THE IMMIGRANT EXPERIENCE: NETWORKS, SKILLS AND THE NEXT GENERATION

by

ANETA KINGA BONIKOWSKA

B.A. (Honours), The University of British Columbia, 2000

M.A., The University of British Columbia, 2001

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Abstract

This thesis explores several issues in the adaptation process of immigrants and their children in Canada.

Chapter 2 investigates why second-generation immigrants are better educated than the remaining population. Using a standard human capital framework where individuals choose how much to invest in both their children's and their own human capital, I show that a gap in education can arise in the absence of differences in unobservable characteristics between immigrants and the native born. Rather, it can arise due to institutional factors such as imperfect transferability of foreign human capital and credit constraints. The model's key implication is a negative relationship between parental human capital investments and children's educational attainment, particularly in families with uneducated parents. I find strong empirical evidence of such tradeoffs in human capital investments occurring within immigrant families.

Chapter 3 re-assesses the effect of living in an ethnic enclave on labour market outcomes of immigrants. I find evidence of cohort effects in the relationship between mean earnings and the proportion of co-ethnics in the CMA which vary by education level. Next, using information on the proportion of one's friends who share one's ethnicity, I test a common assumption that the enclave effect is a network effect. I find that traditional, geography-based measures of the ethnic enclave effect capture the impact of factor(s) other than social networks. In fact, the two effects generally offset each other to some degree in determining immigrant employment outcomes. Neither measure has a statistically significant effect on average immigrant earnings, at least in cross-sectional data.

Chapter 4, co-authored with David Green and Craig Riddell, tests two alternative theories about why immigrants earn less than native-born workers with similar educational attainment and experience - discrimination versus lower skills (measured by literacy test scores). We find that immigrant workers educated abroad have lower cognitive skill levels (assessed in English or French) than similar native-born workers. This skills gap can explain much of the earnings gap. At the same time, foreign-educated immigrants receive no lower returns to skills than the native born. These results offer strong evidence against the discrimination hypothesis.

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Chapter 1

Introduction

Canada has a long-standing tradition as a major immigrant-receiving country. The 2001 Canadian Census indicates that immigrants (foreign-born individuals) form around 22% of Canada's population age 15 and older. A further 16% are second-generation immigrants. Given their large share in the population, the success with which immigrants and their descendants adapt to their new country carries significant consequences for the economic and social well-being of the entire population. Since the 1980s, successive cohorts of immigrants have been entering the Canadian labour market with progressively lower mean earnings, not always offset by faster earnings growth (Green and Worswick (2004)). These observations have sparked renewed research interest in issues relating to immigrant adaptation.

This dissertation focuses on furthering our understanding of the adaptation process of immigrants and their children. Chapter 2 provides a theoretical and empirical exploration of the link between the economic success of immigrants and the educational attainment of their children. The overall message from this analysis is that the ease with which immigrant parents are able to adjust to the host country labour market has consequences that persist through at least the next two generations. The remainder of the thesis focuses on the labour market experiences of first generation immigrants. Chapter 3 provides a re-assessment of the Canadian literature on the ethnic enclave effects. Chapter 4, co-authored with Professors David Green and Craig Riddell, explores differences in cognitive skills between immigrant and native-born workers and their impact on the observed earnings gap between the two groups, conditional on education and experience.

Chapter 2 seeks to understand the source of the well documented observation that children of immigrants in Canada (as well as the US) are on average better educated than the remaining native born. This difference persists even after conditioning on parental education and ethnic origin. The gap is often ascribed to stronger preferences for education or higher ability among immigrant parents. I show, instead, how such a gap can arise in a standard human capital framework where parents choose both how much to invest in their own human capital, and the optimal level of schooling for their children. The key insight from the model is that the gap in education can develop even in the absence of differences between immigrants and the native born along unobservable dimensions such as ability, preferences or discount factors. Rather, it may arise as an optimal response to institutional factors such as imperfect transferability of foreign human capital and the presence of credit constraints among low educated individuals in general.

The model yields several testable implications. I evaluate them using the Ethnic Diversity Survey, a relatively unexplored Canadian post-censal survey with a unique combination of information and sample design. Under reasonable assumptions, immigrant parents with low education are predicted to optimally invest in higher levels of education for their children than similarly educated, native-born parents. In contrast, among children of well educated parents, the second generation – native born gap, if present at all, may be negative. Furthermore, we should not see any difference in educational attainment, conditional on parental education and ethnicity, between third-generation immigrants and the remaining native born. These patterns are indeed present in the data. The model also has direct implications for the relationship between the amount of schooling of immigrant children and the slope of their parents' post-migration earnings profiles. Among children of immigrants with low education levels, we should see educational attainment falling as the slope of parental earnings rises indicating a tradeoff in human capital investments in immigrant families. I find strong evidence of such a tradeoff occurring in families with low educated parents, but not in families where at least one parent has a post-secondary education.

Chapter 3 re-assesses the evidence on ethnic enclaves and their impact on the economic well-being of immigrants in Canada. Cross-sectional studies typically reveal a small, often not statistically significant, correlation between geography-based measures of exposure to co-ethnics and mean earnings or employment of immigrants as a group. Studies that take advantage of several cross sections of data find evidence of a statistically significant association between exposure to co-ethnics and earnings growth. Using four pooled cross sections of the Canadian Census (public use files), I show that the weak correlation with mean outcomes could be attributed to the presence of cohort effects in the relationship between exposure to co-ethnics and the shape of post-migration age-earnings profiles and how this relationship varies with immigrants' education level. Immigrants who arrived in the 1980s and who live in cities with a higher proportion of co-ethnics have higher mean earnings. This is more of an exception than a rule across gender-education subgroups of immigrants who arrived in the 1990s. The earnings decline was more substantial for immigrants with low education levels than those with post-secondary education.

Data on the proportion of co-ethnic friends from the Ethnic Diversity Survey allows a preliminary exploration of what constitutes the ethnic enclave effect. Contrary to common belief, the ethnic enclave effect does not appear to be solely a network effect. Co-ethnic social networks measured more directly by the proportion of co-ethnic friends appear to increase the probability of employment among immigrants with post-secondary education. They also offset to some degree a negative impact of the proportion of co-ethnics in the city of residence. The data do not, however, yield strong results regarding the impact of social networks or ethnic enclaves more generally on immigrant earnings. Small sample sizes and the cross-sectional nature of the data set may be responsible.

Chapter 4 seeks to understand the source of the earnings gap between immigrant and native-born workers with similar education and experience. The objective is to test two common explanations. The first is that skills acquired abroad are not fully transferable to the Canadian labour market, hence well-educated immigrants may hold low-paying jobs. The second is discrimination against immigrants who are in fact no less productive than native-born workers. We use average scores from tests of prose and document literacy, numeracy and problem solving in the International Adult Literacy and Skills Survey (IALSS) data as a measure of cognitive skills. Information on the origin of the immigrant's highest level of education allows us to explore skill differentials between immigrants educated in Canada and abroad.

We find that foreign-educated immigrants do in fact have lower skill levels as measured in English or French than the Canadian-born population. Canadian-educated immigrants, the majority of whom would have arrived in Canada as children, appear to have slightly lower skills as well, although this gap is not statistically significant. In a counterfactual exercise comparing foreign-educated immigrants with native-born workers we find that the skills differential can explain the entire gap in earnings between high school educated immigrants and the native born, and at least half of the difference in wages among the university educated. Immigrants do not however earn lower returns to skills than similar native-born workers. These results considerably weaken the argument that immigrants earn lower wages than similarly educated native-born workers due to discrimination.

Chapter 2

Explaining the Education Gap Between Children of Immigrants and the Native Born: Allocation of Human Capital Investments in Immigrant Families

2.1 Introduction

Immigrants are not a random draw from their source country population and typically differ from the host country population along observable and perhaps unobservable dimensions. The resulting immigrant–native born disparities in labour market experiences have attracted much attention in the literature and continue to do so as the characteristics and outcomes of immigrants to North America continue to change.[1] The contribution of immigrants to a host economy, however, extends beyond the impact of the migrant generation. Equally important are outcomes of their descendants. While intergenerational transmission of earnings among immigrants has been the subject of several studies, one of the key determinants of earnings – education – remains poorly understood in the immigrant context.[2]

[1]As the source country composition of immigrants to North America has been shifting away from European countries over the past three or so decades, successive immigrant cohorts have also been experiencing declining entry earnings. This phenomenon is the subject of several studies in Canada, e.g. Baker and Benjamin (1994), Green and Worswick (2004), and Aydemir and Skuterud (2005), and in the US, e.g. Borjas (1995) and Duleep and Regets (2002).

[2]Aydemir, Chen, and Corak (2007) estimate the intergenerational transmission of education among immigrants in Canada, Aydemir, Chen, and Corak (2005) study intergenerational transmission of earnings among immigrants in Canada, while Card, DiNardo, and Estes (2000), Card (2005) and Borjas (1993, 1994) study earnings of children of immigrants the US, and Epstein and Lecker (2001) do so for Israel.

Second-generation immigrants in Canada and the US are as a group better educated than the native born. The puzzling aspect of this result is that there remains a substantial gap in educational attainment between second-generation immigrants and the native born even after conditioning on several socio-demographic characteristics including parental education and ethnic origin. My objective in this chapter is to explore in an economic framework how such a systematic difference in educational attainment between children of immigrants and the native born could arise.

There have been previous attempts at explaining why children of immigrants are on average better educated than the remaining native born in Canada, e.g. Hansen and Kucera (2004), and the US, e.g. Chiswick and DebBurman (2004). They show that characteristics such as age, ethnicity, language skills, parental education, and geographic location fail to explain the entire difference in mean educational attainment and attribute the remaining gap to factors such as stronger preferences for education or higher ability among immigrant parents. I show that such a gap can arise even in the absence of differences in unobservables such as ability, preferences or discount factors. In a standard human capital framework where parents make simultaneous decisions about investments in their own human capital and education of their children, a gap in education may develop as an optimal response to institutional factors such as imperfect transferability of foreign human capital and credit constraints. This model yields testable implications that stand up in the data.

The key source of differences between immigrant and native-born parents in this model is the standard assumption that human capital is not fully transferable between countries. I follow Duleep and Regets (2002) in assuming that foreign human capital is at least as useful in acquiring new skills as it is in generating earnings. I argue, however, that this is only true for immigrants with high education. As a result, well educated immigrants can be expected to invest more in their human capital than comparable native born, while immigrants with low education would invest less. Under the assumption of binding credit constraints for individuals with low education, the model predicts that children of immigrants will outperform their native-born counterparts in educational attainment, while their parents spend more time in the labour market and less time investing in their own human capital. In contrast, children of immigrants with high education will acquire less schooling than comparable native born if the present value of their parents' earnings is lower than that of similar, native-born parents.

I test the model's implications using data from the Ethnic Diversity Survey (EDS), a Canadian post-censal survey from 2002. This data set contains information on parental education, crucial to testing the model's key predictions. Parental birthplace and rarely available information on the birthplace of grandparents allow me to apply a more precise definition of second generation immigrant status. I am also able to compare outcomes of second and third-generation immigrants with those of the fourth-and-higher generation.

Finally, oversampling on the basis of generation status and ethnic ancestry in EDS provides relatively large samples of each generation group, particularly the second generation. It also ensures that larger non-European ethnic minority groups are well represented in the sample. Given the changing ethnic composition of immigrant inflows, the future second generation will be an increasingly diverse group. This raises the need for analysis based on data reflecting that diversity. To my knowledge, the combination of sample design and information required for the analysis in this chapter is not available in any other US or Canadian micro data set commonly used in immigrant studies.

I find that the gap in educational attainment of second-generation immigrants, conditional on age, parental education and ethnic origin, is indeed driven by individuals from low-education backgrounds. No such advantage is observed among children of well educated immigrants; if anything, their attainment is slightly inferior to that of comparable native born. Third-generation immigrants are also on average better educated than the fourth-and-higher generation. However, once age, parental education and ethnic origin are controlled for, there no longer is a significant difference between the two groups. This is consistent with the model's prediction, since parents of third-generation immigrants are educated in Canada and, therefore, do not experience problems with skill transferability. Further, I find direct evidence of a tradeoff between investment in parental human capital and children's schooling. The growth rate of parental earnings, indicative of investment in parental human capital within the context of a standard human capital model, has a significant negative relationship to total years of schooling among children of immigrant parents who did not complete any post-secondary education. That effect is still negative but much smaller and not statistically significant among children of immigrants with a post-secondary education.

My results highlight areas of policy concern. The points system of immigration in Canada targets well educated immigrants. This policy contributes to high education levels among second and third-generation immigrants, thus raising the overall education level in the country. However, the educational attainment of children of well educated immigrants from more recent cohorts may decline if the falling entry earnings faced by those cohorts also result in falling present value of their post-migration earnings. In contrast, children of immigrants with low education are outperforming their native-born counterparts in educational attainment and will likely continue to do so.

The studies closest in spirit to the analysis in this chapter are Epstein and Lecker (2001) and Caponi (2004). The former paper explains the higher earnings among second-generation immigrants than the native born in Israel in the context of a model of bilateral altruism between two consecutive generations. This specific preference structure yields the prediction of higher investments in human capital among individuals with immigrant parents who earn less than the native born. Further implications of this model regarding outcomes of third-generation immigrants do not match patterns observed in Canadian data, however. Caponi (2004) develops a general equilibrium model in which discounting of foreign human capital in the host country labour market and altruism towards children are shown to generate the observed U-shaped relationship between human capital and the decision to emigrate in the Mexican population. This study differentiates between parental human capital useful in generating earnings and that transferred to children, where the latter is not subject to discounting. This distinction leads to the prediction that children of immigrants from more recent cohorts facing lower entry earnings due to higher discounting of foreign human capital in the labour market will be able to overcome their parents' disadvantage in earnings. In the context of this model, first-generation immigrants would need to have sufficiently higher human capital levels than the native born, different preferences or different human capital production technology in order for their children to outperform the native born in educational attainment.[3] Neither of these studies, however, sets out to explain the observed gap in educational attainment between children of immigrants and the native born, which is the focus of this chapter.

The contributions of this chapter to the literature are as follows. The study explores sources of the observed gap in educational attainment between children of immigrants and the native born in an economic framework. This gap, while documented, has not been previously systematically explored. Further, no previous study of second-generation immigrant outcomes, e.g. earnings, examines the consequences of parental post-migration human capital investments, although the presence of such investments lies at the core of the immigrant literature.[4] The approach I take reveals the presence of human capital investment trade-offs in immigrant families which can give rise to a gap in educational attainment between second-generation immigrants and the native born even in the absence of differences along unobservable dimensions, such as ability, preferences or discount factors. Finally, the data I use allow me to identify and study third-generation immigrants, a group that has received very little attention in previous literature.

