The Relative Performance of International Students and Their Academic Program Choices

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contribution

Chapters 1 and 3 are co-authored with my supervisor, Professor Mikal Skuterud. I was involved in developing the research question, searching for data, and producing the results. Professor Mikal Skuterud wrote the final draft of two chapters. Chapter 2 is solo authored.

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Abstract

Canada is increasingly looking to international students as a source of postsecondary tuition revenues and new immigrants. In Chapter 1, we examine the relative course grades of international undergraduate students in an Ontario university with a large and growing foreign student presence. We identify grade gaps across fields of study, which appear to primarily reflect admission errors from less predictive secondary school grades. While the gaps appear related to English-language proficiency, they are larger among graduates of Canadian secondary schools and in upper- than in first-year courses. Our estimates also suggest that relative foreign student quality has improved over time, despite increasing foreign enrolment.

The academic programs that students choose to pursue have strong implications for their career prospects. In Chapter 2, I shed light on students' academic program choices by examining how co-ethnic peers influence their decisions to change programs during the course of their undergraduate studies. Examining data from a publicly-funded Ontario university with an ethnically diverse student population, I find that students are highly ethnically concentrated within academic programs at the time of their initial enrolment. Moreover, nearly one-quarter of all students change programs at least once during their studies and these program changes further increase the ethnic concentration of students within academic programs. Assuming a model in which students prioritize their grades over co-ethnic peers, the presence of more co-ethnic peers is found to significantly increase the probability of a program change. This suggests that the ethnic concentration of students across programs at the university, which appears to increase over time, may be academically and socially efficient.

International students are considered to be the best source of immigrants. In chapter 3, we compare the labour market performance of former international students (FISs) through the first decade of the 2000s to their Canadian-born-and-educated (CBE) and foreign-born-and-educated (FBE) counterparts. We find FISs outperform FBE immigrants by a substantial margin, but underperform CBE graduates from similar postsecondary programs. We also find evidence of a deterioration in FIS outcomes relative to both comparison groups. We argue that this deterioration is most consistent with a quality tradeoff as the supply of international students has not kept pace with the growth in demand.

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Introduction

Canada ranks among the world's largest international student receiving countries measured as a share of its postsecondary student population. International students have become essential for both Canadian postsecondary institutions and the federal government in the past decade. Canadian universities rely on the enrollment of international students to offset the funding shortfalls and declining postsecondary aged domestic population. The Canadian government considers international students as the best source of immigrants, since they are less likely to have language difficulties and can better adapt to Canadian culture in comparison to foreign educated immigrants. Consequently, the international student shares of all postsecondary graduates and new permanent residents increased from 3% to 11% between 2004 and 2014.

Although the share of international students has increased dramatically, the Express Entry (EE) system, which is designed to facilitate express immigration of skilled workers to Canada, initially prioritized applicants' employment experiences regardless of their educational background. A criticism of the EE system emerged, with arguments that the system should give preference to international students. As a result, the EE system was revised in 2016 so that international students who hold Canadian credentials earn up to 30 additional Comprehensive Ranking System (CRS) points in the system. As the Canadian government and postsecondary institutions elaborate their strategies to attract more international students over time, it raises the question whether there has been any change in the average quality of foreign students. My three-chapter dissertation contributes to an understanding of how international students perform in the labour market and universities, as well as the challenges that the large influx of international students brings to the Canadian government and postsecondary institutions.

Chapter 1 provides evidence on human capital of Canadian international students. Examining data from a publicly-funded university with a large share of international students, we compare the relative academic grades of international students to their domestic counterparts at various percentiles. The results suggest that international students underperform their domestic counterparts. The performance gap reflects the weaker performance of international students graduating from Canadian secondary institutions. This brings the challenge to university administrators during the recruiting process, since we expect the noise in students' entry grades to be higher in some Canadian private secondary schools. As the share of international students has increased across cohorts, we examine whether there is a tradeoff in foreign student quality as the university reaches deeper into the applicant pool to meet their demands for students.

Paths to socioeconomic mobility are largely shaped by educational attainment. Students graduating from different fields of studies end up with large differences in their average earnings. Examining data from a publicly-funded university, Chapter 2 contributes to the Canadian evidence on students' program choices and how those choices are influenced by their co-ethnic peers. First, I obtain evidence on whether students are distributed across academic programs in a way that is related to their ethnic background. Second, I examine whether the ethnic concentration of students within programs changes over the course of their undergraduate studies. The evidence directly informs whether students change to programs with a higher share of their co-ethnic peers. The university administrators should be concerned if students prioritize their co-ethnic peers when making program changes, because it would not provide the best match between students' abilities and their programs.

The evidence on the relative labour market performance of former international students is mixed, with some studies reporting that there is little to no difference in the labour market returns between foreign and Canadian credentials (Ferrer and Riddell 2008; Skuterud and Su 2012; Bonikowska, Hou, and Picot 2015), and others suggesting that the difference is large (Sweetman and Warman 2014; Hou and Lu 2017). Chapter 3 compares the labour market performance of former international students (FISs) to their counterparts: Canadian-born-and-educated graduates (CBEs) and foreign-born-and-educated immigrants (FBEs). This contributes to the Canadian evidence on the relative quality of former international students. It further identifies to what extent the academic performance gap between foreign and domestic students in Chapter 1 reflects the relative quality of FISs to CBEs in the labour market. It is conceivable that employers use the university grades of new graduates as a selection criterion during the recruiting process. In addition, by comparing the labour market outcomes of FISs to FBEs, we obtain direct evidence on whether giving preference to applicants who hold Canadian postsecondary credentials in the EE system is justified. Moreover, since the international student share of graduates has increased over time, it is important to know whether the relative quality of FISs has deteriorated over time.

Chapter 1

The Relative Academic Achievement of International Students: Evidence from an Ontario University

Zong Jia Chen and Mikal Skuterud

1.1 Introduction

Recent years have seen a shift in Canadian immigration policy towards a preference for former international students as a source of economic-class immigrants. To ease their transitions to permanent residency, the government has introduced off-campus work permits, enabling international students to hold part-time jobs during their studies, and extensions to post-graduate work permits, providing open work permits for up three years following graduation. The Provincial Nominee Programs of Ontario and British Columbia now waive all work experience requirements for international students with Canadian Master's or Doctoral degrees.[1] Most significantly, in November 2016, the federal government revised its Express Entry System for processing permanent residency applications by giving bonus

[1]British Columbia requires that the graduate degree be in a STEM field.

points to candidates with Canadian postsecondary educational credentials.[2]

At the same time that the government is easing the immigration pathway for international students, Canadian postsecondary institutions are looking to foreign students to further their internationalization objectives and offset dwindling domestic applications resulting from declining youth populations. Foreign students bring diverse perspectives and ideas, which are believed to enhance innovation and research; they contribute to building international networks and advance institutional reputations internationally; and there is evidence of beneficial spillover effects on domestic student outcomes (Villalpando 2002; Bowman 2010). Moreover, foreign student fees are unregulated, allowing colleges and universities to set foreign fees that are on average four times higher than domestic fees.[3] Combined with the promise of a pathway to Canadian permanent residency, Canada's colleges and universities are experiencing unprecedented increases in foreign student enrolments; a four-fold increase nationally between 1992 and 2016, raising the national foreign student enrolment share from 3% to 12%.[4]

On the surface, the government's preference for international students appears well justified. Their time spent studying in Canada should improve their English/French language skills, allow them to build social networks to aid their job search efforts, and help them acculturate to Canadian society more generally. They should face fewer credential recognition issues and their skills should be more relevant to Canadian workplaces. Nonetheless, there is evidence that former international students who transition to permanent residency experience disparities in labour market outcomes relative to their domestic counterparts graduating from similar academic programs (Sweetman and Warman 2014; Hou and Lu 2017; Chen and Skuterud 2018). The disparities are evident in their relative earnings, employment rates, and the likelihood that their jobs match their educational backgrounds, in terms of field and level of study. Moreover, the disparities appear to persist up to 20 years after graduation. The critical question for policymakers is to what extent they reflect the relative skills of foreign students, as opposed to labour market inefficiencies resulting

[2]The share of new permanent residents who once held a Canadian study permit increased from 6.9% in 2005 to 10.7% in 2015. Unfortunately, more recent data are unavailable. These data were available on the Open Government Data Portal in March 2017 as "Admissions of Permanent Residents who have ever held a Study Permit by Intended Province/Territory of Destination and Immigration Category, 2005-October 2016."

[3]The average tuition fee of international undergraduate students studying in Canada was $27,159 in 2018-2019 compared to $6,838 for domestic undergraduates. The ratio of 3.97 has increased steadily from 3.04 in 2006-2007. See "Canadian and international tuition fees by level of study," Statistics Canada, Table 37-10-0045-01.

[4]Statistics Canada, Post-secondary Student Information System, "Postsecondary enrolments by status of student, country of citizenship, and sex," Table 37-10-0086-01

from, for example, employer discrimination against immigrants.

Distinguishing the relative importance of discrimination versus worker skills in explaining immigrant labour market disparities is fraught with complication. Not only are the rationales underlying employers' recruitment and compensation decisions rarely observable, fully capturing the skills that affect workers' labour market outcomes is far beyond the scope of survey instruments. Canadian evidence of lower employer callback rates for job applicants with foreign names emphasizes the influence of discrimination (Oreopoulos 2011; Banerjee, Reitz and Oreopoulos 2018). However, it is unclear to what extent immigrants are able to mitigate the effects of discriminatory employers by sorting themselves into non-discriminatory firms (Heckman 1998). Moroever, there is compelling evidence that many Canadian immigrants lack basic literacy skills, although it is unclear how relevant these gaps are for immigrants with Canadian postsecondary credentials (Ferrer, Green and Riddell 2006; Clarke and Skuterud 2016).

We provide new evidence on the human capital of Canada's skilled immigrants by examining the relative course-level grade achievement of international undergraduate students at an Ontario university with a large and growing foreign-student presence. There is compelling evidence that university grades are an important predictor of students' starting salaries in the labour market, presumably reflecting overlap in the skills that are evaluated in universities and valued in labour markets (Jones and Jackson 1990; Chia and Miller 2008). Moreover, since course instructors are constrained by formal academic grading processes and interact with students for a longer period than employment recruiters evaluate job candidates, differences in grades within courses are arguably less likely to reflect discrimination than are differences in labour market outcomes. The results of our analysis not only shed light on the nature of the Canadian labour market challenges of former international students, but are also relevant to practitioners and university administrators concerned with foreign student recruitment and admissions.

Using a fixed-effects strategy to isolate grade differentials within courses taught by particular instructors, we reach three main findings. First, we identify gaps in the academic achievement of foreign students, which are remarkably similar in magnitude across faculties and appear to overwhelmingly reflect the lower grade achievement of international students with Canadian secondary diplomas. Second, the disparities in foreign student quality appear to reflect the challenges inherent in using secondary school grades to screen foreign applicants more than differences in the relative quality of foreign applicants. While the gaps appear related to English-language competency, they are larger in upper- than first-year courses. Finally, we examine whether there is any evidence of quantity-quality tradeoffs in foreign student admissions as foreign student shares of enrolment have increased. The results are more consistent with improvements in foreign student quality, which appear primarily attributable to improvements in the screening of foreign applicants.

The reminder of the article is organized as follows. The following section presents a theoretical model of student recruitment, distinguishing three key mechanisms that could give rise to differences in foreign student quality. The following two sections describe the empirical strategies and data used to identify the relative quality of foreign students and changes across entry cohorts. Section 5 interprets the results in the light of the theoretical model. We conclude, in Section 6, by discussing the significance of the main findings for postsecondary institutions and immigration policy.

1.2 Theory

To help us interpret our empirical estimates, we begin by considering a simple theoretical model of student admissions and grades. We define student quality as the ability to succeed in university courses, where success is reflected exclusively in a student's final course grades. Student quality depends on many factors, including work ethic, cognitive ability, prior knowledge in a field, English language skills, and even peer groups; our conception of quality is therefore broad. We recognize that the skills acquired through course learning may not be fully reflected in course grades, particularly in fields where skills are difficult to evaluate. Nonetheless, as noted above, there is compelling evidence that university undergraduate course grades predict labour market earnings. This implies that there is overlap in the skills that are evaluated (and perhaps also learned) in universities and the skills that are rewarded in the labour market.

Student quality in the population of all foreign and domestic secondary-school graduates is assumed normally distributed, that is $q_j \sim \mathrm{N}(\mu_j, \sigma_j)$ for $j = \{f, d\}$, respectively.[5] The university screens applicants for admission on the basis of their measured quality. To measure student quality, the university relies exclusively on the secondary-school grade point average of applicants.[6] We begin by assuming that this "entry grade", notated e, provides a perfect measure of the quality of students (we relax this assumption later).

[5]Since the distribution of observed grades has a [0,100] support, this assumption cannot be strictly true. However, none of the main results change by allowing for truncation of measured quality below 0 and above 100.

[6]Note that in our data, the secondary school grades of applicants who completed secondary school abroad are adjusted using information on the historical success of admitted students from the same origin country. This adjustment is intended to make the grades of foreign applicants directly comparable to that of domestic applicants.

The university engages in marketing efforts domestically and abroad, which attracts the interest of prospective foreign and domestic students with probability π_j for $j = \{f, d\}$, respectively. In order to limit the cost of processing applications, the university posts an *ex ante* cutoff grade required for submitting an application, given by $\underset{\sim}{e}$. If the foreign and domestic populations of prospective students are given by p_j for $j = \{f, d\}$, the number of foreign and domestic qualified applicants is $n_j = p_j\, \pi_f\, (1 - \Phi(\mu_j, \sigma_j; \underset{\sim}{e}))$ and the quality distribution of applicants is a truncated normal distribution with probability density function:

$$\psi(\mu_j, \sigma_j, \underset{\sim}{e}; e) = \frac{\phi(\mu_j, \sigma_j; e)}{1 - \Phi(\mu_j, \sigma_j; \underset{\sim}{e})}. \tag{1.1}$$

The university has capacity c, for which $n = n_f + n_d > c$ foreign and domestic applicants compete. We assume that the university does not discriminate between foreign and domestic applicants in setting the *ex post* entry cutoff grade $\underline{e}$. Instead, they pool applications and determine $\underline{e}$ given exogenous capacity c. Specifically, the entry cutoff grade $\underline{e}$ is determined by:

$$\begin{aligned} c &= n_f \left[\frac{1 - \Phi(\mu_f, \sigma_f; \underline{e})}{1 - \Phi(\mu_f, \sigma_f; \underset{\sim}{e})}\right] + n_d \left[\frac{1 - \Phi(\mu_d, \sigma_d; \underline{e})}{1 - \Phi(\mu_d, \sigma_d; \underset{\sim}{e})}\right] && (1.2) \\ &= p_f\, \pi_f\, (1 - \Phi(\mu_f, \sigma_f; \underline{e}) + p_d\, \pi_d\, (1 - \Phi(\mu_d, \sigma_d; \underline{e}) && (1.3) \end{aligned}$$

The primary objective of our empirical analysis is to identify the relative quality q of admitted foreign and domestic students. Assuming entry grades e capture student quality precisely, the mean quality of admitted students is:

$$\mathrm{E}(e_j | e_j > \underline{e}) = \int_{\underline{e}}^{\infty} e_j \cdot \phi(\mu_j, \sigma_j; e_j)\, de_j \tag{1.4}$$

$$= \mu_j + \sigma_j \cdot \left[\frac{\phi(\mu_j, \sigma_j; \underline{e})}{1 - \Phi(\mu_j, \sigma_j; \underline{e})}\right]. \tag{1.5}$$

Since university acceptance rates are below 50%, the grade cutoff $\underline{e}$ will exceed the domestic population mean quality μ_d.[7] Moreover, we expect mean student quality in China and India, which account for a large majority of foreign applicants in our data, to be lower than in the Canadian population, due in particular to weaker average English-language abilities of foreign students. Hence, we have $\underline{e} > \mu_d > \mu_f$. In this case, equation (2.5) tells us that the average quality of admitted students is increasing in the population mean quality μ_j and its variance σ_j. If anything we expect the variance of student quality to be higher in the foreign population, in particular because the quality of education is likely more variable. However, if the difference in mean quality is large relative to the difference in variance, the mean quality of admitted domestic students will exceed that of admitted foreign students. Moreover, this difference will be zero when comparing the marginal domestic and foreign student admitted, but will increase at higher percentiles of the grade distribution.

1.2.1 Increase in Foreign Student Applications

An increase in the university's marketing efforts to recruit foreign students, without an equivalent increase in capacity, will increase the number of foreign applicants n_f and put upward pressure on entry cutoff grades.[8] The impact of an exogenous distribution-preserving increase in foreign applicants on the relative mean quality of admitted foreign students is then:

$$\frac{d\mathrm{E}(e_j|e_j > \underline{e})}{d\underline{e}} = \lambda(\alpha_j)\left[\lambda(\alpha_j) - \alpha_j\right] > 0 \tag{1.7}$$

where $\lambda(\alpha_j) = \phi(\alpha_j)/(1 - \Phi(\alpha_j))$ is the usual inverse Mill's ratio and $\alpha_j = (\underline{e} - \mu_j)/\sigma_j$. The Mill's ratio is a monotonically increasing function bounded on the open unit interval (it approaches 0 as α_j approaches $-\infty$ and approaches 1 as α_j approaches ∞). An increase in the entry grade cutoff, therefore, necessarily increases the average quality of admitted

[7] To estimate application rates of Ontario secondary graduates, we combined data on the annual number of university applications of Ontario secondary graduates from Statistics Canada's Postsecondary Information System (PSIS) with Census estimates of the Ontario population of 18 year-olds. The results suggest that the application rate increased steadily between 2008 and 2016 from about 45% to just over 50%. Given that university rejection rates are greater than zero, these estimates imply that university acceptance rates are below 50%.

[8] Formally, the marginal impact of a distribution-preserving increase in π_f holding the university capacity c constant is:

$$\frac{d\underline{e}}{d\pi_f} = \frac{p_f\,(1 - \Phi_f(\underline{e}))}{p_f\,\alpha_f\,\phi_f(\underline{e}) + p_d\,\alpha_d\,\phi_d(\underline{e})} > 0, \tag{1.6}$$

where $\Phi_j(\underline{e}) = \Phi(\mu_j, \sigma_j; \underline{e})$ and $\phi_j(\underline{e}) = \phi(\mu_j, \sigma_j; \underline{e})$.

students (the first derivative) and this effect is larger the larger the existing grade cutoff is (the second derivative). The intuition is that as the cutoff $\underline{e}$ increases, holding the quality distribution of students constant, the proportion of students who are displaced (were previously admitted, but are now not) increases. The mean quality of admitted students increases more when the initial entry grade cutoff is higher, because a higher share of students are displaced.

Whether the increase in the entry grade cutoff leads to a bigger improvement in the mean quality of admitted foreign or domestic students depends on the relative magnitude of α_d and α_f. This depends, once again, on the relative magnitudes of the distribution parameters μ_j and σ_j. If, as we assumed above, $\mu_d > \mu_f$ and $\sigma_f > \sigma_d$, but the difference in means is large relative to the difference in variance, then $\alpha_f > \alpha_d$. In this case, admitted foreign students will be selected from further in the upper tail of their quality distribution, which means that the increase in the cutoff grade will result in a larger share of foreign students being displaced (their acceptance rate will decrease more), but a bigger increase in mean quality among those admitted. Moreover, the relative gain in foreign student quality will be larger at the upper end of the grade distribution.

1.2.2 Entry Grades as Imperfect Quality Signal

In reality, secondary school grades provide an imperfect signal of student quality. This is likely to be particularly true for foreign students, due to international differences in secondary school curriculums and non-English instruction. To account for the possibility of noisy entry grades, assume:

$$e = q + u, \text{where}\, q \sim N(\mu_q, \sigma_q)\, \text{and}\, u \sim N(0, \sigma_u), \tag{1.8}$$

that is observed student quality e is the sum of true quality q and measurement error u, which is mean-zero normally distributed. What is the consequence of this purely random measurement error? There are two main effects. First, noisy grades cause university administrators to make false-negative admission errors; qualified students are denied admission. Since there are more small errors than large errors (due to the normality assumption), qualified students who are denied admission will disproportionately be marginal students, whose true quality is only slightly above the cutoff. By not admitting these marginal students, the average quality of admitted students increases. On the other hand, noisy grades also cause administrators to make false-positive admission errors; unqualified students are admitted. This serves to lower the average quality of admitted students, thereby offsetting the impact of false-negative errors. Which effect is larger? As long as there are more false-positive than false-negative errors, the average quality of admitted students will decrease. If the grade cutoff $\underline{e}$ is above the population mean quality, then this must be the case. Hence, if the university selects foreign students from the upper half of their population quality distribution ($\underline{e} > \mu_f$), an increase (decrease) in the noise in foreign students' entry grades will decrease (increase) the average quality of admitted foreign students.[9]

One could argue that the measurement error in secondary school grades is unlikely to be mean-zero normally distributed. In the competition for university admission offers, there may be considerable pressure on secondary schools to inflate their students' grades, so that mean u is positive. In the extreme case where the mean of u is a positive constant ($\mu_q > 0$) and $\sigma_u = 0$, the entry grade cutoff $\underline{e}$ will simply shift upwards by μ_q (assuming constant capacity c) and there will be no impact on the average quality of admitted students. However, if foreign students' grades are inflated more on average, there will be proportionally more false-positive errors among admitted foreign students. Hence, both a higher mean and variance of the error in foreign students' entry grades will lower the relative mean quality of admitted foreign students.

To summarize the main result, if the entry grades of foreign students provide a poorer signal of quality, in terms of either a higher mean or variance of measurement error, the mean quality of admitted foreign students will be lower. Moreover, as long as small errors are more common than large errors, false-positive errors will concentrated just above the entry grade cutoff, so that the consequence of noisy entry grades will be most apparent at the bottom end of the university grade distribution of admitted students. This contrasts with the effect of differences in the quality of the applicant pool or the effects of rising entry standards, which should produce larger differences at the top end of the grade distribution.

[9] The analytical proof of this result is not straightforward as it involves the integration of a complicated function. It is, however, easily shown by simulation. The algorithm is: (i) draw n values of q from a normal distribution with mean μ_q and standard deviation σ_q; (ii) draw n values of u from a normal distribution with mean 0 and standard deviation σ_u; (iii) create n values of e using $e = q + u$; (iv) calculate the sample mean of e in the sample of observations with $e > \underline{e}$; (v) compare to the sample mean of q in the sample of observations with $q > \underline{e}$. For n sufficiently large, the sample mean from (iv) always exceeded the sample mean from (v) in the simulations that were run. Note also that the result holds even if true quality q is uniformly distributed between 0 and 100, which can be shown analytically. In this case, there will necessarily be more false-positive than false-negative errors, as long as the grade cutoff is above 50. The reason is simply that there will be more students below the cutoff (potential false-positives) than above the cutoff (potential false-negatives).

1.3 Data

Our data were obtained from a publicly-funded university located in Ontario, Canada. Since student selection occurs primarily at the level of individual faculties within the university, we conducted the analysis separately by four faculty groups: faculties A, B, C and D. Faculties A, B and C are single faculties with relatively large foreign-student enrolment shares, whereas D includes multiple faculties with relatively low foreign student enrolment. Within all four groups, there exist direct entry programs, which are responsible for their own student selection. There is, therefore, some variation in entry standards within each faculty group. To provide some sense of how fields of study vary across the groups, faculties A and B primarily comprise programs in technology, engineering and mathematics; faculty C includes primarily programs in the arts, humanities, business, and social sciences; and faculty D programs are mostly in the sciences. Therefore, we expect English-language competency to be a relatively important determinant of academic performance in faculty C, followed by D, and A/B.

The data include the final course grades of all undergraduate students who enrolled between 2004 and 2015.[10] This provides us with a sample of 12 entry cohorts observed completing courses over 38 academic terms (Fall 2004 to Winter 2017). The terms-since-enrolment variable varies between 1 and 15, since we drop individuals who completed courses beyond their fifth year. In addition, we exclude "2+2" program students (foreign students who spend the first two years of their four-year programs studying in their home country), as well as students whose age at entry is above 25, since in both cases the selection process and evaluation criteria may be different. For the same reason, we exclude students transitioning from other postsecondary institutions. These restrictions also insure that the students in our sample have not completed any program requirements prior to enrolment. The total sample sizes in the four faculty groups are 439,338; 551,844; 536,560; and 715,701.

We define international students as individuals who were not permanent Canadian residents at the time of their enrollment. Figure 1.1 plots the foreign-student shares of enrolments in the 2004-2015 entry cohorts. All four faculty groups have increased their foreign-student enrolments, particularly in the latter half of the period and in faculties A and B. By 2015, the foreign-student share was highest in faculty A (45%), followed by B (16%), D (8%), and C (7%). However, a substantial share of international students completed their secondary-school diplomas in Canada. Since we expect the noise in their

[10] Note that we restrict our samples to Fall-term enrolments, because the selection process may be different for Winter and Spring applicants. Fall enrolments accounted for 98.5% of total enrolments between 2004 and 2015.

entry grades to be lower and their English-language ability to be superior, we distinguish foreign-educated international students (FEISs) and Canadian-educated international students (CEISs) in all our analyses.[11] Figure 1.1 reveals that by 2015, 45% of foreign students in faculty A had Canadian secondary-school diplomas, down from 52% in 2009. The comparable share was 50% in faculty B, up from 34% in 2009; 54% in faculty C, up from 53%; and 53% in faculty D, down from 59%. Finally, from 2009 to 2015 we were able to identify the secondary school of foreign students with Canadian diplomas, allowing us to distinguish foreign students from public and private institutions. The results reveal a modest shift in all four faculty groups, but especially in faculties A and C, towards graduates from public secondary schools.

We are also able to distinguish the country of citizenship of foreign students. Figure 1.2 reveals that the growth in foreign-student enrolment at the university has overwhelmingly come from China. By 2015, 85% of foreign students in faculty A were Chinese, compared to 59% in B, 54% in C, and 49% in D. The second largest citizenship group is Indian (7% in faculty A, 17% in B, 10% in C, and 5% in D), followed by Pakistani and South Korean.

The theory predicts that increasing foreign student applicants will raise admission standards and, in turn, could impact the relative mean quality of admitted foreign students. Figure 1.3 plots admission offer rates at the university by faculty and student type between the 2009 and 2015 entry cohorts (earlier data are unavailable). The results reveal that admissions have become more competitive in faculties A and B, where foreign applications have increased most, but have changed relatively little in faculties C and D. However, the (proportional) decrease in admission rates has been larger for domestic students than CEISs or FEISs (the possible exception are FEISs in faculty B, particularly between the 2010 and 2015 entry cohorts). These trends should, therefore, have served to decrease the relative quality of admitted foreign students.

Finally, in Figure 1.4 we plot the distributions of entry grades by faculty and student type for the 2007 and 2015 entry cohorts (entry grades are unavailable for FEISs prior to 2007). A feature of the distributions worth noting is that there is little to no truncation in the left tails. If the university screens applicants exclusively on entry grades, there should be a large number of students with exactly the entry cutoff grade, so that the left tails begin well above the horizontal axis. The fact that they asymptote towards zero, particularly for domestic students, likely reflects differing entry cutoffs between programs within faculties

[11] Minor children (under 18 or 19, depending on the province) who intend to study at the secondary level in Canada for six months or more must apply for a student visa before they enter Canada. The application requires a letter of acceptance from the secondary school. Unfortunately, we do not have information on the duration of Canadian postsecondary education for the international students in our data. It can potentially vary from one year to several years.

(and across faculties in D) or the use of supplementary screening criteria, such as resumes, personal statements, portfolios, reference letters, and athletic scholarships. Nonetheless, comparing the left tails of the distributions points to substantial increases in cutoff entry grades over time in all faculties, particularly A, but provides no evidence that they are different for foreign students. This is consistent with our assumption in Section 2 that domestic and foreign applicants are pooled and a common entry standard applied (the exception is faculty B, where there is some evidence of lower entry grades among marginal domestic applicants). Moreover, across the remainder of the distributions in Figure 1.4, entry grades of admitted students do not suggest gaps in foreign student quality in faculty B or C. In C, entry grades of foreign students exceed their domestic counterparts in all cases, while in B, they are virtually identical. In faculty A, on the other hand, entry grades do imply lower CEIS quality across the entire distribution. However, due to differing curriculums, language of instruction, and grading standards, secondary school grades are likely to be noisy measures of student quality among students transitioning from foreign secondary schools.

1.4 Empirical Specification

The objective of our empirical analysis is to identify the relative quality of foreign students and whether their relative quality has changed as their share of enrolments has increased. To identify student quality using student grades we estimate student fixed effects (FEs) using a two-way fixed effects (TWFE) model. The estimated student FEs are then compared in a second stage regression between international and domestic students at various quantiles of the distribution, as well as across entry cohorts. According to the theory in Section 2.2, disparities in foreign-student grades which are larger at the lower end of the grade distribution are consistent with secondary-school grades providing a noisy measure of student quality. Specifically, we estimate the TWFE model:

$$grades_{ijt} = constant + terms'_{it}\gamma + student_i + class_j + \varepsilon_{ijt} \tag{1.9}$$

where $grade_{ijt}$ is the final course grade of student i, enrolled in course-instructor pair j, in term t; $terms_{it}$ is a set of dummy variables indicating the number of terms that have passed since enrollment (there are 3 terms per year); $student_i$ are student FEs; $class_j$ are FEs for course-instructor pairs (e.g., Psychology 101 with Professor Julie Smith); and ε_{ijt}

is a random error term with $\mathrm{E}(\varepsilon_{ijt}|terms_{it}, student_i, class_j) = 0$ and $\mathrm{Var}(\varepsilon_{ijt}) = \sigma^2_{ijt}$.[12] Having estimated the student FEs, they are then regressed on a full set of cohort dummies indicating the term in which student i enrolled (e.g., Fall 2004), as well as an intercept and cohort linear trend specific to foreign students. That is, in a second stage, we estimate:

$$\widehat{student}_i = cohort_i'\pi + foreign_i \cdot (\mu^f + \pi^f cohort2004_i) + \upsilon_i, \tag{1.10}$$

where $\widehat{student}_i$ are the estimated student FEs from equation (1.9); $cohort_i$ are the cohort dummies; $foreign_i$ is a dummy variable indicating whether student i was a foreign student at the time of enrolment; and $cohort2004_i$ is a continuous cohort variable equal to the difference between student i's entry year and 2004 (the first entry cohort we observe in the data). By first estimating the student FEs, we can estimate the parameters of (2.10) by ordinary least squares (OLS) or quantile regressions without needing to condition on a large set of course-instructor FEs. From the quantile regressions, we obtain evidence on the relative quality of foreign students across the grade distribution, and hence on the relative importance of differences in the quality of applicants and noisy entry grades.

The key challenge in identifying whether foreign-student quality has deteriorated across entry cohorts is distinguishing changes in student quality from the effects of other time-varying factors influencing student grades that are unrelated to student quality. For example, the average experience and, in turn, quality of course instructors may be increasing over the sample period, resulting in improved student achievement. However, as long as these time effects influence foreign and domestic students identically, the deviation of foreign student grades, determined by the linear function $\mu^f + \pi^f c_i$, will reflect changes in the *relative* quality of foreign students across entry cohorts. Since instructors do not observe the visa status of students, this seems a reasonable assumption.

We also examine the difference between the estimated student FEs and high school entry grades to obtain an estimate of the noise in secondary grades. That is, for every student in the sample we predict $\hat{q}_i = \widehat{constant} + \widehat{student}_i$ from equation (1.9) and estimate the noise in entry grades using $\hat{u}_i = e_i - \hat{q}_i$. We then compare the mean and standard deviation of $\hat{u}_i$ between foreign and domestic students and across entry cohorts. A higher mean and variance for foreign students is consistent with noisier entry grades. However, to the extent that the university makes adjustments to foreign students' entry grades using data on the

[12] Note that we lose a small number of singleton observations in estimating the TWFE model. This occurs when a single student is observed within a course-instructor pair, which is possible because the estimation is done separately by a student's faculty at the time of enrolment. This could occur, for example, when a single student from Faculty A is enrolled in a course in Faculty B that was taught only once by a particular instructor over the sample period.

performance of former foreign students from the same origin countries, and to the extent that this learning improves over time, the noise in foreign entry grades should decline across entry cohorts.

