and mismatches

3.1 Data and relatedness

This study uses the 20 % sample of the 2006 Canadian Census available in the Canadian Research Data Centres. We restricted the data to include only nonaboriginal, civilian, full-time wage earners living in 10 provinces and who were between 19 and 65 years of age, who worked in 2005 and did not attend school at the time. We also dropped nondegree holders, master's and doctorate degree holders, and those whose field of study contains fewer 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 available with up to six-digit codes.[7] 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 3 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.[8]

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 715,000 cells to calculate the following clustering index:

$$\mathrm{RI}_{of} = \frac{L_{of}/L_f}{L_o/L_T},$$

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 twofold: 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).[9] Second, it adjusts the simple densities (numerator) 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 approach was used by Lemieux (2014) showing the distribution of 9 occupations by

10 fields of study. In Table 2 (p. 13), he identified occupation–field of study cells (table note a) 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 labor force). Lemieux (2014) and Ransom (2014) also used the Duncan index to quantify the occupational distinctiveness of a particular field of study.[10] Lemieux specified the Duncan index, DI_f, in field of study f as follows:

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

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 labor force.[11] DI, as expressed above, is an aggregation showing the occupational distinctiveness of each field of study and gets larger 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.

3.2 Matching

The findings in Lemieux's (2014) work are consistent with those in Ransom's (2014) study for the USA, and both indicate that STEM (Science, Technology, Engineering, Math) fields relative to those in the humanities and social sciences have a higher occupational distinctiveness.[12] Instead of summarizing that evidence, which is very similar in nature to our results, 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 labor 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. We then classify the normalized RI (NRI) into five class intervals (1.0–0.8, 0.8–0.6, 0.6–0.4, 0.4–0.2, and 0.2–0). This allows us to rank each occupation based on the distribution of native-born workers.[13] Table 1 shows the current distribution of workers by NRIs and the highest education degree obtained.

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 relatively better matching occupations, 55 % of native-born wage earners work in unrelated occupations. The mismatch ratio drops to 53 % for holders of bachelor's degree, which is the most populated degree with 1.5 million university graduates. As expected, for medical degree holders, the ratio is at its lowest (23 %). When we use these normalized RIs as a benchmark for immigrants who are educated in Canada, the USA, or the UK, the distribution does not change significantly. However, when we identify the immigrants who are internationally educated, the overall mismatch ratio increases to 76 %. 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. Although they mostly overlap, note that this classification reflects the region of highest degree rather than the region of origin. In line with what was observed in Table 1, it can be seen from Table 2 that whether immigrants work in jobs that

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

	NRI—normalized RI (for native-born)								
	Native born			Immigrants (Canadian educated)			Immigrants (internationally educated)		
Degree	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
Apprenticeship	38.1	61.9	883,215	36.3	63.7	104,895	23.9	76.1	47,865
Trades	46.8	53.2	449,475	41.8	58.2	66,635	26.2	73.8	30,210
College <1 year	38.8	61.2	301,460	38.1	61.9	51,700	23.5	76.5	11,375
College 1–2 years	41.5	58.5	1,199,525	39.7	60.3	173,530	22.6	77.4	52,470
College >2 years	49.5	51.5	916,480	44.3	55.7	147,055	23.6	76.4	78,770
University < bachelor's	44.2	56.8	430,945	37.9	62.1	115,940	20.1	79.9	105,135
Bachelor's	47.3	53.7	1,504,535	42.2	57.8	279,505	24.3	75.7	270,605
University > bachelor's	57.2	43.8	220,400	51.1	48.9	44,485	26.0	74.0	51,915
Degrees in medicine	77.6	23.4	20,605	70.0	30.0	6360	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 associated with a field of study reported here are based on the Statistics Canada classification in the 2006 Census. These are apprenticeship certificate or diploma; other trade certificate or diploma; college, CEGEP, or other nonuniversity certificate or diploma from a program of 3-month to less than 1-year duration; college, CEGEP, or other nonuniversity certificate or diploma from a program of 1- to 2-year duration; college, CEGEP, or other nonuniversity certificate or diploma from a program of more than 2-year duration; university certificate or diploma below the bachelor level; bachelor's degree; university certificate or diploma above the bachelor level; and degree in medicine, dentistry, veterinary medicine, or optometry. (ii) The middle three columns for Canadian-educated immigrants include immigrants whose location of study is the USA or the UK

Table 2 Distribution of all immigrants by NRI and location of study—2006 (weighted)

Location of study	NRI 1.0–0.2 (%)[a]	0.2–0.0 (%)[a]	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]Occupation–field of study cells

match their training depends clearly upon where they obtain their highest educational degree. It is interesting to observe in Table 2 that the quality of occupational matching is higher (and similar) for mainly English-speaking countries and lower and similar for regions which are not largely English-speaking, such as Europe, Asia, and Africa.