The chapter proceeds as follows. Section 2 discusses the relevant literature. Section 3 presents the theoretical framework. Section 4 presents the data. Section 5 explores key patterns in educational attainment among the descendants of immigrants. Section 6 tests the relationship between the slope of parental earnings profiles and children's educational outcomes. Section 7 briefly discusses alternative hypotheses about the sources of the gap in educational attainment between the second generation and the remaining population. Finally, Section 8 concludes.

[3]These appear to be the required conditions in the partial equilibrium version of the model presented in Caponi (2004).

[4]Lower entry earnings and steeper earnings profiles of immigrants relative to the native born have been explained frequently in the context of a human capital model, e.g. Chiswick (1978) and Duleep and Regets (2002) to name a couple of examples. The family investment hypothesis also explores the division of investment and borrowing functions between spouses in immigrant families (Baker and Benjamin (1997)).

2.2 Literature Review

The existing literature that documents earnings and educational attainment of the first and second-generation immigrants in various countries reveals different patterns of intergenerational assimilation. Several European studies provide evidence of smooth assimilation in the second generation in terms of various measures of educational attainment. For example, Van Ours and Veenman (2001) find that in the Netherlands, second-generation immigrants close the gap between their parents' educational attainment and that of the native population. This is true of ethnic groups that are on average less and more educated in the first generation than the average Dutch native. They further show that the gap in attainment between second-generation males and their native counterparts is almost entirely explained by parental education differences, but this is not the case for women. Gang and Zimmermann (2000) also find convergence to the mean in educational attainment among second-generation immigrants in Germany. The gap that still separates that generation from the native Germans cannot be explained by differences in standard socio-economic characteristics. In addition, parental education appears to have no predictive power for the second generation's outcomes. Riphahn (2003) further documents that the gap in educational attainment between children of immigrants and German natives has been growing over the past few decades, a fact that the author attributes to the changing ethnic composition of immigrants to Germany.

A different pattern is documented in studies on data from Canada, the US and Israel, where second-generation immigrants are found to outperform the native-born population in education and earnings. The source of these differences between the European and non-European countries is beyond the scope of this study. It is possible that differences in education systems, ethnic composition and class of immigrant contribute to this cross-country variation in outcomes of immigrant children.

Hansen and Kucera (2004) analyze the educational attainment of second-generation immigrant men in Canada as compared to Canadian natives (i.e. third and higher generations) using the Survey of Labour and Income Dynamics (SLID). They find that after controlling for several individual characteristics including parental education, visible minority status, English or French mother tongue and ethnic origin, there still remains a gap in educational attainment in favour of the second-generation immigrants. Further, once indicators for parental education and mother tongue were included in regressions, ethnic origin had little additional predictive power. One drawback of the SLID data is that the second-generation immigrant sample is composed predominantly of individuals of European origin. It is not obvious that results based on this sample will generalize to other ethnic groups that are becoming increasingly more prominent among second-generation immigrants in Canada.

Worswick (2004) looks at the performance of immigrants' children in Canadian schools using data from the National Longitudinal Survey of Children and Youth covering the 1994-

1999 period. He finds that children age four to six with an immigrant parent have lower performance on vocabulary tests than children of Canadian-born parents. For children with an immigrant parent whose mother tongue is neither English nor French, this initial disadvantage is still evident in performance on reading tests at older ages, but disappears by age fourteen. There is no difference in performance on mathematics tests between children (aged seven to fourteen) with immigrant and Canadian-born parents.

Chiswick and DebBurman (2004) find that second-generation immigrants in the US who have only one immigrant parent have slightly higher education levels than those with two immigrant parents, controlling for several socio-demographic characteristics that do not include parental education. They attribute the overall higher education levels of second-generation immigrants (US-born individuals with at least one immigrant parent) to on average higher ability parents (due to immigrant self-selection) who are therefore "more inclined to invest in their children's schooling than native-born parents" (p. 373).

Aydemir, Chen and Corak (2007) use the 2001 Canadian Census and the Ethnic Diversity Survey to estimate the degree of intergenerational education mobility among immigrants in Canada. They find that the correlation between years of schooling of parents and children is much lower among immigrants than the native born, and stable across birth cohorts. They also find that conditional on education of "potential" fathers, paternal earnings are not significantly correlated with immigrant children's education outcomes, and if anything the correlation is negative.[5] The analysis in Aydemir, Chen and Corak (2007) is intended to document the patterns and trends in intergenerational education mobility among immigrants rather than explain them. The authors speculate that the explanations may lie in the operation of Canadian education institutions and self-selection of immigrants, especially on intergenerational altruism.

The above-average earnings of second-generation immigrants have received more detailed attention in the literature than educational attainment directly. Aydemir, Chen, and Corak (2005) study the intergenerational mobility in earnings among immigrants in Canada and the possible channels of transmission. They take advantage of new information on parental birthplace in the 2001 Canadian Census to identify second-generation immigrants. They find that although paternal earnings (more precisely earnings of "potential" fathers) have a significant impact on years of schooling of children (particularly sons), the overall importance of this channel in the generational earnings elasticity is small. They also find that conditional on average education of "potential" fathers, second-generation immigrants from low-income ethnic groups become above-average earners.

In the US, Card, DiNardo, and Estes (2000) find that controlling for differences in region of residence, age and ethnic composition, second-generation immigrants also have the high-

[5]The Census does not contain information on parental education or earnings, hence the authors calculate average earnings and education of "potential fathers" from the 1981 Census.

est average wages compared to the rest of the US population. Furthermore, this advantage is apparent over the 1970 - mid-1990s period despite increasing wage inequality and the changing age and ethnic composition of the second generation. A study of intergenerational transmission of earnings reveals that education of the second generation is the main transmission mechanism. They find that potential fathers' earnings have a significant effect on education and earnings of second-generation immigrants observed in the 1970 US Census. For second-generation immigrants observed in the 1994-1996 Current Population Survey in contrast, it is paternal education that has a significant effect. Further, when the children's education is controlled for, fathers' outcomes no longer have a significant effect on earnings.

Using data from the 1995-2002 Current Population Survey, Card (2005) shows that the higher wages of second-generation immigrants in the US can be explained to a large extent by their higher education levels relative to the US natives and by their geographic distribution. Children of immigrants obtain above-average education levels even though their parents are on average less educated than the third-and-higher generation.

Borjas (1994) analyzes the intergenerational convergence of skill differentials, measured by education/literacy and earnings, among descendants of the Great Migration in the US (immigrants who arrived between 1880 and 1910). He finds that the skills differences between the various ethnic groups represented among those immigrants were still visible among their grandchildren. This study utilizes the General Social Survey (GSS) to identify potential grandchildren of the Great Migration, third-generation immigrants. The sample size of the individual GSS cross sections is very small, however. One could obtain an overall sample comparable in size to EDS by pooling the 25 cross sections spanning a 32-year period from 1972 to 2004. Further, there is no information on year of immigration of the respondent in this data.

Aydemir and Sweetman (2006) compare education and labour market outcomes of first and second-generation immigrants in Canada and the US. They too show that current second-generation immigrant outcomes in both countries are superior to those of the first generation, and at least as good as those of the remaining native born. Important differences exist, however, between the two groups which point to a divergence of outcomes between the two countries among future second-generation immigrants, with a further improvement in Canada but a deterioration of outcomes in the US.

The earnings advantage of the second generation is also evident in data from Israel analyzed in Epstein and Lecker (2001). The authors are able to identify individuals whose parents immigrated to Israel as young children and treat them as third-generation immigrants. They focus on immigrants from Asian and African origins and identify immigrants from the 1948-1952 period, their potential children and grandchildren from the 1995 Israeli Census data. The study finds that immigrants and third-generation immigrants earn on average less than their native-born counterparts, while the second generation earns more.

The authors explain this pattern in the context of a model of bilateral altruism between two consecutive generations. This specific preference structure yields the prediction of higher investments in human capital among individuals with immigrant parents who earn less than the native born. The model therefore implies that third-generation immigrants will invest less in human capital and earn less than comparable native born. This pattern of education and earnings among third-generation immigrants is not present in Canadian data, where third-generation immigrants are on average better educated and earn more than the fourth-and-higher generation (Bonikowska (2005)).

Two further studies which seek to understand what factors affect the decision to migrate also have implications for human capital and/or earnings of second-generation immigrants. In Borjas (1993) relative returns to skills between countries as well as the degree of intergenerational mobility play a crucial role in the migration decision. The model assumes that only skills valued in the host country labour market are passed on to children. This implies that highly educated immigrants whose credentials are not fully recognized in the host economy will have low earnings post-migration and so will their descendants. This model does not allow for the possibility that children of well educated immigrants will also be well educated. Further, having been educated in the host country, they will not face the loss of human capital their parents did upon entry into the host country labour market and thus could earn higher incomes than their parents. The model also predicts that skilled parents will have no incentive to migrate to countries with relatively high intergenerational mobility since it will be more difficult for them to pass their skills, and hence earnings potential, to their children there. If one is willing to equate education level with skill level, however, this prediction is not easily reconciled with Canadian data. Canada has one of the highest rates of intergenerational mobility in earnings among developed countries, higher than the US and UK (Fortin and Lefebvre (1998), Grawe (2004), Aydemir, Chen, and Corak (2005)), yet it attracts many well educated immigrants.[6]

Caponi (2004) builds on the intergenerational model of migration in Borjas (1993) to explain the U-shaped relationship between human capital and the decision to migrate in the Mexican population. He differentiates between intrinsic human capital, which immigrants accumulate in their source country, and marketable human capital, the fraction of intrinsic human capital that is useful in generating earnings in the host country. It is intrinsic human capital of parents (as opposed to the marketable human capital as in Borjas (1993)) that is assumed to be transferred to children. Children's human capital accumulation is a function of parental human capital as well as schooling inputs purchased by parents, and

[6]Grawe (2004) conducts a cross-country comparison of intergenerational transmission of earnings. He finds that estimates of intergenerational mobility in the US are sensitive to the data set used for the analysis. In particular, the difference in the average intergenerational mobility between Canada and the US is quite large when the US estimates are based on the Panel Study of Income Dynamics (PSID), but very small when based on the Original Cohort National Longitudinal Survey (NLS).

an idiosyncratic shock. One prediction of the model which contrasts with Borjas (1993) is that the disadvantage faced by immigrant parents in the host country labour market due to imperfectly transferable human capital will not be passed on to the second generation. However, lower parental earnings due to foreign human capital discounting in the labour market leave less income to purchase children's schooling inputs with, all else equal. In the context of this model (or at least a partial equilibrium version thereof), we would have to assume differences in preferences, human capital production technology, or the average human capital of parents in order to obtain the prediction that second-generation immigrants will acquire on average more schooling than comparable native born.

2.3 Theoretical Framework

The model presented in this section extends the basic human capital model to include an intergenerational dimension. This framework includes elements of the model used by Duleep and Regets (2002) to examine differences in human capital investments between immigrants and the native born, and the model of intergenerational transmission of income in Becker and Tomes (1986). Parents care about the outcomes of their children, specifically the level of human capital with which adult children enter the labour market.[7] The key difference between immigrant and native-born parents is that the former lose a portion of their foreign-acquired human capital upon migration. Human capital is used in two types of activities: generating earnings and acquiring new skills. The relative degree of transferability of foreign human capital to these two activities will depend on the immigrant's initial level of human capital, shaping incentives to invest more or less in human capital than comparable native born. In contrast to existing models, I explore the tradeoffs and complementarities in investment that arise when immigrant parents choose how to allocate resources between two types of human capital investments simultaneously: their own and their children's.

There are three periods in the model. Period 0 represents childhood where individuals spend their entire time endowment acquiring human capital with schooling inputs purchased by their parents. In period 1, adult individuals decide how to divide their time endowment between working in the labour market, and investing in host country specific human capital, t. They also decide how to allocate period 1 income between schooling inputs for children, S, and their own consumption, C_1. In period 2, individuals spend their entire time endowment working, and collecting the benefits of previous investments in their own human capital. The price of consumption is normalized to 1 in each period. Time endowments in each period are also normalized to 1.

[7]Note that parental utility depends on children's utility in Becker and Tomes (1986) and children's income in Becker and Tomes (1979).

Period 1 and 2 budget constraints are given by:

$$C_1 + pS + x = a\tau_{m1}H_p(1-t) \tag{2.3.1}$$

$$C_2 = x(1+r) + a(\tau_{m2}H_p + H_p') \tag{2.3.2}$$

Labour market earnings per unit of time are a function of human capital, H_p. In case of immigrants, only a fraction τ_{m1} of the source country human capital is productive in the Canadian labour market in period 1. τ_{m2} is the equivalent proportion in period 2, and $\tau_{m2} \geq \tau_{m1}$ allowing for the possibility that initial human capital becomes more transferable with time spent in the host country labour market independently of any human capital investments. The return to a unit of productive human capital, a, is the same for immigrants and the native born. The wage is therefore given by $a\tau_{m1}H_p$. All individuals can save or borrow against future earnings (x) at an interest rate r. Parents cannot however accumulate debt that can be passed to children at the end of the second period.

The main input into the production of human capital in childhood is parental investment:

$$H_c = \gamma_c S^{\xi} \tag{2.3.3}$$

where γ_c is an individual-specific productivity factor and $\xi < 1$. Schooling inputs may represent anything from tuition (for private primary or high school, college or university), tutors, savings for child's post-secondary education, rent-free accommodation during university etc.

Human capital investments after entry into the labour market are the choice of the adult individual. The main inputs into the production of additional human capital, H_p', are assumed to be time and the individual's existing stock of human capital. Skills that an individual already possesses can increase his productivity in acquiring new skills. The production function for new human capital takes the following form:

$$H_p' = \gamma_p t^{\delta_1} (\tau_p H_p)^{\delta_2} \tag{2.3.4}$$

where τ_p is the proportion of initial (foreign-acquired in case of immigrants) human capital useful in the production of new skills, and γ_p is an individual-specific productivity factor or endowment, $\delta_1 < 1$ allowing for diminishing returns to time spent in investment activities, $0 < \delta_2 < 1$.

Immigrant parents maximize the following utility function subject to equations (2.3.1), (2.3.2), (2.3.3) and (2.3.4):

$$U = logC_1 + \beta(logC_2 + \alpha logH_c) \tag{2.3.5}$$

where α is an altruism parameter, or more directly, a preference parameter for the child's education, C_1 and C_2 are period 1 and 2 consumption, respectively, and β is the discount factor.

For native-born individuals, τ_{m1}, τ_{m2} and τ_p are equal to 1. In evaluating the role of imperfect human capital transferability on optimal choices among immigrants, the degree to which foreign human capital is transferable to its two main uses, generating earnings and new human capital, is important. Imperfect transferability in the labour market may take the form of foreign credentials not being recognized in the host country, whether due to imperfect information about what skills these credentials represent, or because the actual skills are lower than or just different from those required in the host country labour market. It may also represent foreign experience being valued at a lower rate than Canadian experience or not recognized at all. Finally, insufficient host country language skills may prevent an immigrant from utilizing his or her other skills in the labour market.