Lastly, we examine to what extent differentials in foreign student grades reflect an integration process. We do this in two ways. First, we add two language variables to equation (1.10) to examine to what extent gaps in the grade performance of foreign students reflect weaker English-language ability. The first variable is an index of linguistic distance, scaled from 0 to 1, constructed by Adserà and Pytlikova (2015). The index measures linguistic proximity between English and the official languages of a foreign student's country of citizenship using information on the number of levels of the linguistic family tree the two languages share. Countries with an English official language have values of 1, whereas countries that do not share any linguistic ancestry with English, such as China and South Korea, have values of 0. The second variable is a binary indicator of whether a student was enrolled in a compulsory language training course in their first term following enrolment. These courses, which are common at Ontario universities, are required for students whose English-language standardized test score (e.g., TOEFL and IELTS) falls below a threshold. These scores must be submitted by all applicants whose first language is not English and whose four most recent years of full-time education were in a non-English language school.

Our second strategy for identifying the integration on foreign students' grade performance is to compare the relative course grades of foreign students in first-, second-, third- and fourth-year level courses. To the extent that gaps in their grade performance reflect integration challenges, we expect the gaps to be lower in fourth- than first-year courses. To insure the differences do not reflect differences in the sample composition due to student attrition, we restrict the samples to 2004-2011 entry cohorts who graduated by 2015.

We conclude our analysis with a robustness check. To this point we have ignored possible non-random sorting of students into course-instructor pairs. As emphasized by Woodcock (2008), the estimation of TWFE models is complicated by potential complementarities between students and course-instructors, so that estimated student quality is influenced by students' match quality with the course-instructor pairs in which they are enrolled. Foreign students may, for example, benefit from the pedagogical approach of an instructor originating from the same origin country or from a course which evaluates or builds on knowledge that foreign students are more likely to have been exposed. If foreign students have less information about course-instructor pairs when selecting courses and sections, we would expect their average match quality to be worse. Unfortunately, in our data, we almost never observe repeated observations on students within course-instructor pairs, which makes the identification of match effects impossible. However, to the extent that students are unable to select their courses and instructors, or have no information on their individual-specific match qualities when selecting, match effects will be zero and can be ignored. Since these conditions are more likely to hold for program-required courses than elective courses, we re-estimate equation (1.10) restricting the sample to program-required courses.[13]

1.5 Results

Before examining relative foreign student quality, we discuss the overall results from the TWFE estimation of equation (1.9). The total variance in student course grades, which the model seeks to account for, is highest, by a substantial margin, in faculty A (228), followed by B and D (both 170), and C (164). The estimated student FEs from the TWFE model account for 54% of grade variance in faculty A, 52% in C, 49% in D, and 44% in B. In other words, roughly half of all the variation in student grades is accounted for by persistent differences in the relative performance of students within courses; some students consistently perform above the average by some margin, while others consistently perform below the average by some margin. Course-instructor FEs, on the other hand, can account for an additional 24% of grade variation in faculty D, 23% in C, 16% in B, and 11% in A. The estimates imply negative assortative matching of students and course-instructor pairs in all faculties, but in particular in faculty C. The correlation between the student and course-instructor FEs is -0.27 in faculty C, -0.19 in D, -0.14 in A, and -0.05 in B. Moreover, the tendency for low-quality (high-quality) students to sort into course-instructor pairs with higher (lower) average grades appears to have increased over time in faculty C, but not elsewhere. These results emphasize the importance of conditioning on the self-selectivity of students into courses and instructors when inferring student quality from course grades.[14]

1.5.1 International student quality

The results from the OLS estimation of equation (1.10) are presented in the final column of Table 1.1. The estimates point to statistically significant gaps in mean foreign student grades within course-instructor pairs in all faculties. The gaps are remarkably similar in magnitude: 3.5 percentage points (ppts) in faculty A, 2.4 ppts in B, and 3.4 ppts in C

[13] Where programs require students to select from a list of courses, we define all listed courses as program-required courses.

[14] These results are available from the authors on request.

and D. However, the insignificant estimates in the second row for faculties B, C, and D provide no clear evidence that the gaps have grown with the increases in foreign student enrolments. In fact, the initial gap of 3.5 ppts for the 2004 entry cohort in faculty A *declined* by a statistically significant 0.117 ppts per year, reducing the gap to 2.2 ppts by the 2015 entry cohort (11 years * 0.117 ppts/year = 1.287 ppts). Therefore, none of the estimates are consistent with a quantity-quality tradeoff in foreign student enrolment.

In the remaining rows of Table 1.1 we present similar results, but distinguish international students by whether their secondary-school diplomas were Canadian or foreign. The striking result is that the overall mean gaps in foreign student grades almost entirely reflect the under-performance of CEISs. The CEIS gaps are 5.6 ppts in faculty A, 2.0 ppts in B, 6.5 ppts in C, and 6.8 ppts in D. In sharp contrast, the differences in the mean grades of FEISs are small and statistically insignificant in faculties A, C and D (it is of roughly equal magnitude for CEISs and FEISs in faculty B). However, there is also evidence of relative improvements in CEIS quality across entry cohorts in faculties A and C. The gains are particularly large in faculty C; the initial gap of 6.5 ppts for the 2004 cohort is reduced to 1.7 ppts across the subsequent 11 entry cohorts. As discussed above, acceptance rates in faculty A (Figure 1.3) do not suggest that this gain reflects rising entry standards displacing proportionally more foreign students, since the decline in CEIS acceptance rates has been small (0.5 to 0.4) relative to domestic students (0.7 to 0.5). This should have, if anything, improved the relative performance of domestic students.

The remaining columns of Table 1.1 report the results from estimating equation (1.10) by quantile regressions. In faculties B, C, and D the gaps in mean grades are clearly driven by larger shortfalls in foreign student achievement at the bottom end of the grade distribution. This pattern is most consistent with more false-positive errors in foreign student admissions (in the following subsection we investigate directly whether this difference is consistent with foreign students' entry grades providing a poorer indicator of student quality than domestic students' entry grades). In faculty A, on the other hand, the gaps are evident across the distribution, but slightly larger at the upper end. This pattern is difficult to reconcile with a single theoretical mechanism. This suggests that some combination of lower quality foreign applicant pools and admission errors are at play.

Examining the quantile estimates separately for CEISs and FEISs, the estimates point to substantial CEIS gaps at the bottom end of the distribution in faculties C and D. The 5th percentile of student quality is 13.5 ppts lower for CEISs relative to domestic students in faculty C and 14.1 ppts lower in faculty D. These large gaps exist despite there being no gap in CEIS entry grades at the bottom end of the distribution in faculties C and D (see Figure 1.4). The estimates also point to bigger gaps at the bottom end of the distribution for FEISs in faculty C, although the magnitude is substantially smaller than for CEISs in faculties C and D (5.9 ppts at the 5th percentile). In faculty A, on the other hand, the CEIS gaps are evident across the distribution, consistent with some combination of admission errors and lower applicant quality. This is consistent with relatively low CEIS entry grades across the distribution in faculty A.

Turning to the cohort trends in the quantile regression estimates, the estimates once again point to significant improvements in the quality of foreign students admitted to faculties A and C. Grouping all foreign student together, the estimates suggest that these gains primarily reflect relative improvements at the upper end of the grade distribution. The point estimate at the 95th percentile for faculty C is particularly large; 0.539 ppts per year implying a nearly 6 ppt relative improvement in foreign student grades within course-instructor pairs between the 2004 and 2015 entry cohorts. Distinguishing CEISs and FEISs in the following rows of Table 1.1, the estimates reveal that the gains are concentrated among CEISs. However, whereas the gains are largest at the upper end of the distribution in faculty A, in faculty C they are evident at the bottom and top ends of the distribution. The increase at the 5th percentile of the distribution for CEISs in faculty C is particularly large; 0.964 per year implying a 10.6 ppt relative improvement in grades, thereby almost entirely closing the initial gap of 13.5 ppts for the 2004 entry over the subsequent 11 entry cohorts. As discussed above, the gains at the upper end for CEISs in Faculty A appear most consistent with improvements in the quality of the applicant pool.

The Table 1.1 estimates also suggest some relative deterioration in the mean quality of FEISs in faculties A and B. In faculty A the deterioration appears concentrated in the middle of the quality distribution. The magnitude is also larger in faculty A; at the 50th percentile it amounts to a 4-ppt decline in relative mean grades between the 2004 and 2015 entry cohorts (0.369 ppts/year * 11 years). This deterioration is also evident in the decline in FEIS entry grades in Figure 1.4, particularly in the middle of the distribution (see Figure 1.4). Hence, whereas the 2004 cohort of FEIS students in faculty A outperformed their domestic counterparts by 2.2 ppts at the median, by 2015 this advantage had been erased. In faculty B, on the other hand, the deterioration is largest and of roughly equal magnitude across the entire bottom half of the distribution. An initial (insignificant) gap of 1.6 ppts at the 50th percentile for the 2004 cohort increased to 3.9 ppts for the 2015 entry cohort, while the initial gap of 5.9 ppts at the 5th percentile grew to 8.3 ppts. Unlike faculty A, this relatively modest deterioration is not consistent with declining entry grades of FEISs. Rather, it is more consistent with rising admission standards doing more to displace marginal domestic applicants over time.

1.5.2 Noise in entry grades

The gaps in foreign student quality in all faculties, except faculty A, are largest at the bottom end of the skill distribution. This is consistent with greater false-positive errors in foreign student admissions resulting from the entry grades of foreign students providing noisier signals of student quality. To obtain more direct evidence of this explanation, we estimate the noise in entry grades directly as described in Section 2.2.

Figure 1.5 presents Kernel density estimates for domestic, CEIS, and FEIS admitted students. Recall that we estimate the error as the difference between a student's secondary school entering average and the estimated student FE in university grades in courses taught by specific instructors. The fact that there is virtually no density below zero in any of the distributions reflects both that mean secondary school grades are substantially higher than university grades, as well as that applicants whose entry grades understate their true quality are less likely to have been admitted, and are therefore not included in the samples used to estimate the distributions in Figure 1.5. Despite this, the domestic-student distributions are remarkably close to being normally distributed, but with some skewing to the right.[15]

Is there any evidence of greater error in foreign students' entry grades consistent with shortfalls in university grades at the bottom end of the distribution? In all faculties, both the mean and variance of the noise is unambiguously greater in the foreign student distributions in Figure 1.5. Moreover, in faculties C and D, where the evidence of admission errors is only evident among CEISs, the densities reveal substantially more noise in the grades of CEISs than FEISs. In faculty B, on the other hand, where FEIS quality gaps are bigger at the bottom end, both the mean and variance of the errors is bigger among FEISs than CEISs, although the difference is minimal. Lastly, in faculty A, where there is the least evidence of admission errors resulting from noisy entry grades, the difference in the domestic and foreign student distributions is smallest.

In Table 1.2, we examine whether there is any evidence of changes over time in the relative error in foreign students' entry grades. In all faculties, there is a clear upward trend between 2004 and 2015 in the mean error in domestic students' entry grades. This is consistent with increasing average entry grades (Figure 1.4) of domestic students, as well as decreasing admission offer rates in faculties A and B. There is, however, no equivalent evidence of an upward trend in either the mean or variance of the prediction error in foreign students' entry grades. In fact, there is some evidence of a decline in the mean error since 2011 for CEISs in every faculty except faculty A. Together these results imply

[15] The skewness is highest in faculty B for all student types (1.01 for domestic students, 0.91 for CEISs, and 0.74 for FEISs) and is higher for domestic students than foreign students in all faculties.

convergence in the effectiveness of entry grades as a screening criterion for domestic and foreign students and helps us to understand the improvements in the relative academic performance of CEISs.

1.5.3 Integration effects

To this point, we have established that international students, particularly those with Canadian secondary school diplomas, under-perform their domestic classmates within courses taught by particular instructors. The implied gap in student quality appears to primarily reflect the relative difficulty in using secondary school grades to screen foreign applicants. This does not, however, tell us to what extent the gaps reflect permanent differences in the quality of foreign students, as opposed to integration challenges, including adjustments to learning a new language and new pedagogical approaches. To the extent that the gaps reflect integration effects, they should be smaller among foreign students from English-speaking countries and in upper-year than first-year courses. In this case, we would expect foreign students' academic achievement gaps to be less likely to carry over to the labour market.

In Table 1.3, we present the results from estimating equation (1.10), but also conditioning on linguistic distance and enrolment in a compulsory English-language training course, as described in Section 4. In faculties B and D, grade performance is lower among foreign students from countries with an official language that is linguistically further from English. Enrolment in English-language training appears to be unrelated to foreign student grades (the latter is only true in the first specification for faculty D). In faculties A and C, however, the opposite appears to be true; language training is important conditional on linguistic distance, but not vice-versa. This difference is difficult to explain, but it is worth noting that in faculty A the mean value of the linguistic distance variable is 0.979, reflecting its concentration of Chinese students, while only 45% are required to complete language training. In faculty B, on the other hand, only 3% are required to complete language, while the mean of the distance variable is 0.885.

More important, with the exception of faculty C, the estimated gaps in foreign students' mean grades decline when we condition on language skills. The influence of language is particularly large in faculty A, where there is no longer a significant difference in academic achievement when we condition on linguistic distance and language training. In fact, comparing course grades of FEISs and domestic students, the results now point to 3 ppt grade advantage for FEISs within course-instructor pairs. In the remaining three faculties, however, the grade disparities do not entirely disappear. Moreover, in all faculties except

B, there is still evidence of 2-7 ppt gaps in mean grades even among those originating from countries where English is an official language (so that both the linguistic distance and training variable are 0). In faculty C there also continues to be evidence that the CEIS gap has been declining over time, so that for the most recent entry cohorts the gap in mean course grades is 2.3 ppts compared to 7.3 ppts for the 2004 cohort. It is, however, unexpected that the language variables appear to be explain the least in faculty C, which comprises primarily arts and social science programs, where we expect most emphasis on language skills. A possible explanation is the nature of the self-selection of foreign students into faculty C is different. Note in particular that linguistic distance is *positively* related to grade achievement in faculty C, which could indicate that foreign students who choose programs in this faculty have exceptional language skills, which neither of our crude measures accurately capture.

Overall, in all but one faculty, English language ability appears to account for an important part of foreign students' academic challenges. Since their language skills should improve with time since enrolment, we should see relatively small gaps if we restrict attention to upper-year courses.[16] In Table 1.4, we compare the estimates of equation (1.10) between 100-, 200-, 300-, and 400-level courses. The results point to larger foreign student gaps in upper-year courses. This is particularly the case in faculty A, where the foreign student gap in mean grades is 4-5 ppts in 300- and 400-level courses, compared to 1-2 ppts in 100- and 200-level courses. This pattern is also evident among FEISs in faculty C and CEISs in faculty D. A possible explanation is that foreign students are better prepared for university-level studies at the time of their enrolment, in terms of the level of their previous knowledge exposure. This, however, puts them on a flatter portion of their learning curves, so that this advantage declines with time since enrolment and relative grades increasingly reflect other, more permanent, challenges. Alternatively, it may be that upper year courses put more emphasis on language skills. Regardless, the estimates do suggest that the language difficulties identified in Table 1.5 are largely time invariant for university-aged migrants.[17]

[16] Note that in order to insure that the differences in the estimates between course levels do not reflect sample differences arising from non-random student attrition, we restrict the samples used to estimate all the columns of Table 1.4 to students who were enrolled between 2004 and 2011 and successfully graduated by 2015.

[17] Another consideration is that the language effects identified in Table 1.5 are capturing other characteristics of international students, which adjust little over time. For example, it may be that both the linguistic distance and language training variables are correlated with the quality of primary and secondary schooling in foreign students' origin countries, which produces longer-term differences in academic achievement.

1.5.4 Match effects

As noted in Section 3, an alternative interpretation of the gaps in foreign students' grades is that foreign students are less well matched to course-instructor pairs where they are most likely to succeed. This could happen if foreign students have poorer information guiding their course selections, perhaps because of weaker peer networks. To gauge to what extent 'match effects' may be driving our estimates, in Table 1.5 we present the results from estimating equation (1.10) using a restricted sample of grades in program-required courses. Since these courses involve less selectivity on the part of students, differences in grade achievement in these courses among students enrolled in the same faculty are less likely to reflect match effects. These courses account for 50.8% of course enrolments in faculty A, 71.7% in B, 52.8% in C, and 70.5% in D. Of course, students may still be able to select instructors where multiple sections of courses are offered, but to the extent that match effects are important in the foreign student achievement gaps, they should be smaller in the restricted sample.

The estimated grade gaps in the first row are almost identical in magnitude to those in Table 1.1, providing evidence that poorer course-instructor matches do not account for the foreign student performance gaps. In all faculties, the estimates are slightly smaller (in absolute value), but remain statistically significant in all cases. In no case is the difference bigger than 0.4 ppts. Distinguishing CEISs and FEISs, also does not provide any evidence that match effects are important. There also continues to be no evidence of deteriorating performance of foreign students across entry cohorts (as in Table 1.1), the single is exception is FEISs in faculty B).

1.6 Discussion

Our analysis indicates that international students underperform their domestic counterparts within undergraduate university courses. The achievement gaps, which are evident across faculties, appear to almost entirely reflect the grades of foreign students with Canadian secondary school diplomas. Although an important part of the achievement gaps appear related to English-language proficiency, they do not decline in magnitude over the course of foreign students' studies.

Despite the gaps in international student academic achievement, we find evidence of improvements in foreign-student quality across entry cohorts, even as the university has expanded its foreign student enrolments. Our analysis suggests that these gains reflect both an improvement in the screening of foreign applicants and relative gains in the quality of foreign applicant pools. Interestingly, the narrowing of the CEIS achievement gaps appear to primarily reflect improved screening. These gains have been largest in faculties which have experienced shifts in CEIS enrolments away from private to public Canadian secondary school graduates. While we have no direct evidence on the relative noise in grades from private and public secondary schools, it is conceivable that for-profit Canadian secondary schools targeting international students have greater financial incentives to inflate students' grades in order to raise the postsecondary acceptance rates of their graduates.

As colleges and universities increasingly look abroad for students, there is growing concern about becoming over-reliant on foreign students from a single source country. Our analysis emphasizes an important advantage of focused recruitment efforts – former students can be used to inform the information content in the entry grades of future applicants. Specifically, the expected noise in entry grades can be estimated by student source (whether origin country or secondary school) and adjusted accordingly to mitigate screening errors in admissions. The substantial correlations between student and course-instructor FEs in our analysis emphasize that in estimating student quality using university course grades, it is critical to account for the self-selection of students across courses and instructors. Our analysis provides a straightforward methodology for making these adjustments.

It is difficult to know how the academic challenges of international students carry over to the labour market. The critical question is whether those who permanently settle in Canada are selected from the upper or lower end of the foreign student quality distribution? If they are selected from the lower end of the distribution, the academic gaps we identify may be larger in the labour market. Should we expect negative selectivity? We find that academic achievement gaps are substantially larger for CEISs, who have spent more time in Canada and may, therefore, be more likely to settle. There is also evidence that the lure of higher U.S. salaries attracts Canada's top graduates, which may be particularly relevant for foreign students, who will have weaker ties to Canada, on average (Clarke, Ferrer and Skuterud 2018). On the other hand, the selection criteria of Canada's skilled immigration programs, particularly requirements for relevant Canadian work experience, may effectively screen out the lower end of the foreign student quality distribution, thereby mitigating the academic challenges we have identified.

These considerations raise the question of whether the academic grades of international students can be used as a criterion in the Comprehensive Ranking System (CRS) used by the federal government to prioritize economic-class applications for permanent residency in the Express Entry System. The current CRS uses a set of criteria which at best predicts 14% of the variation in immigrants' earnings 2-4 years after landing and 8% after

10-11 years (Bonikowska, Hou and Picot 2015). The current system also continues to prioritize candidates with job offers. If employers are averse to recruiting and training job applicants with precarious immigration statuses, the emphasis on arranged employment may be screening out high-achieving former international students whose temporary status is a barrier to successful labour market integration, or in the worst case, forcing these candidates to accept low-quality, and perhaps dead-end, jobs to satisfy immigration requirements. Identifying these high-achieving students using postsecondary grades may address both of these issues.

Table 1.1: Relative distribution of international student quality and trends across entry cohorts

	5th	10th	25th	50th	75th	90th	95th	ols
Faculty A								
is	-3.775**	-3.663***	-2.809***	-3.495***	-4.918***	-3.617***	-3.201***	-3.531***
	(1.569)	(1.164)	(0.652)	(0.631)	(0.626)	(0.721)	(0.693)	(0.505)
is*cohort trend	0.071	-0.046	0.006	0.101	0.331***	0.250**	0.169*	0.117*
	(0.217)	(0.161)	(0.090)	(0.087)	(0.087)	(0.100)	(0.096)	(0.070)
observations	14,059	14,059	14,059	14,059	14,059	14,059	14,059	14,059
R-square	0.021	0.018	0.014	0.011	0.008	0.006	0.006	0.020
ceis	-5.484***	-4.737***	-4.405***	-5.630***	-7.518***	-7.583***	-6.012***	-5.643***
	(1.957)	(1.541)	(0.884)	(0.840)	(0.788)	(0.945)	(0.831)	(0.659)
ceis*cohort trend	0.115	-0.077	0.061	0.189*	0.378***	0.442***	0.338***	0.183**
	(0.249)	(0.196)	(0.113)	(0.107)	(0.100)	(0.120)	(0.106)	(0.084)
feis	0.634	0.136	1.988	2.223*	1.637	0.175	1.005	1.281
	(2.690)	(2.118)	(1.215)	(1.154)	(1.083)	(1.300)	(1.143)	(0.907)
feis*cohort trend	-0.279	-0.248	-0.361***	-0.369***	-0.227*	-0.062	-0.195	-0.269***
	(0.308)	(0.243)	(0.139)	(0.132)	(0.124)	(0.149)	(0.131)	(0.104)
observations	14,059	14,059	14,059	14,059	14,059	14,059	14,059	14,059
R-squared	0.022	0.020	0.016	0.014	0.014	0.011	0.011	0.026
Faculty B								
	5th	10th	25th	50th	75th	90th	95th	ols
is	-5.377***	-4.956***	-3.056***	-1.941***	-1.788**	-0.447	0.582	-2.357***
	(1.969)	(1.580)	(0.892)	(0.696)	(0.763)	(0.926)	(0.954)	(0.626)
is*cohort trend	-0.080	-0.007	-0.109	-0.165*	-0.0466	-0.127	-0.245*	-0.119
	(0.258)	(0.207)	(0.117)	(0.091)	(0.100)	(0.121)	(0.125)	(0.082)
observations	16,053	16,053	16,053	16,053	16,053	16,053	16,053	16,053
R-squared	0.026	0.018	0.012	0.012	0.010	0.011	0.011	0.024
ceis	-3.819	-3.076	-3.477**	-2.003	-1.800	1.821	1.126	-2.022*
	(3.599)	(2.734)	(1.608)	(1.260)	(1.383)	(1.669)	(1.691)	(1.123)
ceis*cohort trend	-0.020	0.025	0.067	-0.047	-0.031	-0.390**	-0.295	-0.066
	(0.400)	(0.304)	(0.179)	(0.140)	(0.154)	(0.186)	(0.188)	(0.125)
feis	-5.891**	-5.016**	-2.525**	-1.588	-1.662	-0.767	-1.048	-2.156**
	(2.806)	(2.132)	(1.254)	(0.982)	(1.078)	(1.301)	(1.319)	(0.875)
feis*cohort trend	-0.222	-0.201	-0.231	-0.212*	-0.077	-0.080	0.019	-0.180*
	(0.335)	(0.254)	(0.150)	(0.117)	(0.129)	(0.155)	(0.157)	(0.105)
observations	16,053	16,053	16,053	16,053	16,053	16,053	16,053	16,053
R-squared	0.026	0.019	0.012	0.012	0.010	0.011	0.012	0.024

Faculty C								
	5th	10th	25th	50th	75th	90th	95th	ols
is	-5.616**	-3.514**	-2.829***	-3.804***	-3.396***	-0.992	-0.216	-3.388***
	(2.388)	(1.494)	(1.005)	(0.842)	(0.948)	(1.223)	(1.823)	(0.756)
is*cohort trend	0.255	0.038	-0.020	0.110	0.178	0.194	0.539**	0.173
	(0.338)	(0.211)	(0.142)	(0.119)	(0.134)	(0.173)	(0.258)	(0.107)
observations	17,530	17,530	17,530	17,530	17,530	17,530	17,530	17,530
R-square	0.006	0.008	0.009	0.009	0.007	0.008	0.008	0.013
ceis	-13.510***	-9.455***	-5.191***	-5.719***	-7.447***	-5.687***	-2.828	-6.513***
	(3.605)	(2.192)	(1.520)	(1.282)	(1.461)	(1.862)	(2.812)	(1.161)
ceis*cohort trend	0.964**	0.454*	0.157	0.143	0.605***	0.793***	0.802**	0.440***
	(0.449)	(0.273)	(0.189)	(0.160)	(0.182)	(0.232)	(0.350)	(0.145)
feis	2.144	0.455	-0.352	-1.856	-0.394	-0.270	0.009	-0.360
	(3.773)	(2.294)	(1.591)	(1.342)	(1.529)	(1.949)	(2.942)	(1.215)
feis*cohort trend	-0.460	-0.215	-0.185	-0.005	-0.182	0.020	0.168	-0.118
	(0.478)	(0.291)	(0.202)	(0.170)	(0.194)	(0.247)	(0.373)	(0.154)
observations	17,530	17,530	17,530	17,530	17,530	17,530	17,530	17,530
R-squared	0.007	0.009	0.010	0.010	0.008	0.008	0.008	0.014

Faculty D								
	5th	10th	25th	50th	75th	90th	95th	ols
is	-5.008**	-4.828***	-4.624***	-3.052***	-2.999***	-0.387	-0.979	-3.435***
	(2.303)	(1.686)	(1.024)	(0.925)	(1.023)	(1.378)	(1.633)	(0.807)
is*cohort trend	-0.128	0.043	0.046	-0.005	-0.001	-0.119	-0.097	-0.011
	(0.305)	(0.223)	(0.135)	(0.122)	(0.135)	(0.182)	(0.216)	(0.107)
observations	20,202	20,202	20,202	20,202	20,202	20,202	20,202	20,202
R-squared	0.010	0.008	0.006	0.005	0.005	0.004	0.005	0.010
ceis	-14.100***	-9.502***	-7.126***	-7.063***	-7.376***	-3.464*	-0.921	-6.836***
	(3.280)	(2.455)	(1.516)	(1.390)	(1.492)	(2.009)	(2.428)	(1.185)
ceis*cohort trend	0.480	0.426	0.130	0.192	0.212	-0.133	-0.227	0.134
	(0.385)	(0.288)	(0.178)	(0.163)	(0.175)	(0.236)	(0.285)	(0.139)
feis	3.407	-0.274	1.150	-0.064	-0.443	1.925	0.770	0.934
	(3.754)	(2.809)	(1.735)	(1.591)	(1.708)	(2.299)	(2.778)	(1.356)
feis*cohort trend	-0.593	-0.331	-0.122	-0.030	0.015	-0.163	0.011	-0.181
	(0.447)	(0.334)	(0.206)	(0.189)	(0.203)	(0.273)	(0.330)	(0.161)
observations	20,202	20,202	20,202	20,202	20,202	20,202	20,202	20,202
R-squared	0.012	0.009	0.007	0.006	0.006	0.005	0.005	0.012

Notes: The dependent variable is the estimated student fixed effect from a two-way fixed effects (TWFE) regression of student-level university course grades on student and course-instructor fixed effects, as well as terms-since-entry dummies. The independent variables are dummy variables indicating an international student (is), a Canadian-educated international student (ceis), and a foreign-educated international student (feis). Coefficients are from quantile regressions at various percentiles and OLS regressions. The R-squared statistic in the quantile regressions is a pseudo R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 1.2: Difference between student quality and entering average by entry cohort and student type

	Faculty A						Faculty B					
cohort	domestic		ceis		feis		domestic		ceis		feis	
	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.
2004	15.88	10.97	21.68	9.48	–	–	17.49	8.30	20.06	9.62	–	–
2005	15.24	9.97	19.96	11.23	–	–	18.68	8.66	21.91	8.48	–	–
2006	16.76	10.96	20.04	10.50	–	–	18.64	8.41	22.03	7.42	–	–
2007	16.73	10.96	18.82	9.97	20.91	14.17	19.57	8.66	19.98	7.40	22.54	7.62
2008	17.86	10.93	20.75	12.37	22.23	12.99	20.10	8.65	23.33	9.45	21.23	10.26
2009	18.33	11.24	22.00	11.67	18.94	13.50	20.09	8.74	25.15	10.39	24.44	12.19
2010	17.72	10.55	21.85	9.84	19.91	12.78	20.25	8.88	21.55	10.27	24.83	10.78
2011	18.03	10.51	24.88	11.76	20.50	14.42	20.45	8.81	23.02	7.88	22.55	10.78
2012	19.24	11.05	20.84	11.38	18.79	13.34	20.26	8.27	26.17	11.37	23.53	10.55
2013	19.25	10.55	21.89	11.16	20.00	11.67	19.46	7.60	22.97	9.22	23.75	10.77
2014	18.32	9.64	20.66	10.61	20.17	10.97	19.82	8.13	20.46	7.40	22.12	11.12
2015	17.97	9.76	19.28	10.38	19.46	11.48	20.23	8.27	21.42	8.91	24.55	9.91
	Faculty C						**Faculty D**					
cohort	domestic		ceis		feis		domestic		ceis		feis	
	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.
2004	10.08	7.99	17.26	10.61	–	–	11.29	8.28	19.63	14.21	–	–
2005	10.28	7.83	13.22	10.08	–	–	11.61	8.21	17.56	10.78	–	–
2006	11.22	8.10	15.73	9.28	–	–	12.10	8.08	16.87	10.24	–	–
2007	11.59	8.52	16.17	10.97	14.94	6.74	12.94	8.07	21.09	10.40	13.93	6.49
2008	11.43	8.12	14.70	10.87	15.39	7.67	13.32	7.99	20.54	10.30	19.00	7.09
2009	12.10	8.38	16.36	9.07	14.20	9.97	13.43	7.70	20.56	7.34	17.84	8.76
2010	12.15	8.15	16.70	13.40	11.62	8.17	13.92	8.28	20.25	9.81	18.70	10.35
2011	12.07	8.24	19.89	7.48	12.49	11.28	14.07	8.27	22.23	6.37	19.12	11.55
2012	12.65	8.04	18.12	7.53	14.68	10.23	14.39	8.02	18.32	10.13	17.85	10.95
2013	13.13	8.51	15.20	9.51	17.47	13.69	14.56	8.39	19.05	10.09	15.71	10.22
2014	12.85	8.45	14.68	10.99	14.94	11.32	13.98	7.99	18.49	11.67	15.87	9.49
2015	12.64	8.24	15.15	10.89	15.06	11.46	14.18	8.42	17.88	9.60	16.57	11.79

Notes: Student quality are student fixed effects from a TWFE regression of university course grades on student and course-instructor fixed effects, as well as terms-since-entry dummies. Entering average is the average unweighted grade in the student's final six high school courses. Results are reported for three types of students: domestic, Canadian-educated international students, and foreign-educated international students.