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 phenomenon 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.[14] Hence, in this paper, this issue is examined by the distribution of immigrant workers in terms of their field of study–occupation match and the years since their migration to Canada (Table 3). It can be seen that the percentage of immigrants working in unrelated occupations remains high, in the 75 % 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 immigrants to Canada (the USA or the UK), the field of study–occupation distribution of internationally educated immigrants would shift in the long run toward that of native-born workers. Yet, the persistency in mismatch suggests that the occupational mobility of immigrants does not translate into better occupational matching as measured by cross-cohort comparisons in Table 2. When this is combined with the evidence that earnings returns to foreign credentials of non-English-speaking, non-European immigrants are discounted to zero in Canadian labor 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 labor markets by better occupational assignments of immigrants.

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

Years in Canada	NRI (for native born) 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
	1143	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
	1195	889	948
Increase in wage	31.2 %	30.2 %	28.6 %
Total	23.7 %	76.3 %	661,675
	1098	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

For brevity, we present only three descriptive tables here and a few additional tables in the 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 labor markets.

4 Statistical framework and estimation results

4.1 Wage earnings and matching

Although it is well documented that estimated returns to education are large, there are different reasons identified in the literature for 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 (2014) calls these channels "occupation upgrading" and "pure education" effects. The third reason that education affects earnings comes from the interaction between these two channels: the assignment of skills obtained through education to jobs that are available in labor markets. Studies have used 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 through matching is a fairly complex process, in practice, the first two channels (occupation upgrading and specialization) are controlled 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 (2014), augmented to include controls for each of the three earnings impacts of education 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, and location of work. 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 for the matching quality between occupation o and field of study f and yields a wage premium, α, which measures the extent to which field of study f is valuable in occupation o. This model could be useful, for example, for estimating the wage premium associated with a university degree for each field of study, when the base in the binary variable b is set to high school graduates. Although the high level of disaggregation in the 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 Eq. (1) that controls for differences across nine education degrees (see notes to Table 1).[15]

A concern in the literature has been the problem of unmeasured ability. Some studies on the impact of education on earnings have used instrumental methods to deal with ability bias (Ashenfelter et al. 1999), but in studies that examine the impact of the field of study, this has not been done due to difficulties in finding credible instruments. Studies in the latter group (Altonji et al. 2012; Nordin et al. 2010) try to control for unobserved ability by including proxy variables. In this paper, we follow Lemieux (2014) who shows why the ordinary least squares (OLS) results of Eq. (1) should be valid when that equation is used to estimate average effects as opposed capturing causal effects.[16]

In light of this, we also estimate the model using OLS but estimate coefficient standard errors using the multi-way clustering method proposed by Cameron et al. (2011) to capture within-occupation and within-field-of-study correlations for better statistical inference 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 labor markets. We hope to understand 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 RIs classified into five groups as noted earlier, which we treat as categorical variables that rank each occupation based on the distribution of native-born workers. Thus, using this categorical variable as a proxy for $m(f, o)$ in Eq. (1) for immigrants allows us not only to estimate the wage penalty that immigrant workers face but also to treat $m(f, o)$ as exogenous, which has otherwise been a major challenge for many studies in the literature.

Before analyzing the effect of relatedness on earnings more systematically, we present an overview of the NRI and average weekly wage earnings in Table 4. The first two columns show the distribution of native-born and Canadian-educated immigrant workers 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. Table 4 reveals two critical features: first, there is a clear wage penalty for immigrants associated with working in occupations that are regarded as relatively less related by native-born