Duleep and Regets (2002) argue that we can assume foreign human capital to be at least as transferable to the production of new human capital as to the host labour market, i.e. $\tau_p \geq \tau_{m1}$, for the following reasons. At least some of the imperfect transferability is the result of imperfect information about foreign credentials and what skills they actually represent, or difficulty in verifying foreign experience. Another reason is that while occupation-specific skills may be difficult to transfer between countries, skills used in acquiring new human capital of any kind should be easier to transfer. Finally, even if occupation-specific skills acquired in the source country do not meet the requirements of the host country labour market, they may make acquiring the host country human capital much easier due to similarities between the two sets of skills.

However, τ_p will still be less than 1 for immigrants if the skills they do possess are not as useful in acquiring new skills as human capital accumulated in the host country would have been. Difficulty with upgrading occupation-specific skills due to lack of proficiency in the host language is the most natural example.

The above argument works best for immigrants with high human capital at arrival, whom I will refer to as immigrants with high education. Immigrants with low education, on the other hand, may in fact have little or no human capital that could be subject to discounting in the labour market. For example, they may be providing unskilled labour services to the labour market identical to those provided by native-born workers with little formal schooling. However, the human capital they do possess may still be less productive in the acquisition of new skills than that of comparable native born. Again, insufficient host country language skills are one example (assuming that unskilled labour services are much less language dependent than skilled labour services). Therefore, we could argue that for immigrants with low education, $\tau_{m1} \geq \tau_p$.

The implication of the above assumption is that the gap between entry earnings of immigrants and earnings of comparable, native-born workers is larger among individuals with high education than among those with low education. I'm essentially assuming a higher compression of wages at the bottom of the wage distribution. This is also a way to prevent wages from falling arbitrarily low in the market. Although not necessary to achieve the results presented in the next two subsections, for ease of exposition I will assume that such a compression is achieved with a minimum wage, and that in fact, immigrants with low education face the same wage, the minimum wage, as native-born workers with low education. Their period 1 earnings, therefore, can be written as $w_{min}(1-t)$.

Optimal investment decisions of immigrants compared to the native born will differ for individuals earning the minimum wage and those earning higher wages, i.e. differ by education level. I will consider these two groups separately.

2.3.1 Optimal investments with borrowing

The first order conditions for the individual's problem are:

$$\frac{1}{C_1} = \lambda_1 \tag{2.3.6}$$

$$\frac{\beta}{C_2} = \lambda_2 \tag{2.3.7}$$

$$\frac{\beta\alpha\xi}{S} = \lambda_1 p \tag{2.3.8}$$

$$0 = \lambda_1(a\tau_{m1}H_p) - \lambda_2(a\gamma_p(\tau_p H_p)^{\delta_2}\delta_1 t^{\delta_1 - 1}) \tag{2.3.9}$$

$$\lambda_1 = \lambda_2(1+r) \tag{2.3.10}$$

From (2.3.9) and (2.3.10) we can obtain the optimal amount of time devoted to investments in own human capital as:

$$t^* = \left(\frac{\gamma_p\delta_1(\tau_p H_p)^{\delta_2}}{(1+r)\tau_{m1}H_p}\right)^{\frac{1}{1-\delta_1}} \tag{2.3.11}$$

The optimal level of schooling inputs purchased for children is given by:

$$S^* = \frac{\beta\alpha\xi}{p(1+\beta+\beta\alpha\xi)}\left[a\tau_{m1}H_p(1-t^*) + \frac{a\tau_{m2}H_p}{1+r} + \frac{a\gamma_p t^{*\delta_1}(\tau_p H_p)^{\delta_2}}{1+r}\right] \tag{2.3.12}$$

From the above two equations, we can derive the comparative statics of interest, namely how optimal investments in parental human capital and children's schooling vary with the degree of transferability of foreign human capital of immigrant parents to its two uses, generating earnings and new skills (see details and caveats in Appendix A):

$$\frac{\partial t^*}{\partial \tau_p} > 0 \tag{2.3.13}$$

$$\frac{\partial t^*}{\partial \tau_{m1}} < 0 \tag{2.3.14}$$

$$\frac{\partial S^*}{\partial \tau_p} > 0 \tag{2.3.15}$$

$$\frac{\partial S^*}{\partial \tau_{m1}} > 0 \tag{2.3.16}$$

Transferability of foreign human capital to human capital production activities and the labour market, (2.3.13) and (2.3.14) respectively, has the opposite marginal effect on the optimal amount of time immigrants spend investing in their human capital. Time is the main input into production of new parental human capital in this model. Foregone earnings, therefore, are the main cost of investment. I am assuming that there are no differences between immigrants and the native born in direct costs of investment in own human capital, and therefore their actual magnitude does not contribute to differences in optimal choices between immigrants and the native born. From (2.3.14), higher transferability to the labour market means higher marginal cost of investment, and therefore lower optimal amount of investment. From (2.3.13), higher transferability to the production of host country-specific human capital implies higher returns to investment, and hence higher optimal investment.

The effect of the two transferability parameters on optimal investment in children's schooling is working through their effect on the present value of post-migration earnings. Since expenditures on children's schooling are a fixed proportion of the present value of lifetime (post-migration) income in this model, from (2.3.16) and (2.3.15) the marginal effect of both τ_{m1} and τ_p on the optimal level of S will be positive, as long as improved transferability raises the present value of post-migration income.

The investment decisions of immigrants with high levels of human capital are influenced by the level of transferability of their foreign-acquired human capital to both labour market and learning activities. They will be facing both lower marginal cost and marginal return to investments in new human capital than the native born. Given the assumption that $\tau_p \geq \tau_{m1}$, immigrants with higher levels of human capital will be making higher investments in their human capital than comparable native born, all else equal.[8] However, as long as the present value of lifetime (post-migration) earnings is lower among well-educated immigrants than comparable native born, immigrants will invest less in their children's schooling. In

[8]This also depends on the complementarity between foreign and host-country specific human capital. See for example Borjas (1998).

this case, imperfect transferability of human capital leads to a tradeoff in human capital investments in immigrant families with well-educated parents.

Among individuals with low human capital, both immigrant and native-born workers will face the same marginal cost of investment in own human capital, the minimum wage. I am considering the case where investments in human capital raise period 2 wage above the minimum wage, so that the marginal benefit of investment is positive. Given that $\tau_p < 1$, immigrants will face lower marginal returns to investing in their own human capital than comparable native born. This implies that the optimal amount of investment in own human capital is lower for immigrants with low education than for their native-born counterparts. Less time spent investing will lead to higher first period earnings but lower second period wage and hence earnings relative to the native born. Since the magnitude of τ_{m1} is not relevant for immigrants with low human capital in the presence of a minimum wage, the comparative statics imply that a lower τ_p will lead to a lower present value of lifetime earnings. Therefore, in the absence of differences in discount rates, β, preferences for children's education, α, or productivity of schooling inputs, ξ, between immigrants and the native born, immigrants with low education will invest less in their own human capital and spend less on their children's schooling than their native-born counterparts, if children's schooling is a normal good.

2.3.2 Optimal investments with borrowing constraints

The assumption that individuals can borrow freely against future earnings may be more applicable to individuals with high rather than low education, immigrant and native born alike. In a theoretical analysis of credit constraints, Bernhardt and Backus (1990) show that credit constrained individuals will invest less in their own human capital, and further will be choosing occupations with low potential for skill acquisition and therefore flatter earnings profiles. An implication of this is that individuals with lower human capital are more likely to be credit constrained, all else equal. The role of borrowing constraints on parental investments has been explored extensively in Becker and Tomes (1986). The model in this section abstracts from the detailed treatment of the role of access to loans, assets, ability to leave bequests in the form of assets and family structure (quantity of children) explored in that paper. Becker and Tomes (1986) focus on differentiating investment decisions of rich versus poor parents in the presence of borrowing constraints. In contrast, this section is meant to investigate whether the inability to borrow might have a different effect on the investment decisions of immigrant and native-born parents with the same observed level of education.

Consider then how optimal investments of immigrants and native-born individuals with low levels of human capital would differ in the presence of binding credit constraints. In this case, optimal expenditures on children's schooling are financed with period 1 earnings only. For simplicity, I am assuming the most extreme version of such constraints, i.e. where there is no possibility of either borrowing or saving (except through investments in own human capital).[9] The details are again provided in Appendix A.

Once again, optimal investments of immigrants with low initial human capital are influenced by τ_p, but not τ_{m1}. The following expression summarizes the effect of τ_p on the relationship between optimal investments in parental and children's human capital:

$$\frac{\partial S^*}{\partial \tau_p} = -\frac{\beta\alpha\xi}{p(1+\beta\alpha\xi)} a\tau_{m1} H_p \frac{\partial t^*}{\partial \tau_p} \tag{2.3.17}$$

It is clear from the above that loss of human capital upon migration induces a tradeoff between investments in parental and children's human capital in immigrant families. If the optimal time that individuals with low education levels devote to their own human capital investments versus work is relatively small, a reasonable assumption, then $\frac{\partial t^*}{\partial \tau_p} > 0$ and therefore $\frac{\partial S^*}{\partial \tau_p} < 0$. Thus in the presence of credit constraints, immigrants with low initial human capital will optimally invest less in their own skills than similar, native-born individuals. As a result, they will devote more time to the labour market and have higher period 1 earnings, resulting in higher expenditures on children's education.

The key insight from this result is that children of immigrants could outperform their native-born counterparts in educational attainment even in the absence of any differences in preferences for education, ability and/or discount factors between the two groups. Rather, their achievement may be due to the optimal allocation of resources in immigrant families in response to institutional factors - imperfect transferability of foreign human capital in the presence of credit constraints.

The model does not give an unambiguous prediction for the relationship between investments in parental human capital and children's schooling among well-educated immigrants relative to similar, native-born individuals in the presence of credit constraints. A comparison of investments of credit constrained immigrants to native-born individuals not facing such constraints does not yield clear predictions regarding optimal investments in parental human capital of the two groups either. However, since immigrants would only have their period 1 earnings available for purchasing their children's schooling inputs, these expenditures would necessarily be lower than those of comparable, native-born parents.

In summary, it is reasonable to assume that individuals with low education are more likely to experience credit constraints than those with high education. Under this assumption, the model predicts that immigrants with low education will spend more time in the labour market and less time investing in their own human capital, but will spend more on their children's education than similar, native-born parents. In contrast, well-educated immigrants will spend more time investing in their own human capital (in the absence

[9] In the benchmark model presented in the previous subsection, it is always optimal to borrow in the first period.

of binding credit constraints) but purchase fewer schooling inputs for their children if the present value of their earnings is lower than that of comparable native born. In the context of a standard human capital model, higher human capital investments are reflected in steeper earnings profiles. Therefore, we should see a negative relationship between the slope of the earnings profiles of immigrant parents and their children's schooling, especially among immigrants with low education.

2.3.3 Alternative model

One alternative way of modeling children's human capital accumulation is to assume that it is parental time rather than schooling resources (parental income essentially) that enter the production function:

$$H_c = \gamma_c t_c^{\xi} \tag{2.3.18}$$

with the first period budget constraint taking on the following form:

$$C_1 + x = a\tau_{m1} H_p (1 - t_p - t_c) \tag{2.3.19}$$

where t_p is the fraction of period 1 time dedicated to accumulation of parental human capital, and t_c is the fraction dedicated to the production of child's human capital.

Under assumptions described in previous subsections, this version of the model yields predictions similar to those derived above. The degree to which parental human capital is transferable to the production of parental human capital has a positive marginal effect on the time dedicated to that activity, but a negative effect on time dedicated to children. As before, this suggests a tradeoff in human capital investments in immigrant families with low education levels. For well-educated parents the predictions regarding the marginal effect of human capital transferability in generating parental human capital on the proportion of time dedicated to that activity are identical to those in the benchmark model described above. The direction of its marginal impact on time dedicated to the production of child's human capital depends on the magnitude of model parameters. Once again the model does not yield clear predictions about immigrant – native born differences in the relationship between parental investments in their own and their children's human capital in well-educated families.

However we choose to model the relationship between parental resources and the child's human capital production, the simple model outlined in this section illustrates the basic idea of tradeoffs in human capital investments between immigrant parents and their children. Although both parental time and resources may in reality affect a child's educational attainment, I chose to model child's human capital accumulation as a function of parental earnings rather than time for several reasons. First, it circumvents the necessity of making additional assumptions about the relative productivity of parental time in child's human capital production and its other uses, and further how that may differ between immigrant and native-born parents. Second, immigrant parents in particular may substitute tutors for their own time in providing their children with extra help with school work to compensate for lower host language skills (child's and/or parents') as suggested by anecdotal evidence. The model presented in this chapter does not differentiate between the various educational resources that parents may purchase for their children, e.g. tutors, private versus public schools etc., nor does it address the possibility that the Canadian public school system has a different effect on the outcomes of immigrant versus native-born students, perhaps preferential to the former. Such considerations are outside the scope of this chapter.

2.4 Data and Definitions

2.4.1 The data

The empirical analysis in this study is based primarily on data from the master files of the Ethnic Diversity Survey (EDS).[10] The data were collected through telephone interviews conducted in ten Canadian provinces between April and August of 2002. EDS is a post-censal survey, i.e. respondents were selected from among those who answered the "long form" of the 2001 Canadian Census questionnaire. Answers of EDS respondents to several Census questions collected in 2001 were also included in the EDS data set. The target population for the survey includes individuals age 15 and older who live in private dwellings. Individuals living on Indian reserves and those who reported Aboriginal ancestry or identity on the 2001 Census were not within the target population, although a small number of EDS respondents still report Aboriginal ancestry or identity. The total EDS sample consists of 42,476 individuals.

Respondents in EDS were selected based on their answers to the 2001 Census questions regarding ethnic origin, birthplace and the birthplace of parents. This resulted in relatively large samples of the population groups of interest, particularly second-generation immigrants. Further, the sample was constructed such that around two-thirds of the respondents report at least one ethnic origin other than British, French, Canadian, American, Australian or New Zealander. This ensured that a good mix of individuals with other European and non-European origins was selected. For example, the fraction of sampled second-generation individuals who report visible minority status is around 11.5 percent. Random sampling would have resulted in less than 7 percent visible minorities. To the extent that decisions about investment in education differ across ethnic groups, it is not obvious that results from an analysis based on a sample of second-generation individuals from traditional European

[10]These files were accessed through the British Columbia Interuniversity Research Data Centre funded by Simon Fraser University, The University of British Columbia, The University of Victoria, the Social Sciences and Humanities Research Council of Canada and Statistics Canada.

source countries will also hold for other ethnic groups. Given the changing ethnic composition of immigrant inflows, the future second generation in Canada will be an increasingly diverse group, raising the need for analysis based on data which reflects that diversity.