Table 1.3: Relative mean international student quality conditional on language

	Faculty A		Faculty B		Faculty C		Faculty D	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
is	-0.452	–	-1.309**	–	-4.168***	–	-1.790**	–
	(0.560)		(0.631)		(0.763)		(0.833)	
is*cohort trend	0.013	–	-0.078	–	0.205**	–	0.058	–
	(0.069)		(0.080)		(0.104)		(0.110)	
ceis	–	-2.259***	–	-0.701	–	-7.342***	–	-5.097***
		(0.713)		(1.110)		(1.149)		(1.207)
ceis*cohort trend	–	0.072	–	-0.037	–	0.456***	–	0.196
		(0.083)		(0.122)		(0.140)		(0.143)
feis	–	2.982***	–	-1.245	–	-1.267	–	2.241*
		(0.913)		(0.868)		(1.189)		(1.360)
feis*cohort trend	–	-0.275***	–	-0.136	–	-0.078	–	-0.147
		(0.102)		(0.102)		(0.149)		(0.161)
linguistic distance	0.042	0.140	-1.572***	-1.618***	0.476	0.540	-2.636***	-2.518***
	(0.304)	(0.304)	(0.243)	(0.244)	(0.336)	(0.336)	(0.313)	(0.313)
language training	-5.167***	-4.787***	-0.561	-0.637	-4.379***	-3.960***	-2.318**	-1.676
	(0.348)	(0.352)	(1.225)	(1.226)	(1.121)	(1.125)	(1.165)	(1.175)
constant	-2.571***	-2.427***	0.836***	0.838***	-6.258***	-6.249***	-2.819***	-2.848***
	(0.447)	(0.448)	(0.298)	(0.298)	(0.273)	(0.273)	(0.287)	(0.287)
observations	14,059	14,059	16,053	16,053	17,530	17,530	20,202	20,202
R-squared	0.041	0.044	0.025	0.026	0.018	0.018	0.012	0.014

Notes: The dependent variable is the estimated student fixed effect from a two-way fixed effects (TWFE) regression of student-level university course grades on student and course-instructor fixed effects, as well as terms-since-entry dummies. The independent variables are dummy variables indicating an international student (is), a Canadian-educated international student (ceis), and a foreign-educated international student (feis). Coefficients are from quantile regressions at various percentiles and OLS regressions. The R-squared statistic in the quantile regressions is a pseudo R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 1.4: Relative mean international student quality by course level

	Faculty A							
	100-level		200-level		300-level		400-level	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
is	-2.336***	–	-1.054	–	-5.429***	–	-4.226***	–
	(0.608)		(0.703)		(0.744)		(0.693)	
is*cohort trend	0.227*	–	-0.230	–	0.241	–	0.254*	–
	(0.135)		(0.156)		(0.164)		(0.152)	
ceis	–	-3.540***	–	-2.337**	–	-6.665***	–	-5.832***
		(0.836)		(0.968)		(1.027)		(0.977)
ceis* cohort trend	–	0.045	–	-0.270	–	0.075	–	0.195
		(0.164)		(0.190)		(0.200)		(0.191)
feis	–	1.593	–	4.280***	–	-1.888	–	-0.433
		(1.221)		(1.415)		(1.459)		(1.339)
feis*cohort trend	–	-0.088	–	-0.745***	–	-0.029	–	-0.133
		(0.208)		(0.241)		(0.250)		(0.228)
constant	1.418***	1.477***	-2.040***	-1.933***	1.189**	1.248**	-0.652	-0.579
	(0.450)	(0.450)	(0.519)	(0.519)	(0.577)	(0.576)	(0.490)	(0.489)
observations	6,795	6,795	6,529	6,529	5,464	5,464	5,600	5,600
R-squared	0.013	0.023	0.012	0.019	0.030	0.038	0.019	0.025

	Faculty B							
	100-level		200-level		300-level		400-level	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
is	0.251	–	-1.220	–	-0.703	–	-1.040*	–
	(0.925)		(0.872)		(0.948)		(0.576)	
is*cohort trend	-0.379**	–	-0.104	–	-0.128	–	-0.065	–
	(0.191)		(0.179)		(0.191)		(0.117)	
ceis	–	-1.035	–	0.336	–	-1.473	–	-0.812
		(1.852)		(1.748)		(1.939)		(1.203)
ceis* cohort trend	–	-0.120	–	-0.236	–	0.210	–	-0.082
		(0.330)		(0.312)		(0.337)		(0.209)
feis	–	1.488	–	-1.921	–	-0.274	–	-1.052
		(1.336)		(1.257)		(1.349)		(0.812)
feis*cohort trend	–	-0.508**	–	-0.020	–	-0.254	–	-0.056
		(0.228)		(0.214)		(0.226)		(0.138)
constant	2.074***	2.076***	-0.793**	-0.796**	0.613*	0.616*	-0.259	-0.259
	(0.341)	(0.341)	(0.328)	(0.328)	(0.372)	(0.372)	(0.213)	(0.213)
observations	8,522	8,522	7,799	7,799	6,955	6,955	7,735	7,735
R-squared	0.009	0.009	0.009	0.010	0.002	0.002	0.007	0.007

Faculty C								
	100-level		200-level		300-level		400-level	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
is	-4.055***	–	-3.124***	–	-4.273***	–	-4.364***	–
	(1.032)		(0.936)		(0.975)		(1.110)	
is*cohort trend	0.368	–	0.244	–	0.294	–	0.384	–
	(0.251)		(0.228)		(0.237)		(0.259)	
ceis	–	-5.561***	–	-3.846**	–	-4.261**	–	-4.332**
		(1.807)		(1.679)		(1.759)		(2.073)
ceis* cohort trend	–	0.307	–	0.182	–	0.123	–	-0.042
		(0.368)		(0.344)		(0.366)		(0.396)
feis	–	-3.253*	–	-2.852*	–	-4.682***	–	-5.062***
		(1.698)		(1.515)		(1.571)		(1.723)
feis*cohort trend	–	0.402	–	0.277	–	0.397	–	0.761**
		(0.338)		(0.300)		(0.307)		(0.339)
constant	-5.045***	-5.041***	-3.481***	-3.480***	-3.291***	-3.293***	-1.913***	-1.914***
	(0.312)	(0.312)	(0.273)	(0.273)	(0.285)	(0.285)	(0.315)	(0.315)
observations	9,096	9,096	8,720	8,720	6,965	6,965	5,939	5,939
R-squared	0.010	0.011	0.009	0.009	0.011	0.011	0.007	0.008
Faculty D								
	100-level		200-level		300-level		400-level	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
is	-0.236	–	0.361	–	-1.733	–	-2.523**	–
	(1.014)		(1.047)		(1.218)		(1.030)	
is*cohort trend	-0.421*	–	-0.676***	–	-0.255	–	0.095	–
	(0.253)		(0.261)		(0.312)		(0.252)	
ceis	–	-0.799	–	-0.679	–	-6.785***	–	-4.975***
		(1.746)		(1.837)		(2.173)		(1.888)
ceis* cohort trend	–	-0.578	–	-0.647*	–	0.249	–	0.253
		(0.363)		(0.374)		(0.448)		(0.375)
feis	–	1.240	–	2.492	–	2.768	–	-0.930
		(1.703)		(1.730)		(1.996)		(1.633)
feis*cohort trend	–	-0.291	–	-0.663*	–	-0.584	–	0.032
		(0.348)		(0.360)		(0.430)		(0.337)
constant	-2.943***	-2.948***	-0.348	-0.355	-0.839**	-0.855**	-1.491***	-1.495***
	(0.294)	(0.294)	(0.293)	(0.293)	(0.346)	(0.345)	(0.286)	(0.286)
observations	9,710	9,710	9,460	9,460	7,712	7,712	8,152	8,152
R-squared	0.002	0.003	0.003	0.004	0.002	0.005	0.005	0.006

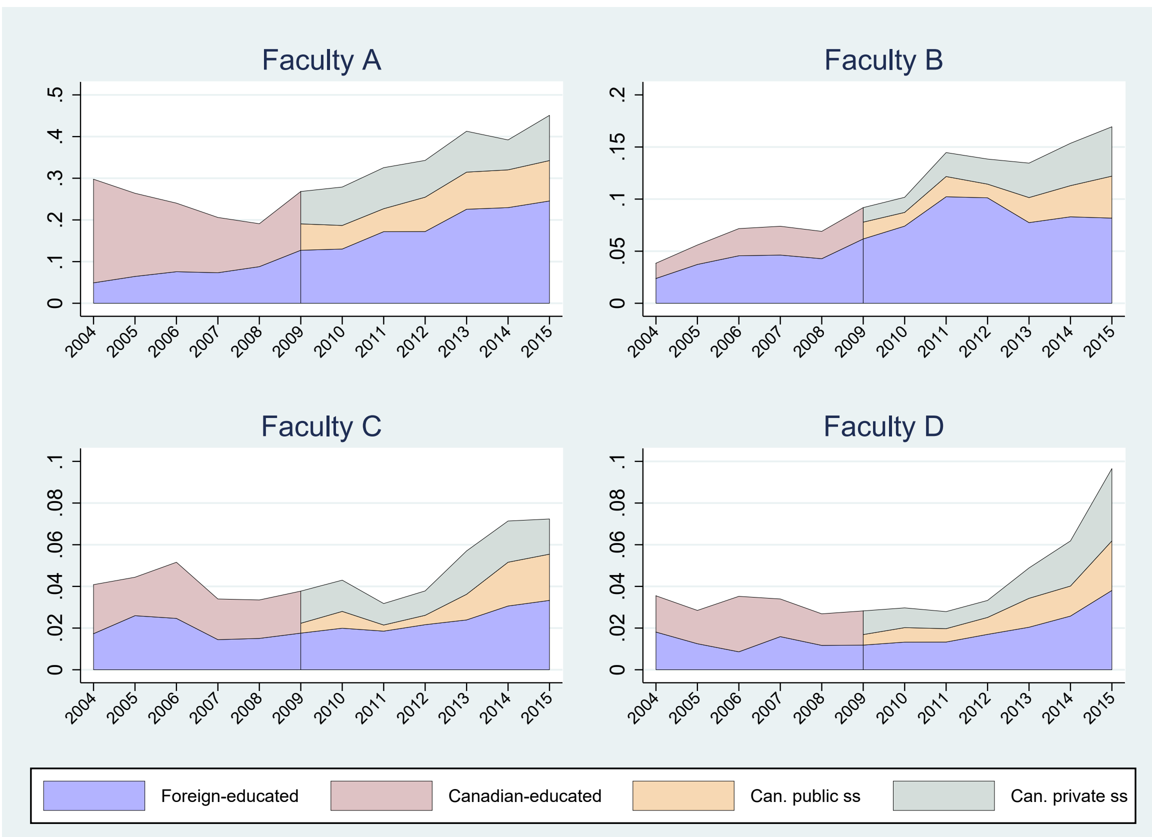
Notes: The dependent variable is the estimated student fixed effect from a two-way fixed effects (TWFE) regression of student-level university course grades on student and course-instructor fixed effects, as well as terms-since-entry dummies. The independent variables are dummy variables indicating an international student (is), a Canadian-educated international student (ceis), and a foreign-educated international student (feis). Coefficients are from quantile regressions at various percentiles and OLS regressions. The R-squared statistic in the quantile regressions is a pseudo R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 1.5: Relative mean international student quality, program-required courses

	Faculty A		Faculty B		Faculty C		Faculty D	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
is	-3.291***	–	-2.358***	–	-3.041***	–	-3.128***	–
	(0.565)		(0.665)		(0.833)		(0.831)	
is*cohort trend	0.090	–	-0.086	–	0.209*	–	-0.003	–
	(0.078)		(0.087)		(0.120)		(0.110)	
ceis	–	-5.494***	–	-2.099*	–	-6.328***	–	-6.566***
		(0.738)		(1.194)		(1.277)		(1.225)
ceis*cohort trend	–	0.136	–	-0.028	–	0.477***	–	0.143
		(0.094)		(0.133)		(0.160)		(0.144)
feis	–	1.952*	–	-2.160**	–	0.113	–	1.226
		(1.014)		(0.931)		(1.352)		(1.391)
feis*cohort trend	–	-0.308***	–	-0.152	–	-0.083	–	-0.172
		(0.116)		(0.111)		(0.176)		(0.166)
constant	-2.143***	-1.910***	3.305***	3.300***	-7.928***	-7.914***	-5.939***	-5.960***
	(0.506)	(0.507)	(0.322)	(0.322)	(0.308)	(0.308)	(0.297)	(0.296)
observations	14,059	14,059	16,053	16,053	17,530	17,530	20,202	20,202
R-squared	0.021	0.027	0.018	0.018	0.013	0.014	0.009	0.011

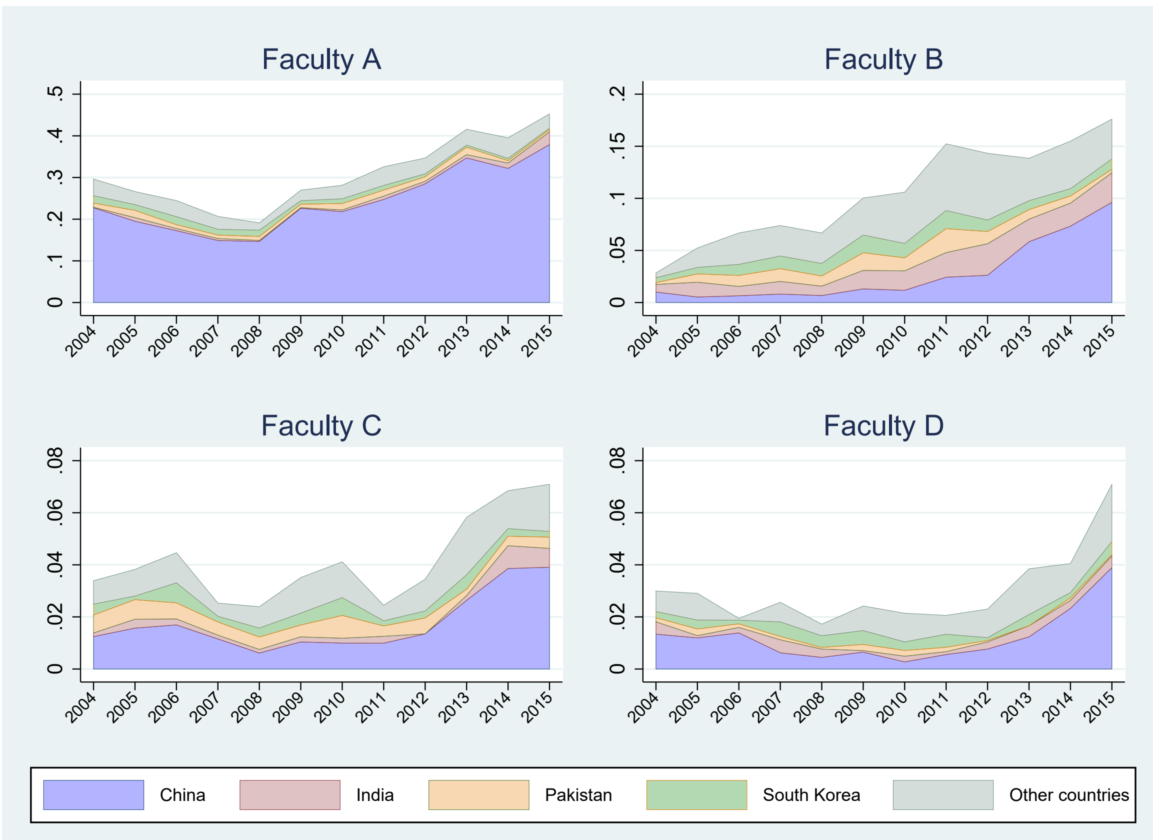
Notes: The dependent variable is the estimated student fixed effect from a two-way fixed effects (TWFE) regression of student-level university course grades on student and course-instructor fixed effects, as well as terms-since-entry dummies. The independent variables are dummy variables indicating an international student (is), a Canadian-educated international student (ceis), and a foreign-educated international student (feis). Coefficients are from quantile regressions at various percentiles and OLS regressions. The R-squared statistic in the quantile regressions is a pseudo R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1.1: International student share of enrolments by student type, 2004-2015 entry cohorts



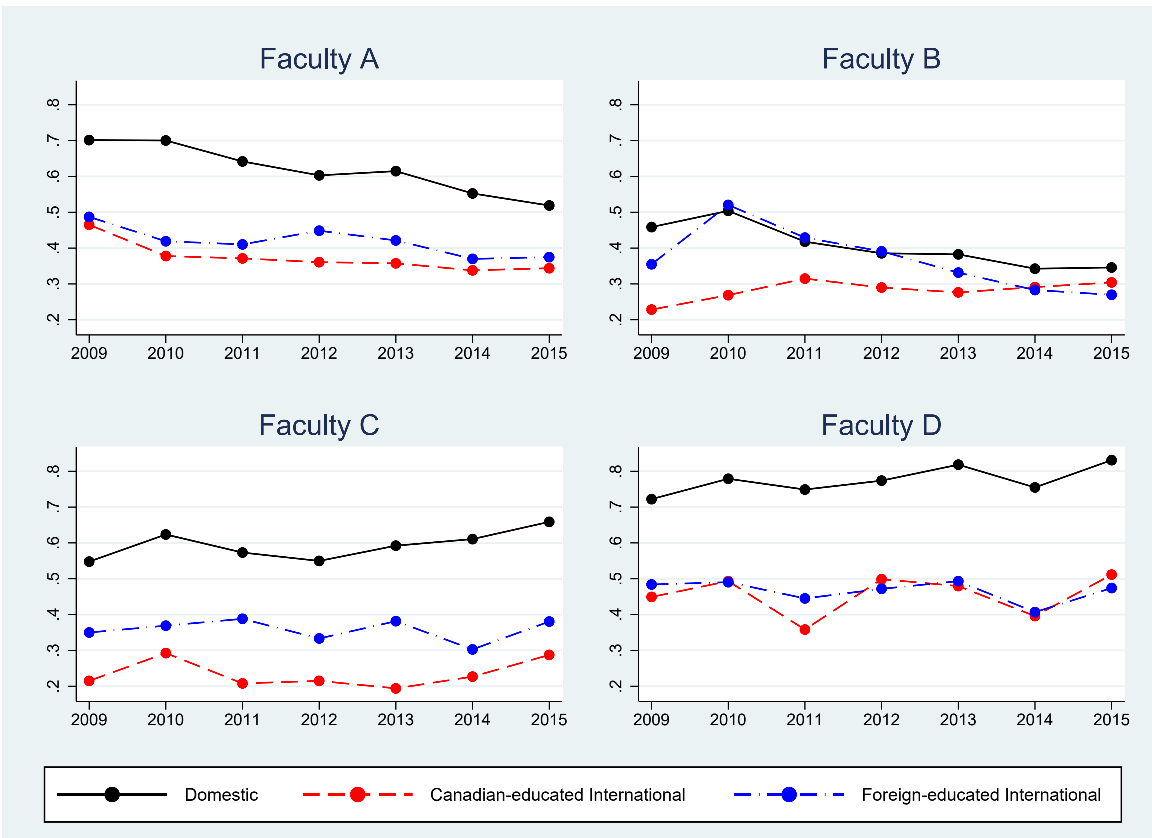
Note: the vertical axes vary between faculties.

Figure 1.2: International student share of enrolments by student citizenship, 2004-2015 entry cohorts



Note: the vertical axes vary between faculties.

Figure 1.3: Proportion of applications receiving admission offers, 2009-2015



Source: “Admissions Report 1A”, Internal University Data and Statistics

Figure 1.4: Distribution of entry grades, 2007 and 2015 entry cohorts

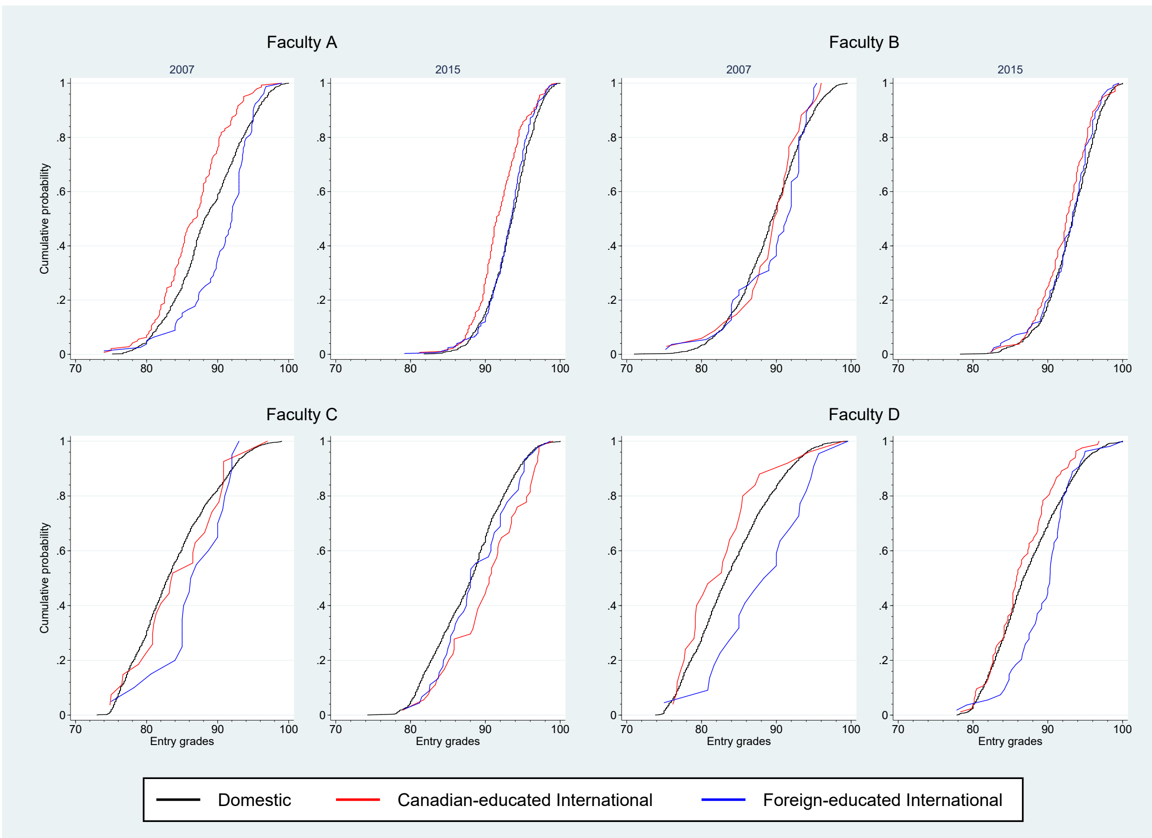
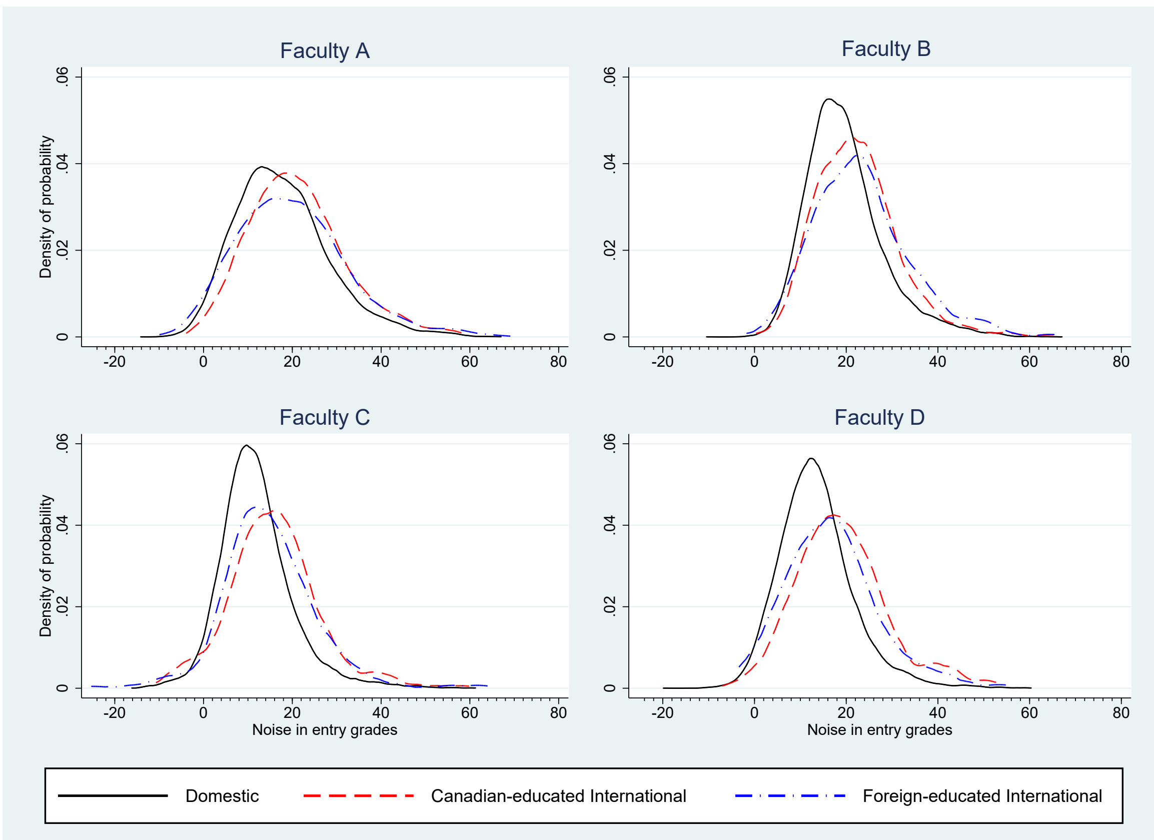


Figure 1.5: Distribution of noise in entry grades by faculty



Chapter 2

The Influence of Co-Ethnic Peers on Students' Academic Program Choices: Evidence from an Ontario University

Zong Jia Chen

2.1 Introduction

The academic programs that students choose to pursue have strong implications for their career prospects. There are large differences in the average earnings of people who choose different fields of study at university. Programs in the fields of science, technology, engineering, and mathematics (STEM) are associated with high earnings in the labour market, while programs such as fine arts, education, and social work are associated with relatively low earnings (Finnie et al. 2016). Previous studies have produced an extensive body of literature on the determinants of university program choice, including gender, socioeconomic status, parental occupation, and expected labour market conditions (Paglin and Rufolo 1990; Leppel, Wulliams, and Waldauer 2001; Montmarquette, Cannings, and Mahseredjian 2002; Malgwi, Howe, and Burnaby 2010).

Ethnic sorting is an important phenomenon in postsecondary institutions, and several studies in the U.S. have found that ethnic groups are not randomly distributed across academic programs (Trusty, Ng, and Ray 2000; Staniec 2004; Poter and Umbach 2006; Dickson 2010). However, most existing studies on program choices either tend to focus on how students are ethnically distributed across programs at the time of their enrollment or their graduation. Unlike the previous studies, this paper includes an analysis of the influence of co-ethnic peers on students' ethnic concentration in university academic programs and their probability of switching programs over the course of their undergraduate studies.

University program choice is an ongoing process after university entry, and it is common for students to change their field of study during the course of their studies. Students change their program of study for many reasons. In this paper, I propose two main factors which motivate students' program changes: (i) academic aptitude and (ii) social considerations. Students who are motivated by academic grades are those who sort themselves into programs in which their academic aptitudes give them a comparative advantage. Students have different sets of skills. For example, some have strong quantitative skills, but weak language skills. Ideally, students should specialize in programs in which they have a comparative advantage. The question then arises: if students sort themselves into programs based on their relative aptitudes in different programs at the time of their initial program choices, why would they switch programs? The answer could be that students do not have perfect information about their own skills during the initial sorting. After they enter the university, they use their grades as an indicator of where their skills are. As a result, they switch to programs in which their pre-existing aptitudes give them a comparative advantage.

On the other hand, socially-driven students are those who make program changes based on social considerations, such as interacting with peers who have similar interests. The idea of program changes influenced by this social consideration is that students value being in the same program with peers who are from the same ethnic background as them. This is commonly observed in immigrant-receiving countries that recent immigrants often seek to live in communities and work at places established by previous settlers from their own ethnic groups (Card 2001; Hou 2009). They rely on ethnic resources and networks for employment opportunities to overcome barriers that they are facing in the labour market (Hou 2006).

When students make decisions on what programs and universities to apply to and which offers to accept, they have less information about the ethnicity of their classmates compared to when they arrive on campus and attend their first lectures. Therefore, the ethnicity of students' peers should be a relatively weak determinant in driving their initial program choices. However, as students begin to receive new information about the ethnic composition of programs throughout their studies, do they make program changes which appear to be related to the co-ethnic shares of their programs? If students have a preference for co-ethnic peers in their programs, the data should reveal a tendency for students to be more ethnically concentrated in programs over time.

Understanding the effect of ethnic peers on students' program choices is particularly important because some scholars have suggested that the university program choices of minorities contributes to differential earnings (Leslie and Oaxaca 1998). To the extent that students value being in the same program with co-ethnics, their program choices may not provide the best match between their aptitudes and their programs. The university should be concerned about students who prioritize social considerations over their academic aptitudes. For instance, students prefer to study with co-ethnics who have a shared sense of identity, which may lead to a slower acculturation process, such as learning a new language and adapting to a new culture's behaviour, values, and customs. Studying in programs where most of the students are non-native speakers will create hurdles for students to learn the language, particularly for international students who want to transition to permanent residency. Inefficient matching of students and programs may adversely impact their labour market outcomes, which could have long-run effects on the reputation of the university.

Using a large sample of undergraduate students at a publicly-funded Ontario university, I reach three main findings. First, I find that students are highly ethnically concentrated across academic programs when they first arrive at this university. This ethnic concentration has increased not only across entry cohorts, but also tends to increase over the course of students' undergraduate studies. Second, I find that if students expect to maintain their grades after program changes, they prefer to change to programs where they share an ethnicity with their classmates. Last, the presence of co-ethnic peers appears to have a bigger impact on influencing students' choices to switch programs across faculties than it does on program changes within faculties. This pattern is likely explained by the fact that program required courses overlap within faculties. Therefore, students who change programs within faculties are more likely to be with the same co-ethnic peers.

The remainder of the chapter is organized as follows. The following section describes how I use students' surnames to infer their ethnicities. Section 2.3 introduces an index to measure how ethnic groups are concentrated as well as a theoretical model of students' program choices. The following two sections describe the data and empirical strategies. Section 2.6 interprets the results. Finally, the concluding section summarizes the significance of the main findings.

2.2 Student Ethnicity

Canadian universities do not currently collect information on the ethnicity of their students or course instructors, although it appears to be on the horizon. All Canadian universities recently committed to collecting and making demographic data public, including ethnicity, on faculty and students as part of the Action Plan for Inclusive Excellence (Berg 2017). This explains why there is a dearth of research examining how the presence of co-ethnic peers affect students' academic choices.

There is a growing body of research that uses surnames to infer the ethnic origin of individuals as an alternative to ethnicity self-identification information when this is not directly provided in the data. In epidemiologic and health service research studies, surname ethnicity matching databases are widely used (Ginsburg et al. 2015; Stevenson et al. 2018). Kerr (2007) uses the names of inventors in patent applications to infer the ethnic composition of US inventors. Kerr and Lincoln (2010) use a similar ethnic identification strategy to relate the H-1 B visa program of temporary workers to patent counts across ethnic groups in U.S. cities. Blit, Skuterud, and Zhang (2018) use the name-ethnicity matching algorithm, developed and customized by Kerr (2007), to estimate the patenting rates of 11 ethnic groups in the Canadian population.

In this paper, two databases are used to identify the ethnicity of students. The first database includes Chinese and South Asian surnames and was constructed by Baiju Shah and his colleagues from the Sunnybrook Research Institute in Toronto, Canada. This database has been used to identify Chinese and South Asian people for studying differences between the two ethnicities in breast cancer incidence (Ginsburg et al. 2015; Shah et al. 2018). Validity of the Chinese surname list was examined by measuring sensitivity (the proportion of individuals in their data who identified themselves as Chinese, who were detected as such by the surname list), specificity (the proportion of individuals who identified themselves as not being Chinese, who were detected as such by the surname list), positive predictive value (the proportion of those detected by the surname list as Chinese who self-identified as such) and negative predictive value (the proportion of those detected by the surname list as not being Chinese who self-identified as such). Similar calculations were made to validate the South Asian surname list. The results of their sensitivity, specificity, positive predictive value, and negative predictive value were 80.2%, 99.7%, 91.9%, and 99.2%, respectively, for the Chinese list, and 50.4%, 99.7%, 89.3%, and 97.2%, respectively, for the South Asian list (Shah et al. 2010).

The second database comes from Lauderdale and Kestenbaum (2015). They obtain ethnicity and surnames from the U.S. Social Security Administration's file of applications for social security cards. Six Asian ethnicities (Chinese, Indian, Japanese, South Korean, Filipino, and Vietnamese) are classified in their paper. The sensitivity and predicted positive values are 78% and 89% for the Chinese list, 60% and 83% for the Indian list, 79% and 96% for the Japanese list, 64% and 82% for the South Korean list, 76% and 98% for the Filipino list, and 79% and 86% for the Vietnamese list.

Combining these two databases along with direct information on students' citizenship provided in the university data, I assign all the undergraduate students in my sample to one of seven ethnic groups: Chinese, South Asian, Korean, Filipino, Japanese, Vietnamese, and non-Asian.[1] It is possible that some students from mixed ethnicities will be misclassified. However, based on the findings of Canada's Ethnocultural Mosaic in 2006 Census, it is noteworthy that people of Chinese and South Asian origins are the least likely to report being married to someone from outside their ethnic group. One limitation of these lists is that the sensitivity of the South Asian list (the proportion of people self-identified as South Asian who were detected as such by the surname list) was low. This is due to the fact that many surnames common to both South Asian and other populations were deliberately excluded from the surname list (e.g., Khan, Ahmed, DeSouza or Fernandes) for a better positive predictive rate.