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

	NB	Immigrants (Canadian educated)	NRI (for native born) 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
Apprenticeship	26.5 %	24.0 %	14.7 %	1.3 %	2.2 %	5.9 %	76.1 %	47,865
	833	859	885	885	850	697	769	785
Trades	38.4 %	32.3 %	17.5 %	1.2 %	2.1 %	5.4 %	73.8 %	30,210
	1076	1033	978	931	918	811	858	879
College <1 year	18.3 %	17.4 %	6.9 %	2.1 %	4.8 %	9.7 %	76.5 %	11,375
	821	813	1128	833	887	711	693	737
College 1–2 years	21.4 %	20.3 %	8.7 %	2.1 %	4.0 %	7.7 %	77.4 %	52,470
	919	926	875	840	853	734	701	728
College >2 years	29.0 %	24.3 %	12.4 %	2.3 %	2.7 %	6.1 %	76.4 %	78,770
	1032	1099	1082	985	908	794	764	815
University < bachelor's	20.4 %	16.6 %	7.3 %	2.0 %	3.1 %	7.8 %	79.9 %	105,135
	1203	1203	1173	1124	874	814	766	811
Bachelor's	24.8 %	20.7 %	10.6 %	2.9 %	2.9 %	8.0 %	75.7 %	270,605
	1325	1371	1212	1126	957	895	781	850
University > bachelor's	33.3 %	28.2 %	12.2 %	3.0 %	3.1 %	7.7 %	74.0 %	51,915
	1375	1535	1226	1232	1180	1091	904	976
Degrees in medicine	57.8 %	51.2 %	18.5 %	7.6 %	0.2 %	0.4 %	73.2 %	13,355
	1691	1959	1733	1965	919	1390	818	1076
Total	25.8 %	22.2 %	11.0 %	2.5 %	2.9 %	7.3 %	76.3 %	661,700
	1083	1145	1137	1134	935	855	781	839

Notes: (i) NB denote native-born Canadians, while Canadian-educated immigrants include those educated in the USA and the UK. (ii) For educational degrees, see notes to Table 1. (iii) Weekly average wages are reported under % distributions

workers; second, the wage differences between the 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 RIs between 1.0 and 0.8. The first observation is in line with the evidence that Canadian-educated immigrants have much better labor market outcomes than native-born workers and far better than those for foreign-educated immigrants (McBride and Sweetman 2003). 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.

4.2 Estimation results

Table 5 summarizes the estimation results for three specifications of the earnings function given by Eq. (1). The first specification shows the results for native-born workers. The last two specifications report the results for full-time, immigrant workers educated in Canada (the USA or the UK) and those educated abroad, respectively. All specifications include controls for age square, marital status, disability, visible minority status, primary

Table 5 OLS estimates of weekly wage earnings—2006

	Native born		Immigrants (Canadian educated)		Immigrants (internationally educated)	
	Coefficient	$P > \|z\|$	Coefficient	$P > \|z\|$	Coefficient	$P > \|z\|$
Dummies for NRI classes						
1.0–0.8	Base		Base		Base	
0.8–0.6	−0.0187	0.225	−0.0208	0.273	−0.0259	0.472
0.6–0.4	−0.0169	0.182	−0.0293	0.169	−0.0399	0.252
0.4–0.2	−0.0382	0.000	−0.0326	0.034	−0.0526	0.038
0.2–0.0	−0.1259	0.000	−0.1276	0.000	−0.1166	0.000
Dummies for degrees						
Apprenticeship	Base		Base		Base	
Trades	0.0418	0.000	0.0195	0.197	−0.0432	0.056
College—less than 1 year	−0.0035	0.697	−0.0265	0.138	−0.0196	0.057
College—1 to 2 years	0.0355	0.007	0.0138	0.370	−0.0314	0.124
College—more than 2 years	0.0752	0.000	0.0583	0.000	−0.0256	0.183
University—below bachelor's	0.1040	0.000	0.0509	0.017	0.0033	0.888
Bachelor's degree	0.1728	0.000	0.1210	0.000	−0.0079	0.732
University—above bachelor's	0.2156	0.000	0.1521	0.000	0.0354	0.183
Degrees in medicine	0.0873	0.048	0.1367	0.042	−0.0125	0.837
Male	0.1641	0.000	0.1276	0.000	0.1437	0.000
Age	0.0796	0.000	0.0802	0.000	0.0455	0.000
Age^2	−0.0008	0.000	−0.0008	0.000	−0.0004	0.000
R^2	0.358		0.314		0.244	
Observations	1,150,617		190,624		12,706	
Number of clusters (Occupations)	520		518		513	
Number of clusters (Fields of study)	915		877		838	

Notes: (1) The dependent variable is log weekly wage. (2) Standard errors are adjusted at occupation and field of study cells by using the two-way clustering method (Cameron et al. 2011), and the number of clusters for each specification is reported at the bottom of the table. (3) All equations also control for 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, and occupation fixed effects at 520 categories. (4) The equations also include industry fixed effects at 21 categories. However, results do not change significantly when industry fixed effects are excluded

earner status, spoken language, regional fixed effects for 10 provinces, and industry fixed effects for 21 categories. Moreover, the sample size allows us to control for field of study fixed effects for 1375 categories and occupation fixed effects for 520 categories, which helps us isolate the effect of relatedness from the wage differences across fields of study and occupations. Both the second and the third columns use dummy variables created using the normalized RIs for the native-born workers, and not those of immigrants.