In describing the main patterns in educational attainment, I control for ethnic origin. In previous studies, ethnic or national origin of immigrants was often defined by the respondents' country of birth, and that of second-generation immigrants, by their father's country of birth. Given that I am trying to create a measure of ethnic ancestry that I can apply to four generation groups, this method is not very useful. Instead, I classify individuals by the ethnic ancestry they report. Since up to eight ethnic ancestries can be reported in EDS, I use the self-reported importance ratings for each ancestry listed in assigning respondents with multiple ethnic ancestries to a single ethnic ancestry group. I assign them to the first-reported highest-rated ethnic origin group. I can identify 43 ethnic origins (41 in probit analysis), or groups of origins, where each group represents at least 30 observations in each of the male and female samples.[11] Remaining ethnic origins reported are grouped in an "other" category. Individuals with multiple ancestries who did not give a valid importance rating for at least one of their ancestries, whose first-reported highest-rated ancestry was uncodeable, who reported a single ancestry which was also uncodeable, or who did not respond to the ethnic ancestry question at all were not assigned to any ethnic origin group. These observations are identified with a separate indicator variable in all regressions.

In addition to sample design, a major advantage of the EDS for the analysis in this chapter is that it contains data on several crucial variables not commonly found together in data sets used in immigrant studies. The first one is information on parental education. Respondents were asked about the highest level of schooling of each of their mother and father. Responses were grouped into nine categories: graduate or medical degree, undergraduate university degree, college diploma or certificate, degree or diploma from university or college, some university, some college, some university or college, high school, and less than high school.[12] I construct a variable which represents the higher of the father's and mother's reported level of schooling and use it as a measure of parental education in all empirical analysis. Where education of only one parent was reported, I used that information as the highest parental education.

[11]The 43 groups are: English, Irish, Scottish, Welsh, British other, French, Austrian, Belgian, Dutch, German, Swiss, Finnish, Danish, Norwegian, Swedish, Baltic Rep, Czechoslovakian, Hungarian, Polish, Romanian, Russian, Ukrainian, Yugoslavian, Greek, Italian, Portuguese, Jewish, European other, Lebanese, West Asian other, East Indian, South Asian other, Chinese, Filipino, Japanese, East and Southeast Asian other, African (excluding North Africa), Jamaican, Caribbean other, Latin, Central and South American, American, Canadian, and Canadian (French).

[12]Respondents who were unable to provide the exact level of parental education were prompted for an approximate answer about whether they thought their parent completed a post-secondary degree or diploma at a university or college, has some post-secondary education at a university or college, graduated from high school, or did not graduate from high school. Responses to the first two options only were coded into separate categories.

Two other variables crucial to the analysis are the birthplaces of parents and, rarely found in surveys, of grandparents. Information on parental birthplace is necessary to identify the children of immigrants – second-generation immigrants. Data on grandparents' birthplace allows a more detailed generation classification. The point is essentially to avoid classifying foreign-born individuals who are Canadian by birth as immigrants, or individuals who are in fact third-or-higher generation with one or both of their parents born outside Canada as second-generation immigrants.[13] The details of the generation status classification are given in the following subsection. It turns out that the classification which considers the birthplace of three generations to determine immigrant status makes little difference in the analysis at hand, because the number of individuals affected by this reclassification is not large enough to significantly affect results.

The EDS data set also contains respondents' answers to several questions from the 2001 Census. I use the derived variable for total years of schooling as the main measure of educational attainment in subsequent analysis. I update this variable using information collected in EDS on the respondents' main activity in the 12 months prior to the survey. Specifically, I add one extra year of schooling for respondents who reported attending school as their main activity, regardless of whether attendance was full or part time. I also examine two other measures of educational attainment: the probability of graduating from high school or more (i.e. of not dropping out of high school) and the probability of completing university. These two variables are based on answers collected in the EDS.[14]

2.4.2 Generation status

I define as second-generation immigrants individuals born in Canada with at least one immigrant parent (i.e. parent who is foreign born and has at least one foreign-born parent of his/her own)[15], but also children of immigrants who were themselves born outside Canada and immigrated at age 17 or younger. Some previous studies have considered children up to age 10 or 11 at arrival as second-generation immigrants. I expand the definition to include all individuals whose parents are immigrants and who did not independently undertake the decision to migrate.[16] The reason for this is to capture all children of immigrant parents in order to analyze the effect of having a parent who experienced the post-migration assimilation process. In analyzing basic patterns in educational attainment in the data, I divide the entire second generation group into four subgroups: individuals who immigrated between the ages of 14-17, 6-13, 0-5, and those born in Canada, in order to account for the

[13] Card et al. (2000) have previously excluded foreign-born individuals with US parents from the immigrant group, classifying them instead as third-and-higher generation.

[14] Educational attainment of EDS respondents was coded into 7 categories, corresponding to those reported for parental education, except for the two separate categories where the exact level of education was unknown.

[15] A more restrictive version of the definition used in some previous literature requires that both parents be foreign born.

[16] 18 is the youngest age at which an individual can apply for immigration to Canada.

effect of age at migration on educational attainment. In some of the analysis, I also divide the Canadian-born, second-generation immigrants into those with one immigrant parent, and those with two.

For much of the analysis, I compare educational attainment of children of immigrants to that of the remaining non-immigrant population, as do most previous studies. In a further section, however, I divide the latter group into third-generation immigrants and the fourth-and-higher generation. Within the sample of individuals who are neither first nor second-generation immigrants, the third-generation is defined as individuals with at least one foreign-born grandparent. The fourth-and-higher generation, or simply the fourth generation, are individuals with four Canadian-born grandparents, regardless of their or their parents' place of birth. This split is used to test further predictions of the theoretical model but also reveals information about third-generation immigrants who to date have not received much attention in the literature.

2.4.3 The sample

The sample selected for this study is restricted to respondents age 25 and older at the time of the survey since most individuals may be expected to have completed their education by that age. There is no question in the EDS regarding current student status, only one about the respondent's main activity in the preceding 12 months. Since the EDS interviews were conducted in the summer, one cannot infer that individuals who reported their main activity in the previous year as "student" were still students at the time of the survey. Individuals who reported Aboriginal ancestry or identity were excluded from analysis, as were temporary residents and individuals with invalid information on residence status.

A further sample restriction resulted from the data requirements in assigning generation status and missing information. Observations with missing information on one or more of the birthplaces of the respondent, the parents, the grandparents or age at immigration (when applicable) were excluded from the sample if the available information was such that it was impossible to classify the respondent into one of the four generation groups. As a result 1,393 observations were dropped. Of these excluded observations, 4.8 percent were dropped because of missing age at immigration, and the remaining due to missing birthplace information. Birthplace of at least one grandparent was the most common missing birthplace information, followed by the birthplace of at least one parent, and finally that of the respondent. Observations with missing information on birthplaces of family members or own age at immigration (when applicable) appear not to be a random draw from the population. In particular, they tend to have lower levels of education. Those excluded from the sample have 11.5 years of schooling on average, compared to an average of roughly 13 years for individuals in the sample. The final sample size is 25,143 (smaller in case of probit regressions given the higher incidence of missing information on highest level of schooling reported in EDS than years of schooling reported in the Census).

2.5 Empirical Evidence

2.5.1 Basic cross-generation patterns

I begin by presenting the basic patterns in educational attainment among the children of immigrants compared to all remaining native-born individuals. I report OLS estimates of differences in years of schooling between second-generation immigrants and the remaining native born, and marginal effects from probit analysis on the differences in probability of having completed high school or more, and the probability of having completed a university degree. These regressions are meant to be descriptive in nature, and to characterize the gap in educational attainment that this study seeks to explain.

In addition to presenting the unconditional mean educational outcomes, I report the "unexplained" gap in schooling, i.e. the difference in educational attainment conditional on three main factors which can be expected to influence children's schooling level but are exogenous to the outcome: age, parental education and ethnicity.

Family background is an important, if not the most important determinant of a person's educational attainment (e.g. Haveman and Wolfe (1995)). The positive correlation between parental education and that of their children is also well established. Given that the Canadian immigration system targets educated immigrants, and that in fact immigrants in Canada as a group are on average better educated than the rest of the population (see also Schaafsma and Sweetman (2001)), one might expect that their children would also be better educated than the native born.

Given the changing national origin mix of successive immigrant cohorts over the 20th century, the ethnic composition of the native-born population, or third-and-higher generation, is vastly different from that of the first, and increasing so, the second generation. In the context of investment in education, ethnic origin can reflect several different factors like different returns to education (e.g. Sweetman and Dicks (1999), different fertility choices and family size (e.g. Chiswick (1988)), differences in unobserved skills due to the nature of self-selection of immigrants (e.g. Borjas (1994)), and potentially different attitudes towards or preferences for education. Ethnic origin indicators will capture these differences to the extent that they persist across generations and as long as the type of selection of immigrants from a given source country has not changed over time. If it has, the ethnic indicator may be representing very different things for the different generation groups.

I break down the second generation group into four subgroups by place of birth (in Canada versus outside) and age at arrival. As age at immigration rises, educational attainment falls (see also Schaafsma and Sweetman (2001)). One reason for this may be that some of the children's human capital acquired before migration is non-transferable. Worswick (2004) shows that children of immigrants attain lower scores on vocabulary tests than children of native-born parents. Given that a certain period of time in the host country and school system are required for the child of immigrant parents to make up any loss in human capital, children who arrive in their teens may not have enough time to overcome this disadvantage. This may manifest itself in a lower probability of pursuing any post-secondary studies. I therefore subdivide second-generation immigrants born outside Canada into three groups: those who arrived before age 6, those who arrived during grade school, age 6-13, and those who arrived in high school, age 14-17.

Table 2.1 presents the estimated differences in total years of schooling between second-generation immigrants and the native born. Columns 1 and 4 report the unconditional relative means for males and females, respectively. In the population as a whole, children of immigrants who arrived between the ages of 0 and 5 have nearly one year of schooling more than the native born. This difference falls to roughly half a year for individuals who arrived in grade school, and disappears completely among those who arrived in high school. Canadian-born children of immigrants have between a third and a half year of schooling more than the native born. After conditioning on age (five-year age groups), highest parental education and ethnic origin, columns 2 and 5, the difference between Canadian-born children of immigrants and the native born rises to half a year for females and 0.6 of a year for males. This gap diminishes with age at immigration. Immigrants who arrived before the age of six also have a slight advantage, about 1/3 of a year, although this is only statistically significant among females. Those who arrived in primary or grade school are no different than the remaining native born in terms of total years of schooling. However, arriving in high school is associated with approximately a one-year disadvantage in years of schooling. This gap is larger among women than men.

A commonly known fact is that immigrants, particularly the more recent cohorts, tend to settle in large urban centers in Canada. This means their children live closer to colleges and universities. Geographic proximity to post-secondary institutions lowers costs of attendance and raises the probability of attending university (e.g. Frenette (2004, 2006)). To control for this effect, columns 3 and 6 of Table 2.1 include an indicator for residence in a census agglomeration or census metropolitan area (CA/CMA). Also included are province of residence controls. These account for differences in educational systems across Canada, specifically whether it takes 12 or 13 years to graduate from high school. On the other hand, geographic location could be endogenous if immigrant parents take the educational opportunities of their children into consideration when choosing where to settle. Also, geographic location indicators pertain to the respondent's residence at the time of the interview, which may be different from the place where the respondent completed his/her education. For these reasons, I present most of the results in this study both with and without controlling

Table 2.1: Years of Schooling Gap

	Males			Females			Joint Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Generation								
Arrived age 14 - 17	0.12	-0.67**	-0.91***	-0.41	-1.18***	-1.38***	-0.92***	-1.13***
	(0.30)	(0.29)	(0.29)	(0.33)	(0.25)	(0.25)	(0.20)	(0.20)
Arrived age 6 - 13	0.53**	0.01	-0.23	0.46**	-0.16	-0.31*	-0.08	-0.28**
	(0.22)	(0.21)	(0.21)	(0.20)	(0.17)	(0.17)	(0.14)	(0.14)
Arrived age 0 - 5	0.97***	0.30	0.07	0.87***	0.35**	0.18	0.3**	0.10
	(0.23)	(0.19)	(0.20)	(0.18)	(0.17)	(0.17)	(0.13)	(0.13)
Born in Canada	0.46***	0.58***	0.43***	0.33***	0.49***	0.37***	0.53***	0.40***
	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)	(0.09)	(0.06)	(0.07)
Controls:								
Age Group		X	X		X	X	X	X
Parental Education		X	X		X	X	X	X
Ethnic Origin		X	X		X	X	X	X
Geography			X			X		X
R-square	-	0.26	0.28	-	0.33	0.34	0.29	0.31
Sample Size	11,546	11,546	11,546	13,597	13,597	13,597	25,143	25,143

Specifications (1) and (4) represent mean years of schooling of children of immigrants by age at arrival and relative to the third-and-higher generation. Specifications (2), (5) and (7) condition on age group, highest parental education and ethnic origin. Specifications (3), (6) and (8) further condition on residence in a CA/CMA and province of residence. Female dummy included in regressions on the joint sample. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

for geographic location. Columns 3 and 6 of Table 2.1 show that geographic location explains very little of the education gap, especially for the Canadian-born, second-generation immigrants.

While there are some gender differences in the magnitude of the education gap between various subgroups of children of immigrants and the native born, the overall patterns are very similar. It is those overall patterns that I seek to explain in this chapter. Since some of the analysis that follows would be difficult to conduct separately by gender for sample size reasons, in the analysis that follows I combine both samples and include a female dummy in all subsequent regressions. Columns 7 and 8 in Table 2.1 report the corresponding results (with and without geographic controls, respectively) for the joint sample.

Table 2.2 reports marginal effects from probit estimation (for the joint, males and females, sample) on the probability of having completed at least a high school diploma, conversely, the probability of not dropping out of high school (columns 1 and 2), and the probability of holding a university degree (columns 3 and 4). Column 1 shows that Canadian-born, second-generation immigrants have a 5 percentage points higher probability of not dropping out of high school, conditional on gender, age, parental education and ethnic origin. There is no significant difference between those who arrived before the age of 14, while those arriving in high school are over 12 percentage points more likely not to graduate from high school. Controlling for province of residence and residence in a CA/CMA lowers the gap between Canadian-born children of immigrants and the native born by 2 percentage points.

Column 3 in Table 2.2 shows the marginal effects on the probability of holding a university degree. This probability is 2 percentage points higher among Canadian-born children of immigrants than the native born, and interestingly, controlling for geographic location does not affect this gap at all. There is again no significant difference in university attendance (and completion) between native-born individuals and children of immigrants who arrived before the age of 14. Individuals arriving in high school however, are about 3 percentage points less likely to hold a university degree than are the native born, and this gap increases to nearly 5 percentage points when geographic location controls are added.