2.3 Theory

2.3.1 Ethnic concentration index

In order to examine if there is any evidence that students' program choices are influenced by the presence of co-ethnic peers, this study first looks at how ethnic groups of students are sorted into different programs when they first arrive at the university, and then looks at whether the ethnic concentration in programs tends to increase over the course of students' studies. If the ethnic concentration increases over time, it suggests that students sort themselves into programs which are influenced by the share of their co-ethnics.

Here I use an adaptation of the Herfindahl-Hirschman Index (C) (Hirschman 1945; Herfindahl 1950), which is usually used as a measure of trade or industrial concentration, to measure the ethnic concentration of students in programs.

[1] If a student with a Chinese name has Indian citizenship, I will assign South Asian as her ethnicity. In other words, I prioritize citizenship over identified ethnicity. This only applies to non-Canadian citizenship students because the university data do not collect information on students' country of birth. Non-Asian group includes students other than Chinese, South Asian, Japanese, South Korean, Vietnamese, and Filipino.

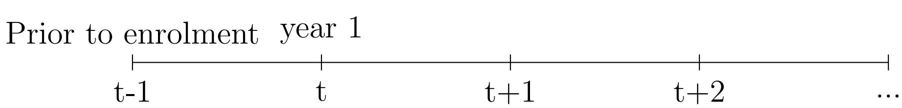
Suppose that the student population in a program is distributed over E ethnic groups. For each ethnic group e ($e = 1, ..., E$) and program j ($j = 1, ..., J$), the index of ethnic concentration C is constructed as follows:

$$C_j = \sum_{e=1}^{E} n_{j,e}^2 \tag{2.1}$$

where $n_{j,e}$ is the proportion of students in program j who belong to ethnic group e. C ranges from 0 to 1 (no ethnic concentration to monoethnicity). If, for example, all students within a program belong to a single ethnicity, that program's concentration index will be exactly 1. If, on the other hand, 20 percent of students are Chinese and 80 percent are non-Chinese, the concentration index (C) will be 0.68 ($0.2^2 + 0.8^2$). To measure the ethnic concentration index at the university level, the average concentration index of academic programs can be constructed, where the contribution of each program to the average is weighted by the total number of students in each program.

2.3.2 University program choice

To examine changes in students' program choices during the course of their studies, I model the program choice process as consisting of different periods during students' undergraduate studies. The underlying assumption is that when students first enrol in programs, they have less information about their actual ability and the attributes of programs, such as the co-ethnic shares of programs, program completion rates, the expected unemployment rate of programs in which students graduate from, and the expected annual earnings of programs. Therefore, students maximize their utility based on their expectations of their abilities and attributes of programs. A broad outline of the sequential structure of students' decisions is summarized below.



1. Before entering the university (period $t-1$), admitted students are confronted with the decision to choose a university program k from the choice set J to maximize their expected utility and then declare their program of study at the beginning of period t. Their program choice is based on their specific demographic information (e.g., immigration status,

subject of major interest), expected academic aptitude, expected program completion rate, the expected unemployment rate of programs in which students graduate from, and the expected annual earnings of programs.

2. After enrolling in the university and beginning course work, students begin to receive new information about their abilities (through course grades), the likelihood of completing the program, labour market conditions (through unemployment rate and annual earning of programs in which they graduate from), and the ethnic composition of programs (through co-ethnic share) throughout period t. Before the end of period t, they need to make a program choice in order to preselect their courses in the next period.

3. In period $t+1$, based on the updated information students acquired in period t, students potentially revise their program choices and declare their programs at the beginning of this period - either stay in their current programs or switch to another program.

4. Similarly, for the rest of periods, students are going through the same procedure of making program choices based on the updated information they received from the previous period.

For simplicity, consider a two-period model, where students make program choices between period t and $t+1$. Define student i's utility received while studying in program j at time t as U_{ijt}. In this paper, I assume that a student's utility is affected by different factors: personal taste, academic standing, co-ethnic share, program completion rate, unemployment rate, and annual earnings. The utility is given by

$$U_{ij} = [x_i, E(e_{ij}), E(g_j), E(z_j), E(u_{ij}), E(m_j)] \quad j = 1, 2, ..., k, ..., J \tag{2.2}$$

where x_i is a vector consisting of student-specific demographic variables (e.g., gender, immigration status, subject of major interest), $E(e_{ij})$ is the key variable of interest indicating that the expected share of students in program j that share the ethnicity of student i; $E(g_j)$ is student i's expected cumulative grade-point-average (CGPA) in program j; $E(z_j)$ is the expected completion rate in program j; $E(u_{ij})$ represents the expected unemployment rate for program j facing the student after graduation; and $E(m_j)$ is the expected annual earnings of student i graduating from program j.[2]

[2]Cumulative GPA is a student's overall average of all the courses she has taken so far. I group the numerical CGPA into different ranges of grades to avoid ties on grades. The program completion rate data came from the Ministry of Colleges and Universities (2015). The unemployment rate and annual earnings were obtained from the 2001, 2006, 2016 Canadian Census and 2011 National Household Survey (NHS) public use microdata file. Detailed classification is shown in Section 2.5.

I assume that utility is linearly additive over time, then the utility in program j in the case of ordering 1 is:

$$U_{ijt} = \alpha_j x_i + \beta_j E(g_{jt}) + \gamma_j E(e_{ijt}) + \theta_1 E(z_{jt}) + \theta_2 E(u_{jt}) + \theta_3 E(m_{jt}) + \epsilon_{ijt} \tag{2.3}$$

Student i chooses the academic program k that maximizes utility at the beginning of period t:

$$U_{ik} = max(U_{i1}, U_{i2}, ..., U_{iJ}) \tag{2.4}$$

Each student chooses the program with the highest expected utility, so the probability that student i chooses program k over all other j alternatives is:

$$\begin{aligned}\pi_{ikt} &= Prob(U_{ikt} \geq U_{ijt}) \\ &= Prob(U_{ijt} - U_{ikt} \leq 0) \\ &= Prob((\alpha_k - \alpha_j)x_i + \beta(E(g_{kt} - g_{jt})) + \gamma(E(e_{ikt} - e_{ijt})) + \\ &\theta_1(E(z_{kt} - z_{jt})) + \theta_2(E(u_{kt} - u_{jt})) + \theta_3(E(m_{kt} - m_{jt})) + \epsilon_{ikt} - \epsilon_{ijt} > 0) \quad \forall j \neq k\end{aligned} \tag{2.5}$$

Under the assumption that the residuals (e_{ijt}) have a Type I extreme value distribution and are independently and identically distributed, the estimation procedure follows the multinomial logit formulation and the choice probabilities take the form:

$$\pi_{ikt} = \frac{exp(\alpha_k x_i + \beta E(g_{kt}) + \gamma_k E(e_{ikt}) + \theta_1 E(z_{kt}) + \theta_2 E(u_{kt}) + \theta_3 E(m_{kt}))}{\sum_{j=1}^{J}[exp(\alpha_j x_i + \beta E(g_{jt}) + \gamma_k E(e_{ijt}) + \theta_1 E(z_{jt}) + \theta_2 E(u_{jt}) + \theta_3 E(m_{jt}))]} \tag{2.6}$$

2.3.3 Lexicographic ordering

The methodology employed in the literature on university program choice normally uses a multinomial logit to estimate the relationship between the student's university program choice and the student's aptitude and the attributes of programs. In the literature, university academic programs are categorized into a limited number of broader groups, such as business, social sciences, engineering and computer science (Dickson 2010). If we were to similarly categorize programs into broad groups in this paper, it would be difficult to capture any changes in the ethnic concentration of programs, since most of the variation of the ethnic concentration occur within narrower program groups. Based on the theory, in every period, students choose programs which maximize their utility based on the updated information. However, it is not feasible to run multinomial logit estimation for students in every period to obtain their highest expected utility because there are over a hundred academic programs at the university. The primary objective of this paper is to examine the influence of co-ethnic share on the *probability of a program change*. Therefore, I propose a binary response model that follows a lexicographic preference as a way to solve this challenging problem.

It is reasonable to assume that the preference ordering of previously mentioned factors follows a lexicographic ordering during students' program-change decision making process. The lexicographical ordering works in the same way that a dictionary orders words. This paper is interested in the two main factors that drive students' decisions to change academic programs during their studies: relative academic aptitude considerations (g) and social considerations (e). Therefore, I propose two alternative lexicographic orderings:

$$\begin{aligned} ordering\,1 &: g > e > z > u > m \\ ordering\,2 &: e > g > z > u > m \end{aligned}$$

In ordering 1, when students consider changing their programs, they care most about whether they can obtain a higher grade (g) after the program change. This is particularly true for students who face academic challenges in their current program. The secondary consideration is whether the programs in which students intend to switch to have a higher share of their co-ethnic peers (e). The rest of the ordering are assumed to be followed by the program completion rate (z), unemployment rate (u), and annual earnings in the labour market (m).[3] In ordering 2, students prioritize co-ethnic share (e) over their academic standing (g), the remaining order stays the same. The way lexicographic ordering works in the case of ordering 1 is that student i will choose program k over program j if her expected grade in program k is higher than in program j. In other words, if a student sees her expected grade in program k is higher, she will switch to program k regardless of the values of e, z, u, and m between programs. If, however, two programs have an equal expected grade interval of student i, then the student will compare the co-ethnic share to break the tie. A student will switch to program k if program k has a higher share of

[3]Students are assumed to prioritize program completion rate over program attributes in the labour market, since they first need to consider the probability of graduating from the university, then take the return to education into account.

student i's co-ethnic peers. If two programs have the same academic grade and co-ethnic share, then student i will choose the program with a higher program completion rate to break the tie, and so on. Similarly, in the case of ordering 2, student i will first compare academic grades in program k and j. If there is a tie on the grades, student i will compare co-ethnic shares in programs, and so on.

After making initial university program choices and receiving the updated information mentioned above, co-ethnic shares in particular, throughout the period t, the key research question in this analysis is how much more likely an individual would be to change programs in period $t+1$? Note that from equation (2.3), the x_i component represents individual i's characteristics that are time invariant. As students progress through undergraduate studies, these time-invariant characteristics or tastes will not affect their program changing behaviour.

Suppose in period $t+1$, student i, who follows ordering 1, changes from program k to q. In the convenient log odds form, the log odds of student i choosing program q relative to the reference program k in period $t+1$ is then:

$$\begin{aligned} Prob(Change=1)_{i,t+1} &\equiv ln(\pi_{iqt}) - ln(\pi_{ikt}) \\ &= \alpha_q x_i + \beta_q E(g_{qt}) + \gamma_q E(e_{iqt}) + \theta_1 E(z_{iqt}) + \theta_2 E(u_{iqt}) + \theta_3 E(m_{iqt}) \\ &- \prod_{j=1}^{J} (\alpha_j x_i + \beta_j E(g_{jt}) + \gamma_j E(e_{ijt}) + \theta_1 E(z_{ijt}) + \theta_2 E(u_{ijt}) + \theta_3 E(m_{ijt}) \\ &- \alpha_k x_i + \beta_k E(g_{kt}) + \gamma_k E(e_{ikt}) + \theta_1 E(z_{ikt}) + \theta_2 E(u_{ikt}) + \theta_3 E(m_{ikt}) \\ &+ \prod_{j=1}^{J} (\alpha_j x_i + \beta_j E(g_{jt}) + \gamma_j E(e_{ijt}) + \theta_1 E(z_{ijt}) + \theta_2 E(u_{ijt}) + \theta_3 E(m_{ijt}) \\ &+ \epsilon_{iqt} - \epsilon_{ikt} \\ &= \beta E(g_{qt} - g_{kt}) + \gamma E(e_{qt} - e_{kt}) + \theta_1 E(z_{qt} - z_{kt}) + \theta_2 E(u_{qt} - u_{kt}) \\ &+ \theta_3 E(m_{qt} - m_{kt}) + \epsilon_{it} \end{aligned} \tag{2.7}$$

The nature of the lexicographic ordering alters the assigned value of each covariate in the data structure. For instance, if program q has the highest expected CGPA for student i (i.e., $E(z_{qt} - z_{kt}) > 0$), then the values of the remaining covariates are zero for the student in equation (2.7). If programs q and k have the same expected CGPA, and program q has a higher co-ethnic share for student i than program k does (i.e., $E(z_{qt} - z_{kt}) = 0$ and $E(e_{qt} - e_{kt}) > 0$), the values assigned to $E(z_{qt} - z_{kt})$, $E(u_{qt} - u_{kt})$, and $E(m_{qt} - m_{kt})$

become zero for student i, but $E(e_{qt} - e_{kt})$ takes on its actual value. If programs q and k have the same g and e, and student i has a higher expected z in program q than in k (i.e., $E(z_{qt} - z_{kt}) = 0$, $E(e_{qt} - e_{kt}) = 0$, and $E(z_{qt} - z_{kt}) > 0$), the values assigned to $E(u_{qt} - u_{kt})$ and $E(m_{qt} - m_{kt})$ become zero. Similarly, if g, e, and z are tied for programs q and k, and program q has a relatively low u (i.e., $E(z_{qt} - z_{kt}) = 0$, $E(e_{qt} - e_{kt}) = 0$, $E(z_{qt} - z_{kt}) = 0$, and $E(u_{qt} - u_{kt}) = 0$), then the value of $E(m_{qt} - m_{kt})$ becomes zero for the student. By doing this, the lexicographic ordering assumption allows each individual student has one value attached to the covariates in the data, which makes the model estimation feasible.

2.4 Data

The data were obtained from a publicly-funded university in Ontario. I grouped faculties into four categories based on the share of ethnic groups. Faculty A, B, and C are single faculties with a relatively large share of Asian students, whereas D is comprised of multiple faculties with relatively low Asian enrolment. To provide a sense of how academic programs vary between faculties, faculty A and B consist of programs primarily in engineering, mathematics, computer science, and technology; faculty C programs are mostly in arts, social science, business and languages; and programs in faculty D are primarily in science and health fields.

The data provide a sample of 12 cohorts who entered the university between 2004 and 2015. They contain detailed information about the course-level grades and enrolled academic programs of individual students. In this paper, I primarily focus on the student-term level, because students have opportunities to change their programs of study and report such changes at the beginning of each term. I restrict my sample to students within their four years of undergraduate studies as well as students enrolled in the Fall term.[4] In addition, I exclude "2+2" program students from the sample.[5] Moreover, students over the age of 25 at the time of enrolment are excluded from the sample. With these restrictions, there are 112 different academic programs, and the total sample size in the analysis is 516,733.

As I mentioned in Section 2.2, all undergraduate students are classified into seven ethnic groups. To provide a sense of the ethnic group shares at the time of enrolment across entry

[4]These students account for 84.2% of total fall enrolments between 2004 and 2015.

[5]These collaborative programs between Canadian and abroad universities are aimed for the program continuation. Students participating in "2+2" programs are mostly from China. They spend the first two years of their four years program in their home country and continue studying the same programs in Canada.

cohorts, I grouped these seven ethnic groups into three groups, which are Chinese, other Asian, and non-Asian. Other Asian includes Japanese, South Asian, Vietnamese, Filipino, and Korean; non-Asian includes students other than Chinese, Japanese, South Asian, Vietnamese, Filipino, and Korean.[6] Figure 2.1 reveals that the shares of both Chinese and other Asian groups increase between 2004 and 2015. By 2015, the share of Chinese group increases from 22% to 33%, and the share of other Asian group increases from 15% to 19%. Therefore, more than 50% of students are Asian, up from 37% in 2004.

Figure 2.2 breaks down the ethnic enrolment share separately for non-international and international students. It reveals that the increase in the Asian shares is largely reflected by the increased enrolment of Chinese international students. Among all Chinese students, the share of Chinese non-international students experiences a slight increase between 2004 and 2015, from 17% to 19%. On the other hand, the share of Chinese international students increases from 5% in 2004 to 14% in 2015, which accounts for 60% of the total increased Asian shares.[7] It is consistent with the fact that Canadian universities are increasingly reliant on the enrolment of Chinese international students (Chen and Skuterud 2020). The shares of non-international and international students for other Asian group experience a modest shift between 2004 and 2015, from 13% and 2% to 16% and 3%, respectively. For non-Asian group, the share of international students experiences a similar increase trend compared to other Asian group. However, the share of non-international students decreases dramatically between 2004 and 2015, from 60% to 44%.

Figure 2.3 reveals the ethnic enrolment shares by faculty. The growth in the Asian enrolment share at university entry is largely driven by Chinese students. By 2015, nearly 60% of students in faculty A are Chinese, up from 44% in 2004. The Chinese share also increases dramatically in faculty C, from 13% in 2004 to 26% in 2015. While in faculty B and D, there is a slight increase in the share of Chinese students, from 22% and 15% in 2004 to 28% and 19% in 2015, respectively. In contrast, the share of other Asian group has been quite modest between 2004 and 2015 in faculty A and B. with the exception of a slight increase in faculty C and D.

2.4.1 Ethnic sorting

To understand and quantify how ethnic groups of students are sorted at university entry, I use the concentration index introduced in Section 2.3.1. Table 2.1 reports the concentration

[6] Other Asian group excludes students from west Asia. Therefore, west Asian students are included in the non-Asian group.

[7] 60% is calculated as the ratio between the increased Chinese international student share (9%) and the increased Asian share (33%+19%-22%-15%=15%).

index based on seven ethnic groups by entry cohort. The share of non-Asian students decreased from 62.7% to 47.8% between 2004 and 2015. Consequently, the concentration index decreased from 0.508 to 0.431 (column 3). This trend is consistent with the fact that the university attracts more students from a broader range of countries in more recent years.

However, the decrease in the concentration index could either reflect changes over time in how students sort themselves across programs or changes in the ethnic diversity of entering cohorts. I have created a simple example to show that even if students of a particular ethnic group do not change their program choice behaviour, the concentration index could decrease over time if there is an increase in the diversity of incoming students. For instance, assuming the university has two academic programs, where program A contains 20 Chinese students and 20 non-Asian students, and program B only contains 60 non-Asian students, the concentration index will be 0.80.[8] In the next year, the ethnic composition of program A stays the same, but there are 20 incoming Korean students enrolled in program B. That is, program B now contains 20 Korean and 60 non-Asian. In this case, the concentration index decreases from 0.80 to 0.58.[9]

In order to control for the changes in the ethnic diversity over time and test if the sorting is non-random, I construct the concentration index under the null hypothesis that students are sorted across programs in a way unrelated to their ethnicity. To do this, I randomly assign students to academic programs and recalculate the concentration index. This approach ensures that the program-size distribution remains constant. From 1,000 replications of this random resorting, I use the 25^{th} and 975^{th} highest values of the index to construct a 95% confidence interval. The empirical ethnic concentration indexes in column 3 fall far outside of the 95% confidence intervals, shown in column 4, which indicates that students are highly non-randomly distributed across academic programs at the university, in a way that is related to their ethnicity.

To examine if ethnic sorting has increased across entry cohorts, I first calculate the mean estimate of the index obtained through randomly sorted students across programs from the 1,000 replications. I then take the ratio of the empirical index to the mean estimate, which is shown in column 5. Figure 2.4 reveals that this ratio increases from 1.099 to 1.182 between 2004 and 2015, which indicates that incoming students are increasingly non-randomly sorted across programs by ethnicity, even after taking into account the increasing diversity of students at the university level over time. Although the magnitude of the increase appears small, it is significant, as shown by the 95% confidence intervals.

[8]The index is calculated as $(40/100) * [(20/40)^2 + (20/40)^2] + (60/100) * (1^2) = 0.80$.

[9]The index is calculated as $(40/120) * [(20/40)^2 + (20/40)^2] + (80/100) * [(20/80)^2 + (60/80)^2] = 0.58$.

To provide some sense of the magnitude of the resorting required to produce an increase in the ratio from 1.099 to 1.182, I have created a simple example, in which the ratio of interest increases precisely by this amount. Consider a simple case in which the university is comprised of 100 students and two academic programs (A and B). Chinese students account for 20% of total students and the rest of students are non-Chinese. If students are randomly sorted across the two programs, then within both programs, the shares of Chinese and non-Chinese students are expected to be 20 percent and 80 percent, respectively. However, in reality students are not randomly sorted, but are instead sorted in a way that is related to their ethnicity. Below is the assumed structure for the illustrative example.

cohort	non-random sorting			random sorting			ratio
	program A	program B	index	program A	program B	index	
2004	63 non-Chinese 5 Chinese	17 non-Chinese 15 Chinese	0.748	40 non-Chinese 10 Chinese	40 non-Chinese 10 Chinese	0.680	1.099
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
2015	61 non-Chinese 0 non-Chinese	19 non-Chinese 20 non-Chinese	0.804	40 non-Chinese 10 Chinese	40 non-Chinese 10 Chinese	0.680	1.182

Assume that in 2004, program A is comprised of 63 non-Chinese students and 5 Chinese, while program B is comprised of 17 non-Chinese students and 15 Chinese. From a non-random sorting, the ethnic concentration index at the university level will be 0.748.[10] On the other hand, the index is 0.68 from random sorting, where programs A and B are each comprised of 40 Canadians and 10 Chinese. Similar calculations are made for the 2015 cohort. The indexes from non-random and random sorting for the 2015 cohort are 0.804 and 0.680, respectively. In this way, the ratio in the last column increases from 1.099 to 1.182 between 2004 and 2015, which is equivalent to what actually happened at the university over these years.

How much sorting was necessary to produce the increase in the ratio from 1.099 to 1.182? In 2004, the hypothetical actual shares of Chinese and non-Chinese students in program A are 7.4% and 92.6% compared to 20% and 80% from random sorting. However, in 2015, the shares of Chinese and non-Chinese students in program A change to 0% and 100%, which move further away from the shares under the assumption of random sorting. Students are clearly much more non-randomly sorted across programs in 2015. This pattern is also evident in program B. That is, the shares of Chinese and non-Chinese

[10] The index is calculated as $0.68 * [(63/68)^2 + (5/68)^2] + 0.32 * [(17/33)^2 + (15/33)^2] = 0.748$.

students change from 46.9% and 53.1% to 51.3% and 48.7% compared to 20% and 80% under the assumption of random sorting between 2004 and 2015.

The findings that the ethnic concentration of students has been increasing across entry cohorts can be better understood by examining changes over time in the distribution of ethnic shares across academic programs. In Figure 2.5, I plot the cumulative density function of ethnic shares by ethnic group and program for the 2004 and 2015 entry cohorts. As the share of Chinese students has increased over this period, the distribution of Chinese students for cohort 2015 lies below the distribution for cohort 2004, except between 0.16 to 0.23. This reveals that Chinese students are more concentrated in programs with a high share of Chinese students in 2015. This pattern is also evident for other Asian students. However, non-Asian group students become less concentrated within programs for cohort 2015 compared to cohort 2004.

Figure 2.6 shows the distribution of ethnic shares by faculty. It reveals that the increase in the concentration index between 2004 and 2015 is largely reflected by the increased Chinese students shares in faculty A, B, and C during this period. For faculty D, the distributions of Chinese students shares are equivalent between cohort 2004 and 2015, which implies that there is not much change in the ethnic concentration of Chinese students. The increase in the ethnic concentration of other Asian students reveals a modest shift towards cohort 2015 in all faculties. For non-Asian students, cohort 2015 become less concentrated within programs in faculty A compared to cohort 2004.

To dig deeper, based on the student's status (permanent resident, citizen, or foreign student) provided in the data, I could find out which type of Chinese students contributes most to the increase in the concentration index. Figure 2.7 plots the distribution of Chinese students shares across programs by student status and program. The 2015 cohort distribution for Chinese Canadians lies below the 2004 cohort distribution. It suggests that Chinese Canadians are becoming more concentrated within programs in 2015 compared to 2004. For Chinese permanent residents, the distribution of cohort 2015 is above cohort 2004 in the left tail. It suggests that Chinese permanent residents are less concentrated in programs with a low co-ethnic share in 2015 compared to 2004. However, they are becoming more concentrated in programs with a higher co-ethnic share in 2015 than in 2004. This pattern is also evident for Chinese foreign students, with a relatively smaller magnitude.[11]

To have a sense of whether students' program changes following enrolment serve to increase or decrease their ethnic concentration within programs, I once again use the ethnic

[11] Unfortunately, the data do not contain information on students' country of birth. It is difficult to know whether Chinese Canadians were Canadian born or not.

information to calculate the ratio of the empirical estimates to the mean estimates from random sorting by cohort and study year at the university level (see Table 2.2). To obtain the standard errors of the ratio, I use a bootstrap resampling procedure to produce the bootstrapped standard errors for both the empirical estimate and the mean estimates from random sorting. Then, I use Taylor expansion to estimate the bootstrapped standard errors of the ratio. To obtain the standard errors of the ratio, I use a bootstrap resampling procedure to produce the bootstrapped standard errors for both the empirical estimate and the mean estimates from random sorting. Then, I use Taylor expansion to estimate the bootstrapped standard errors of the ratio.[12] The table reveals that there is clearly an upward trend in the ratio from year 1 to year 4 for most of the cohorts.[13] The difference in the ratio becomes more obvious starting from year 2. To measure the change in the ethnic concentration index across all cohorts, the average concentration index is constructed, where the contribution of each cohort to the average is weighted by the total enrolment of students in each entry cohort. The bottom panel reveals that the ratio, on average, increases from 1.155 to 1.166. The magnitude of this increase is statistically significant at the one percent significance level.[14] This implies that as students progress through their undergraduate studies and make program changes, those program changes are made in such a way that leads to an increase in the ethnic concentration of students within those programs.

2.4.2 Descriptive statistics

Table 2.3 reveals that the proportion of students who make program changes during the course of their studies. Among all undergraduate students, 23.7% make at least one pro-

[12]To obtain the bootstrapped standard errors for the empirical estimate, I draw a student from the sample one at a time and returning them to the data sample after they have been chosen. To obtain the bootstrapped standard errors for the mean estimate from random sorting, I randomly assign students to academic programs each year and repeat this random assignment 1,000 times. The Taylor expansion formula for the standard errors of the ratio $\approx \frac{\sigma_x^2}{\mu_y^2} + \frac{\mu_x^2 \sigma_y^2}{\mu_y^4}$, where x is the empirical estimate and y is the mean estimate from random sorting.

[13]The available data only cover the term up to January 2018. Therefore, year 4 of cohort 2015 is missing in the table.

[14]The t-statistic for this difference $= \frac{\mu_2 - \mu_1}{\sqrt{\sigma_1^2/N_1 + \sigma_2^2/N_2}} = \frac{1.166 - 1.155}{\sqrt{0.00025^2 + 0.00005^2}} \approx 43$

gram change during their four years of study.[15] For those who change programs, 75.4% of these program changes are within a faculty, while 24.6% are between faculties. This difference is likely explained by the fact that the cost of changing program is lower within than between faculties. For example, changing from mathematics to statistics would likely have a lower cost than changing from mathematics to history because of the overlapping courses in program requirements.

Korean students change programs at the highest rate (26.0%), followed by non-Asian students (24.1%). Japanese students have the lowest program change rate (20.3%). With regards to visa status, 24.3% of international students have changed program, compared to 23.6% of domestic students. Female students are significantly more likely to change programs compared to male students. This is consistent with findings that women are more likely to switch out of male-dominated STEM programs in response to a relatively low grades (Kugler, Tinsley, and Ukhaneva 2017). Finally, students enrolled in faculty C have the highest program switching rate (30.0%), followed by faculty A (26.7%), faculty D (25.3%), and faculty B (13.1%).[16]

Table 2.4 reports students' mean co-ethnic shares within their academic programs separately by ethnic group, immigration status, and gender. I also report the mean co-ethnic share separately for students who do not change programs and for those who make program changes. For those who make program changes, I calculate the mean co-ethnic share before and after the program change. Overall, the mean co-ethnic share is 0.470 among students who do not switch program during their studies. On the other hand, the mean co-ethnic share for students who do switch programs is 0.499 before they switch programs and 0.524 after. This means that students who make program changes have higher co-ethnic shares before they switch programs and their switches serve to further increase this difference.

This pattern is evident across ethnic groups, with the exception of Chinese students.

[15] At this university, there are direct-entry and general programs in first year. Direct-entry program: a specific program selected by a student when she applies to a faculty, and she continues to study this program during her undergraduate study. General program: a generalized program selected by a student when she applies to a faculty. After the freshman year, she may choose a specialized program from the generalized program to study. I define a program change in the following two cases: (1) a student first enrols into a direct-entry program and then changes to another program; (2) a student first enrols into a general program and chooses a specialized program, she then switches to another program. An example of a program change in case (2) is that a student first enrols into general Arts program and chooses to specialize in Economics, she then switches to History later on.

[16] It is not surprising that students enrolled into faculty B have the lowest program switching rate because most of the programs in faculty B are direct-entry programs. Therefore, they are less likely to change programs compared to students enrolled in other faculties, since Faculty A, C, and D are mostly comprised of general programs in the first year.

One possible explanation is that every faculty consists of large proportion of Chinese students (see Figure 2.3). This might drive the lower mean co-ethnic share result for Chinese since they are more likely find many Chinese classmates after program changes, which is particularly true if the program changes happen within faculties. The mean co-ethnic share for Chinese students is 0.473 before their program changes and 0.430 after the changes. This is evident in the immigration status and ethnic by immigration status panels. For all Chinese students, whether they are on a student visa, permanent resident or Canadian citizen, the share of their classmates who are also Chinese decreases on average, rather than increases, when they switch programs. For students who hold a study permit, the mean co-ethnic share increases after program changes. Finally, for both male and female students, mean co-ethnic shares increase on average after program changes are made.

2.5 Empirical Specification

The results to this point show that more recent cohorts of incoming students are more ethnically concentrated within academic programs. Students' decisions to change their programs after entry serve to further increase their ethnic concentration as they tend to switch to programs with higher co-ethnic shares. In the analysis that follows I seek to more directly identify to what extent this pattern reflects students' preferences to be in programs in which they share an ethnicity with their classmates. From the structure provided by the theory in Section 2.3.2, I estimate the following probit model:

$$\text{Under the assumption of ordering } 1 : g > e > z > u > m$$

$$c^*_{i,t+1} = \Phi(\beta\widetilde{g}_{it} + \gamma\widetilde{e}_{it} + \theta_1\widetilde{z}_t + \theta_2\widetilde{u}_t + \theta_3\widetilde{m}_t + \theta_4 female_i + \theta_5 CGPA_{t,65} + ethnic_i'\delta) \quad (2.8)$$

where $c_{i,t+1}$ is a binary outcome variable indicating whether student i made a program change in period $t+1$; Φ is the cumulative distribution function of the standard normal distribution; since it is impossible to know what a student's grades would be if she chose to switch programs, I use the average grades of a student's co-ethnics in other programs to estimate how a student would perform in these programs. $\widetilde{g}_{it}$ is calculated as follows. First, I calculate the average cumulative grade-point-average (CGPA) of i's co-ethnic students in all other programs. Then, I pick the highest average CGPA among all other programs and subtract student i's CGPA in the current program. Note that, similar to the mechanism of converting numerical grades to letter grades, I have grouped the numerical grades into

13 intervals, and assigned a value of 1 to 13 to each interval;[17] $\widetilde{e}_{it}$ is the difference between the highest co-ethnic share among all programs and the co-ethnic share in i's current program in period t; $\widetilde{z}_t$ is the difference between the highest program completion rate among all programs and the completion rate in a student's current program in period t; $\widetilde{u}_t$ is the difference between the lowest unemployment rate among all programs and the unemployment rate in a student's current program in period t; $\widetilde{m}_t$ is the difference between the highest annual earnings among all programs and the earnings in a student's current program in period t; $female_i$ is an indicator of whether student i is female; $CGPA_{t,65}$ is an indicator of whether student i has obtained a CGPA below 65; and $ethnic_i$ is a set of dummy variables indicating the ethnic group that student i belongs to.

The program completion rate data came from the Ministry of Colleges and Universities (2015). The unemployment rate and annual earnings were obtained from the 2001, 2006, 2016 Canadian Censuses and 2011 National Household Survey (NHS) public use microdata file. The sample is restricted to individuals between age 20 and 29 to make them more relevant for recent graduates. I use the unemployment rate and annual earning by major field of study in the Census and NHS to map with the program code in the university data.[18]

Recall that the variables in the empirical model are defined by the lexicographic ordering of the factors that influence students' program choices. Arguably, equation (2.8) uses ordering 1, which assumes that students give priority to their expected grades when making program changes, is more realistic. There is compelling evidence suggesting that university grades have an impact on students' future success in the labour market (Chia and Miller 2008). If undergraduate students want to pursue a Master's degree or Professional degree, grades will be critical and top priority in gaining admission to these degrees. Ordering 2, which assumes that students give first priority to co-ethnic shares, rather than grades, is less realistic.