Regardless of birthplace or location of study, the results indicate a positive impact on wages of relatedness. The results also show that the wage effect of mismatch for workers with NRIs between 0.8 and 0.4 is not robust, perhaps reflecting their very small share in the labor force. Note that this relationship as structured in Eq. (1) appears to be correlational rather than causational, particularly when self-reported answers to survey questions (Robst 2007; Lemieux 2014) 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 exogeneity in relatedness. In particular, as we see 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 lower-paid 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 who are working in the least matching occupations (NRI = 0.2–0.0). Considering that more than 76 % 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 that, when labor markets are less rewarding for immigrants who were educated abroad (Li and Sweetman 2014), a better occupational match becomes less rewarding as well. Some final observations are worth noting. 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 labor 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. 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 outside of Canada, the USA, and the UK. Finally, in order to assess whether gender plays a role in modifying the impact of NRI on wages, we estimated the model (specification 3 in Table 5) by interacting NRI with a gender dummy variable. The results (not reported here) show that differential wage effects of NRI dummies are only significant at the lowest NRI category (0.2–0.0) with the P value of 0.039. While the wage penalty for female workers at the lowest NRI level is −15.75 %, it is −8.34 % for male workers. Although the distribution of internationally educated immigrant workers across the five NRI categories is very similar by gender, a higher wage penalty of occupational mismatch for female foreign-educated immigrant workers is in line with the evidence that there are major differences in most issues related to the integration of immigrants in hosting labor markets.

5 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 larger question: how would one approximate the overall cost of a labor 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 overeducation. In a recent paper, Leuven and Ooesterberg (2011) extensively reviewed the ORU literature and concluded 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 of 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 labor 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 underutilized, 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 NRIs lower than 0.8 were reassigned to the most related occupations (with NRIs 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 % of the total weekly wage bill), which can be considered 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 labor markets.

A more meaningful approach would be to quantify the wage gain that would result if the occupational matching quality of immigrants were identical to that currently experienced by native-born workers. Also, since the absolute wage gains for immigrants and the 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 an adjustment for these differences. Our measure is as follows:

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

where CG, TWB, WG, m, n, and c denote the comparative gain, total wage bill, wage gain, immigrants, 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 WGs comparable.[17] Table 6 reports the calculations based on (2) and explains each term in detail.

The number of workers in Table 6 is taken from Table 9 in the Appendix, while the total weekly wage bill for the native born and immigrants is 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 Eq. (1) reported in Table 5, for internationally educated immigrants and the native born, respectively. The total weekly WG is then the product of these coefficients and the total weekly wage bill for 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 WGs comparable. Since this adjustment rate, which works out to 9.35 % (as shown in Table 5), removes from the WGs differences in average wages and labor market sizes, the difference between WGs in (2) shows the wage gain of immigrant workers had their occupational matching improved to what native-born workers experience in labor markets. The calculations in Table 6 show that, when the occupational match of immigrants is measured relative to that of native-born workers, the total weekly wage gain that immigrants would experience amounts to no more than 2 % of the total weekly wage bill (10.3/554.9), implying that the wage gain of 8.8 % 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 five-category classification reported in this paper, the cost associated with immigrants' occupational mismatch should be calculated in relative terms 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

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 (×1000)	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) (×1000)		492	711	2170	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 (×1000)	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) (×1000)		6462	5363	21,539	384,223	417,586
TWB(m)/TWB(n) = (554,993/5,936,339)						9.35 %
Weekly CG (×1000)						10,331
Annual CG (×1000)						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 represent predicted values 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 the Conference Board of Canada (2001).

It could be argued that averaging the wage gains can mask the differential wage rewards for different segments of the labor 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 Eq. (2) can be affected in 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. By way of illustration, we present in Table 7 the estimates of the same cost for medical degree holders.