2.5.2 Parental education

The specification in the previous subsection restricted the effect of highest parental education to be the same for second-generation immigrants and the native born. One clear prediction of the theoretical model is that this is not the case. I re-estimate regressions with total years of schooling as the dependent variable, allowing the effect of parental education to vary by generation status. The interaction terms between generation status and parental education are jointly statistically significant for the subgroups of children of immigrants except for individuals who arrived between the ages of 6 and 13.

Table 2.2: Highest Level of Education Gap

	High School or More		University	
	(1)	(2)	(3)	(4)
Second Generation				
Arrived age 14 - 17	-0.125***	-0.134***	-0.033**	-0.048***
	(0.034)	(0.033)	(0.013)	(0.016)
Arrived age 6 - 13	-0.003	-0.021	-0.003	-0.014
	(0.022)	(0.020)	(0.012)	(0.014)
Arrived age 0 - 5	0.007	-0.012	0.018	0.011
	(0.022)	(0.021)	(0.014)	(0.016)
Born in Canada	0.053***	0.033***	0.020***	0.020**
	(0.011)	(0.009)	(0.007)	(0.008)
Controls:				
Age Group	X	X	X	X
Parental Education	X	X	X	X
Ethnic Origin	X	X	X	X
Geography		X		X
Obs. P	.766	.766	.219	.219
Pred. P (at x)	.799	.845	.114	.147
pseudo R-square	0.23	0.24	0.14	0.16
Sample Size	24,880		24,880	

Marginal effects from probit estimation on the probability of completing at least high school and completing a university degree. Specifications (1) and (3) represent differences between second-generation immigrants by age at arrival and the third-and-higher generation, conditional on age group, highest parental education and ethnic origin. Specifications (2) and (4) further condition on residence in a CA/CMA and province of residence. Female dummy included in all regressions. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The first column of Table 2.3 shows the mean predicted years of schooling of the native born by highest parental level of education, conditional on gender, age and ethnic origin. The remaining columns report the gap in predicted years of schooling between second-generation immigrants and the native born by parental education. Canadian-born, second-generation immigrants and those arriving before age 6 whose parents did not complete high school have around one year of schooling more than the native born with uneducated parents. No such difference is observed for immigrants who arrived at age 6-13, while those arriving during high school face a nearly 2 year disadvantage relative to their native-born counterparts. For children of immigrants who arrived before age 6 and the Canadian-born, second-generation immigrants whose parents have a high school education or less, the patterns in educational attainment are consistent with predictions obtained from the theoretical model under the assumption of binding credit constraints among individuals with low education.

At the other end of the parental education distribution, foreign-born children of immigrants with completed post-secondary education have on average less schooling than

Table 2.3: Years of Schooling Gap By Parental Education

	(1)	(2)	(3)	(4)	(5)
	Third + Gen	Arrived 14-17	Arrived 6-13	Arrived 0-5	Cdn-born, Second Gen
Highest Parental Education:					
Graduate Degree	14.27***	0.70	-0.32	-0.12	-0.04
	(0.24)	(0.69)	(0.55)	(0.50)	(0.28)
University	13.31***	-0.99*	-0.62*	-0.59**	-0.17
	(0.17)	(0.53)	(0.36)	(0.28)	(0.19)
Non-Univ Post-Sec	12.26 ***	-0.36	-0.53	-0.30	0.05
	(0.16)	(0.48)	(0.46)	(0.33)	(0.17)
Some University	*12.50****	*-1.48***	*0.22*	0.88	0.18
	(0.31)	*(0.59)*	*(0.79)*	(0.93)	(0.40)
Some Non-Univ Post-Sec	*11.78****	-2.30**	0.01	0.15	0.15
	(0.22)	(0.98)	(0.62)	(0.54)	(0.27)
Some University/Non-Univ Post-Sec	*10.43****	*1.27*	*1.12*	0.80	0.39
	(0.36)	*(1.68)*	*(1.42)*	(0.54)	(0.45)
High School	11.49***	0.17	-0.35	-0.22	0.30**
	(0.13)	(0.34)	(0.28)	(0.39)	(0.12)
Less Than High School	10.14***	-1.82***	0.09	0.85***	0.97***
	(0.13)	(0.30)	(0.21)	(0.20)	(0.10)
R-square	0.30				
Sample size	25,143				

Column (1) reports average years of schooling among third-and-higher generation individuals by highest parental education. Columns (2) - (5) report years of schooling of second-generation individuals *relative to* the third-and-higher generation, by age at arrival and highest parental education. The regression included the following controls: 5-year age groups, highest parental education, ethnic origin and a female dummy. Numbers in italics represent cell counts of less than 30 observations. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

comparable native born. The tradeoff appears smallest in families where at least one parent has a graduate degree, and the largest where the parent has an undergraduate university degree. In the latter group, the gap is about 0.6 years of schooling for those arriving before age 14, and 1 year for those arriving in high school. Canadian-born, second-generation immigrants, however, are essentially no different from their native-born counterparts with educated parents.

The outcomes of foreign-born children of immigrants appear to deteriorate with age at arrival, regardless of how much education the parents have (with the possible exception of parents with graduate degrees). The loss of years of schooling, however, is smaller when the parents are university educated than when they have less than a high school education.

2.5.3 Third-generation immigrants

If loss of foreign human capital after arrival changes the human capital investment behaviour of immigrant parents relative to native-born individuals, rather than or in addition to factors like preferences, then we should see a smaller difference, or none at all, in schooling outcomes between third generation immigrants and the remaining native-born population conditional on age, parental education and ethnic origin. In Table 2.4 I divide the population thus far referred to as the native born into two groups: the third generation – individuals with at least one foreign-born grandparent – and those with all four Canadian-born grandparents.

Table 2.4: Years of Schooling Gap - Second and Third Generation

	(1)	(2)	(3)	(4)	(5)
Second Generation					
Arrived age 14 - 17	0.08	-0.12	-0.42**	-0.91***	-1.17***
	(0.23)	(0.21)	(0.19)	(0.20)	(0.20)
Arrived age 6 - 13	0.73***	0.56***	0.30**	-0.07	-0.32**
	(0.15)	(0.14)	(0.14)	(0.15)	(0.15)
Arrived age 0 - 5	1.15***	0.91***	0.61***	0.31**	0.06
	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)
Born in Canada	0.63***	0.94***	0.76***	0.54***	0.37***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.09)
Third Generation	0.63***	0.52***	0.15**	0.02	-0.06
	(0.09)	(0.08)	(0.07)	(0.08)	(0.09)
Controls:					
Age		x	x	x	x
Highest Parental Education			x	x	x
Ethnic Origin				x	x
Geography					x
R-Square	-	0.16	0.27	0.29	0.31
Sample Size	25,143	25,143	25,143	25,143	25,143

Specification (1) represents mean years of schooling of children of immigrants by age at arrival and grandchildren of immigrants (third generation) relative to the fourth-and-higher generation. Each subsequent column adds a set of controls as indicated in the lower panel of the table. The geography controls include a dummy for residence in a CA/CMA and province of residence dummies. Female dummy included in all five regressions. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The estimated coefficients reported in Table 2.4 represent gaps in years of schooling between subgroups of second and third-generation immigrants and the remaining native born, or the fourth-and-higher generation. In order to highlight differences between the second and third generation, I present regression results where I add the three sets of controls one by one. Column 1 shows the differences in mean years of schooling, controlling only for gender. Third-generation immigrants have on average around 0.6 years of schooling more than the fourth generation, as much as the Canadian-born, second-generation immigrants. Column 2 adds age group indicators and the difference between third generation and Canadian-born second generation becomes apparent – the gap is nearly twice as large for the latter group. Controlling for parental education reduces the gap between Canadian-born, second-generation immigrants and the fourth generation by about 20%, but reduces the gap between the third and fourth generations by about 70%. The addition of ethnic origin controls leaves no further gap between the third and fourth generations. In contrast, a half year gap remains between Canadian-born, second-generation immigrants and the fourth generation.

Table 2.5 shows predicted gaps in education by parental education. The set of interactions between parental education and the third generation is jointly statistically not significant. Conditional on gender, age, and ethnicity, there is no significant difference in the educational attainment of third-generation immigrants and the fourth generation at any level of parental education. Comparing educational attainment of the second generation to that of the fourth, we see a similar pattern as in Table 2.3. Children of immigrants with less than a high school education have on average one year of schooling more than the fourth generation if they were born in Canada or arrived before age 6. A negative gap of over half a year of schooling is evident among foreign-born children of university-educated immigrants. As before, we can reject the hypothesis of equality of parental profiles between the second generation groups and the fourth generation (with the exception of children of immigrants who arrived between the ages of 6 and 13).

2.5.4 Family composition

Another implication of the model is that immigrant parents who arrived as children and completed some or all of their education in Canada are not likely to face any or as much discounting of their skills in the Canadian labour market as those who completed their education prior to migration. While I do not have information on the period of arrival or age at arrival of immigrant parents, I can exploit the observation that immigrants who arrive as children are more likely to be married to a native born (potentially a second-generation immigrant) than to another immigrant.[17] Therefore, we are likely to see less of a gap in schooling between second-generation immigrants and the native born when the second-generation individuals have one non-immigrant parent than if both parents are immigrants. On the other hand, family composition, or more specifically the number of foreign-born grandparents, should not matter within the third generation group.

[17] Aydemir, Chen and Corak (2005) find that among married immigrant men, 43.6% of those who arrived at age 11 or younger are married to a native (third-or-higher generation), and 30.6% are married to an immigrant (immigrant women who arrived young are more likely to marry another immigrant than are men). Among immigrant men who arrived at age 12 or older, only 10.8% are married to a native, and 82.3% are married to an immigrant.

Table 2.5: Years of Schooling Gap By Parental Education - Second and Third Generation

	(1)	(2)	(3)	(4)	(5)	(6)
	Fourth + Gen	Arrived 14-17	Arrived 6-13	Arrived 0-5	Cdn-born, Second Gen	Third Gen
Highest Parental Education:						
Graduate Degree	14.56***	0.41	-0.61	-0.40	-0.32	-0.59
	(0.30)	(0.71)	-(0.58)	-(0.53)	-(0.33)	-(0.40)
University	13.40***	-1.08**	-0.71*	-0.68**	-0.26	-0.21
	(0.22)	-(0.55)	-(0.39)	-(0.31)	-(0.23)	-(0.24)
Non-Univ Post-Sec	12.28***	-0.37	-0.54	-0.31	0.04	-0.03
	(0.20)	-(0.50)	-(0.47)	-(0.35)	(0.21)	-(0.22)
Some University	*12.36* ***	*-1.35**	*0.36*	1.01	0.32	0.25
	(0.48)	*-(0.69)*	*(0.87)*	(0.99)	(0.54)	(0.58)
Some Non-Univ Post-Sec	*11.88* ***	-2.39**	-0.08	0.06	0.06	-0.23
	(0.29)	-(1.00)	-(0.65)	(0.56)	(0.32)	-(0.38)
Some University/Non-Univ Post-Sec	*10.52****	*1.19*	*1.04*	0.71	0.30	-0.22
	(0.53)	*(1.73)*	*(1.47)*	(0.67)	(0.60)	-(0.66)
High School	11.61***	0.04	-0.47	-0.34	0.18	-0.27*
	(0.16)	(0.35)	(0.29)	(0.40)	(0.15)	(0.15)
Less Than High School	10.06***	-1.74***	0.17	0.93***	1.04***	0.25*
	(0.14)	-(0.31)	(0.22)	(0.21)	(0.12)	(0.13)
R-square	0.30					
Sample size	25,143					

Column (1) reports average years of schooling among fourth-and-higher generation individuals by highest parental education. Columns (2) - (5) report years of schooling of second-generation individuals *relative to* the fourth-and-higher generation, by age at arrival and highest parental education. Column (6) reports years of schooling of third-generation individuals *relative to* the fourth-and-higher generation). The regression included the following controls: 5-year age groups, highest parental education, ethnic origin and a female dummy. Numbers in italics represent cell counts of less than 30 observations. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

I subdivide Canadian-born, second-generation immigrants into those with one immigrant and one second-or-higher generation parent and those with two immigrant parents.[18] I further subdivide the third generation into individuals with one to three foreign-born grandparents and those with four immigrant grandparents.[19] Among both second and third-generation immigrants, some individuals do not provide birthplace of all parents and grandparents making it difficult to classify them into the subgroups defined above. They are therefore assigned a separate category (one for each of the second and third generation). I do not devote much discussion to these two groups, except to note that individuals who do not report birthplace information of their parents and/or grandparents, or education of parents, show consistently lower educational attainment than individuals who are able to provide that information.

Column 1 of Table 2.6 shows that second-generation immigrants with two immigrant parents have 0.85 years of schooling more than the fourth generation, while the mean gap for individuals with only one immigrant parent is 0.58 years. These numbers are essentially reversed among the two categories of third-generation immigrants. Once we condition on age, the gap between the two third generation groups becomes identical, at just over 0.6 years. Among second-generation individuals, the gap is largest for Canadian-born individuals with two immigrant parents, at just over 1 year of schooling. Conditioning on parental education and further on ethnic origin does not reveal much of a difference between third-generation immigrants with four and those with fewer foreign-born grandparents. In contrast, family composition makes a difference among Canadian-born, second-generation immigrants. Conditioning on parental education reduces the gap between second-generation immigrants with one immigrant parent and the fourth generation by about 40%. Among individuals with two immigrant parents, this gap remains unchanged, and is now twice as large as that between individuals with only one immigrant parent and the fourth generation. It remains twice as large after controlling further for ethnic origin and finally geographic location, even though both sets of controls reduce the magnitude of both gaps.

2.6 Parental Earnings Profiles and Children's Schooling

The key testable implication of the model described in this chapter is that there is a relationship between the amount of post-migration human capital investment of parents and their children's educational attainment. In the context of the standard human capital model, the slope of a person's earnings profile is a reflection of the amount of human capital investment undertaken by that person. Therefore, we should observe a relationship between the slope of earnings profiles of immigrant parents and their children's schooling. I construct earnings profiles of potential parents of the children of immigrants in EDS and include a

[18] Although according to the rule adopted for defining immigrant status in this chapter, I consider a person to be an immigrant if he or she is foreign born and has at least one foreign-born parent, in the current exercise, second-generation immigrants with two immigrant parents are only individuals whose both parents and all four grandparents are foreign born.

[19] I also tried a subdivision where one or two grandparents are foreign born, versus three or four. The results were essentially unaffected.