I also examine the effect of co-ethnic peers separately for program changes that occur within faculty and between faculty. To do this, instead of using a binary outcome variable as the dependant variable, I distinguish the following three nominal outcomes: no program change, change within faculty, and change between faculty. I estimate a multinomial logit

[17]The idea to group the numerical grades is due to the fact that there would rarely be ties on grades so that the co-ethnic share would always be zero in the regression. The classified groups are listed as follows: CGPA[0,50)=1; CGPA[50,53)=2; CGPA[53,57)=3; CGPA[57,60)=4; CGPA[60,63)=5; CGPA[63,67)=6; CGPA[67,70)=7; CGPA[70,73)=8; CGPA[73,77)=9; CGPA[77,80)=10; CGPA[80,85)=11; CGPA[85,90)=12; CGPA[90,100]=13. I have obtained similar results using the grade percentile instead of grade level.

[18]Classified instructional programs in the Census and NHS are grouped into 12 major field of study.

model using the same regressors as in equation (2.8).

2.6 Results

Table 2.5 reports the results under the arguably more realistic assumption that students prioritize their academic grades over co-ethnic shares. Two different specifications are presented in the table. The first specification only includes the difference in the CGPA, co-ethnic share, program completion rate, unemployment rate, and annual earnings. The second specification includes an additional set of dummy variables that affect students' program choices. It aims to capture if the additional controls have any impact on the magnitude of the five factors in the first specification.

The estimate on the cumulative grade-point-average (CGPA) difference in column (1) tells us that a one level increase in the difference between the program with a student's highest expected grades and her current program serves to increase the likelihood of a program change by 2.0 ppts. The estimate on the co-ethnic share difference suggests that a one percentage point (ppt) increase in the co-ethnic share difference between the program with the highest co-ethnic share and a student's current academic program serves to increase the likelihood that she will change her academic program by 2.1 ppts. In other words, if students expect to maintain their grades when making program changes, they are more likely to change to programs with a higher share of their co-ethnics. The program completion rate difference is positively correlated with students' probability of changing programs. That is, a one ppt increase in the program completion rate difference between the program with the highest completion rate and the current program increases the probability of a program change by 1.4 ppts. The coefficient on the unemployment rate difference shows that a one percentage point increase in the difference between the program with the lowest unemployment rate and a student's current program serves to increase the likelihood that she will make program changes by 7.2 ppts. Lastly, the coefficient on the earnings difference suggests that a one ppt annual earnings increase between the program associated with the highest earnings and a student's current program will serve to increase her likelihood of making program changes by 0.5 ppts.

Column 2 adds female, CGPA below 65, ethnic group dummies, and interaction dummies between student visa status and ethnic groups into the model.[19] Compared to column 1, including additional control variables lowers the effect of the CGPA difference on the

[19] The reference group for ethnic group dummies is Chinese students; and the reference group for interaction terms is Chinese international students.

probability of a program change from 2.0 ppts to 0.7 ppts. However, the coefficient estimates on the co-ethnic share difference, program completion rate difference, unemployment rate difference, and earnings difference vary little. The female dummy estimate shows that women are 7.1 ppts more likely to change programs compared to men. The coefficient on the CGPA below 65 dummy shows that students whose CGPA is below 65 are 15.8 ppts more likely to change programs. Non-Asian students and Korean students are 2.3 and 3.5 ppts more likely to make program changes compared to Chinese students. The remaining ethnic groups are either equally likely (Filipino) or less likely to change programs than Chinese students. However, the estimated effects are not statistically significant at the 10 percent significance level. Compared to Chinese international students, non-Asian and Korean international students are less likely to make program changes, while Vietnamese and Japanese international students are more likely to change their programs.

Table 2.6 presents the results from a less realistic ordering, which assumes that students give priority to co-ethnic shares, rather than academic grades. The estimate on the co-ethnic share difference in column (1) suggests that a one ppt increase in the co-ethnic share difference between the program with the highest co-ethnic share and a student's current academic program serves to decrease the likelihood that she will change her academic program by 7.0 ppts. This contrasts with what the theory predicts. It reflects that the share of co-ethnic peers are not the top consideration when students make program changes at this university. Consistent with the findings in Table 2.5, the CGPA difference has a positive and significant effect on the probability of changing programs. Similarly, both the unemployment rate and earnings differences have positive effects on the probability of a program change. That is, a one ppt increase in the difference between the program with the lowest unemployment rate and a student's current program will increase the likelihood of switching program by 7.5 ppts. A one ppt increase in the difference between the program with the highest annual earnings and a student's current program will serve to increase the probability that she will change program by 0.6 ppts.

Adding more controls in columns (2) does little to change the magnitude of the estimates in column (1). In column (2), women are 6.7 ppts more likely to change programs, and students who obtained a CGPA below 65 are 17.8 ppts more likely to change programs. The coefficients on the ethnic group dummies tells us that non-Asian students are 1.8 ppts more likely to make program changes compared to Chinese students. The remaining ethnic groups are either equally likely (Korean) or less likely to change programs than Chinese students.

To this point, I have established the extent to which the increase in students' ethnic concentration within programs reflects their preferences to be in programs with co-ethnic peers. The results show that co-ethnic peers have a positive impact on program changes in the model in which grades are prioritized over peers. Since program changes could occur either within or between faculty, I compare the effect of co-ethnic peers on program changes that occur within and between faculty. Table 2.7 represents the results using a multinomial logit regression under the assumption that students prioritize grades over co-ethnic peers. The base outcome is students who do not change their program.

Similar to the specifications in the previous tables, columns (1) and (2) differ in the number of controls. By comparing the coefficients on the CGPA difference in column (1), the results suggest that a one level increase in the difference between the expected grade in the competing program and the grades in the current program appears to have a smaller effect on students' choices to change programs within their faculties (9.4 ppts) than to entirely change faculties (11.1 ppts). As students start updating their academic abilities after university entry and revise their program choices, they are more likely to switch to easier programs which are outside of their current faculties. Similarly, conditioning on the CGPA difference, one ppt increase in the co-ethnic share difference between the program with the highest co-ethnic share and a student's current program tends to have a lower probability of a within faculty program change (4.5 ppts) compared to a between faculty change (47.6 ppts). Intuitively, when students consider making between faculty program changes and expect to maintain their grades, having more co-ethnic peers would help them adapt quickly to the new learning environment.

With regards to the earning difference, it has a larger and significant impact on the probability of making between faculty program changes (5.6 ppts) than within faculty program changes (1.9 ppts). This pattern is also evident in column (2) despite adding more controls in the model. Because the differences in the labour market returns between programs are smaller within faculties than between faculties, if students want to flee outside of their faculties, the effect of labour market returns would have a larger impact on the probability of a program change. Column (2) also shows that compared to men, women are more likely to make within faculty than between faculty program changes. Moreover, students who obtained CGPA below 65 are more likely to make between faculty program changes than within faculty program changes. Since mandatory courses overlap across programs within faculties, students with lower grades are more likely to switch to other faculties. The coefficients on the ethnic group dummies tell us that compared to Chinese students, the rest of the ethnic groups are more likely to make between faculty program changes than within faculty program changes. Finally, compared to Chinese international students, international students in the rest of ethnic groups are more likely to make between than within faculty program changes, with the exception of Filipino international students.

2.7 Conclusions

This chapter seeks to shed light on the determinants of students' university program choices. The results of my analysis indicate that students' program choices at the time of initial enrolment lead to a concentration of ethnic groups within academic programs. The increase in the ethnic concentration of students across cohorts is largely driven by the enrolment of Chinese international students. That is, Chinese international students are becoming more concentrated in programs with a higher share of their co-ethnic peers when they first arrive at the university.

As students receive new information about their abilities and program information after enrolling, they begin to update their expectations and revise their program choices. Program changing is common, with nearly one-quarter of students changing their program at least once over the course of their undergraduate studies. Among those students who make program changes, three-quarters of them change programs within faculties. The proportion of students who change programs is higher among women than men. Foreign students change their programs at a higher rate than domestic students. The mean share of co-ethnic peers increases after program changes for all ethnic groups, except Chinese.

These program changes lead to a further increase in the ethnic concentration of students over the course of their undergraduate studies. This raises the concern that students are making program changes based on social considerations which might lead them to make academically inefficient choices. Students may be too short-sighted and exhibit a tendency towards myopic behaviour. That is, students trade off their current utility gains from being with their co-ethnic peers, but they choose programs in which their skills are not the greatest. They may go into professions or careers where they are not most capable. However, the empirical results suggest otherwise. The more realistic model suggests that if students expect to maintain their academic standings when considering program changes, the presence of more co-ethnic peers increases the likelihood of a program change. The alternative model in which students prioritize co-ethnic peers over grades provides no evidence that the share of co-ethnic peers is positively correlated with students' probability of program changes. In other words, students' program changes are driven by their academic aptitudes, rather than social considerations. The results from two models imply that students make efficient program choices, which provide the best match between their academic aptitudes and their programs.

Finally, I find that the effect of having more co-ethnic peers in programs is found to have a larger and significant effect on the probability of a between- than within-faculty program change. The most obvious explanation is that if students change programs within faculties, they are more likely to be with the same co-ethnic peers, because program required courses overlap within faculties. On the other hand, if they change to an entirely different faculty, they benefit more from having a higher share of co-ethnic peers. For instance, their peers can help them better adapt to the new program through collaborative learning, since the course materials may be entirely different from the old program. Also, having more peers in programs creates a relaxed environment where student will be less likely crowded out.

Table 2.1: Ethnic concentration of students within programs across entry cohorts

cohort	non-Asian student share	empirical index	mean estimate random sorting	ratio	95% CI of mean estimate		95% CI ratio	
2004	0.627	0.508	0.463	1.099	0.461	0.465	1.103	1.095
		(0.025)	(0.003)	(0.047)				
2005	0.596	0.490	0.433	1.131	0.432	0.435	1.136	1.126
		(0.024)	(0.003)	(0.048)				
2006	0.564	0.463	0.408	1.134	0.407	0.411	1.138	1.128
		(0.022)	(0.003)	(0.048)				
2007	0.572	0.469	0.416	1.127	0.415	0.418	1.131	1.121
		(0.023)	(0.003)	(0.044)				
2008	0.548	0.463	0.400	1.157	0.399	0.402	1.161	1.151
		(0.022)	(0.003)	(0.041)				
2009	0.549	0.464	0.407	1.141	0.405	0.408	1.145	1.136
		(0.021)	(0.003)	(0.041)				
2010	0.537	0.459	0.393	1.167	0.392	0.395	1.172	1.163
		(0.020)	(0.003)	(0.037)				
2011	0.513	0.441	0.380	1.163	0.378	0.382	1.167	1.157
		(0.020)	(0.002)	(0.040)				
2012	0.509	0.436	0.377	1.157	0.376	0.379	1.162	1.152
		(0.019)	(0.003)	(0.039)				
2013	0.483	0.426	0.362	1.177	0.361	0.364	1.182	1.172
		(0.018)	(0.002)	(0.035)				
2014	0.489	0.424	0.369	1.149	0.368	0.371	1.154	1.145
		(0.017)	(0.003)	(0.036)				
2015	0.478	0.431	0.364	1.182	0.363	0.366	1.186	1.177
		(0.017)	(0.002)	(0.033)				

Notes: non-Asian group includes students other than Chinese, South Asian, Japanese, South Korean, Vietnamese, and Filipino. ratio = empirical index/mean estimate; 95% CI ratio = empirical index/95% CI of mean estimate. Bootstrapped standard errors (*100) are in parentheses.

Table 2.2: Calculated ratio within programs over the course of undergraduate studies

cohort	year 1	year 2	year 3	year 4
2004	1.100	1.098	1.103	1.104
	(0.048)	(0.044)	(0.043)	(0.047)
2005	1.135	1.127	1.137	1.136
	(0.048)	(0.045)	(0.044)	(0.047)
2006	1.135	1.126	1.137	1.143
	(0.047)	(0.044)	(0.043)	(0.045)
2007	1.126	1.127	1.148	1.148
	(0.043)	(0.040)	(0.039)	(0.041)
2008	1.160	1.153	1.163	1.172
	(0.039)	(0.038)	(0.037)	(0.038)
2009	1.142	1.145	1.142	1.149
	(0.039)	(0.037)	(0.037)	(0.038)
2010	1.167	1.163	1.174	1.170
	(0.037)	(0.035)	(0.034)	(0.036)
2011	1.170	1.158	1.160	1.170
	(0.039)	(0.037)	(0.037)	(0.038)
2012	1.162	1.164	1.165	1.168
	(0.037)	(0.036)	(0.035)	(0.037)
2013	1.184	1.167	1.166	1.173
	(0.034)	(0.033)	(0.033)	(0.036)
2014	1.178	1.177	1.193	1.247
	(0.034)	(0.033)	(0.034)	(0.042)
2015	1.188	1.194	1.221	–
	(0.032)	(0.032)	(0.041)	–
average	1.155	1.151	1.160	1.166
	(0.005)	(0.004)	(0.013)	(0.025)

Notes: The ratio is calculated as empirical index/mean estimate. Bootstrapped standard errors (*100) are in parentheses. The numbers in the last row represent the weighted average of ratio.

Table 2.3: Proportion of students who change programs at least once

Program changes	%	s.e
overall	23.72	0.001
within faculty among switchers	75.38	0.002
between faculty among switchers	24.62	0.001
Ethnic group		
non-Asian	24.07	0.002
Chinese	23.03	0.003
South Asian	23.35	0.005
Korean	26.03	0.011
Vietnamese	23.78	0.012
Filipino	22.99	0.014
Japanese	20.30	0.037
Visa status		
non-international student	23.63	0.002
international student	24.31	0.005
Gender		
male	22.26	0.002
female	25.42	0.003
Faculty at the enrolment		
A	26.69	0.004
B	13.10	0.002
C	30.01	0.004
D	25.33	0.003

Notes: The total sample size is 516,733. The sample includes all the undergraduate students except "2+2" students, dropouts, and students over the age of 25. A program change is defined as follows: (1) a student first enrols into a direct-entry program and then changes to another program; (2) a student first enrols into a general program and chooses a specialized program, she then switches to another program. The proportions of program changes in Faculty A, B, C, and D do not sum to one.

Table 2.4: Mean co-ethnic shares in students' academic programs

	No program changes		Program changes			
			before the change		after the change	
	mean	s.e	mean	s.e	mean	s.e
Overall	0.470	0.000	0.499	0.001	0.524	0.001
Ethnic group						
non-Asian	0.608	0.000	0.644	0.001	0.688	0.001
Chinese	0.429	0.001	0.473	0.002	0.430	0.002
South Asian	0.178	0.000	0.160	0.001	0.205	0.002
Korean	0.072	0.001	0.066	0.002	0.130	0.004
Vietnamese	0.054	0.001	0.056	0.003	0.110	0.005
Filipino	0.045	0.001	0.046	0.003	0.108	0.005
Japanese	0.028	0.002	0.083	0.025	0.085	0.011
Immigration status						
Canadian	0.479	0.001	0.512	0.001	0.535	0.001
PR	0.376	0.001	0.383	0.004	0.389	0.003
IS	0.459	0.001	0.488	0.003	0.477	0.003
Ethnic X immigration status						
Status = Canadian						
non-Asian	0.618	0.000	0.652	0.001	0.690	0.001
Chinese	0.362	0.001	0.389	0.002	0.349	0.002
South Asian	0.168	0.001	0.155	0.002	0.187	0.002
Korean	0.058	0.001	0.061	0.003	0.093	0.004
Vietnamese	0.049	0.001	0.052	0.003	0.095	0.005
Filipino	0.040	0.001	0.042	0.003	0.096	0.006
Japanese	0.023	0.002	0.020	0.004	0.043	0.005
Status = permanent resident						
non-Asian	0.535	0.002	0.546	0.006	0.598	0.005
Chinese	0.483	0.002	0.497	0.004	0.477	0.005
South Asian	0.183	0.001	0.158	0.003	0.209	0.004
Korean	0.069	0.002	0.055	0.004	0.135	0.008
Vietnamese	0.090	0.020	0.022	0.002	0.118	0.039
Filipino	0.033	0.001	0.034	0.004	0.048	0.004
Japanese	0.022	0.003	–	–	–	–

Status = international student						
non-Asian	0.485	0.002	0.492	0.007	0.557	0.006
Chinese	0.544	0.001	0.575	0.003	0.560	0.003
South Asian	0.177	0.001	0.150	0.003	0.190	0.004
Korean	0.100	0.005	0.069	0.005	0.177	0.015
Vietnamese	0.043	0.003	0.026	0.003	0.090	0.025
Filipino	0.038	0.003	0.025	0.003	0.077	0.021
Japanese	0.023	0.002	0.230	0.087	0.101	0.024
Visa status						
non-international student	0.468	0.000	0.497	0.001	0.519	0.001
international student	0.459	0.001	0.488	0.003	0.477	0.003
Gender						
male	0.439	0.001	0.460	0.002	0.487	0.001
female	0.509	0.001	0.538	0.002	0.560	0.002

Notes: The sample includes all the undergraduate students except "2+2" students, dropouts, and students over the age of 25. A program change is defined as follows: (1) a student first enrols into a direct-entry program and then changes to another program; (2) a student first enrols into a general program and chooses a specialized program, she then switches to another program. If a student makes multiple times program change, each program change is included in the calculation of mean co-ethnic shares.

Table 2.5: The effect of different factors on the probability of students' program changes under the assumption that students prioritize grades over co-ethnic shares

	(1)	(2)
	program change	program change
CGPA difference	0.020***	0.007***
	(0.001)	(0.001)
co-ethnic share difference	0.021***	0.028***
	(0.003)	(0.003)
program completion rate difference	0.014*	0.016**
	(0.009)	(0.008)
unemployment rate difference	0.072**	0.070***
	(0.026)	(0.026)
earnings difference	0.005***	0.007***
	(0.001)	(0.001)
female		0.071***
		(0.001)
CGPA below 65		0.158***
		(0.002)
non-Asian		0.023***
		(0.002)
South_Asian		-0.001
		(0.002)
Korean		0.045***
		(0.004)
Vietnamese		-0.003
		(0.005)
Filipino		0.009
		(0.006)
Japanese		-0.0461**
		(0.015)
is*non-Asian		-0.010*
		(0.005)
is*South_Asian		-0.005
		(0.005)
is*Korean		-0.072***
		(0.010)
is*Vietnamese		0.070*
		(0.028)
is*Filipino		-0.035
		(0.024)
is*Japanese		0.108**
		(0.038)
observations	516,733	516,733
pseudo R-squared	0.006	0.020

Notes: The dependent variable is a binary outcome variable indicating whether a student has made a program change. The independent variables are five main factors that affect students' program changes, female, CGPA, and ethnicity dummies. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6: The effect of different factors on the probability of students' program changes under the assumption that students prioritize co-ethnic shares over grades

	(1)	(2)
	program change	program change
co-ethnic share difference	-0.070***	-0.073***
	(0.003)	(0.003)
CGPA difference	0.020***	0.008***
	(0.002)	(0.002)
program completion rate difference	0.012	0.014
	(0.008)	(0.008)
unemployment rate difference	0.075**	0.063*
	(0.026)	(0.026)
earnings difference	0.006***	0.007***
	(0.001)	(0.001)
female		0.067***
		(0.001)
CGPA below 65		0.178***
		(0.002)
non-Asian		0.018***
		(0.002)
South_Asian		-0.019***
		(0.002)
Korean		0.013**
		(0.004)
Vietnamese		-0.035***
		(0.005)
Filipino		-0.021***
		(0.005)
Japanese		-0.079***
		(0.014)
is*non-Asian		0.001
		(0.005)
is*South_Asian		-0.005
		(0.005)
is*Korean		-0.072***
		(0.010)
is*Vietnamese		0.070*
		(0.028)
is*Filipino		-0.035
		(0.024)
is*Japanese		0.106**
		(0.038)
observations	516,733	516,733
pseudo R-squared	0.001	0.020

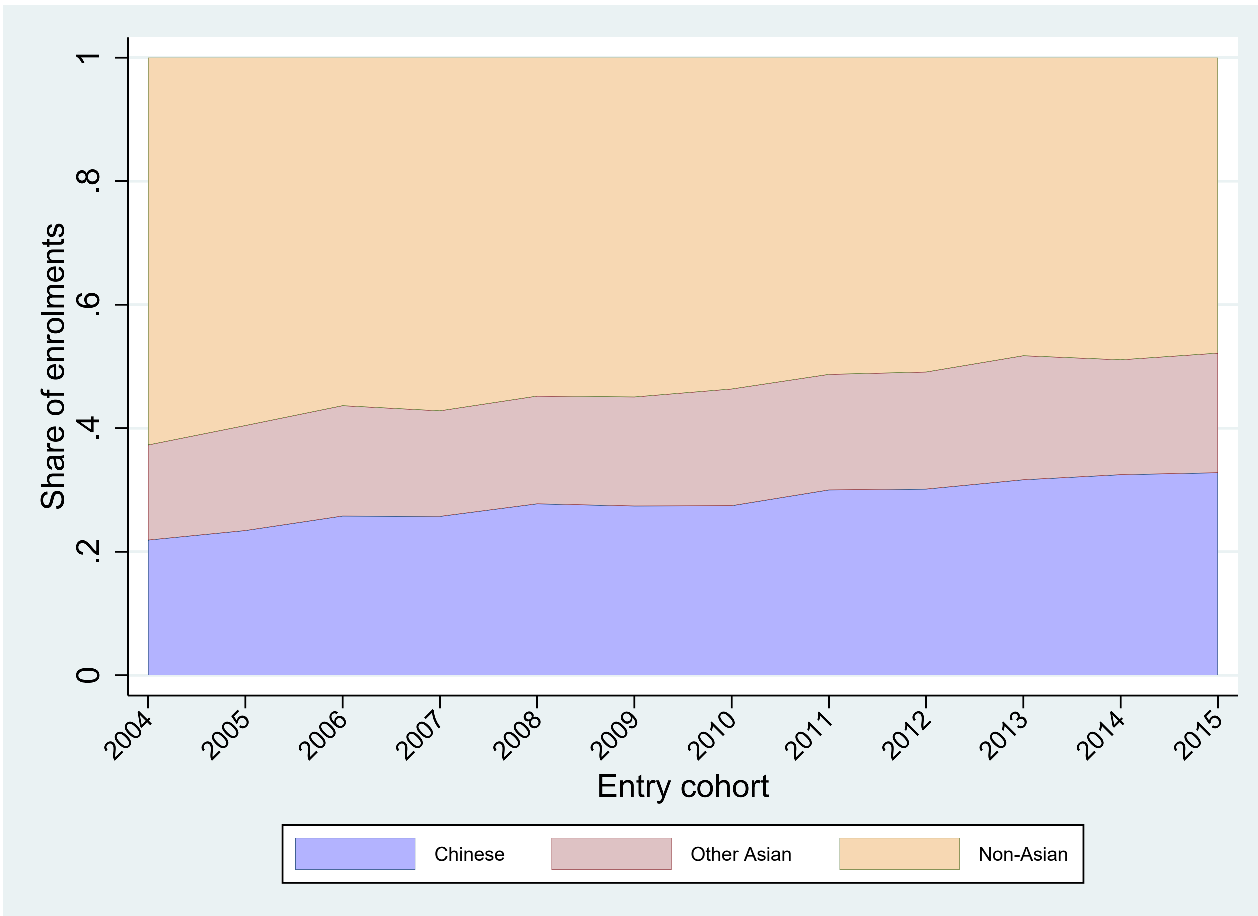
Notes: The dependent variable is a binary outcome variable indicating whether a student has made a program change. The independent variables are five main factors that affect students' program changes, female, CGPA, and ethnicity dummies. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7: The effect of different factors on the probability of making within and between faculty program changes under the assumption that students prioritize grades over co-ethnic shares

no program change (base outcome)	within faculty		between faculty	
	(1)	(2)	(1)	(2)
CGPA difference	0.094***	0.042***	0.111***	-0.004
	(0.002)	(0.002)	(0.004)	(0.004)
co-ethnic share difference	0.045***	0.061***	0.476***	0.630***
	(0.016)	(0.017)	(0.034)	(0.036)
program completion rate difference	0.064	0.072	0.078	0.087
	(0.037)	(0.037)	(0.061)	(0.062)
unemployment rate difference	0.381**	0.372**	0.213	0.245
	(0.134)	(0.135)	(0.204)	(0.209)
earnings difference	0.019***	0.028***	0.056***	0.062***
	(0.004)	(0.004)	(0.007)	(0.007)
female		0.401***		-0.084***
		(0.007)		(0.014)
CGPA below 65		0.612***		1.189***
		(0.010)		(0.019)
non-Asian		0.106***		0.180***
		(0.008)		(0.017)
South_Asian		-0.025*		0.165***
		(0.012)		(0.026)
Korean		0.113***		0.718***
		(0.021)		(0.038)
Vietnamese		-0.067**		0.322***
		(0.025)		(0.050)
Filipino		-0.011		0.386***
		(0.028)		(0.057)
Japanese		-0.354***		0.422**
		(0.088)		(0.158)
is*non-Asian		-0.072**		0.100*
		(0.024)		(0.049)
is*South_Asian		-0.076**		0.213***
		(0.028)		(0.051)
is*Korean		-0.366***		-0.379***
		(0.058)		(0.010)
is*Vietnamese		0.154		0.829***
		(0.136)		(0.198)
is*Filipino		-0.038		-1.778**
		(0.128)		(0.584)
is*Japanese		0.469**		0.481
		(0.180)		(0.297)
observations	516,733 3	516,733	516,733	516,733
pseudo R-squared	0.006	0.020	0.006	0.020

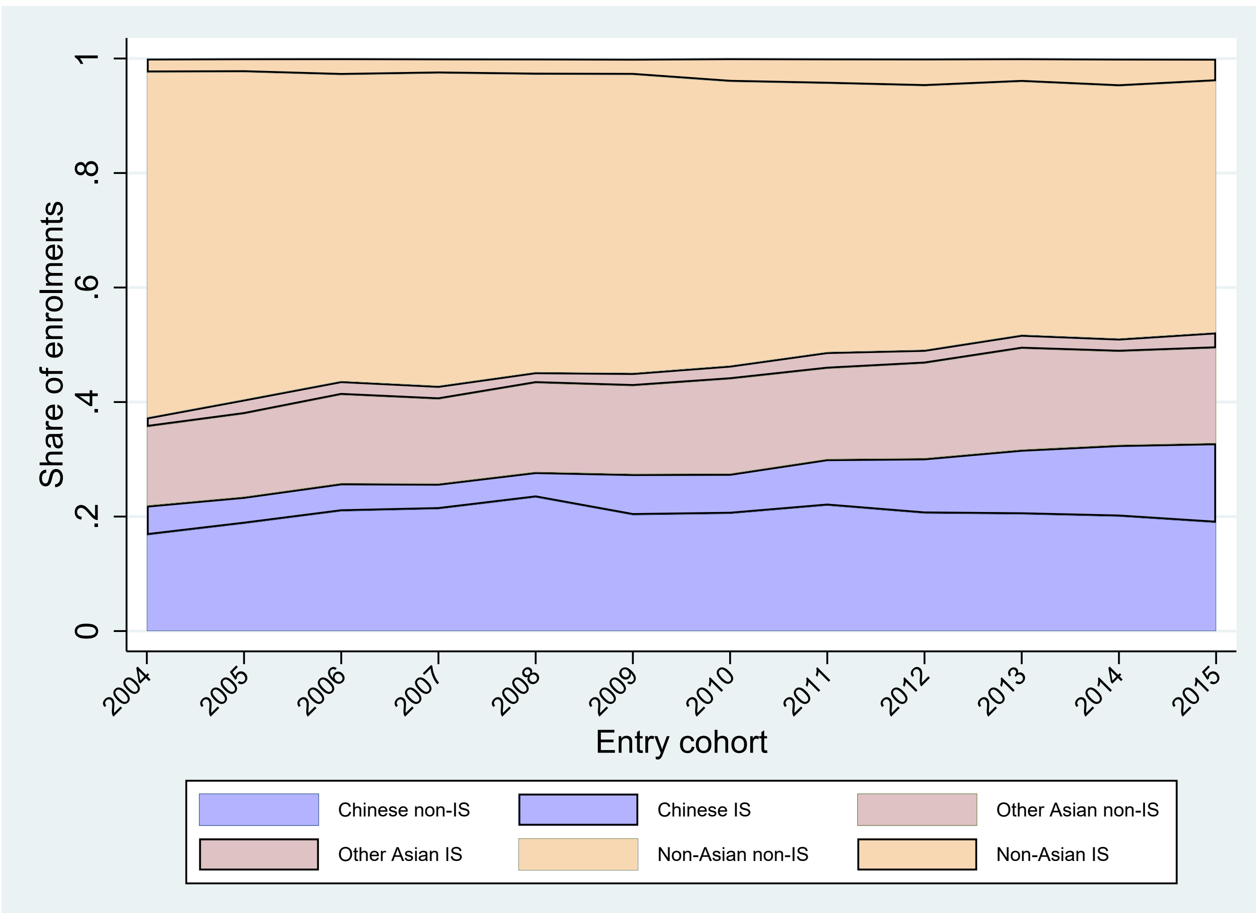
Notes: The dependent variable is a categorical variable which includes no program change, change within and between faculties. The independent variables are five main factors that affect students' program changes, female, CGPA, and ethnicity dummies. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 2.1: Share of enrolments by broader ethnic group, 2004-2015 entry cohorts



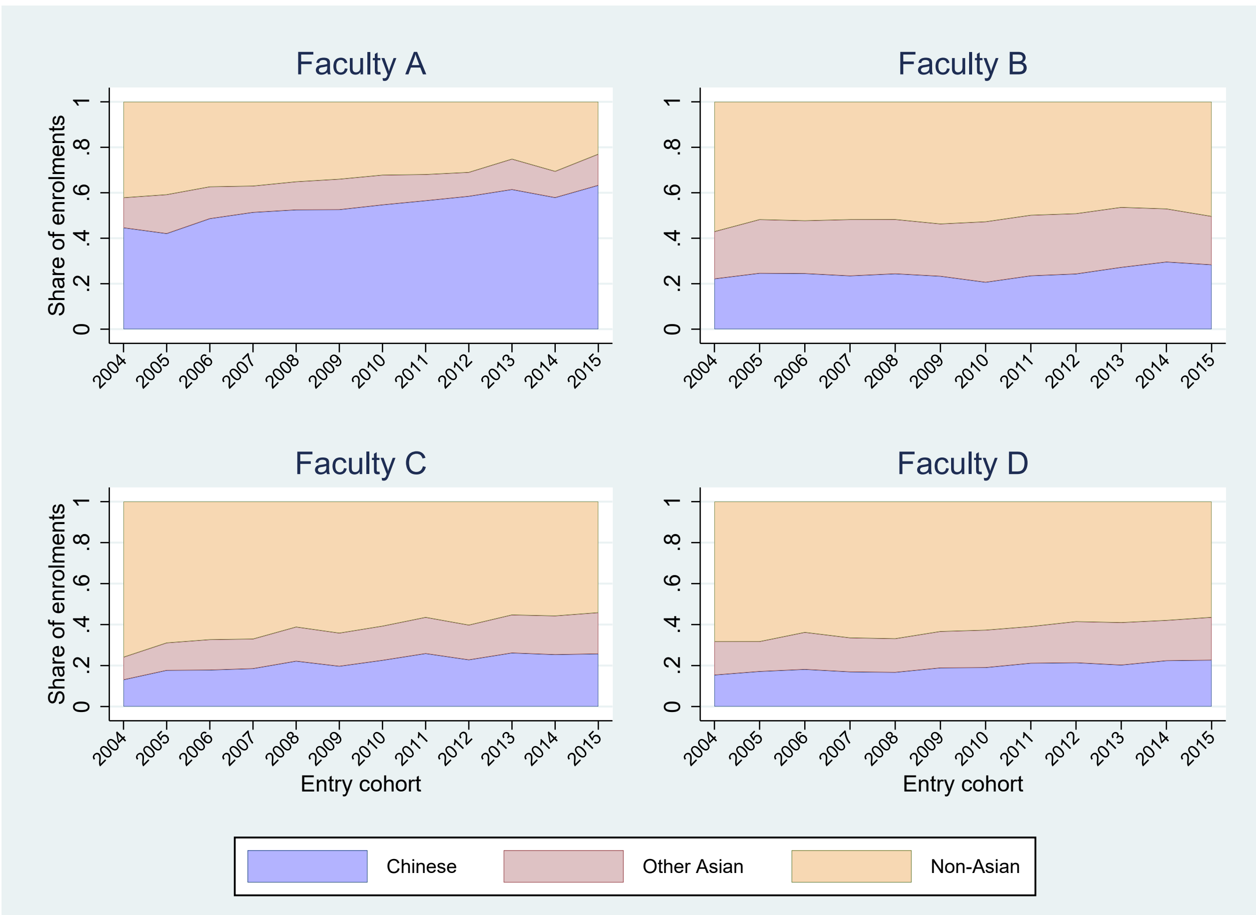
Notes: Other Asian includes: Filipino, Japanese, South Asian, South Korean, and Vietnamese; non-Asian includes everybody other than Chinese and other Asian groups.