Without comparing their gain relative to that of native-born workers, the total weekly gain for immigrants holding a medical degree amounts to 6.8 % of the total weekly wage bill. The comparative gain, on the other hand, is 585,000 dollars, which is 4 % 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 % 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 % of all immigrant workers (661,675), their comparative weekly wage gain (30.4 million dollars) makes up more than 6 % of the total weekly wage gain of all immigrant workers (537 million dollars).

One may consider whether a complete equalization of immigrant and native-born distributions is desirable, give that immigrants, especially those coming through the point system, are supposed to fill labor shortages. This argument goes back to the question of whether immigrants are substitutes or complements in host-country labor markets (Green 1999). In this context, the difference between pre- and postimmigration occupations may,

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	2470	1020	30	55	9785	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	2144	3948	932,995	991,101
Number of native-born workers	11,905	3565	100	215	4820	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	2096	8047	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 thus, not constitute a mismatch. Our approach does not impose an identical occupational distribution on immigrant and native-born workers but uses the native-born field of study–occupation distribution to define immigrants' occupational match. We argue that the assessment of occupational mismatch for any segment of labor 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 from that of 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 labor markets.

Our findings also help us approximate the part of the wage gap between native-born and immigrant workers than can be attributed 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 % 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 % of the gap) if only improvements in the immigrants' occupational matching were taken into account,[18] which shows the importance of calculating wage gains in relative terms.

These findings contradict a common view in public circles that impediments to entering hosting labor 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 with the literature. Green and Worswick (2012) found 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 shifts in 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 postmigration labor market outcomes. These findings imply that, if the occupational mismatch results from a combination of immigrants' poor (or nonequivalence of) foreign education quality, language

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	1002	417,586	6,353,924	1072
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	1052
Immigrant	505,113	303,573	601	45,998	349,571	692
Wage gap	%		55.41			51.95

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 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 % of immigrants and 55.1 % of native-born workers, 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 % of the initial wage gap for workers who work in the least related occupations.[19] 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.

6 Conclusions

Given the large sample at our disposal, we developed a continuous index that reflects the degree of 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 labor 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 that would result if they were distributed identically to 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 perhaps it is not the occupational mismatch of immigrants that penalizes their wage earnings in hosting labor markets. Rather, it is the nonportability of their foreign credentials, which appears to be the root cause of the mismatch and is largely attributable to the shifting source-country composition of immigrants (Green and Worswick 2012). In other words, the occupational mismatch of immigrant is much more a "source-country problem" rather than being a "host-country problem" that can be efficiently dealt with by postarrival policies. As our findings point out, since it is a symptom of other 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 the return to their human capital. Therefore, solutions to problems associated with the poor economic integration of immigrants into Canadian labor markets should lie more in policies targeting the source-country human capital characteristics of new immigrants rather than policies designed for postmigration improvements alone.

Endnotes

[1]The latest research on skill mismatch can be found at a workshop program 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).

[2]The same rates decline slightly in 2011 to 43 and 35 %, respectively.

[3]Sweetman et al. (2015) provide an excellent overview of occupational regulation and foreign qualification recognition.

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

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

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

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

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

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

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

[11]$L_{of}/L_f = \theta_{of}$ and $L_o/L_T = \theta_{o.}$

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

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

[14]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.

[15]This might capture some which 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.

[16]Lemieux used Eq. (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 labor markets for immigrants.

[17]This is better seen 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 the number of immigrants and native-born, respectively. With this notation, we can 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 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.

[18]The difference between 19.42 % and 9.7 % ((1002–913)/913) accounts for almost 50 % of the gap.

[19](55.41–51.95)/55.41 = 6.2 %.