Table 2.6: Years of Schooling Gap - Family Composition

	(1)	(2)	(3)	(4)	(5)
Second Generation					
Arrived age 14 - 17	0.08	-0.12	-0.42**	-0.82***	-1.10***
	(0.23)	(0.21)	(0.19)	(0.20)	(0.20)
Arrived age 6 - 13	0.73***	0.56***	0.3**	-0.0005	-0.26*
	(0.15)	(0.14)	(0.14)	(0.15)	(0.15)
Arrived age 0 - 5	1.15***	0.91***	0.61***	0.36**	0.11
	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)
Born in Canada - 2 Immig Parents	0.85***	1.11***	1.07***	0.82***	0.59***
	(0.09)	(0.09)	(0.08)	(0.10)	(0.10)
Born in Canada - 1 Immig Parent	0.58***	0.91***	0.52***	0.42***	0.28***
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)
Born in Canada - unknown	-0.79***	-0.06	-0.04	-0.12	-0.27
	(0.17)	(0.17)	(0.17)	(0.17)	(0.18)
Third Generation					
Third Gen - 4 Immig Grandparents	0.55***	0.63***	0.32***	0.17	0.08
	(0.13)	(0.13)	(0.11)	(0.12)	(0.13)
Third Gen - 1-3 Immig Grandparents	0.81***	0.64***	0.2**	0.09	0.01
	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
Third Gen - Unknown	-0.18	-0.3*	-0.42***	-0.54***	-0.58***
	(0.17)	(0.16)	(0.15)	(0.15)	(0.15)
Controls:					
Age		x	x	x	x
Highest Parental Education			x	x	x
Ethnic Origin				x	x
Geography					x
R-square		0.17	0.28	0.29	0.31
Sample Size	25,143	25,143	25,143	25,143	25,143

Specification (1) represents mean years of schooling of children of immigrants by age at arrival and immigrant status of parents (whether born in Canada or abroad) and grandchildren of immigrants (third generation) by immigrant status of grandparents relative to the fourth-and-higher generation. Each subsequent column adds a set of controls as indicated in the lower panel of the table. The geography controls include a dummy for residence in a CA/CMA and province of residence dummies. Female dummy included in all five regressions. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

measure of entry earnings, 10-year growth rate of earnings and the interaction of the two in a regression of years of schooling. In this part of the analysis I focus on the outcomes of children of immigrants alone, rather than in comparison to the native born.

2.6.1 Estimating parental earnings profiles

I use data from the public use files of the Canadian Census 1971, 1981, 1986, 1991, 1996, and 2001 to construct earnings profiles for synthetic cohorts of immigrants defined by region of origin, education level and period of arrival. There are seven arrival periods: 1961-66, 1967-70, 1971-75, 1976-80, 1981-85, 1986-90, and 1991-95, where 1967 is the beginning of the points system of immigration in place today.[20] I defined six groups of immigrants'

[20] Year of immigration is not a continuous variable in the public use files, and the grouping of years changes across censuses. This leads to some inconsistencies in the years covered by a particular synthetic cohort.

country of birth: United Kingdom, continental Europe, Asia (including the Middle East), Africa, South and Central America and the Caribbean, and the USA.[21] Finally, I separate immigrants into two groups by education: those with a post-secondary diploma/certificate or a university degree (high education) and those without any completed post-secondary program (low education).[22]

To estimate earnings profiles of synthetic cohorts of immigrants, I select all immigrants age 20 to 50 at the time of immigration as the potential parents of immigrants age 0-17 at the time of arrival. I "follow" a specific origin-arrival-education cohort for up to 15 years, across two to four census years. I exclude immigrants residing in the Atlantic Provinces because their responses to several key questions are grouped into broader categories than is the case for immigrants residing in the remaining six provinces. I may therefore gain or lose individuals across the census cross sections if they happen to move to or out of the Atlantic Provinces or the Territories between census years. I drop individuals for whom highest level of schooling, country of birth or year of immigration are unknown.

I do not exclude individuals based on their labour force status, therefore individuals with zero earnings remain in the sample. The reason for this is two-fold. First, unemployment among immigrants shortly after arrival is one reflection of imperfectly transferable human capital and likely influences human capital investment decisions. I believe that excluding individuals with zero earnings removes an important part of the variation I am trying to capture. Second, movements in and out of employment and/or the labour force over a person's lifetime imply that excluding anyone on the basis of labour force status means we're no longer "following" the same group of individuals across the census cross sections.

Earnings are measured by the sum of wages and salaries and self-employment income, deflated with the CPI to 1992 dollars. Ideally, I would like to be able to run a regression of the log of individual real earnings on the following sets of indicators: origin-arrival-education cohort dummies, years since migration and its square, and interactions of these two sets of variables. However, I drop information for a given cohort in a given census if there are fewer than 30 observations in that cell. Even when cell counts are not a problem, I cannot estimate quadratic earnings profiles for all cohorts because I cannot follow all cohorts through at least three census years. Instead, I estimate linear profiles for each cohort and a region-specific curvature parameter which is constant over time. I also control for the province of residence. Even with this more restrictive specification there are a number of cohorts which are dropped from the sample because I only observe them in one census year. These are: all origin groups other than UK and Europe with high education who arrived between 1961 and 1966, and individuals with low education who arrived from the UK or

Thus the sample of 1981-1985 arrival cohorts in the 1986 census also include individuals who arrived in the first few months of 1986, prior to enumeration day, and similarly for the 1991-1995 cohorts. The sample of 1967-1970 arrival cohorts observed in the 1986 census exclude individuals who arrived in 1967.

[21]Immigrants from the central Asian, former USSR Republics are counted as part of Europe up until the 1991 census, but as part of Asia from 1996 census onwards.

[22]The 1971 census has vastly different education questions. Individuals are asked about completing high school or university in one question, and about other post-secondary training in a separate question. I classify individuals into the 'high education' group if they completed a university degree or a post-secondary training course 6 months or more in duration.

the US in 1991-1995. The intercept term for each cohort is taken as a measure of entry earnings. Using the estimated coefficients, I construct the predicted 10-year earnings growth rate for each cohort, i.e. the difference in log earnings over a 10-year period beginning with the period of entry.

Matching EDS respondents to their "potential" parents in the census data requires information on period of arrival, region of origin and education level of the parents. Region of origin is determined by the father's birthplace. If the father is born in Canada and only the mother is an immigrant (from one of the six regions I am able to identify in the census data), it is the mother's birthplace. EDS respondents are separated into two groups, those with at least one parent who has completed a post-secondary program, and those without. The EDS does not contain information on the period of arrival in Canada of the respondents' ancestors. More specifically, I cannot tell when the immigrant parent(s) of Canadian-born, second-generation immigrants arrived in Canada. For foreign-born children of immigrants, however, I can assume that their period of immigration coincides with their parents' period of arrival. For this part of the analysis, therefore, I look only at individuals born outside Canada who immigrated before age 18. Each EDS respondent can now be matched with parental earnings profiles predicted from census data by period of arrival, highest level of parental education, and region of origin.[23]

2.6.2 Empirical analysis

I use the following econometric specification:

$$\begin{aligned} S_{ica} = \mathbf{X_{ica}}\beta + \eta_1 ENTRY_{ca} + \eta_2 GROWTHRT_{ca} \\ + \eta_3 ENTRY_{ca} * GROWTHRT_{ca} + \sum_{c=1}^{C} \kappa_c + \sum_{a=1}^{A} \gamma_a \end{aligned} \tag{2.6.20}$$

The control variables, X_{ica}, include a female indicator, 2 to 3-year age at immigration indicators, and an indicator for whether English or French was the respondent's mother tongue. κ_c represents region of origin effects, and γ_a period of arrival effects. This equation is estimated separately for the two parental education groups.

Beginning with Chiswick (1978), the stylized fact that immigrants face lower earnings than observationally equivalent native born shortly after arrival accompanied by faster earnings growth rate has been attributed in large part to imperfectly transferable human capital. Green and Worswick (2004) compare the earnings profiles of immigrants to Canada over the 1980s and 1990s. They find that about 40% of the documented decline in entry earnings of immigrants who arrived in Canada over the period 1993-96 compared to the 1980-82 cohort can be explained by falling returns to human capital acquired through foreign experience. This is in large part due to the different source country composition. Duleep and Regets (2002) show that lower immigrant entry earnings, conditional on education, are

[23] I was unable to construct earnings profiles for immigrants from Australia, New Zealand or Oceania; therefore, respondents with parents arriving from these countries are excluded from analysis.

on average associated with steeper earnings profiles in the US. This observation may not hold for all immigrant cohorts, however. Green and Worswick (2004) find that in Canada, immigrant cohorts from the late 1980s had lower entry earnings but not steeper earnings profiles compared to the early 1980s cohort. The 1990s cohorts, on the other hand, had entry earnings that were lower still, but accompanied by faster growth. These studies suggest that there is considerable variation in the shape of earnings profiles across both arrival cohorts and immigrants from different source countries. This variation will be used to identify coefficients on the parental human capital investment variables.

We can expect considerable variation in the degree of transferability of foreign-acquired human capital across source countries, leading to different incentives to invest in host country human capital, and hence differently shaped earnings profiles. This may stem from differences in technologies between countries, differences in the level of host country language skills that immigrants from a given country/region arrive with on average and the ease with which they are able to acquire host country language skills, as well as the size of their co-ethnic community and opportunities for finding employment in ethnic enclaves, as some examples.

However, some of the variation in children's schooling across source countries may be due to other factors that vary with source country or ethnicity, like preferences. If poorly educated immigrants from a particular country or group of countries face systematically low human capital transferability and also have preferences that favour more schooling for their children, this could automatically result in a negative relationship between the growth rate of parental earnings and their children's education. To the extent that preferences in the source country are fairly constant over time, controlling for region of origin will soak up that variation.

The degree of foreign human capital transferability may also change over time in a way not related to the changing source country composition of immigrant inflows. For example, immigrants arriving in recession times may find it more difficult to transfer their skills to the host country labour market than those who arrive during economic recovery, across all source countries. Green and Worswick (2004) show that the overall drop in returns to foreign experience for immigrants arriving in Canada over the 1980s and 1990s is not entirely explained by the changing source country composition of successive arrival cohorts.

On one hand, such changes in host country labour market conditions create useful variation in parental choices regarding investments in their own human capital. On the other hand, changes in immigrant characteristics across immigrant cohorts not related to source country composition could influence both parental labour market outcomes and their children's educational outcomes. Immigrant class could reflect such unobserved characteristics. For example, the recessionary periods in the 1970s and 1980s were characterized by low inflows of immigrants, restricted mainly to the family class. Controlling for both time invariant origin effects and source country invariant arrival cohort effects leaves variation generated by the interaction of origin and arrival effects, i.e. changes in transferability of foreign human capital within a country of origin group across time, to identify the effect of parental earnings profiles on children's schooling.

Tables 2.7 and 2.8 present results from the estimation of equation (2.6.20) on two separate samples - children of uneducated and well-educated immigrant parents, respectively. The standard errors reported in these two tables are clustered at the region of origin–arrival cohort level. They are also adjusted for the fact that the parental human capital variables are generated regressors, a function of coefficients estimated from a different sample. I assume that the first and second stage samples are in fact independent, i.e. that there are no common households in the two samples. Although the EDS sample was selected from among respondents to the long form questionnaire of the 2001 Canadian Census, it is unlikely that there are many, if any, individuals in both the public use Census data and the EDS that belong to the same household. In estimating the variance-covariance matrix I further assume that the two sources of error are independent and additively separable. The regression error term is assumed to take the following form:

$$u_i = e_i + r_i \tag{2.6.21}$$

where r_i is an individual-specific error resulting from the generated regressor problem, and e_i takes the following form:

$$e_i = \theta_{ca(i)} + \epsilon_i \tag{2.6.22}$$

where $\theta_{ca(i)}$ is an origin-cohort-specific effect and ϵ_i is an idiosyncratic error with the usual properties.[24]

2.6.3 Results

Results for the sample of second-generation immigrants with poorly educated parents are presented in Table 2.7. Column 1 shows estimated coefficients from equation (2.6.20) with controls for region of origin but not period of arrival. The results provide strong evidence that there exists a tradeoff in human capital investments of parents and children in immigrant families. The coefficient on the growth rate of parental post-migration earnings is negative and highly statistically significant.

[24] The asymptotic variance is estimated as $Var = V + R$. V is the estimate of the variance-covariance matrix as if there were no generated regressor error and allowing the standard errors to be clustered at the origin-arrival period level: $V = \begin{pmatrix} \Sigma_1 & & & & 0 \\ & \ddots & & & \\ & & \Sigma_m & & \\ & & & \ddots & \\ 0 & & & & \Sigma_M \end{pmatrix}$, where Σ_m is the covariance matrix for the origin-arrival period cluster m. The term R is the correction term necessary to account for the fact that the parental earnings variables are generated regressors. $R = \frac{1}{N_2}(\widehat{X}'\widehat{X})^{-1}\frac{N_2}{N_1}(\widehat{G}\widehat{V_1}\widehat{G}')(\widehat{X}'\widehat{X})^{-1}$, where $\widehat{G} = \frac{1}{N_2}\sum_i^{N_2}(\beta \bigotimes x_i)'\nabla_\delta f(m_i, \widehat{\delta})$, N_2 is the number of observations in the second stage (schooling regression), β is the vector of second stage estimated coefficients, $\widehat{X} = f(m_i, \widehat{\delta})$, $\widehat{\delta}$ is a vector of coefficients from first stage estimation, N_1 is the number of observations in first stage estimation, and $\widehat{V_1}$ is the estimated variance-covariance matrix from the first stage regression (adapted from Appendix 6A in Wooldridge (2002)).

Table 2.7: Years of Schooling and Parental Earnings Profiles - Low Parental Education

	(1)	(2)	(3)
Entry Earnings	-0.46	-0.94	-0.88
	(0.42)	(0.57)	(0.56)
10-year Growth Rate	-5.05***	-5.49***	-5.43***
	(1.72)	(1.90)	(1.94)
Entry X Growth Rate	0.86**	1.07***	1.09***
	(0.32)	(0.33)	(0.33)
Female	-0.08	-0.01	0.02
	(0.22)	(0.23)	(0.23)
Age at Arrival			
3 - 5	-0.18	-0.02	-0.16
	(0.60)	(0.57)	(0.57)
6 - 8	-0.39	-0.35	-0.35
	(0.39)	(0.42)	(0.41)
9 - 11	-0.68*	-0.75*	-0.84**
	(0.39)	(0.39)	(0.37)
12 - 13	-1.25**	-1.40***	-1.42***
	(0.46)	(0.43)	(0.45)
14 - 15	-1.71***	-1.81***	-1.89***
	(0.42)	(0.47)	(0.45)
16 - 17	-2.84***	-2.94***	-2.91***
	(0.65)	(0.65)	(0.65)
First Language Eng or Fr	0.72**	0.68**	0.70**
	(0.32)	(0.28)	(0.28)
Controls:			
Region of Origin	x	x	x
Arrival Cohort		x	x
Geography			x
R-square	0.19	0.22	0.24
Sample Size	776	776	776

Sample of foreign-born children of immigrants who arrived in Canada by age 18. Specification (1) includes controls for broad regions of origin. Specification (2) adds controls for arrival cohorts. Specification (3) adds a dummy for residence in a CA/CMA and province of residence dummies. Standard errors (in brackets) are clustered and adjusted to account for presence of generated regressors (entry earnings, earnings growth and the interaction between the two). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The coefficient on the interaction term between log entry earnings and growth rate of earnings is positive and significant, indicating that the negative effect of increased investments in parental human capital on the children's schooling diminishes as entry earnings rise (for a given level of investment in parental human capital). Note that for a given earnings growth rate, higher entry earnings mean higher lifetime earnings, all else equal. The sign of this coefficient could imply, therefore, that children's schooling in low-education families increases in parental income, and/or that as income rises, credit constraints become less binding and therefore the tradeoff in human capital investments within the family is no longer occurring.