Figure 2.2: Share of student enrolments by visa status and broader ethnic group, 2004-2015 entry cohorts



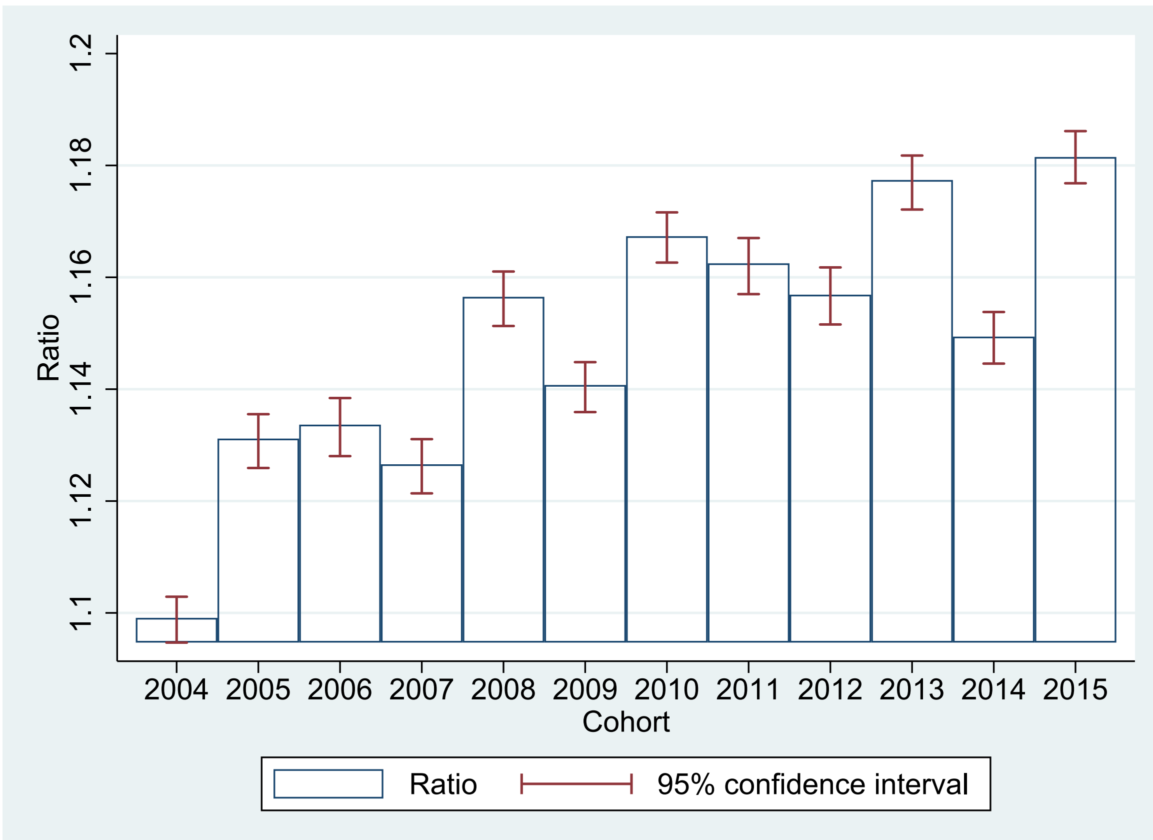
Notes: Other Asian includes: Filipino, Japanese, South Asian, South Korean, and Vietnamese.

Figure 2.3: Share of enrolments by broader ethnic group and faculty, 2004-2015 entry cohorts



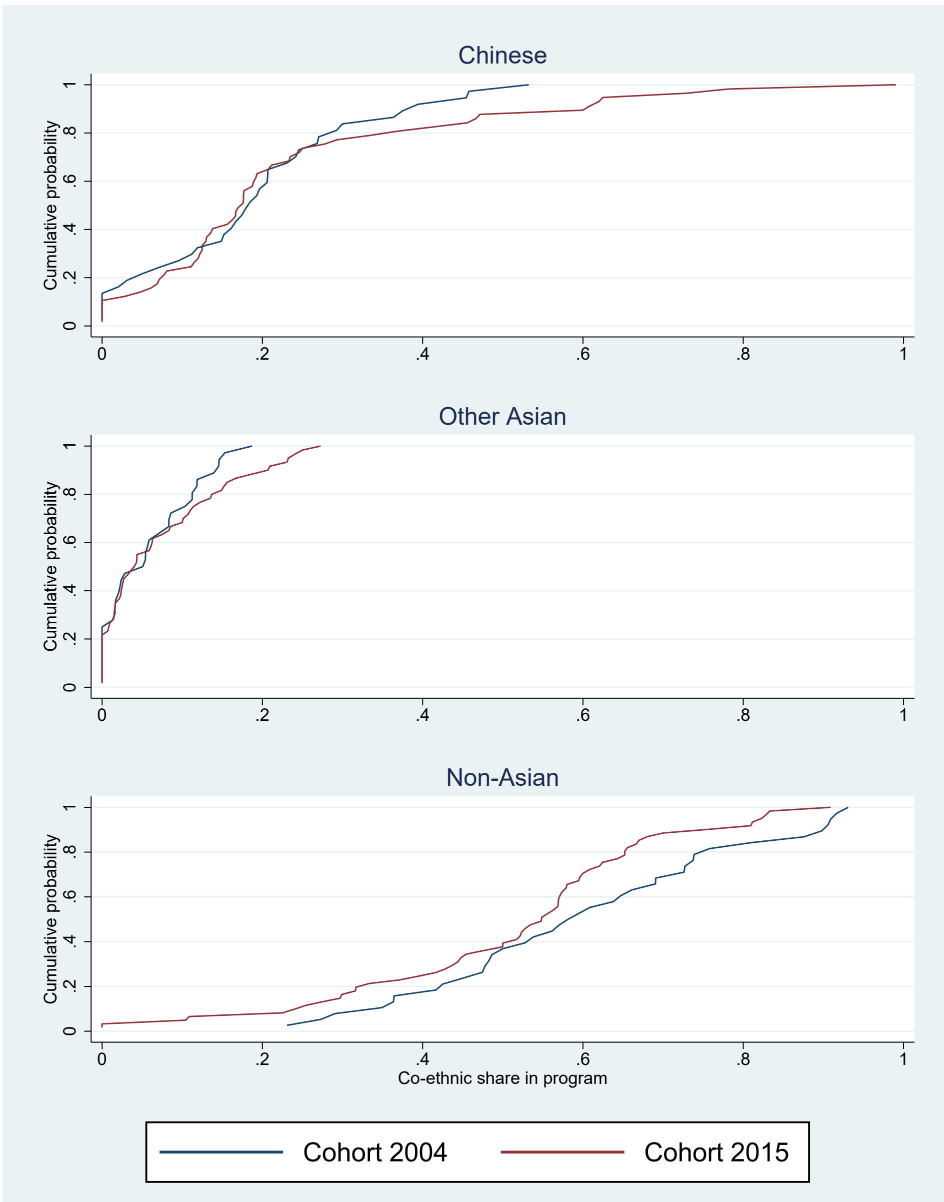
Notes: Other Asian includes: Filipino, Japanese, South Asian, South Korean, and Vietnamese; non-Asian includes everybody other than Chinese and other Asian groups.

Figure 2.4: A measure of how students are ethnically concentrated across cohorts



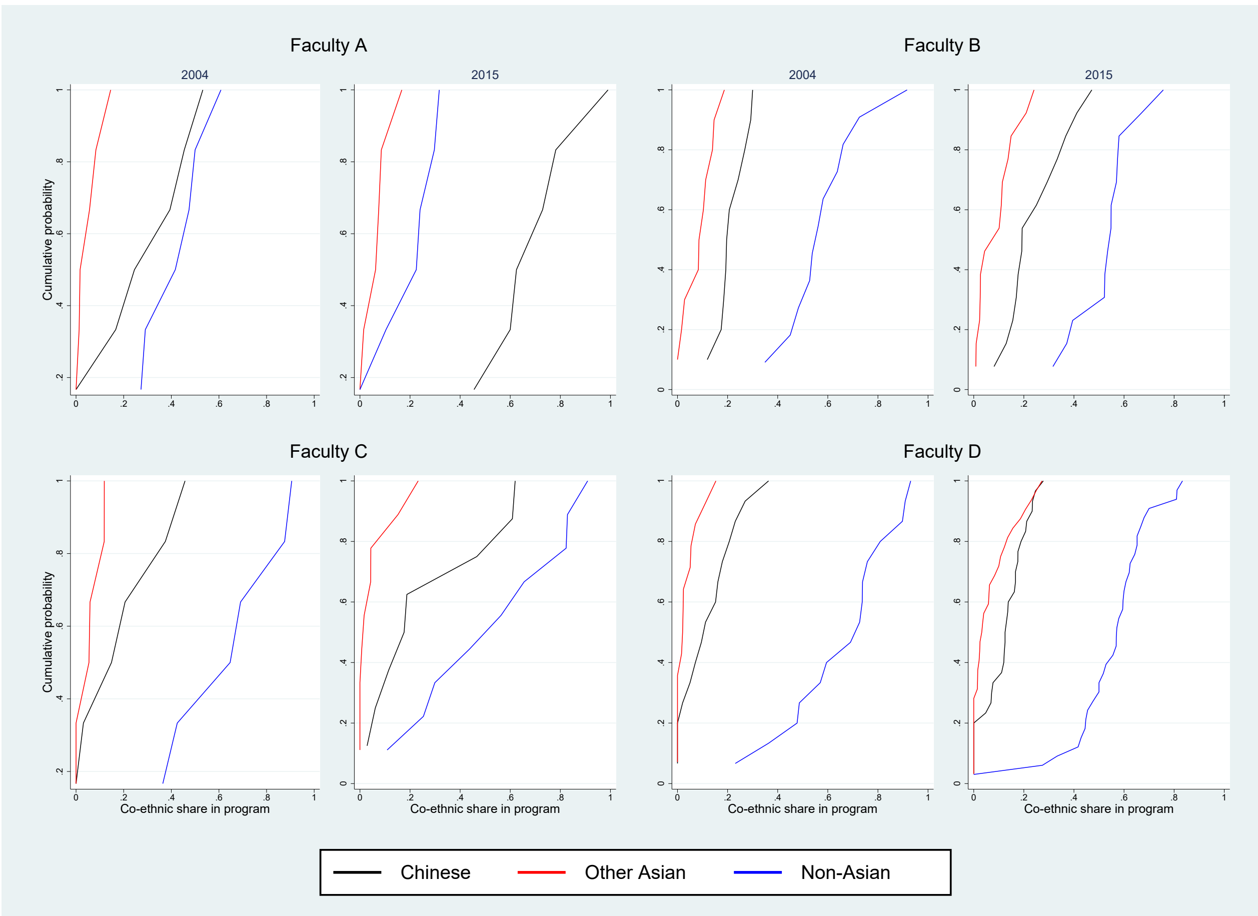
Notes: The ratio is calculated as empirical index/mean estimate.

Figure 2.5: Cumulative distribution function of ethnic shares by program, 2004 and 2015 entry cohorts



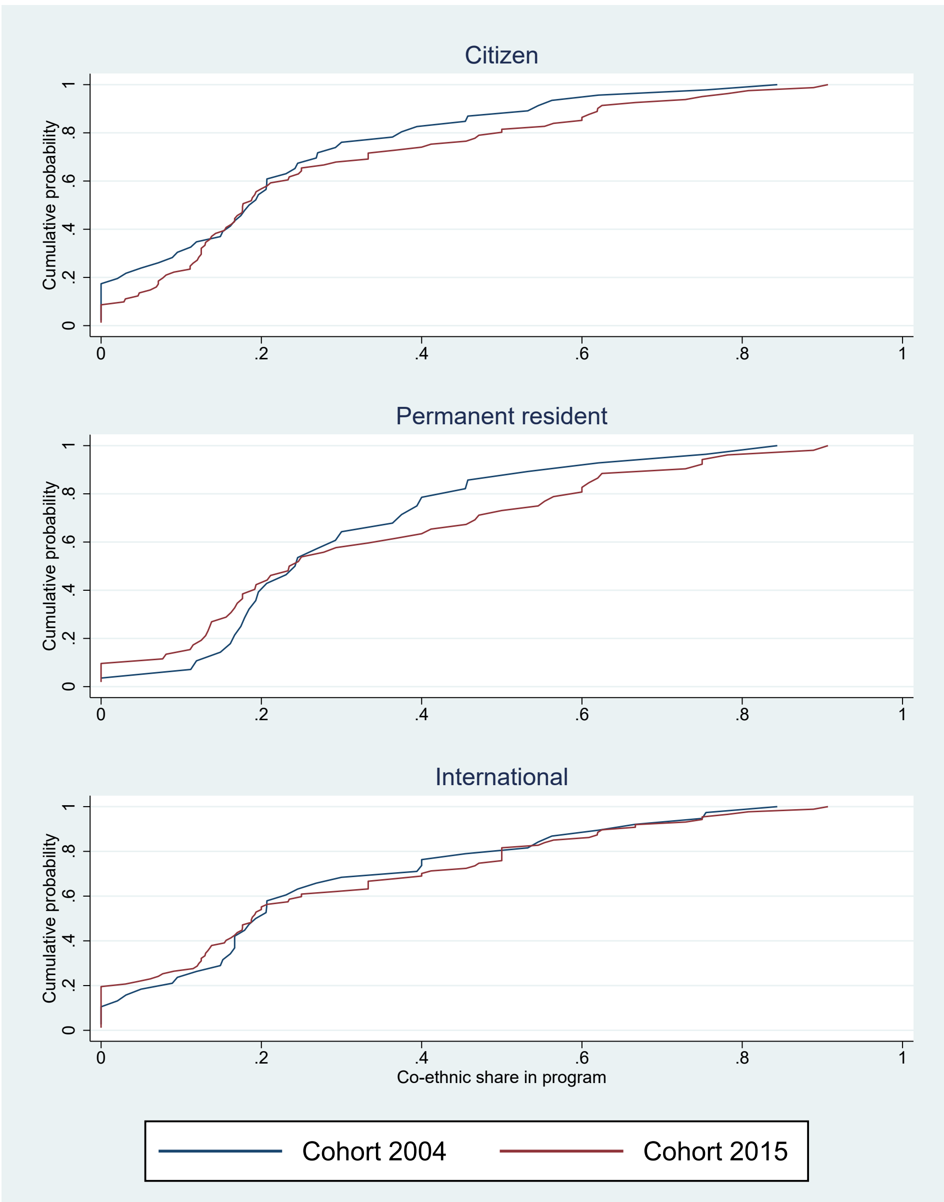
Notes: Other Asian includes: Filipino, Japanese, South Asian, South Korean, and Vietnamese; non-Asian includes everybody other than Chinese and other Asian groups.

Figure 2.6: Cumulative distribution function of ethnic shares by faculty and program, 2004 and 2015 entry cohorts



Notes: Other Asian includes: Filipino, Japanese, South Asian, South Korean, and Vietnamese; non-Asian includes everybody other than Chinese and Other Asian groups.

Figure 2.7: Cumulative distribution function of Chinese shares by student status and program, 2004 and 2015 entry cohorts



Chapter 3

The Relative Labour Market Performance of Former International Students: Evidence from the Canadian National Graduates Survey

Zong Jia Chen and Mikal Skuterud

3.1 Introduction

In January 2015, Canada introduced a new system for processing economic-class immigrants in response to a growing application backlog. Rather than process applications on a first-in first-out basis, the new Express Entry (EE) system gives priority to candidates deemed most likely to succeed economically. Within months of its introduction, the EE system was criticized for being unfairly biased against international students, as the criteria used to rank candidates gave no preference to candidates with Canadian educational credentials. Instead, the system prioritized candidates with arranged employment, regardless of their educational backgrounds. In response to growing concerns that foreign students were being bypassed in the applicant pool, the government revised the EE system in November 2016 stating that it sought to increase its reliance on international students as a source of new immigrants.

Arguably, the biggest proponents of the government's objective to ease the transition to permanent residency for international students, besides foreign students themselves, are Canada's postsecondary institutions. Following significant cuts to provincial funding through the 1990s, universities and colleges were forced to increase their reliance on tuition revenues. This provided a solution while enrolments were increasing, but recent demographic shifts are resulting in a decline in the domestic university-aged population. Postsecondary institutions are responding by looking to the tuition fees of foreign students to balance their budgets, which unlike domestic fees, are not capped by provincial governments.[1] Critical to foreign student recruitment are immigration policies that promise international students a pathway to Canadian permanent residency. In this regard, recent changes in immigration policy are highly complementary to the efforts of postsecondary institutions.

In theory, the government's preference for international students is well justified. Canadian educated immigrants are less likely to experience credential recognition issues. The skills they have acquired are more likely to be relevant to the Canadian workplace. Their time spent studying in Canada should help them to acculturate more easily to Canadian society. This includes acquiring superior English and French skills, as well social networks that may be critical in job search following graduation. Canadian education may also provide opportunities to gain Canadian work experience, through cooperative education for example, which may be advantageous in finding good jobs following graduation. In justifying his intention to revise the EE System, former Minister of Immigration, John McCallum, argued: "International students are the best source of immigrants, in the sense that they're educated, they're young, they speak English or French, and they know something of the country. So we should be doing everything we can do to court them."[2]

Notwithstanding the conventional wisdom, the Canadian evidence on the labour market performance of former international students (FISs) is mixed. Studies estimating separate labour market returns to foreign and Canadian sources of education have consistently found little to no evidence that immigrants' foreign credentials are discounted relative to their Canadian credentials (Ferrer and Riddell 2008; Skuterud and Su 2012; Bonikowska, Hou, and Picot 2015).[3] Sweetman and Warman (2014) compare weekly and hourly earnings of FISs who immigrated to Canada as principal applicants under the Federal government's Skilled Worker Program (FSWP) to other immigrants, who entered under this program and find some evidence of higher earnings among FISs four years after landing. Their results,

[1]The number of foreign students enrolled in Canadian universities and colleges increased from 43,296 to 214,782 between 1999-2000 and 2014-2015 (see CANSIM table 477-0031).

[2]See Michelle Zilio and Simona Chiose, "Ottawa looks to ease international students' path to permanent residency," *Globe and Mail*, March 14, 2016.

[3]The decision not to differentially reward foreign and Canadian education in the Express Entry point system, known as the Comprehensive Ranking System (CRS), was based on this evidence.

however, vary significantly depending on which FSWP criteria are used to define the sample and whether individuals with zero earnings are included in the sample. Finally, Hou and Lu (2017) employ a linkage of administrative immigration and tax data to compare the annual earnings of two cohorts (early-1990s and mid-2000s) of university-educated FISs to both foreign-born-and-educated (FBE) immigrants and Canadian-born-and-educated (CBE) university graduates who entered the labour market at similar times. In contrast to much of the existing evidence, they find significantly higher average earnings among FISs than among FBE immigrants, both in the short run and 10 years after arrival. However, this earnings advantage is small in comparison to the gap relative to the CBE comparison group.

In this article, we exploit data from the Canadian National Graduates Survey (NGS), which samples graduates of postsecondary programs and identifies whether respondents were enrolled as international students during their studies. Using the 2002, 2005, 2007, and 2013 waves, we compare the labour market performance of three graduating cohorts (2000, 2005, and 2009/2010) of FISs who have transitioned to permanent residency to their CBE counterparts graduating at the same time with similar credentials in similar fields of study. In addition, using data from the Labour Force Survey (LFS), we extract a sample of FBE immigrants whose landing years in Canada correspond to the graduating years of the FISs in our NGS sample and compare labour market outcomes among similarly educated FISs and FBE immigrants from similar regions of the world.

The contribution of our analysis is threefold. First, in comparing FISs and FBE immigrants, we obtain evidence on whether using the Canadian postsecondary education system to screen immigrants leads to better labour market outcomes than screening immigrants on their educational credentials, regardless of their source. This evidence directly informs whether giving preference to Canadian-educated applicants in the EE system is optimal. Second, in comparing FISs with CBE individuals graduating from similar academic programs, we obtain evidence on the challenges FISs experience, thereby informing immigrant settlement policies. Of particular importance are: (i) job search frictions, as FISs are likely to have weaker social networks; (ii) discrimination in recruitment by Canadian employers against FISs with foreign names (Oreopoulos 2011); and (iii) English/French language difficulties, which will may present communication challenges in the job search process and in the workplace. However, note that in comparing FISs to CBE individuals from the same academic programs, credential recognition issues, emphasized in much of the current literature, cannot be a contributing factor.

Finally, with three cohorts of FISs spanning the first decade of the 2000s, we obtain evidence on whether there has been any deterioration in the labour market performance of FISs as postsecondary institutions and governments have reached deeper into foreign student pools to meet their student and immigration demands. As Canada moves to increase its reliance on international students, monitoring the relative labour market performance of FISs is critical.[4] Since FBE immigrants from common origin countries are likely to be similarly affected by weak social networks, discrimination, and language difficulties, evidence that the labour market outcomes of FISs are declining relative to both comparison groups is arguably most consistent with a tradeoff in the average labour market quality of FISs as their share of postsecondary graduates and immigrants has increased.

Consistent with the findings of Hou and Lu (2017), we find that FISs outperform FBE immigrants by a substantial margin, but lag their CBE counterparts. This is true for men and women and over a wide range of labour market outcomes. However, the FIS gaps we identify relative to the CBE comparison group are modest. In fact, we find essentially no shortfall in the average earnings of male FISs and CBE postsecondary graduates and only small gaps for women when we do not condition on education level and field of study. However, when we compare FISs and CBE graduates from similar academic programs, the gaps become larger and tend to be largest for women with college diplomas, in fields outside of math and computer science, among Chinese men and South-Asian women, and at the lower end of the earnings distribution than at the top. Moreover, we find some evidence, particularly among women, that the relative performance of FISs has tended to deteriorate over time relative to both the FBE and CBE comparison groups.

The remainder of the paper is organized as follows. In the following section, we examine recent changes in the international student share of Canadian postsecondary graduates and new immigrants. The following two sections describe the NGS and LFS data and the methodology we use to examine the relative labour market performance of FISs. Section 4 examines the results and the concluding section summarizes our main findings and discusses their implications for foreign student selection and settlement policies of postsecondary institutions and governments.

[4]There is evidence that Australia experienced such a tradeoff in immigrant quality following a 2000 policy revision favouring international students, which spurred the growth of a vocation education sector targeting foreign students with questionable quality standards, as well as compromised academic and progression standards in more select established institutions (Birrell, Hawthorne, and Richardson 2006; Hawthorne 2010).

3.2 International Student Shares of Graduates and Immigrants

According to data from Statistics Canada's Post-Secondary Information System (PSIS), the international student share of postsecondary student enrolments and graduates increased steadily from about 3% in 1999 to slightly more than 10% by 2014.[5] In Figure 3.1, we plot the international student shares of graduates separately for universities and colleges and by gender. The data reveal a shift towards foreign student enrolments within both colleges and universities. Although universities relied more on foreign students than colleges did throughout the period, recent years have seen a larger shift within colleges. Among male college students, the increase has been particularly dramatic, doubling from 6% to 12% between 2010 and 2014. As postsecondary institutions reach deeper into the foreign student applicant pools, the question is whether there has been any tradeoff in the average quality of graduating foreign students. Of course, to the extent that pools of applicants have been similarly growing, through the student recruitment efforts of postsecondary institutions and immigration policy changes luring students with ambitions to settle permanently in Canada, it is possible that quality has been maintained.

In Figure 3.2, we use administrative data from Immigration, Refugees, and Citizenship Canada (IRCC) to plot the share of new permanent residents who had any point in the past held a study visa in Canada by broad immigration category. The FIS share of new permanent residents was stagnant at 6-7% between 2005 and 2010, but has been increasing steadily since, so that by 2016, 11% of all new immigrants were FISs. This increase appears to be entirely driven by economic-class immigration, as the FIS share of humanitarian immigration decreased over the period to below 5%, while the FIS share of family class immigration was relatively stable between 6% and 9%. By 2016, 15% of economic-class immigrants were FISs, which was twice as large as the FIS share five years earlier. This increase is entirely consistent with shifts in immigrant selection policy favouring FISs.

In Figure 3.3, we examine this increase further by considering through which economic-class programs FISs are entering. The data reveal an important shift since 2005 away from the FSWP towards both the Canadian Experience Class (CEC) and Provincial Nominee Programs (PNPs) so that by 2016, each of these three programs accounted for roughly one-third of FIS immigration (within the economic-class stream). There is good reason to believe that the major immigration hurdle for FISs is satisfying Canadian work experience requirements. The challenge reflects, at least in part, the hesitancy of employers to recruit

[5]The PSIS data are based on the administrative data of Canada's postsecondary institutions, which are provided to Statistics Canada. See CANSIM tables 473-0031 and 473-0032.

workers with a precarious immigration status. In this respect, the Ontario and British Columbia PNPs are particularly attractive to international students as both waive the job offer requirement for those with Master's or Doctoral degrees (although BC requires the graduate degree be in a STEM field). According to our NGS data (described in the following section), roughly one-half of foreign students who graduated in 2010 and subsequently transitioned to permanent residency held graduate degrees. More generally, the PNP and CEC programs are attractive as the selection criteria are simplified, thereby reducing application costs and processing times. For example, both programs remove the requirement for an adaptability assessment by an immigration officer.

The increasing FIS share of immigration may not only reflect the increase in foreign students graduating from Canadian postsecondary institutions, but could also reflect an increase in the probability that they transition to permanent residency. Certainly, as PNPs and the CEC program ease the transition to permanent residency, we would expect FIS transition rates to permanent residency to increase. In addition to the PNPs and CEC program, the Federal Government has since 2003 gradually increased the length of time that foreign students are permitted to remain in Canada following graduation enabling them to acquire Canadian work experience. As of April 2008, the Post-Graduation Work Program (PGWP) provides open work permits for up to three years to all international students graduating from a recognized Canadian postsecondary institution with no restrictions on the type of employment obtained. While the impact of extending the duration of permits on the labour market earnings of international students is theoretically ambiguous, the PGWP should unambiguously increase the likelihood of transitions to permanent residency.[6]

To obtain evidence on the permanent residency transition rates of international students, Lu and Hou (2015) examine administrative immigration data linking temporary visas and permanent landing records. The results of their analysis suggest that 27% of foreign students who received their first study permit in the early 1990s had transitioned to permanent residency within the following 10 years. This transition rate was, in comparison, 20% for international students arriving in the late 1990s and 25% in the early 2000s. Combining our data on FIS graduates who were permanent residents at the time of being sampled in the NGS and PSIS data on total international student graduates (reported in Figure 3.1), we estimate that 44%, 25%, and 35% of the 2000, 2005, and 2010

[6] Prior to 2003, foreign students were able to remain in Canada for one year following graduation. The impact of extending work permits on the wage rates of foreign students is theoretically ambiguous, because on the one hand it should increase reservation wages during job search. This is because individuals have more time to obtain job offers, so that the likelihood of obtaining an offer exceeding a given reservation wage increases. However, it is also possible that the value of the option of returning to one's home country decreases with time in Canada if, for example, the psychological costs of returning home increase as deeper roots have been planted in Canada.

postsecondary graduation cohorts had transitioned to permanent residency by the time they were surveyed. However, while the 2000 and 2005 cohorts sampled individuals two years following graduation, the 2010 cohort sampled three years after graduation, which could account for all of the increase for the most recent cohort. Therefore, both our data and that of Lu and Hou (2015) do not suggest that transition rates to permanent residency have been rising, which implies that all of the increase in FIS immigration reflects the large increase in the number of international students graduating from Canadian postsecondary institutions.

3.3 Data

The National Graduates Survey (NGS) is a nationally representative survey of postsecondary graduates from Canadian public postsecondary institutions. The 2002 and 2005 cycles of the NGS surveyed individuals who graduated in 2000; the 2007 cycle surveyed 2005 graduates; and the 2013 cycle surveyed 2009/2010 graduates. Critical to our analysis is that each of these cycles of the NGS questionnaire asked all respondents who were not Canadian citizens at the time of registration in their academic program: "Were you ever a visa student (study permit holder) while pursuing post-secondary education in Canada?" To obtain our sample of FISs, we pool these four cycles of the NGS and extract the sample of respondents who answered "yes" to this question and reported being a landed immigrant when surveyed.[7] This provides samples of 1,824 male and 1,147 female FISs, who are observed 2, 3, or 5 years following graduation.

We compare the labour market outcomes of FISs to both CBE graduates and FBE immigrants. To obtain the CBE comparison group, we extracted the sample of individuals in the 2002, 2005, 2007, and 2013 NGS cycles who are Canadian-born and finished their highest level of schooling in Canada. This provides samples of 35,705 male and 51,682 female CBE postsecondary graduates. The NGS does not sample graduates of foreign postsecondary institutions. To obtain a sample of FBE immigrants, we instead rely on the Labour Force Survey (LFS), which since January 2006 has identified not only the country of birth and current immigration status of all respondents, but also the country in which they obtained their highest level of schooling. We pool the LFS data in all months between 2006 and 2013 and extract the sample of individuals who are foreign born, but were landed immigrants at the time that they were surveyed, and whose highest level of schooling is a

[7]In addition to college and university graduates, the NGS samples individuals who have completed a trade or vocational degree. We exclude these individuals from our analysis. In addition, we restrict our sample to individuals who were under the age of 65 at the time of graduation.

postsecondary diploma or degree obtained outside Canada. In addition, we include only FBE individuals who are observed between 17 and 78 months after landing in Canada, in order to match the range of months since program completion of the FIS and CBE samples. In this way, we are comparing Canadian- and foreign-educated immigrants who entered the Canadian labour market at similar times. Together these restrictions result in samples of 8,998 male and 10,363 female FBE immigrants.[8]

Our analysis of labour market performance is based on 10 outcome variables: log hourly earnings and binary indicators of employment, unemployment, part-time jobs (usual weekly hours under 30), occupation type, and two self-reported indicators of whether an individual's job matches his/her educational background in terms of the field and level of the academic program completed. The occupation variable groups occupations into one of four types: nonroutine cognitive, routine cognitive, nonroutine manual, and routine manual. The approach of distinguishing jobs by whether the tasks performed are primarily cognitive versus manual and routine versus nonroutine is due to Autor, Katz, and Kearney (2006). They argue that nonroutine cognitive jobs experienced the greatest real wage growth through the 1990s, because these jobs are complementary with computerization, whereas jobs with routine tasks tend to be substitutes. In examining this variable we consider whether FISs are more or less likely to be employed in cognitive nonroutine occupations, which include managers, professionals, and various technical occupations in engineering and computing, as opposed to routine jobs, and whether this has been changing over time.[9]

Table 3.1 reports the sample means of the variables used in our analysis separately for the FIS, CBE, and FBE samples. The first rows report the raw means of the 10 labour market outcome variables. The estimates reveal that male and female FISs have mean log hourly earnings that exceed that of FBE immigrants by roughly 30 log points. This is a substantial advantage, which is also evident in higher employment rates, lower unemployment rates, a lower incidence of part-time jobs, higher incidence of being employed in non-routine cognitive jobs, and a higher likelihood that jobs match the educational requirements of jobs in terms of level and field of study. Male FISs also have significantly higher mean hourly earnings than CBE men, whereas the average hourly earnings of female FISs and CBE women are almost identical. This pattern is also evident in the occupation types, where male FISs are significantly more likely to have nonroutine cognitive jobs, whereas female FISs appear similar to CBE women. The only remaining large difference worth

[8] To reduce sampling costs, the LFS resamples the same households for six consecutive months. To avoid the complications in variance estimation that this resampling creates, we restrict our sample of FBE immigrants to the first month in which individuals are observed in the LFS (the "birth rotation").