Appendix

Table 9 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						
Apprenticeship	26.5 %	1.5 %	3.4 %	6.6 %	61.9 %	883,215
Trades	38.4 %	1.6 %	2.5 %	4.2 %	53.2 %	449,475
College <1 year	18.3 %	3.0 %	5.9 %	11.6 %	61.2 %	301,460
College 1–2 years	21.4 %	3.1 %	5.8 %	11.1 %	58.5 %	1,199,525
College >2 years	29.0 %	4.8 %	6.0 %	9.6 %	50.5 %	916,480
University < bachelor's	20.4 %	6.3 %	6.1 %	11.5 %	55.8 %	430,945
Bachelor's	24.8 %	7.2 %	4.9 %	10.5 %	52.7 %	1,504,535
University > bachelor's	33.3 %	11.1 %	3.8 %	9.0 %	42.8 %	220,400
Degrees in medicine	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						
Apprenticeship	24.0 %	1.2 %	3.8 %	7.4 %	63.7 %	104,895
Trades	32.3 %	1.4 %	3.0 %	5.1 %	58.2 %	66,635
College <1 year	17.4 %	2.6 %	6.6 %	11.5 %	61.9 %	51,700
College 1–2 years	20.3 %	3.3 %	5.6 %	10.5 %	60.3 %	173,530
College >2 years	24.3 %	4.9 %	5.6 %	9.6 %	55.7 %	147,055
University < bachelor's	16.6 %	4.2 %	5.4 %	11.7 %	62.1 %	115,940
Bachelor's	20.7 %	6.7 %	4.5 %	10.3 %	57.8 %	279,505
University > bachelor's	28.2 %	9.5 %	4.1 %	9.3 %	48.9 %	44,485
Degrees in medicine	51.2 %	18.0 %	0.2 %	0.6 %	30.0 %	6360
Total	22.2 %	4.6 %	4.9 %	9.7 %	58.7 %	990,105
Immigrants—internationally educated						
Apprenticeship	14.7 %	1.3 %	2.2 %	5.9 %	76.1 %	47,865
Trades	17.5 %	1.2 %	2.1 %	5.4 %	73.8 %	30,210
College <1 year	6.9 %	2.1 %	4.8 %	9.7 %	76.5 %	11,375
College 1–2 years	8.7 %	2.1 %	4.0 %	7.7 %	77.4 %	52,470
College >2 years	12.4 %	2.3 %	2.7 %	6.1 %	76.4 %	78,770
University < bachelor's	7.3 %	2.0 %	3.1 %	7.8 %	79.9 %	105,135
Bachelor's	10.6 %	2.9 %	2.9 %	8.0 %	75.7 %	270,605
University > bachelor's	12.2 %	3.0 %	3.1 %	7.7 %	74.0 %	51,915
Degrees in medicine	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 associated with a field of study reported here are based on the Statistics Canada classification in the 2006 Census. These are apprenticeship certificate or diploma; other trade certificate or diploma; college, CEGEP, or other nonuniversity certificate or diploma from a program of 3-month to less than 1-year duration; college, CEGEP, or other nonuniversity certificate or diploma from a program of 1- to 2-year duration; college, CEGEP, or other nonuniversity certificate or diploma from a program of more than 2-year duration; university certificate or diploma below the bachelor level; bachelor's degree; university certificate or diploma above the bachelor level; degree in medicine, dentistry, veterinary medicine, or optometry

Competing interests

The IZA Journal of Migration is committed to the IZA Guiding Principles of Research Integrity. The authors declare that they have observed these principles.

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References

Altonji JG, Blom E, Meghir C. Heterogeneity in human capital investments: high school curriculum, college major, and careers. Annual Review of Economics, Annual Reviews. 2012;4(1):185–223.

Ashenfelter O, Harmon C, Oosterbeek H. A review of estimates of the schooling/earnings relationship, with tests for publication bias. Labour Econ. 1999;6(4):453–70.

Borjas G. "The slowdown in the economic assimilation of immigrants: aging and cohort effects revisited again," NBER Working Papers 19116, National Bureau of Economic Research, Inc. 2013.

Boudarbat B, Chernoff V. Education-job match among recent Canadian university graduates. Appl Econ Lett. 2012; 19(18):1923–6.

Cameron AC, Gelbach J, Miller D. Robust inference with multi-way clustering. J Bus Econ Stat. 2011;29(2):238–49.

Conference Board of Canada. Brain grain. Economic benefits of recognizing learning and learning credentials in Canada. 2001. http://grantinsights.com/pdfs/brain_gain.pdf.

Duncan GJ, Hoffman SD. "The incidence and wage effects of overeducation." Economics of Education Review 1981;1(1):75–86.

Dustmann C, Fabbri F. "Immigrants in the British labour market", CReAM Discussion Paper Series 0507, Centre for Research and Analysis of Migration (CReAM). UK: Department of Economics, University College London; 2005.

Ferrer A, Riddell WC. Education, credentials, and immigrant earnings. Can J Econ. 2008;41(1):186–216.

Ferrer A, Green DA, Riddell WC. The effect of literacy on immigrant earnings. J Hum Resour. 2006;41(2):380–410.