These results are robust to the inclusion of period of arrival indicators in column 2. They are also unaffected by the inclusion of controls for province of residence and an indicator for urban residence in column 3.

The age at immigration indicators confirm the pattern observed in earlier results that educational attainment drops with age at arrival. This effect is particularly large for those who arrive at age 16 - 17. First language also has an important effect on educational attainment. Those whose first langauge is either English or French have on average 0.7 years of schooling more than the remaining immigrant children. These factors influence attainment through channels other than parental decisions about investments in their own human capital.

Table 2.8 presents regression results for individuals with at least one parent with a completed post-secondary program. The first striking difference between this table and the previous one is that regardless of the specification chosen, parental investment variables do not have a statistically significant effect on the schooling of children. The coefficient on parental earnings growth rate is negative, roughly half the size of that estimated for the sample with poorly educated parents, conditional on region of origin (comparing column 1 in the two tables), and not statistically significant. The magnitude of this coefficient suggests that a tradeoff in investments is still possible in immigrant families with high human capital, although it is not well defined. To the extent that such a tradeoff exists, it appears to be a function of the period or arrival. Column 2 shows that this coefficient declines in magnitude dramatically once arrival period indicators are included in the regression. Note that in Table 2.3, only (foreign-born) second-generation immigrants with at least one parent with an undergraduate degree showed significantly lower years of schooling compared to the native born. The lack of a significant effect of the growth rate of parental earnings on children's schooling may be at least partly the result of combining in one sample individuals with parents with any kind of completed post-secondary education. This possibility needs to be investigated further.

To evaluate the importance of tradeoffs in human capital investments in immigrant families with poorly educated parents, we can calculate the proportion of foreign-born second-generation immigrants for whom the marginal effect of parental earnings growth is negative. In the context of the theoretical framework, we can interpret a negative effect as evidence of a tradeoff in investments. Looking at column 1 of Table 2.7, the estimated coefficients imply that under 4% of immigrant children with poorly educated parents are affected by such tradeoffs. Given the strong significance of the estimated coefficients, this number seems exceedingly low. One possibility for this is that the functional form chosen is too restrictive. More specifically, the relationship between a child's educational attainment and parental earnings growth may not be linear in entry earnings. I therefore estimate the effect of parental earnings growth at each entry earnings quartile for the sample of individuals with low parental education. In Table 2.9 the marginal effect of parental earnings growth is negative at the first and second entry earnings quartiles, positive but not statistically significant at the third quartile and positive and significant at the fourth quartile. This result suggests that as many as half of the immigrant children from low-education

Table 2.8: Years of Schooling and Parental Earnings Profiles - High Parental Education

	(1)	(2)	(3)
Entry Earnings	-0.59	-0.78	-1.16*
	(0.68)	(0.63)	(0.61)
10-year Growth Rate	-2.26	-0.66	-1.53
	(1.67)	(1.60)	(1.68)
Entry X Growth Rate	0.24	0.12	0.21
	(0.19)	(0.17)	(0.19)
Female	0.34	0.41	0.32
	(0.35)	(0.34)	(0.36)
Age at Arrival			
3 - 5	0.09	0.08	0.18
	(0.32)	(0.33)	(0.34)
6 - 8	-0.46	-0.50	-0.45
	(0.41)	(0.39)	(0.37)
9 - 11	0.25	0.15	0.29
	(0.53)	(0.49)	(0.56)
12 - 13	-1.54	-1.67	-1.74
	(1.00)	(1.01)	(1.05)
14 - 15	0.08	-0.03	0.05
	(0.60)	(0.63)	(0.61)
16 - 17	-0.46	-0.42	-0.44
	(0.55)	(0.63)	(0.62)
First Language Eng or Fr	0.45	0.38	0.30
	(0.54)	(0.53)	(0.54)
Controls:			
Region of Origin	x	x	x
Arrival Cohort		x	x
Geography			x
R-square	0.06	0.08	0.10
Sample Size	572	572	572

Sample of foreign-born children of immigrants who arrived in Canada by age 18. Specification (1) includes controls for broad regions of origin. Specification (2) adds controls for arrival cohorts. Specification (3) adds a dummy for residence in a CA/CMA and province of residence dummies. Standard errors (in brackets) are clustered and adjusted to account for presence of generated regressors (entry earnings, earnings growth and the interaction between the two). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

backgrounds are affected by within-family tradeoffs in human capital investments. At the highest quartile, parental earnings appear to be high enough that parental human capital investments do not crowd out investments in their children's education. Given the patterns observed in the data, these tradeoffs are likely to work in favour of children who immigrated at a young age, and against those that immigrated at an older age. Note that functional form does not change the conclusions drawn for well-educated immigrant families.

Table 2.9: Years of Schooling and Parental Earnings Growth by Entry Earnings Quartile - Low Parental Education

Entry Earnings	-2.41**
	(1.04)
10-year Growth Rate	-1.62**
	(0.75)
Growth Rate X 2^{nd} quartile	0.27
	(0.29)
Growth Rate X 3^{rd} quartile	2.34**
	(0.88)
Growth Rate X 4^{th} quartile	4.59**
	(2.02)
R-square	0.20
Sample Size	776

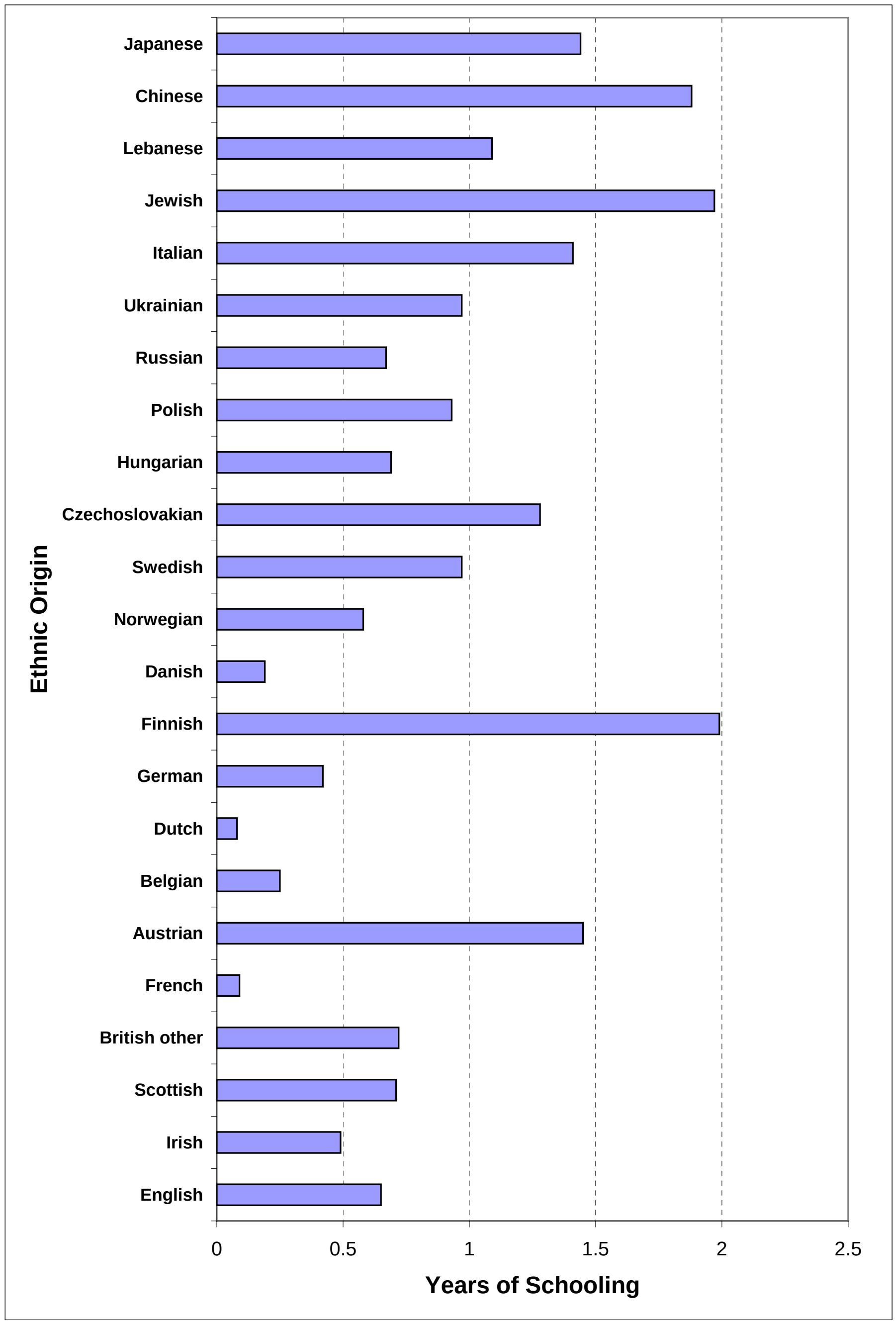
Sample of foreign-born children of immigrants who arrived in Canada by age 18. The regression includes a female dummy, age at arrival indicators, a dummy for first language English or French and region of origin dummies. Standard errors (in brackets) are clustered and adjusted to account for presence of generated regressors (entry earnings, earnings growth and interactions between the two). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

2.7 Alternative Explanations

The model presented in this chapter shows that it is possible for a gap in educational attainment to arise between children of immigrants and the native born in the absence of differences between the two groups in unobservable characteristics like ability, preferences, and/or discount factors. There is a notion in the immigrant literature, however, that such differences exist and underlie the unexplained portion of the educational gap between second-generation immigrants and the native born. Below I briefly consider the leading alternative explanations for the observed educational gap, while a more detailed treatment is left to further research.

One common belief is that immigrants are on average positively selected on ability. Assuming that children inherit their parents' ability, second-generation immigrants are also on average high-ability individuals and this drives their above-average educational attainment. In the context of Roy's model, immigrants should be positively selected only from countries with lower dispersion of earnings than the host country (Borjas (1987)). Immigrants from countries with more unequal distribution of earnings should be negatively selected. This means that we should see higher levels of schooling among descendants of European immigrants than those from many Asian countries for example. In fact we see the opposite (see Figure 2.1). Further, in the context of Roy's model, the negatively selected low earners from countries with more unequal earnings distribution should also have low education levels. But it is children of poorly educated immigrants who outperform their native-born counterparts. A further observation which is not consistent with the ability story is that

Figure 2.1: Years of Schooling Gap Between Children of Immigrants and the Third and Higher Generation by Ethnic Origin of the Children of Immigrants



The horizontal bars represent the difference in years of schooling between children of immigrants from selected ethnic origins and the fourth-and-higher generation, conditional on gender, age and highest parental education. Most of the gaps are statistically significant, except the following groups: French, Belgian, Dutch, Danish and Russian.

children with one immigrant parent have slightly less education on average than children with two immigrant parents (conditional on age, parental education, and ethnicity). If higher ability were the driving force behind the overall educational gap, we would have to make some rather non-standard assumptions about how ability enters the self-selection process by which some immigrants marry other immigrants, while others marry second-or-higher-generation individuals. Therefore, ability differences alone are not a convincing explanation for the observed educational gap.

Another possibility is that immigrants have different preferences for how much education their children acquire. This is represented by the parameter α in the model. Assuming that these are cultural preferences that vary across ethnic groups but are fairly constant across time, controlling for ethnic origin should remove this effect. Instead, we still see a gap in schooling conditional on ethnic origin between second-generation immigrants and the native born.[25] It may be that immigrants self-select on how much they value education. Parents who value education for their children but live in countries where access to education is limited may choose to migrate to a country like Canada. This possibility deserves a more careful consideration. However, even if true, it is not obvious why differences in preferences alone would generate the negative relationship between children's schooling and the slope of their parents' earnings profiles.

Immigrants may discount the future at a lower rate than non-migrants. The argument here is that individuals who self-select for migration are willing to bear the costs of immigration for higher returns down the road. Assuming parents are altruistic towards their children, immigrant parents may be willing to migrate whether those higher returns accrue to them directly or to their children. Without assuming any other differences between immigrants and the native born, it is unclear why immigrants with lower earnings growth would have better educated children than immigrants with higher earnings growth, conditional on entry earnings.

Individuals entering Canada as skilled immigrants are required to show proof of sufficient funds to support themselves and any dependants after arrival. Immigrants entering under the investor/entrepreneur category are required to possess substantial assets. It is possible that there are differences in wealth levels between immigrant and native-born parents with the same observed education level. To explore this possibility assume the Becker and Tomes (1986) model, where parents care about their children's utility rather than human capital directly and can leave bequests. Parents will invest in their children's human capital until the rate of return to those investments equals the rate of return on capital and invest in assets after that. Well-educated parents are likely to reach the optimal human capital investments for their children, immigrant or not, while poorly educated parents are not. If less educated immigrants arrive with more assets than similarly educated native born possess on average, they may be able to invest more in their children's human capital than the native born. However, in order for us to further observe the negative relationship between parental earnings growth and children's schooling, we would have to assume that

[25]See also Chiswick (1988) for an argument that differences in preferences for education are not responsible for observed differences in schooling across ethnic groups in the US.

parents with more assets invest less in their own human capital and hence have relatively flat earnings profiles. In the context of the model in Section 2.3, this would require that immigrants with less transferable human capital have more wealth. We could imagine that immigrants plan for the loss of human capital before migrating by accumulating a sufficient amount of wealth to compensate for the loss of future earnings potential following migration. However, it is unlikely that immigrants can accurately predict exactly how much of their human capital acquired through foreign credentials and foreign experience will be usable in the Canadian economy before arriving in Canada.

Finally, in the same setup, assume a situation where ability is rewarded in the labour market but does not enter the human capital production function. If parents with low education cannot borrow to finance their children's human capital investments and have no assets (or immigrant and native-born parents have the same level of assets but not enough to fully finance the optimal level of human capital for their children), they will have to trade off their consumption for investments in children's human capital. Parents of high-ability children will not need to invest as much in their human capital since the children will have high earnings anyway. They will therefore invest less and consume more. If there were any differences in abilities between children of immigrants and the native born with poorly educated parents, it would have to be the case that children of immigrants are lower-ability individuals and hence receive more human capital investments from their parents. This setup, however, is contrary to common assumptions about the production of human capital. If ability does enter the human capital production function and immigrant children are higher-ability individuals than children of native-born, poorly educated parents, then poorly educated immigrant parents could invest less in their children, consume more, and still have better educated children than their native-born counterparts. As argued earlier, such differences in ability do not appear consistent with some other patterns in the data.