[9] For the mapping of occupation codes to occupation types, see Table A.3. in Cortes et al. (2014).

noting is that among women the FIS unemployment rate is significantly higher (10.3%) than the CBE (5.5%) and FBE (8.2%) comparison groups. This is an unexpected result that disappears when we condition on the current year and the unemployment rate in the year of labour market entry.

The remaining rows of Table 3.1 compare sample means of the set of explanatory variables used to account for the differences in labour market outcomes. First, with regard to the large performance advantage of FISs over FBE immigrants, FISs are more likely to have graduate degrees than FBE immigrants. Specifically, 60% of male and 47% of female FISs have graduate degrees, compared to 31% of male and 24% of female FBE immigrants. They are, however, also younger and are observed fewer months since labour market entry, on average. In terms of regions of origin, FISs are more likely to come from Africa and East Asia and less likely to come from Eastern Europe and South Asia. With regard to the comparison with CBE graduates, the education advantage of FISs is even larger. Specifically, 90% of male and 84% of female FISs have university degrees, compared to 60% of male and 72% of female CBE postsecondary graduates. FISs are about 3 years older on average. Finally, they are more likely to have studied mathematics and engineering and less likely to have diplomas and degrees in education, health, and other personal, protective, and transportation services.

Before turning to the estimation of relative labour market outcomes, Table 3.2 estimates the distribution of graduates across levels of postsecondary education by graduation cohort, as well as the estimated populations of FISs, CBE graduates, and FBE immigrants. Consistent with Figure 3.1, our population estimates of FISs and CBE individuals in the final column of Table 3.1 point to a significant increase in the FIS share of Canadian postsecondary graduates from 1.6% in 2000, to 2.0% in 2005, to 3.5% in 2010. The increase is slightly larger for men (2.1% to 4.7%) than for women (1.3% to 2.7%). Table 3.2 also indicates that the growth in male FISs primarily reflects growth at the college and undergraduate levels; the share of male FISs with graduate degrees decreased from nearly 75% in 2000 to less than 50% by 2010. This pattern is not evident among the male CBE comparison group or among female FISs, where the growth, which has been roughly equivalent to the male FIS growth, is much more evenly spread across education levels. There is, however, evidence of a shift towards postsecondary diplomas below the university level among FBE male immigrants. Despite these shifts, both male and female FISs continue to be significantly more likely to have graduate degrees than either CBE postsecondary graduates or FBE immigrants. The difference among women is particularly large, as 51% of the most recent cohort of FISs have graduate degrees, compared to 20% of CBE postsecondary graduates and 24% of FBE immigrants with postsecondary educational credentials.

3.4 Methodology

The primary objective of our regression analysis is to compare the labour market outcomes of FISs to CBE graduates and FBE immigrants who are observed at a similar time since labour market entry facing similar labour market conditions. However, we are also interested in knowing to what extent differences in outcomes reflect educational backgrounds and regions of origin. We, therefore, provide two sets of estimates for our analysis: (i) estimates that are "unconditional" on education level, field of study, and region of origin; and (ii) estimates that are "conditional" on these variables.

To make the estimated differences in labour market outcomes as transparent as possible, we begin by first estimating the following regression separately for men and women using only one of the comparison group samples (either CBE or FBE):

$$y_{it} = \beta_0 + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 mse_{it} + \beta_4 ur_i + y_t'\gamma + pr_{it}'\delta + x_{it}'\theta + \varepsilon_{it} \tag{3.1}$$

where the dependent variable y_{it} is one of the 10 outcome variables defined above for individual i observed in year t; age_{it} is individual i's age in survey year t; mse_{it} is months since labour market entry (where "entry" is defined as month of program completion for the CBE sample and month of landing for the FBE sample); ur_i is the national-level unemployment rate in individual i's month of labour market entry; pr_{it} is a set of province dummy variables indicating individual i's residence in year t; x_{it} is a vector of dummy variables indicating postsecondary education level, field of study (in the CBE case), and region of origin dummy (in the FBE case); and ε_{it} is a random error with expected value zero, individual-specific variance σ_i^2, which is assumed to be uncorrelated with each of the explanatory variables on the right-hand-side of equation (3.1).[10] In all cases, the "unconditional" estimates exclude x_{it}, whereas the "conditional" estimates include x_{it}.[11]

Having estimated the parameters of equation (3.1), we then predict individual-level outcomes for FISs using their observed values of the explanatory variables in equation (3.1). The difference between their actual observed labour market outcomes and their predicted outcomes, that is $(y_{it} - \hat{y}_{it})$, are "unexplained" in the sense that these differences are unrelated to the set of explanatory variables. Many factors can potentially account for these unexplained differences. For example, we expect the average outcomes of FISs

[10] There are repeated observations on some individuals in FIS and CBE samples extracted from the NGS. We cluster standard errors by the individual identifier.

[11] Appendix Tables A.1 (CBE graduates) and A.2. (FBE immigrants) present the estimates from the first-stage regressions using log hourly earnings as the dependent variable. The first-stage regression results for the other nine dependent variables are available from the authors upon request.

to exceed the average outcomes of observably similar FBE immigrants, since FISs are less likely to face credential recognition issues and have superior English/French language skills, even conditional on region of origin. Therefore, we expect the average "unexplained" difference $(y_{it} - \hat{y}_{it})$ in the sample of FISs to be positive in the FBE comparison case. On the other hand, we expect FISs to have weaker social networks in job search relative to CBE graduates. Consequently, we expect $(y_{it} - \hat{y}_{it})$ to be negative on average for FISs when equation (3.1) is estimated using the CBE graduates.

To examine whether there is any evidence of deteriorating labour market outcomes for FISs, we define the variable $time_i$ for FISs as the year of program completion minus 1998 (year of program completion ranges from 1999 to 2010) and then regress $(y_{it} - \hat{y}_{it})$ on $time_i$ and an intercept. A negative coefficient on $time_i$ provides evidence of a deterioration in the average labour market outcomes of FISs relative to either CBE graduates or FBE immigrants, depending on which comparison the predicted outcomes $\hat{y}_{it}$) are based. This relative deterioration is consistent with postsecondary institutions and governments reaching deeper into foreign student pools to raise quantity without a commensurate increase in the supply of foreign students. It is not consistent with broader labour market factors, which adversely affect the labour market outcomes of all immigrants, such as increasing discrimination against applicants with foreign names, since these factors should influence all immigrants, including FBE immigrants from a common origin region.

We conclude our analysis by extending the analysis in two ways. First, we examine whether the unconditional and conditional "unexplained" differences in FIS labour market outcomes vary across the education levels, fields of study, and regions of origin of FISs. To do so, we regress the values of $(y_{it} - \hat{y}_{it})$ on x_{it} (and an intercept) separately for male and female FISs. Second, we examine whether the differences in the hourly earnings of FISs tend be larger at the upper or lower ends of the earnings distribution. To do this, we estimate equation (3.1) by quantile regressions using the combined sample of FISs and either CBE or FBE individuals, but include a dummy variable indicating FISs.

3.5 Results

In Table 3.3 we report the mean predicted differences in labour market outcomes for FISs, that is the mean values of $(y_{it} - \hat{y}_{it})$ for each of the 10 outcome variables. When we do not condition on education level and field of study, FISs consistently outperform FBE immigrants and have outcomes that are roughly similar to CBE graduates. In fact, among men, mean log hourly earnings of FISs are indistinguishable from CBE graduates, while female FISs lag CBE graduates by 7 log points. Moreover, male FISs are less likely to be employed in part-time jobs; a 3.9 percentage point (ppt) difference. They are also more likely to have nonroutine cognitive jobs (6.2 ppt difference). Male FISs are, however, substantially more likely to report being overqualified for their jobs (11.9 ppt difference), as are female FISs (9 ppt difference). Of course, we know from Table 3.1 that FISs have substantially higher postsecondary educational levels, on average, than FBE immigrants and CBE graduates. The question is to what extent their performance advantage over FBE immigrants and parity with CBE graduates (at least male FISs) reflects this educational advantage.

The "conditional" estimates in Table 3.3 indicate that both male and female FISs underperform Canadians graduating from similar programs across all 10 labour market outcomes. Most notably, the mean log hourly earnings of male and female FISs are 15 log points below that of CBE graduates. They are also significantly less likely to be employed (5 and 11 ppt differences for male and female FISs, respectively); less likely to be in nonroutine cognitive jobs (6 and 10 ppt differences); more likely to be employed in routine cognitive jobs (4 and 8 ppt differences); less likely to report that their job matches their field of study (5 and 9 ppt differences), and more likely to report being overqualified for their job (15 and 9 ppt differences). Furthermore, female FISs, but not male, are significantly more likely to be unemployed (4.7 ppt difference).

Conditioning on educational backgrounds or even region of origin does little to change the differences relative to FBE immigrants. The "conditional" estimates in Table 3.3 consistently point to substantial performance advantages of FISs over FBE immigrants. Mean log hourly earnings, for example, are nearly 30 log points higher for male and female FISs. In addition, employment rates are higher (6 and 20 percentage points higher for male and female FISs, respectively), unemployment rates are lower (2 and 4 ppts, although the female difference is not statistically significant), part-time job rates are lower (6 and 9 ppt differences), and FISs are more likely to be employed in nonroutine cognitive jobs (24 and 26 ppt differences). A potential explanation for these substantial advantages is that FISs may have more Canadian work experience. Unfortunately, neither the NGS nor LFS identify previous work experience. However, it is not obvious that this can account for the differences, since we are comparing FISs and FBE immigrants with similar years since labour market entry, where entry is defined as school completion for FISs and year of landing for FBE immigrants. It is unclear whether FISs graduating from Canadian postsecondary institutions in the 2000s were more likely to work in Canada before graduating than FBE immigrants were to work on temporary work permits before landing.

In Table 3.4, we present the results from regressing the FIS "unexplained" log hourly earnings differences ($y_i - \hat{y}_{it}$) on a linear time trend in the enrolment cohort of FISs (and an intercept). Both the "unconditional" and "conditional" estimates imply deteriorating relative log hourly earnings of FISs. Moreover, this is true relative to both the CBE and FBE comparison groups. However, the magnitudes of the trends are modest and, for men, in all cases statistically insignificant at the 10% level. The imprecision of the estimates is evident in Figure 3.4, where we plot the mean values of $(y_i - \hat{y}_{it})$ and 95% confidence intervals for the seven observed enrollment cohorts (1999, 2000, 2004, 2005, 2008, 2009, and 2010) and the estimated linear time trend. While the 2008 and 2009 cohorts have particularly poor mean outcomes relative to both comparison groups, their sample sizes are small leading to confidence intervals that include values that do not suggest deterioration. The estimates for female FISs, on the other hand, are larger and, in the CBE-comparison case, statistically significant at the 10% confidence level. Specifically, they suggest that the FIS earnings gap relative to CBE graduates grew by about 1 to 1.5 log points per year through the 2000s, while the earnings advantage relative to FBE immigrants has been declining by roughly the same amount.

In Table 3.5, we examine how the unexplained earnings gaps vary across education levels, fields of study, and countries of origin of FISs. In CBE comparison case, the reference group are FISs with a Ph.D. in the field of mathematics who originate from East Asia (the vast majority are from China). Not surprisingly, when we do not condition on education in the first stage, FISs with lower education levels face larger earnings gaps relative to the average CBE graduate. The difference is particularly large among women, as female FISs with college diplomas have expected earnings that are 70 log points below female FISs with PhDs in similar fields of study from similar origin regions. More interesting, when we condition on education in the first stage the FIS-CBE gaps do not vary significantly across education levels for men, but they do for women. In particular, the log hourly earnings gap of college-educated FISs is roughly 20 log points higher than for university-educated FISs. In other words, the FIS-CBE earnings gap for women is substantially larger when we compare FIS college graduates to CBE college graduates than when compare FIS university graduates to CBE university graduates. This suggests that perhaps the deterioration in the labour market outcomes of female FISs over time, shown in Table 3.3, reflects a shift among female FISs towards more college graduates. However, the sample means in Table 3.2 indicate that this has not happened. In fact, the proportion of FISs who are college, as opposed to university, graduates was lower for the 2010 graduation cohort than for the 2000 or 2005 cohorts (13.2% compared to 16.7% and 21.0%, respectively).[12]

[12]We also estimated the specifications in Tables 5 and 6 including the linear trend in year of program completion. The results suggest that the deterioration in female FIS outcomes is, by and large, not accounted for by compositional shifts between education levels, fields of study, and origin regions. The only exception is there is some evidence of a significant increase in female FISs from South Asia, who the results in Table 3.5 indicate, have particularly poor earnings outcomes. This increase in the South Asian international student share is also evident in the administrative data used in Figure 3.1.

With regard to fields of study, the "unconditional" results in Table 3.5 point to lower FIS-CBE earnings gaps for FISs graduating from all fields relative to mathematics (the sole exception is visual and performing arts, although the estimates are very imprecise, due to the small sample). Earnings appear particularly low in education, social sciences and law, sciences, agriculture, and services. In contrast, they appear relatively modest for business and engineering graduates. Of course, without controlling for education in the first stage, these results are simply indicating which fields of study lead to higher earnings for all graduates. Indeed, the "conditional" estimates suggest much smaller earnings differences across fields. For men, none of the differences in the FIS-CBE gaps are statistically significant, with the exception of education, where FISs face large earnings gaps, and arts, where they face a large earnings advantage. However, for women, the FIS-CBE earnings gaps are significantly higher among science, engineering, agriculture, and health graduates. In fact, female FISs graduating from mathematics and computer science programs are the exception, as all other fields have substantially larger FIS-CBE earnings gaps (with the exception of visual and performing arts).

Finally, with regards to the region of origin differences, the "unconditional" and "conditional" estimates in Table 3.5 are virtually identical, since the first stage regression using the CBE sample does not control for origin region (since CBE graduates are, by definition, all Canadian-born). Relative to East Asian FISs (the reference group), male FISs from Europe, particularly Southern Europe, as well as West, Central, and South Asia face relatively modest FIS-CBE earnings gaps. For women, on the other hand, FISs from Africa and South Asia have significantly higher FIS-CBE gaps than their East Asian counterparts. The difference between South Asian men and women is particularly stark, but this is partially explained by the fact that the reference group for men (East Asian men with PhDs in mathematics) face a FIS-CBE earnings gap of 13 log points (see the estimate of the constant in the "conditional" model for men), whereas their female counterparts (East Asian women with PhDs in mathematics) face a FIS-CBE earnings advantage (7 log points, but statistically insignificant).

In Table 3.6, we present similar results to those in Table 3.5, but based on the comparison to FBE immigrants. Since we are unable to condition on field of study in the first stage (because the LFS does not provide this information), we do not include field of study in the second stage.[13] As in Table 3.6, the "unconditional" results largely capture returns to education, as FISs with graduate degrees face significantly larger earnings advantages relative to the average FBE immigrant than do FISs with college diplomas. When we

[13] We could compare the FIS-FBE earnings differentials across fields, but they would capture the same broad earnings differences as the "unconditional" estimates in Table 3.5. For example, earnings are higher for all graduates from mathematics, business, and engineering programs

condition on education level and origin region in the first stage, there is once again little difference across education levels for men, but evidence of substantially smaller earnings advantages for college-educated than university-educated female FISs. This implies that the advantage of Canadian over foreign education for immigrants is substantially larger for university-educated than college-educated women.

In the remaining rows of Table 3.6, we compare the FIS-FBE earnings advantages across origin regions. The "unconditional" results for men point to larger advantages for FISs from Northern and Western Europe, West and Central Asia, and South Asia. For women, on the other hand, the "unconditional" results indicate relatively small earnings advantages for FISs from Africa and South Asia. When we compare FISs and FBE immigrants with similar education levels and from similar regions (the "conditional" estimates), the results for men suggest relatively large advantages of Canadian over foreign education for immigrants from China, West and Central Asia, and South Asia. Male FISs from the US, UK, Australia, and New Zealand, on the other hand, have exceptionally low earnings relative to their FBE counterparts. This likely reflects the selectivity of FISs from these countries, rather than differences in education quality between Canada and these countries. For women, we also find small advantages of Canadian education (relative to the advantage for Chinese immigrants) among FISs from Northern and Western Europe, Africa, the US, UK, Australia, and New Zealand, and South Asia.

We complete our analysis by estimating quantile regressions using the pooled sample of FISs and either CBE graduates or FBE immigrants. To identify conditional differences in FIS earnings across the earnings distribution, we include a dummy variable identifying FISs. Figure 3.6 and 3.7 plot the results for the CBE and FBE comparisons, respectively. For men, the results point to FIS-CBE earnings gaps, which decrease in magnitude as we move up the earning distribution. Below the 10th percentile, the "unconditional" gaps are roughly 5 log points and the "conditional" gaps are roughly 20 logs. In comparison, median earnings are roughly equivalent for FISs and CBE graduates when we do not condition on education (level and field) and are slightly bigger than 10 log points when we do. This changes little as we move from the 50th to the 99th percentile, as the "unconditional" gap is essentially constant and the "conditional" gap is slightly smaller than 10 log points above the 90th percentile. The results for women in Figure 3.6 similarly point to declining FIS-CBE gaps as we move up the earnings distribution. The exception is below the 20th percentile, where the gaps are growing as we move up the distribution. In other words, female FISs face smaller FIS-CBE gaps at the 1st percentile than at the 20th percentile. This u-shaped pattern is particularly evident in the "conditional" earnings results. There is also some (weaker) evidence of increasing gaps at the very top end of the earnings distribution, particularly in the "conditional" estimates.

In Figure 3.7, we plot the quantile regression results based on the FBE comparison group. In all cases, the inverted u-shaped patterns imply smaller FIS-FBE earnings advantages in the tails of the distribution than in the middle of the distribution. In other words, the difference in FIS and FBE earnings at the 10th and 90th percentiles of their respective distributions are small relative to the differences in their median earnings.

Finally, we have also tried estimating the quantile regressions allowing the FIS differential to vary across program completion cohorts (including an interaction of the international student dummy variable and the $time_i$ variable described in Section 4). The results suggest that, if anything, the deterioration in the labour market outcomes of female FISs has been driven by changes at the upper end of the earnings distribution, not the lower end. That is, the relatively small FIS-CBE earnings gaps at the upper end of the earnings distribution in Figure 3.6 have tended to grow over time, while the relatively small FIS-FBE earnings advantages at the upper end of the distribution in Figure 3.7 have tended to become even smaller.[14]

3.6 Conclusions

Combining data from Canada's National Graduates Survey (NGS) and Labour Force Survey (LFS), we compare the labour market performance of FISs to both CBE graduates and FBE immigrants entering the Canadian labour market at the same time. The results of our analysis indicate that FISs clearly outperform their foreign-educated counterparts by substantial margins. The implied advantage of Canadian over foreign postsecondary education is evident for men and women and across education levels, although bigger at higher education levels and in the middle of the earnings distribution. These results suggest that the federal government's decision to give preference to Canadian-educated applicants in Express Entry (EE) system is justified, particularly for applicants with university degrees.

However, we also find that the labour market outcomes of FISs lag behind their CBE counterparts graduating from similar academic programs. The performance gaps we identify tend to be larger for college-educated women, in fields outside of math and computer science, among Chinese men and South-Asian women, and at the lower end of the hourly earnings distribution than at the top. The critical question for policymakers is to what extent these gaps reflect pre-market differences in labour market productivity, such as English/French language disparities, as opposed to market challenges, due to weaker job search networks or employer discrimination, for example. Although the driving factors have very

[14]These results are available from the authors upon request.

different implications for policy, identifying their relative importance is extremely difficult. The fact that CBE gaps are largest at the lower end of the hourly earnings distribution suggests that something more than discrimination is playing a role, since we would expect immigrants with the weakest language skills to face the largest gaps, but it is unclear the effect of discrimination would vary across immigrant from a similar origin region. However, more direct evidence is clearly needed. A potentially fruitful approach we are currently exploring is to examine whether there is evidence of productivity differences between foreign and domestic students, including English/French language skills, using data on the relative grades of international students enrolled in Canadian postsecondary institutions.

Finally, we find some evidence, particularly among women, that the relative labour market performance of FISs has tended to deteriorate over time. The fact that this deterioration is evident in the comparison to both CBE graduates and FBE immigrants suggests to us that it reflects something about FISs as opposed to changing labour market conditions, since there is no clear reason why CBE graduates or FBE immigrants would not have been similarly adversely affected by changing labour market conditions. The most obvious explanation for this deterioration, in our view, is a tradeoff in the average labour market "quality" of foreign students as postsecondary institutions and governments have reached deeper into pools of prospective international students through the 2000s to meet their demands for students and new immigrants.

Table 3.1: Sample means by gender and student type

	Men			Women		
	FIS	*CBE*	*FBE*	*FIS*	*CBE*	*FBE*
Outcomes:						
Log hourly earnings (2013$)	3.313	3.187	3.008	3.122	3.110	2.808
	(0.030)	(0.005)	(0.008)	(0.036)	(0.004)	(0.007)
Employed	0.841	0.883	0.799	0.775	0.882	0.602
	(0.018)	(0.003)	(0.005)	(0.026)	(0.003)	(0.006)
Unemployed	0.062	0.059	0.083	0.103	0.055	0.082
	(0.010)	(0.002)	(0.004)	(0.021)	(0.002)	(0.003)
Part-time weekly hours	0.030	0.066	0.069	0.120	0.133	0.131
	(0.004)	(0.003)	(0.003)	(0.022)	(0.003)	(0.004)
Nonroutine cognitive	0.755	0.622	0.424	0.659	0.674	0.357
	(0.029)	(0.006)	(0.007)	(0.037)	(0.004)	(0.007)
Routine cognitive	0.049	0.072	0.113	0.066	0.087	0.205
	(0.013)	(0.003)	(0.004)	(0.019)	(0.003)	(0.006)
Nonroutine manual	0.137	0.162	0.194	0.271	0.221	0.349
	(0.025)	(0.005)	(0.006)	(0.036)	(0.004)	(0.007)
Routine manual	0.059	0.144	0.269	0.010	0.018	0.089
	(0.017)	(0.004)	(0.006)	(0.002)	(0.001)	(0.004)
Education-field match	0.614	0.575	–	0.551	0.626	–
	(0.028)	(0.006)		(0.036)	(0.005)	
Education-level match	0.604	0.703	–	0.640	0.712	–
	(0.027)	(0.005)		(0.034)	(0.004)	
Controls:						
Age	32.984	29.373	38.946	32.336	29.884	37.093
	(0.362)	(0.066)	(0.109)	(0.477)	(0.060)	(0.101)
Months since labour market entry	39.007	37.681	46.190	38.593	37.565	46.044
	(0.612)	(0.155)	(0.234)	(0.860)	(0.127)	(0.217)
Unemployment rate at entry	7.045	6.729	6.210	6.211	6.226	5.802
	(0.085)	(0.020)	(0.022)	(0.063)	(0.008)	(0.013)
Education level:						
Below Bachelor's	0.095	0.398	0.217	0.164	0.347	0.280
	(0.021)	(0.005)	(0.005)	(0.027)	(0.004)	(0.005)
Bachelor's	0.300	0.439	0.475	0.368	0.487	0.485
	(0.026)	(0.005)	(0.007)	(0.033)	(0.004)	(0.006)
Master's	0.426	0.148		0.384	0.154	
	(0.023)	(0.003)	0.308	(0.031)	(0.003)	0.235
Ph.D.	0.178	0.016	(0.006)	0.084	0.012	(0.005)
	(0.011)	(0.001)		(0.007)	(0.001)	
Field of study:						
Education	0.021	0.058	–	0.045	0.130	–
	(0.009)	(0.002)		(0.012)	(0.003)	
Visual and performing arts	0.030	0.047	–	0.030	0.053	–
	(0.012)	(0.002)		(0.007)	(0.002)	

Humanities	0.027	0.066	–	0.101	0.078	–
	(0.005)	(0.002)		(0.027)	(0.002)	
Social sciences and law	0.083	0.118	–	0.117	0.186	–
	(0.014)	(0.004)		(0.016)	(0.004)	
Business	0.232	0.213	–	0.328	0.219	–
	(0.026)	(0.005)		(0.035)	(0.004)	
Physical and life sciences	0.077	0.055	–	0.073	0.050	–
	(0.008)	(0.002)		(0.009)	(0.001)	
Math and computer science	0.129	0.068	–	0.086	0.021	–
	(0.012)	(0.002)		(0.013)	(0.001)	
Engineering	0.324	0.225	–	0.085	0.034	–
	(0.022)	(0.004)		(0.012)	(0.001)	
Natural resources	0.038	0.033	–	0.024	0.017	–
	(0.005)	(0.001)		(0.004)	(0.001)	
Health	0.031	0.067	–	0.096	0.186	–
	(0.007)	(0.003)		(0.018)	(0.003)	
Services	0.008	0.043	–	0.003	0.021	–
	(0.003)	(0.002)		(0.001)	(0.001)	
Other	0.002	0.005	–	0.012	0.005	–
	(0.001)	(0.001)		(0.007)	(0.001)	
Origin region:						
South and Central America	0.080	–	0.099	0.099	–	0.096
	(0.013)		(0.004)	(0.016)		(0.004)
Northern and Western Europe	0.053	–	0.040	0.080	–	0.032
	(0.007)		(0.003)	(0.011)		(0.002)
Eastern Europe	0.027	–	0.090	0.057	–	0.107
	(0.005)		(0.004)	(0.015)		(0.004)
Southern Europe	0.027	–	0.015	0.026	–	0.012
	(0.011)		(0.002)	(0.007)		(0.001)
Africa	0.248	–	0.126	0.143	–	0.100
	(0.020)		(0.004)	(0.027)		(0.004)
West and Central Asia	0.073	–	0.081	0.040	–	0.074
	(0.010)		(0.004)	(0.011)		(0.003)
East Asia	0.257	–	0.167	0.358	–	0.189
	(0.023)		(0.005)	(0.032)		(0.005)
US, UK, Australia, and NZ	0.039	–	0.039	0.087	–	0.029
	(0.010)		(0.002)	(0.024)		(0.002)
Southeast Asia	0.034	–	0.120	0.044	–	0.164
	(0.012)		(0.004)	(0.011)		(0.004)
South Asia	0.163	–	0.224	0.066	–	0.196
	(0.018)		(0.006)	(0.014)		(0.005)
Sample size	1,824	35,705	8,998	1,147	51,682	10,363

Notes: FBE immigrants have three levels of schooling (below bachelor, bachelor, and above bachelor) instead of four, since Masters and Ph.D. degrees are not distinguished in the LFS data. The social science and law field of study includes behavioural studies, such as psychology. The business field includes accounting and public administration. The science field includes physical and life sciences, as well as science technologies/technicians. The engineering field includes architecture and related technologies. The natural resources field includes conservation and agriculture. Finally, the services field of study includes personal, protective, and transportation services.

Table 3.2: Education level distribution by gender, student type, and graduation cohort

	College	Bachelor's	Master's	Ph.D.	Estimated Population
Men:					
FIS cohort					
2000	0.034	0.233	0.495	0.238	1,896
2005	0.061	0.329	0.474	0.137	2,700
2010	0.174	0.342	0.348	0.136	5,932
CBE cohort					
2000	0.381	0.423	0.175	0.022	88,119
2005	0.403	0.455	0.131	0.010	95,248
2010	0.395	0.425	0.163	0.017	118,972
FBE cohort					
2000	0.158	0.480	0.362		1,992
2005	0.195	0.480	0.325		21,262
2010	0.245	0.451	0.304		23,702
Women:					
FIS cohort					
2000	0.167	0.376	0.361	0.096	1,804
2005	0.210	0.394	0.333	0.063	2,300
2010	0.132	0.363	0.421	0.084	5,075
CBE cohort					
2000	0.341	0.473	0.173	0.013	132,716
2005	0.349	0.511	0.132	0.008	150,364
2010	0.331	0.469	0.183	0.016	182,309
FBE cohort					
2000	0.272	0.457	0.271		2,419
2005	0.267	0.492	0.241		23,616
2010	0.280	0.479	0.241		27,812

Table 3.3: Unconditional and conditional mean FIS difference in labour market outcomes relative to CBE and FBE immigrants

	Men				Women			
	Unconditional		Conditional		Unconditional		Conditional	
	CBE	*FBE*	*CBE*	*FBE*	*CBE*	*FBE*	*CBE*	*FBE*
Log hourly earnings	-0.012	0.352***	-0.146***	0.295***	-0.067*	0.353***	-0.148***	0.294***
	(0.030)	(0.036)	(0.030)	(0.035)	(0.037)	(0.036)	(0.032)	(0.034)
Employed	-0.055***	0.026	-0.054***	0.058***	-0.111***	0.215***	-0.109***	0.203***
	(0.018)	(0.020)	(0.017)	(0.021)	(0.028)	(0.028)	(0.028)	(0.028)
Unemployed	0.007	-0.009	0.007	-0.021*	0.048*	-0.037*	0.047**	-0.036
	(0.010)	(0.011)	(0.010)	(0.012)	(0.021)	(0.022)	(0.021)	(0.022)
Part-time weekly hours	-0.039***	-0.053***	-0.022***	-0.061***	-0.027	-0.076***	-0.008	-0.085***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.023)	(0.024)	(0.023)	(0.024)
Nonroutine cognitive	0.062**	0.352***	-0.059**	0.243***	-0.059*	0.340***	-0.096***	0.264***
	(0.030)	(0.031)	(0.027)	(0.028)	(0.035)	(0.040)	(0.030)	(0.036)
Routine cognitive	-0.002	-0.051*	0.037*	-0.045	0.077**	-0.116***	0.082***	-0.103***
	(0.025)	(0.028)	(0.021)	(0.029)	(0.033)	(0.038)	(0.028)	(0.038)
Nonroutine manual	-0.012	-0.064***	0.024*	-0.033**	-0.009	-0.140***	0.020	-0.093***
	(0.012)	(0.015)	(0.013)	(0.015)	(0.021)	(0.021)	(0.020)	(0.022)
Routine manual	-0.041*	-0.229***	0.005	-0.157***	-0.008***	0.008	-0.005**	-0.068***
	(0.022)	(0.017)	(0.019)	(0.017)	(0.002)	(0.011)	(0.002)	(0.006)
Education-field match	0.010	–	-0.054*	–	-0.104***	–	-0.093***	–
	(0.030)		(0.029)		(0.033)		(0.032)	
Education-level match	-0.119***	–	-0.150***	–	-0.085**	–	-0.076**	–
	(0.029)		(0.029)		(0.038)		(0.038)	

Notes: Bootstrapped standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.4: Time trends in unconditional and conditional differences in mean outcomes

	Men				Women			
	Unconditional		Conditional		Unconditional		Conditional	
	CBE	*FBE*	*CBE*	*FBE*	*CBE*	*FBE*	*CBE*	*FBE*
Log hourly earnings	-0.007	-0.011	-0.004	-0.003	-0.015*	-0.013	-0.012*	-0.010
	(0.008)	(0.010)	(0.007)	(0.010)	(0.008)	(0.010)	(0.007)	(0.009)
Employed	0.003	0.004	0.002	0.008*	0.002	0.001	0.003	0.005
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)	(0.008)	(0.007)	(0.008)
Unemployed	0.000	-0.003	0.000	-0.004	0.004	0.003	0.003	0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Part-time weekly hours	-0.003***	-0.007***	-0.002*	-0.008***	-0.001	-0.003	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.005)	(0.006)
Nonroutine cognitive	-0.003	-0.006	0.001	0.002	0.002	0.008	0.002	0.009
	(0.007)	(0.008)	(0.006)	(0.007)	(0.010)	(0.011)	(0.008)	(0.010)
Routine cognitive	0.005	0.004	0.000	0.003	-0.002	-0.010	-0.002	-0.012
	(0.006)	(0.007)	(0.005)	(0.007)	(0.009)	(0.011)	(0.008)	(0.011)
Nonroutine manual	0.007**	0.005	0.008**	0.006	-0.002	-0.007*	-0.001	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Routine manual	-0.007*	-0.002	-0.007*	-0.009*	0.002**	0.009***	0.001	0.006***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Education-field match	-0.010	–	-0.007	–	-0.007	–	-0.005	–
	(0.007)		(0.006)		(0.009)		(0.009)	
Education-level match	0.007	–	0.010	–	-0.014	–	-0.014	–
	(0.006)		(0.007)		(0.009)		(0.009)	

Notes: Bootstrapped standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.5: Mean FIS-CBE log hourly earnings difference by education, major field of study, and origin region