Green DA. Immigrant occupational attainment: assimilation and mobility over time. J Labor Econ. 1999;17(1):49–79.

Green D, Worswick C. Immigrant earnings profiles in the presence of human capital investment: measuring cohort and macro effects. Labour Econ. 2012;19(2):241–59.

Hartog J. "Over-education and earnings: where are we, where should we go?" Economics of Education Review. 2000;19(2):131–147.

Imai S, Stacey D, Warman C. "From engineer to taxi driver? Occupational skills and the economic outcomes of immigrants." Canada: Queen's University Economic Department Working Paper No: 1275; 2011.

Jantzen L. Do economic principal applicants work in their intended regulated occupation? Introducing the national household survey and immigration landing file linkage database. Can Public Pol. 2015;41(1):48–63.

Kaushal N, Lu Y, Denier N, Wang JS, Trejo SJ. "Immigrant employment and earnings growth in Canada and the U.S.: evidence from longitudinal data." IZA Discussion Papers, IZA DP No. 9495. 2015.

Lemieux T. "Occupations, fields of study, and returns to education." Can J Econ. 2014;47(4):1047–1077.

Leuven E, Ooesterberg H. "Over-education and mismatch in the labor market." IZA Discussion Papers, IZA DP No. 5523. 2011.

Li Q, Sweetman A. The quality of immigrant source country educational outcomes: do they matter in the receiving country? Labour Econ. 2014;26(C):81–93.

Li C, Gervais G, Duval A. "The dynamics of over qualification: Canada's underemployed university graduates." Canada: Statistics Canada Analytical Papers; 2006. Catalogue no. 11-621-MIE -No. 039.

McBride S, Sweetman A. Immigrant and non-immigrant earnings by postsecondary field of study. In: Beach CM, Green AG, Reitz JG, editors. Canadian immigration policy for the 21st century. Kingston and Montreal: McGill-Queen's University Press; 2003. p. 413–62.

Nordin M, Persson I, Rooth D. Education-occupation mismatch: is there an income penalty? Econ Educ Rev. 2010;29(6): 1047–59.

Picot G, Sweetman A. "Making it in Canada: immigration outcomes and policies." IRPP Study no. 29. Montréal: Institute for Research on Public Policy (IRPP); 2012.

Plante, J. "Characteristics and labour market outcomes of internationally-educated immigrants." Canada: Statistics Canada – Culture Tourism and Centre for Education Statistics Research Papers; 2010. Catalogue n. 81-595-M No. 084.

Plante, J. "Integration of internationally-educated immigrants into the Canadian labour markets: determinants of success." Canada: Statistics Canada – Culture Tourism and Centre for Education Statistics Research Papers; 2011. Catalogue n. 81-595-M No. 094.

Ransom MR. "The Changing Occupational Distribution by College Major". 2014. http://www.iza.org/conference_files/2015_Skill_Mismatch/ransom_m1284.pdf.

Reitz JG. Immigrant skill utilization in the Canadian labour market: implications of human capital research. J Int Migr Integr. 2001;2(3):347–78.

Robst J. Education and job match: the relatedness of college major and work. Econ Educ Rev. 2007;26:397–407.

Sweetman A, McDonald JT, Hawthorne L. Occupational regulation and foreign qualification recognition: an overview. Can Public Pol. 2015;41(1):1–13.
Uppal S, LaRochelle-Cote S. "Overqualification among recent university graduates in Canada." Statistics Canada – Insights on Canadian Society, Catalogue no. 75-006-X. 2014.
Warman C, Worswick C. Technological change, occupational tasks and declining immigrant outcomes: implications for earnings and income inequality in Canada. Can J Econ. 2015;48(2):736–72.
Warman C, Sweetman A, Goldman G. The portability of new immigrants' human capital: language, education, and occupational skills. Can Public Pol. 2015;41(1):64–79.
Xue, L. and Xu, L. "Employment outcomes of postsecondary educated immigrants, 2006 Census." Citizenship and Immigration Canada. Canada: Research and Evaluation; 2010. Ref. No.: RR20120702.
Yuen J. "Job-education match and mismatch: wage differentials." Canada: Statistics Canada; 2010. Perspectives: Catalogue no: 75-001-X.
Zeitsma D. "Immigrants working in regulated occupations." Canada: Statistics Canada; 2010. Perspectives: Catalogue no: 75-001-X.