	Men		Women	
	Unconditional	Conditional	Unconditional	Conditional
Education level: (ref=PhD)				
Below Bachelors	-0.306***	0.065	-0.698***	-0.234**
	(0.073)	(0.070)	(0.093)	(0.093)
Bachelors	-0.163***	0.031	-0.273***	-0.065
	(0.055)	(0.055)	(0.059)	(0.058)
Masters	-0.062	0.005	-0.144***	-0.077
	(0.042)	(0.041)	(0.050)	(0.048)
Field of study: (ref=Math)				
Education	-0.423**	-0.356**	-0.159	-0.137
	(0.172)	(0.164)	(0.125)	(0.127)
Visual and performing arts	0.068	0.404*	0.092	0.307
	(0.221)	(0.219)	(0.322)	(0.329)
Humanities	-0.153	0.098	-0.209*	-0.073
	(0.110)	(0.105)	(0.116)	(0.110)
Social sciences and law	-0.172**	-0.016	-0.171**	-0.093
	(0.069)	(0.069)	(0.076)	(0.074)
Business	-0.041	-0.042	-0.080	-0.105
	(0.084)	(0.083)	(0.071)	(0.069)
Physical and life sciences	-0.343***	-0.102	-0.263***	-0.147*
	(0.072)	(0.072)	(0.076)	(0.076)
Engineering	-0.034	-0.087	-0.034	-0.160**
	(0.056)	(0.055)	(0.071)	(0.070)
Natural resources	-0.216**	-0.088	-0.288***	-0.206**
	(0.093)	(0.092)	(0.105)	(0.102)
Health	-0.120	-0.025	-0.115	-0.209**
	(0.105)	(0.105)	(0.1)	(0.090)
Services	-0.236	-0.062	-0.428*	-0.315
	(0.158)	(0.150)	(0.234)	(0.228)
Other	-0.126	0.050	-0.519**	-0.408**
	(0.135)	(0.130)	(0.209)	(0.199)

Origin region: (ref=East Asia)				
South and Central America	-0.133	-0.122	0.097	0.091
	(0.093)	(0.089)	(0.096)	(0.087)
Northern and Western Europe	0.163***	0.166***	-0.112	-0.132
	(0.061)	(0.062)	(0.101)	(0.101)
Eastern Europe	0.162**	0.160**	0.141	0.106
	(0.078)	(0.079)	(0.111)	(0.101)
Southern Europe	0.332*	0.328*	0.086	0.088
	(0.199)	(0.194)	(0.177)	(0.159)
Africa	-0.051	-0.044	-0.182**	-0.176**
	(0.056)	(0.056)	(0.077)	(0.076)
West and Central Asia	0.193***	0.192***	-0.010	-0.009
	(0.059)	(0.059)	(0.161)	(0.161)
US, UK, Australia, and NZ	-0.451	-0.450	0.088	0.069
	(0.302)	(0.299)	(0.077)	(0.077)
Southeast Asia	-0.096	-0.100	0.057	0.059
	(0.256)	(0.257)	(0.111)	(0.110)
South Asia	0.152**	0.147**	-0.258***	-0.259***
	(0.071)	(0.071)	(0.100)	(0.099)
Constant	0.163***	-0.129**	0.340***	0.074
	(0.060)	(0.059)	(0.069)	(0.068)
R-squared	0.164	0.116	0.275	0.149
Sample size	1295	1295	764	764

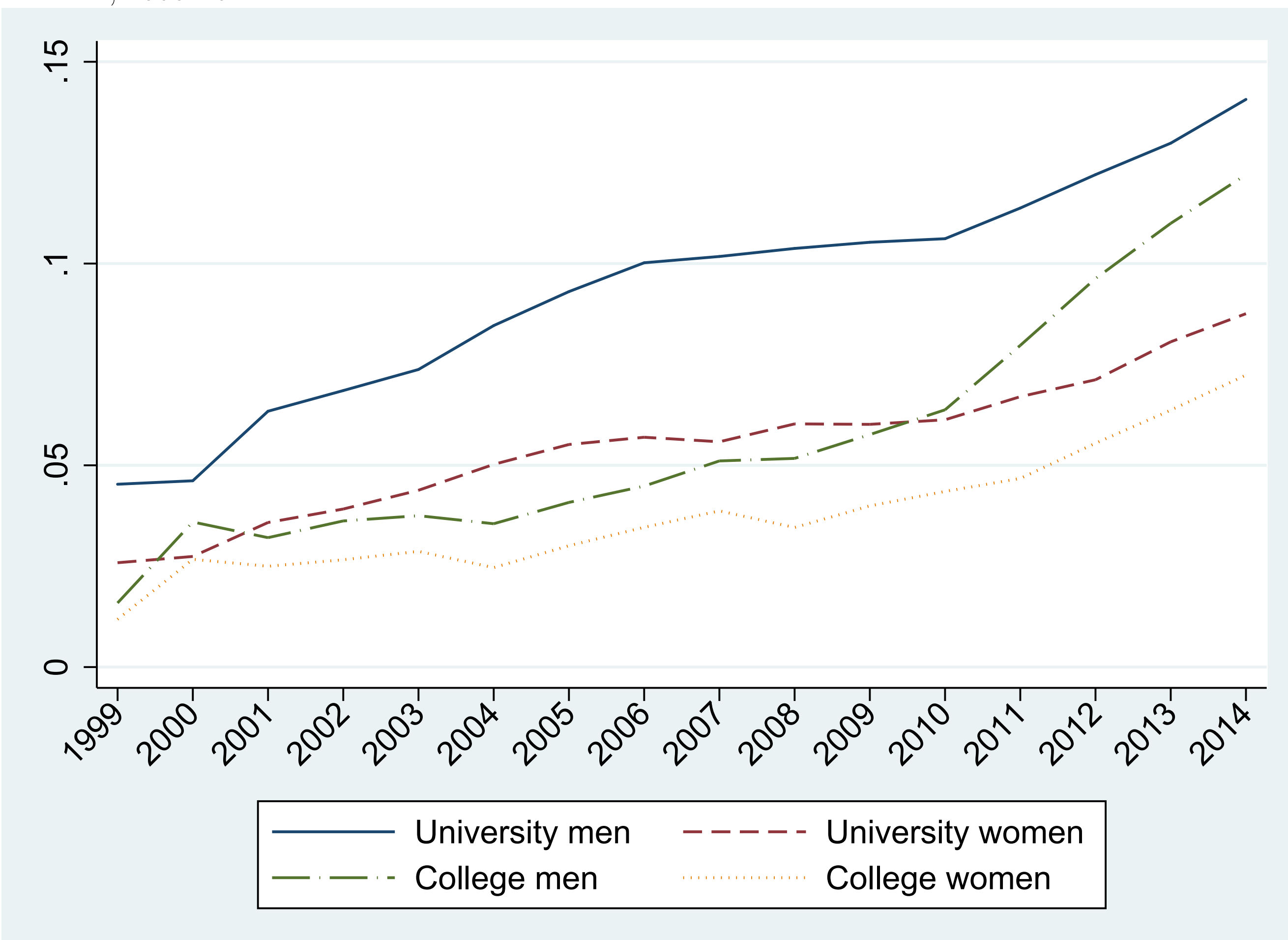
Notes: Bootstrapped standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.6: Mean FIS-FBE log hourly earnings difference by education level and origin region

	Men		Women	
	Unconditional	Conditional	Unconditional	Conditional
Education level: (ref=MA & PhD)				
Below Bachelor's	-0.330***	-0.090	-0.531***	-0.289***
	(0.061)	(0.059)	(0.103)	(0.104)
Bachelor's	-0.139	-0.021	-0.153***	-0.024
	(0.066)	(0.065)	(0.056)	(0.057)
Origin region: (ref=East Asia)				
South and Central America	-0.072	-0.183**	0.136	0.053
	(0.093)	(0.091)	(0.115)	(0.114)
Northern and Western Europe	0.192**	-0.136	-0.009	-0.298***
	(0.083)	(0.084)	(0.100)	(0.101)
Eastern Europe	0.128	-0.013	0.097	0.019
	(0.083)	(0.082)	(0.076)	(0.072)
Southern Europe	0.226	0.036	0.259	0.176
	(0.204)	(0.189)	(0.204)	(0.206)
Africa	-0.004	-0.064	-0.173**	-0.244***
	(0.058)	(0.057)	(0.078)	(0.082)
West and Central Asia	0.230***	0.163**	0.054	-0.001
	(0.071)	(0.073)	(0.201)	(0.189)
US, UK, Australia, and NZ	-0.509*	-0.908***	0.096	-0.300***
	(0.307)	(0.291)	(0.085)	(0.087)
Southeast Asia	-0.051	-0.069	0.128	0.104
	(0.234)	(0.237)	(0.115)	(0.116)
South Asia	0.149*	0.158**	-0.229**	-0.190*
	(0.078)	(0.078)	(0.110)	(0.109)
Constant	0.409***	0.359***	0.524***	0.444***
	(0.042)	(0.041)	(0.055)	(0.054)
R-squared	0.158	0.205	0.248	0.181
Sample size	1095	1095	660	660

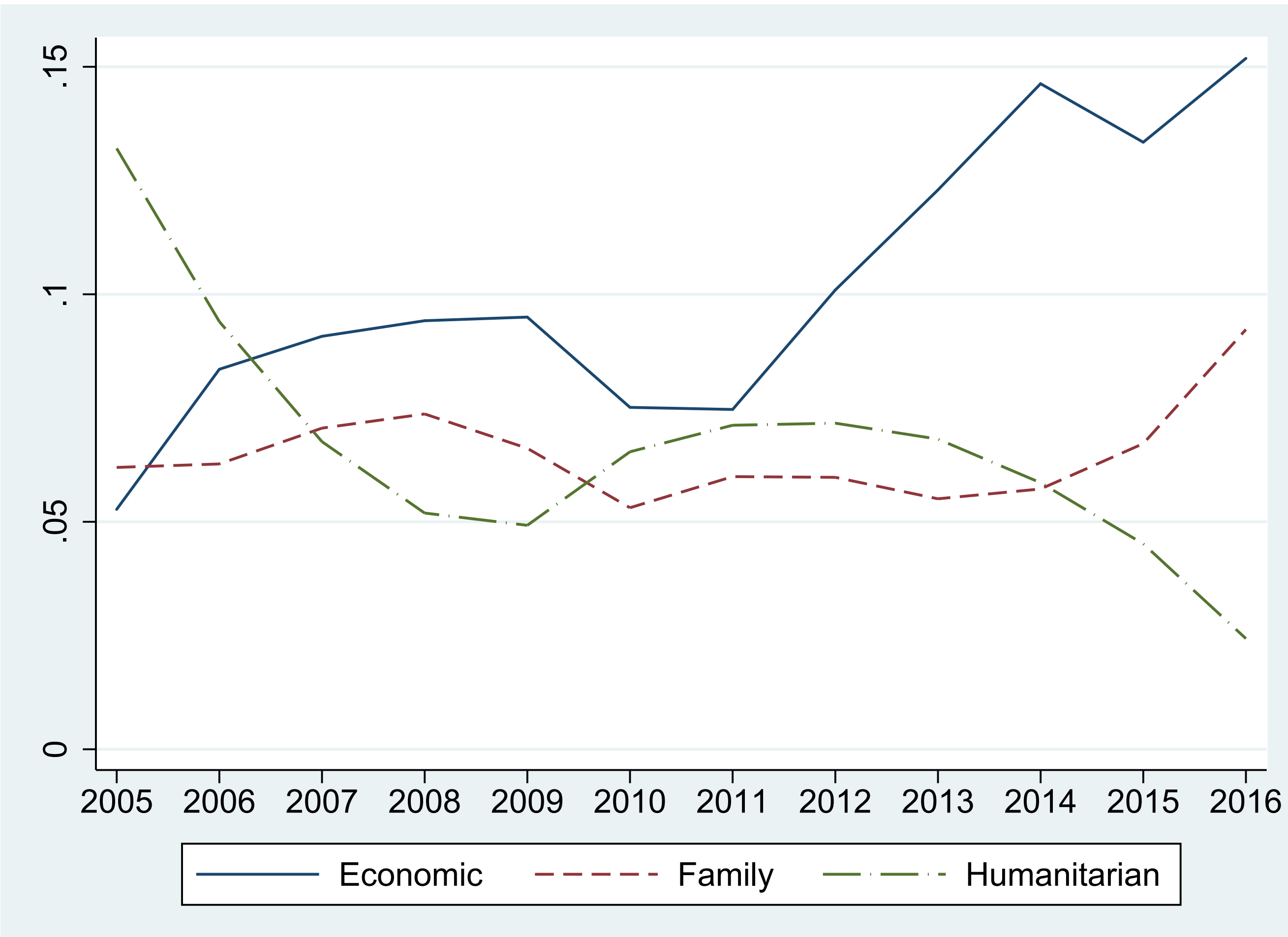
Notes: Bootstrapped standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 3.1: International student share of postsecondary graduates by gender and education level, 1999-2014



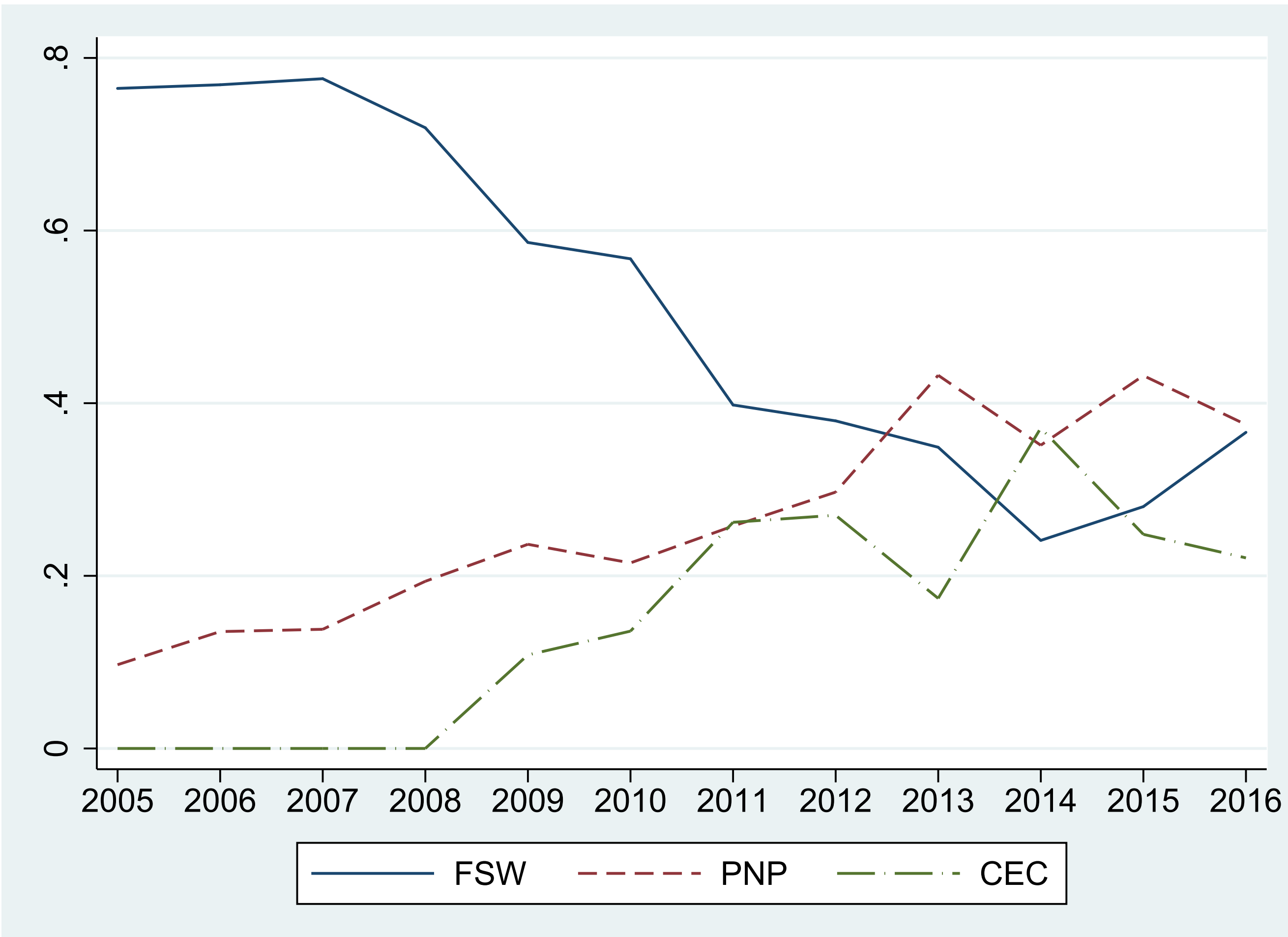
Source: Postsecondary Information System (PSIS), Statistics Canada, CANSIM tables 477-0031 and 477-0032.

Figure 3.2: FIS share of new permanent residents by broad immigration category, 2000-2016



Source: Immigration, Refugees, and Citizenship Canada (IRCC). Available on the Open Government Data Portal as "Admissions of Permanent Residents who have ever held a Study Permit by Intended Province/Territory of Destination and Immigration Category, 2005-October 2016."

Figure 3.3: Economic-class immigration programs of FISs, 2005-2016



Note: Programs are the Federal Skilled Worker (FSW) Program, Provincial Nominee Programs (PNP), and the Canadian Experience Class (CEC) Program. Shares do not sum to one. A decreasing share (14% in 2005 to 4% in 2016) entered through other economic class programs, including business class programs, such as the investor program.
Source: Immigration, Refugees, and Citizenship Canada (IRCC). Available on the Open Government Data Portal as "Admissions of Permanent Residents who have ever held a Study Permit by Intended Province/Territory of Destination and Immigration Category, 2005-October 2016."

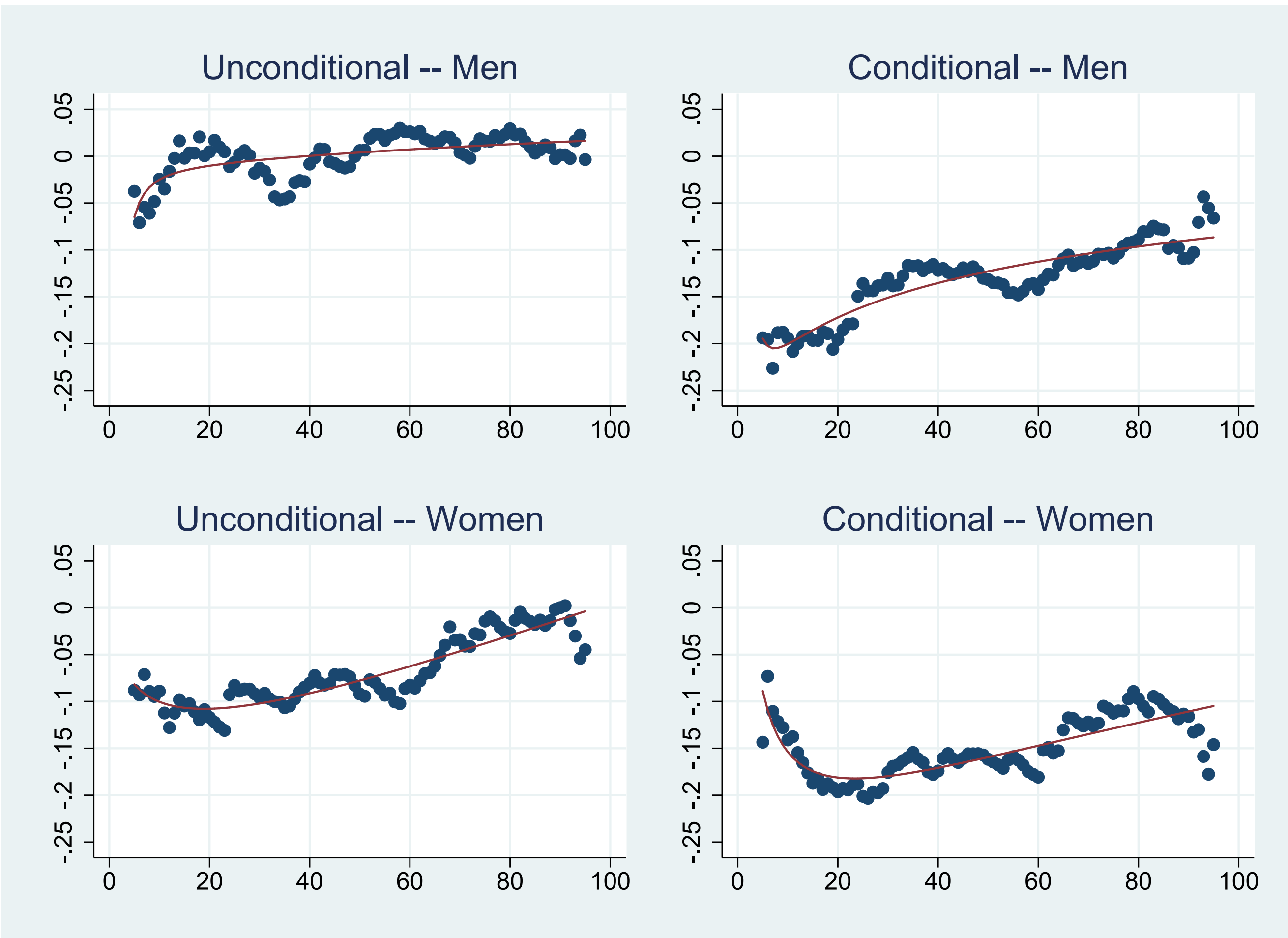
Figure 3.4: Time trends in FIS-CBE log hourly earnings differentials

Note: Dots indicate the mean values of the unexplained earnings difference $(y_{it} - \hat{y}_{it})$ across program completion cohorts of FISs. Bands indicate the 95% confidence intervals of the sample means. The red line indicates the estimated linear time trends reported in Table 3.4.

Figure 3.5: Time trends in FIS-FBE log hourly earnings differentials

Note: Dots indicate the mean values of the unexplained earnings difference $(y_{it} - \hat{y}_{it})$ across program completion cohorts of FISs. Bands indicate the 95% confidence intervals of the sample means. The red line indicates the estimated linear time trends reported in Table 3.4.

Figure 3.6: FIS-CBE differentials in log hourly earnings quantiles



Note: Dots are the estimated differences in FIS log hourly earnings at the 1st through 99th percentiles. "Unconditional" estimates are the coefficients on a FIS dummy variable in a conditional quantile regression, which includes controls for age, age squared, months since labour market entry, unemployment rate at entry, and survey year. The "conditional" estimates also include controls for education level and field of study in the CBE comparison case and education level and region of origin in the FBE comparison case.

Figure 3.7: FIS-FBE differentials in log hourly earnings quantiles

Note: Dots are the estimated differences in FIS log hourly earnings at the 1st through 99th percentiles. "Unconditional" estimates are the coefficients on a FIS dummy variable in a conditional quantile regression, which includes controls for age, age squared, months since labour market entry, unemployment rate at entry, and survey year. The "conditional" estimates also include controls for education level and field of study in the CBE comparison case and education level and region of origin in the FBE comparison case.

Table A.1: First-stage CBE log hourly earnings regressions

	Men		Women	
	Unconditional	Conditional	Unconditional	Conditional
Age	0.091***	0.064***	0.099***	0.060***
	(0.005)	(0.005)	(0.004)	(0.004)
Age squared /100	-0.098***	-0.066***	-0.113***	-0.065***
	(0.007)	(0.007)	(0.005)	(0.005)
Months since labour market entry	0.007***	0.004***	0.007***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment rate at entry	0.002	-0.001	-0.012***	-0.009***
	(0.003)	(0.003)	(0.004)	(0.003)
Survey year 2005	-0.155***	-0.048	-0.160***	-0.026
	(0.053)	(0.052)	(0.038)	(0.037)
Survey year 2007	0.016	0.019	0.040***	0.037***
	(0.013)	(0.012)	(0.010)	(0.010)
Survey year 2013	-0.053**	0.001	-0.029	0.019
	(0.026)	(0.025)	(0.020)	(0.019)
Below Bachelor's		-0.420***		-0.529***
		(0.022)		(0.035)
Bachelor's		-0.233***		-0.273***
		(0.020)		(0.035)
Master's		-0.087***		-0.110***
		(0.021)		(0.035)
Education		-0.047		0.017
		(0.029)		(0.021)
Visual and performing arts		-0.337***		-0.200***
		(0.028)		(0.024)
Humanities		-0.258***		-0.143***
		(0.027)		(0.025)
Social sciences and law		-0.155***		-0.095***
		(0.024)		(0.022)
Business		0.003		0.029
		(0.021)		(0.021)
Physical and life sciences		-0.235***		-0.114***
		(0.026)		(0.025)
Engineering		0.052***		0.124***
		(0.019)		(0.025)
Natural resources		-0.124***		-0.067**
		(0.023)		(0.027)
Health		-0.082***		0.117***
		(0.027)		(0.021)
Services		-0.065**		-0.101***
		(0.027)		(0.035)
Other		-0.164**		-0.081
		(0.069)		(0.051)
Constant	1.186***	2.119***	1.105***	2.226***
	(0.092)	(0.104)	(0.073)	(0.085)
R-squared	0.162	0.25	0.156	0.287
Sample size	27,527	27,527	40,753	40,753

Notes: Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Both specifications also include province of residence dummies.

Table A.2: First-stage FBE log hourly earnings regressions

	Men		Women	
	Unconditional	Conditional	Unconditional	Conditional
Age	0.060***	0.052***	0.047***	0.040***
	(0.007)	(0.007)	(0.007)	(0.007)
Age squared / 100	-0.075***	-0.066***	-0.059***	-0.053***
	(0.009)	(0.009)	(0.009)	(0.009)
Months since labour market entry /10	0.038***	0.037***	0.024***	0.029***
	(0.005)	(0.004)	(0.004)	(0.004)
Unemployment rate at entry	-0.002	-0.001	-0.003	0.005
	(0.007)	(0.007)	(0.008)	(0.008)
Survey year 2007	-0.021	-0.008	-0.037	-0.019
	(0.030)	(0.029)	(0.030)	(0.029)
Survey year 2008	0.018	0.023	0.036	0.046
	(0.031)	(0.029)	(0.030)	(0.029)
Survey year 2019	-0.001	-0.004	0.047	0.054
	(0.032)	(0.031)	(0.030)	(0.029)
Survey year 2010	-0.022	-0.015	0.028	0.042
	(0.032)	(0.030)	(0.030)	(0.029)
Survey year 2011	-0.034	-0.023	-0.018	-0.001
	(0.031)	(0.030)	(0.028)	(0.027)
Survey year 2012	-0.019	-0.008	0.004	0.006
	(0.031)	(0.030)	(0.028)	(0.027)
Survey year 2013	-0.014	-0.008	0.054	0.046
	(0.029)	(0.028)	(0.028)	(0.026)
Below Bachelor's		-0.256***		-0.266***
		(0.021)		(0.020)
Bachelor's		-0.135***		-0.146***
		(0.019)		(0.019)
South and Central America		0.129***		0.117***
		(0.032)		(0.029)
Northern and Western Europe		0.366***		0.340***
		(0.040)		(0.037)
Eastern Europe		0.139***		0.079***
		(0.032)		(0.026)
Southern Europe		0.193***		0.123***
		(0.061)		(0.057)
Africa		0.088***		0.121***
		(0.032)		(0.030)
West and Central Asia		0.088**		0.075**
		(0.038)		(0.037)
US, UK, Australia, and NZ		0.422***		0.402***
		(0.039)		(0.049)
Southeast Asia		0.013		0.033
		(0.027)		(0.022)
South Asia		-0.021		-0.045*
		(0.026)		(0.026)
Constant	1.705***	1.946***	1.817***	1.974***
	(0.152)	(0.148)	(0.145)	(0.141)
R-squared	0.063	0.144	0.034	0.123
Sample size	6,245	6,245	5,861	5,861

Notes: Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Both specifications also include province of residence dummies.

Conclusion

The three chapters of my dissertation shed light on how international students fare in Canadian postsecondary institutions and the labour market. According to the Statistics Canada, the total enrollment of international students in Canadian postsecondary institutions quintupled between 1999 and 2015. As Canadian universities are increasingly reliant on the enrollment of international students, Chapter 1 finds that both Canadian-educated international students (CEISs) and foreign-educated international students (FEISs) underperform their domestic counterparts at various percentiles. We find improvements in the quality of foreign students between 2004 and 2015. The gains reflect the improvements in the screening of foreign applicants, which have served to improve the relative quality of foreign students.

Chapter 2 provides insights into the effect of ethnic peers on students' program choices, which is relevant to university administrators. Consistent with studies in the U.S. (Trusty, Ng, and Ray 2000; Staniec 2004; Poter and Umbach 2006; Dickson 2010), students at the university are ethnically concentrated with certain academic programs at the time of their initial enrollment. Moreover, students' program changes further serve to increase the ethnic concentration of students over the course of their undergraduate studies. Lastly, students change to programs in which match with their skills, even though the programs they switch to have a higher share of their co-ethnic peers.

International students represent an attractive pool of new immigrants who have potential to contribute to Canadian economic growth. To examine the economic impacts of international students, Chapter 3 compares a wide range of labour market outcomes of former international students (FISs) to foreign-born-and-educated immigrants (FBEs) and Canadian-born-and-educated-graduates (CBEs). The results from Chapter 3 reveal that FISs outperform FBEs by a substantial margin. However, FISs lag behind CBEs when conditioning on the education level and field of study. Last, the relative quality of FISs has tended to deteriorate among college graduates, while the share of international-student applicants has increased.

These studies provide direct policy implications for the integration of international students and the immigration selection system. Perhaps the biggest motivation for international students to choose Canada as their destination, besides education opportunities, is the possibility of applying for permanent residency post-graduation. Based on the survey results from Canadian Bureau for International Education (CBIE), the proportion of international students in Canadian postsecondary institutions who are interested in exploring permanent residency increased from 51% in 2015 to 60% in 2018. International students have become a lucrative source of spending and high skilled immigration. In 2016, international students contributed $15.5 billion to economic activities in Canada. Former international students have a much stronger labour market performance than foreign educated immigrants. Therefore, the federal government should continue capitalizing on international students by expanding international education. In the meantime, policymakers should be aware that a large influx of international students also brings challenges to their social and economic integration and the federal government's immigration screening process.

One of the key hurdles identified in international students' social integration process concerns the cultural differences between their culture of origin and the Canadian culture. As the international student share has increased dramatically in Canadian postsecondary institutions, some academic programs have become minority-majority programs. The social integration challenges international students face may be reflected by the fact that students are increasingly ethnically concentrated within programs. According to 2013 survey results from CBIE, nearly 58% of international students report having very few or no Canadian friends, and only 7% of international students are friends primarily with Canadian students. To help international students fit in, institutions could offer programs that connect international students and off-campus communities and enhance international students' class participation, such as mix international and domestic students in assignment or presentation group.

The economic integration period experienced by foreign students is often stressful. Our evidence suggests that FISs are less likely to be employed; less likely to have jobs that match their field of study, and more likely to being overqualified for their job, compared to CBEs. Both the education institutions and government should implement programs to raise the awareness about the suitable employment opportunities for international students. For instance, postsecondary institutions can serve as intermediaries with the Canadian labour market, by helping international students better understand the labour market and providing recruitment sessions to them. The municipal/provincial government could provide education sessions to employers in order to increase their confidence in hiring international students.

Turning to the immigration screening process, it appears that giving bonus points to international students in the EE system is justified. However, as the Canadian government eases the transition to permanent residency for international students, our evidence suggests that former international student quality has deteriorated over time, particularly among college graduates. This is reflected by the fact that the enrollment of international students has shifted from universities towards colleges in recent years. The Canadian government should be concerned whether providing the same amount of CRS points to international students who hold a college or university credential is optimal.[1] Policymakers should consider giving more points to applicants with a bachelor degree than with a college degree.

In addition, the relative weaker academic performance of foreign students partially reflect the earning gap of FISs to CBEs. However, it is unclear which part of the foreign student quality distribution FISs were selected from, since academic grades are not accounted for when screening applicants' skills in the EE system. If former international students were selected from the lower end of the distribution, the difference in student quality may be larger in the labour market. The primary objective of the immigration selection system is to attract high quality foreign students as future citizens and screen out the relatively low quality of foreign student applicants. Our evidence suggests that it would be beneficial for the federal government to incorporate postsecondary grades as a selection criterion in the EE system.

[1]Under the current EE system, applicants with Canadian post-secondary program of 3 or more years could earn 210 CRS points.

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