The above scenarios suggest that while there are many hypotheses about why children of immigrants are better educated than observationally similar native born, they cannot generate predictions about as many of the patterns observed in the data as the framework presented in this chapter. Specifically, none of these alternative potential explanations can account for the negative relationship between the slope of parental earnings and the educational attainment of children from low-education families, at least not without the necessity of additional and rather non-standard assumptions.

2.8 Conclusions

This chapter seeks to explain in an economic framework why children of immigrants acquire on average more education than the native born, conditional on age, parental education and ethnic origin. This gap has been documented in the literature but not studied systematically. Uncovering the sources of this gap is important for at least two reasons. First, education is an important determinant of earnings as well as other individual outcomes. Understanding what motivates the education choices of children of immigrants will help inform research on the intergenerational transmission of earnings among immigrants and other outcomes of second-generation immigrants. Second, the changing characteristics and outcomes of immigrants to North America may have important consequences for the educational attainment of future second-generation immigrants.

I present a simple model in which parents make simultaneous choices about investments in their own human capital and the amount of schooling inputs purchased for their children. I show that under the assumptions of imperfectly transferable foreign human capital, comparable wages for poorly educated immigrant and native-born workers, and binding credit constraints among the poorly educated, immigrant children from low-education backgrounds will outperform their native-born counterparts in educational attainment, while their parents work more and invest less in their own human capital. Well-educated immigrants, on the other hand, are likely to invest more in their own human capital than their native-born counterparts, but will invest less in their children.

I use the Ethnic Diversity Survey to test the implications of the model. I find that it is indeed children of poorly educated immigrants who are driving the overall observed gap in education. Among individuals with educated parents, the gap, to the extent that it exists, appears to favour the native born, perhaps contrary to what one might expect a priori. Further, I find strong evidence of a negative relationship between the slope of parental earnings profiles, which in the context of the human capital model reflects the amount of investment in parental human capital, and schooling outcomes among children of immigrants with low education levels. The tradeoff may affect as many as half of the immigrant children from low-education backgrounds. Among children of educated immigrants, the marginal effect of parental earnings growth is negative but not statistically significant. Consistent with the implications of the model, there is no difference in educational attainment between third-generation immigrants and the fourth-and-higher generation, once parental education and ethnic origin are controlled for. Third-generation immigrants do have an advantage in unconditional mean years of schooling, however. This appears to be due largely to differences in the distribution of parental education between that group and the remaining native born.

My results hold potential policy implications. Targeting well-educated individuals through the current points system in Canada contributes to higher education levels among descendants of immigrants, not just the second but also third generation, and therefore raises the education level in the population as a whole. However, it's not all bad news for immigrants with lower education levels. Their children outperform their native-born counterparts in educational attainment and may continue to do so if earnings of poorly educated immigrants do not decline dramatically and there are no changes in unobservable characteristics across immigrant cohorts. Well-educated immigrants stand to lose more on arrival than those with low human capital from the falling value placed on foreign human capital in the Canadian labour market. Declines in their post-migration earnings (in present value), if indeed they occur, could lead to declining educational attainment among their children.[26] This suggests

[26] Aydemir, Chen, and Corak (2007) find that the intergenerational transmission of education among immigrants has not changed across birth cohorts. However, there may have been offsetting changes along the parental education distribution across cohorts which would not show in the population as a whole. Furthermore, we still do not have data on the educational attainment of children of the more recent immigrant

that the current policy of attracting well-educated immigrants should be accompanied by some process which would make it easier for them to transfer their foreign-acquired credentials and experience to the host labour market. Improved transferability would not only benefit the economy in the short run, to the extent that imperfect information is an important reason for the imperfect skill transferability, but also improve outcomes of the second and further generations.

cohorts.

Chapter 3

Ethnic Composition of Social Networks: Effect on Immigrant Labour Market Outcomes

3.1 Introduction

Friends and relatives are a nontrivial resource in the job search process. Several studies (summarized in Montgomery (1991)) of workers' job search techniques and firms' hiring practices suggest that up to 50% of job openings in the US are filled through employee referrals. There also exists some evidence that in an ethnically diverse society individuals with ethnically homogeneous networks are also more likely to rely on co-ethnic job contacts in finding employment (Ooka and Wellman (2003)). Ethnic minority groups differ in occupation distribution and overall economic success. The job opportunities available within an ethnic community or through co-ethnic job contacts may be limited. Immigrants with ethnically segregated social networks, i.e. those who have relatively few friends (or none at all) of ethnic origin other than their own, may find it more difficult to access the broader labour market in the host country. In this chapter I examine the role of ethnic enclaves and ethnically segregated social networks on labour market outcomes of immigrants in Canada.

Existing studies of ethnic enclave effects often motivate the analysis in terms of how interaction with members of one's origin group could impact an immigrant's labour market outcomes (e.g. Borjas (2000), Edin, Fredriksson and Aslund (2003)). Data on the ethnic composition of social networks is rarely available though. Instead what is actually estimated is the relationship between some measure of geographic concentration or segregation of immigrants from a particular country or ethnic origin and their labour market outcomes. Other studies explicitly proxy for co-ethnic social networks with the supply of co-ethnics at some geographic level (e.g. Bertrand, Luttmer and Mullainathan (2000)). However, we can think of the overall ethnic enclave effect captured by the proportion of a city or neighbourhood population that belongs to a particular origin group, as being composed of several different effects. Apart from network effects, this geography-based measure could be capturing preferences of employers for hiring members of their own origin group, preferences of immigrants to seek employment with co-ethnics rather than in the broader labour market, or preferences of majority group employers for hiring immigrants of a particular origin group (to the extent that these vary with the fraction of a minority group in the city population), etc. None of these effects need be strongly correlated with the relative amount of interaction between an immigrant and his or her co-ethnic community.

The main goal of this chapter is to investigate whether ethnic enclave effects are in fact network effects. I use data on the proportion of an immigrant's friends who share his or her ethnic ancestry from the Ethnic Diversity Survey, a Canadian post-censal survey, as a more direct measure of co-ethnic networks. By including both the traditional measure of enclave size and a measure of the ethnic composition of an immigrant's social network in regressions of labour market outcomes, like earnings and employment, I can separate out the co-ethnic network effect from the remaining enclave effects, if any. If the standard measure of ethnic enclave size captures only network effects, the coefficient on that measure should go down to zero once we control for the proportion of co-ethnic friends. In order to do this, however, I must first establish what the incidence and magnitude of the overall ethnic enclave effect in Canada is.

Two Canadian studies in particular provide the starting point for this analysis. Hou and Picot (2003) find a small negative, usually not statistically significant association between a measure of exposure to members of one's group and mean earnings, employment, and occupational segregation among members of the largest visible minority groups in Canada, in individual cross sections of the Canadian Census 1986 - 1996. Using the same data, Warman (2005) finds a statistically significant relationship between several measures of exposure to members of one's origin group and earnings growth rate of immigrants, conditional on initial earnings. The latter study further provides evidence of cohort effects in this relationship. Drawing on the above results, as well as several international studies which find that the enclave effect differs across education groups (e.g. Borjas (2000) and Edin, Fredriksson and Aslund (2003)), I re-assess the Canadian literature on enclave effects.

Using the Canadian Census public use data for 1986 - 2001, I show that there is in fact a statistically significant relationship between immigrant earnings and the proportion of co-ethnics in a city but which is offsetting across education groups and arrival cohorts. I find that the 1980s were characterized by a positive relationship between exposure to co-ethnics and mean earnings, but that this association has turned into a disadvantage for the late 1990s cohorts. Furthermore, the cross-cohort decline was most pronounced among immigrants with a high school or lower education. The nature of these cohort effects and the differences across education groups could explain why the estimated relationship between exposure to co-ethnics and earnings for all immigrants as a group may well appear negligible in a single cross section of data.

With these results in hand, I proceed to explore the relationship between the proportion of co-ethnics in a city and the proportion of co-ethnics in immigrants' social networks using the EDS data. I find that the correlation between the proportion of co-ethnics in a city and ethnically segregated social networks (measured by an indicator for whether most/all friends are co-ethnic) is not as high as we might expect, about 0.25 among immigrant men, and even lower among immigrant women. Co-ethnic networks appear to improve the chances for employment, especially among immigrants with post-secondary education. This effect to some extent offsets the negative impact of the proportion of co-ethnics in the city of residence. There appears to be no statistically significant effect of either the relative enclave size or co-ethnic social networks on immigrant earnings. If these two effects are indeed present but not precisely estimated with the available data, they may well be orthogonal to one another. In fact, there is very little evidence from the analysis on either immigrant earnings or employment to suggest that traditional measures like the proportion of co-ethnics in a city capture the impact of ethnically segregated social networks.

The available data pose some difficulties in pinpointing the magnitude of the enclave and interaction effects on immigrant labour market outcomes. Estimates of the ethnic enclave effect obtained using the public use 2001 Census data and the EDS are not comparable across education groups. To the extent that the EDS sample is just too small to yield precise and reliable estimates of the actual ethnic enclave effect, the analysis in the latter part of this chapter should be treated as an exploratory exercise into the relationship between exposure to co-ethnics and ethnic composition of actual social networks rather than a robust evaluation of the effect of either exposure or interaction with co-ethnics on immigrant labour market outcomes.

The rest of the chapter is structured as follows. Section 2 reviews the relevant literature. Section 3 explores the nature of cohort effects in the relationship between the proportion of co-ethnics in the city of residence and earnings across education groups. Section 4 separates the effect of co-ethnic social networks on labour market outcomes from the overall ethnic enclave effect. Section 5 concludes.

3.2 The Literature

3.2.1 Immigrant enclave effects

Borjas (2000) examines the effect of residential segregation on wage growth of immigrants in the US, using Census data from 1980 and 1990 and focusing on immigrant men with positive earnings in paid employment. Country of birth is used as a measure of affiliation. Two measures of segregation are examined. The first is an exposure index - the proportion of population in the city of residence born in the same country as the respondent; the other is a relative clustering index, the exposure index divided by the proportion of immigrants from a given country in the US as a whole. He finds a negative relationship between segregation and immigrant wage growth, conditional on initial wage levels. This negative relationship is actually driven by the newly arrived immigrants in the sample, those who arrived in the second half of the 1970s. The relationship appears to be positive among the earlier cohorts who have also lived in the US for a longer period of time. Also, it is the least-educated workers who on average experience lower earnings growth rates in more segregated cities. In much of the analysis, there is no correction for the potential endogeneity of city of residence, and therefore the segregation measure. Borjas does re-run his basic specification on a sample of refugees (although refugee status information is not available, rather the analysis is restricted to individuals from countries where most US refugees originate from). There is still evidence of a negative impact of segregation, although it depends on the model specification; it is not significant when city fixed effects are added to the regression.

Chiswick and Miller (2002) examine the relationship between minority language concentration and English proficiency as well as earnings of immigrants in the US. They also treat enclave residence as exogenous. They find a negative relationship with both outcomes. The relationship with earnings remains significant even after controlling for English language proficiency, suggesting that language acquisition is only one channel through which residence in an ethnic (or minority language) enclave affects labour market outcomes.

The endogeneity of enclave residence is addressed in a study by Edin, Fredriksson and Aslund (2003). The authors exploit a Swedish government policy of random assignment of refugees across municipalities and a panel data set which allows them to observe the original municipality an immigrant was assigned to, the municipality of residence eight years later and earnings. The analysis focuses on estimating the effects of enclave size (measured as the log of the number of individuals from the same country of origin as a given immigrant in the study sample residing in the same municipality). Although refugee status is not known with certainty, the authors, similarly to Borjas (2000), select immigrants from countries that make them likely to be refugees. They instrument for the enclave size in the municipality of residence eight years after arrival with the enclave size in the municipality the refugee was originally assigned to. While they find no significant effect of the size of the enclave on immigrant earnings in the sample as a whole (combining men and women), there is a positive and significant effect on earnings of immigrants with ten years of schooling or less and a negative but insignificant effect on those with ten or more years of schooling.

Studies of ethnic or racial segregation are not limited to the effects on outcomes of immigrants. Comparing outcomes of Blacks in segregated and non-segregated cities in the US, Cutler and Glaeser (1997) find that segregation lowers earnings, probability of employment, high school graduation rates, and increases probability of single motherhood among Blacks. Segregation appears to have a small positive impact on the white population, however. Further, controlling for three commonly hypothesized channels of neighbourhood effect transmission accounts for only a third of the estimated effect. These three channels are: job proximity (the spatial mismatch hypothesis states that Blacks in segregated neighbourhoods are worse off because they live far from where the jobs are), presence of good role models (exposure to people with at least some post high school education) and segregation by income (if racial segregation coincides with income segregation).

The relative clustering of individuals speaking the same language at home is taken as a measure of network size in Bertrand, Luttmer and Mullainathan (2000) who analyze its effect on the probability of welfare uptake by minority group women in the US. The study focuses on the interaction between (potential) network size and its quality as measured by the average welfare use among members of a given language group in the country as a whole. The argument presented is that the bigger the network, the more potential exposure to members of one's language group, the higher the likelihood of being influenced by the norms and information imparted by them. The study finds that increasing language group size raises the probability of welfare uptake more for members of high welfare dependent groups.

3.2.2 Canadian studies

Warman (2005) reproduces some of the analysis in Borjas (2000) with Canadian Census data from 1981 to 1996. With four Census cross sections at his disposal, Warman is able to separate cohort effects from time-since-arrival effects by reproducing the analysis for different base years. He also finds evidence of an overall negative relationship between segregation and wage growth of immigrant males in Canada. However, once the segregation measure is interacted with arrival cohort dummies, the results differ markedly from the findings for the US. The overall negative association between segregation and wage growth (5, 10 or 15 year growth rate and three base years examined) appears to be driven by the oldest immigrant cohorts, those that arrived before 1950. The remaining arrival cohorts experience wage growth rates that rise with the degree of segregation. The study also examines the correlation between segregation and wage levels of newly arrived immigrants. Segregation is associated with lower entry wages and this negative relationship is stronger among earlier arrival cohorts. A similar negative relationship appears between employment rates among new immigrants and segregation (as measured by the exposure index but not when measured by the relative clustering index). There is no correction for possible bias due to selection of immigrants into specific cities in this study.

The many robustness checks provided in the above study include different ways of measuring group affiliation. While most of the analysis relies on place of birth as group affiliation, the author also explores measures such as language, ethnicity and visible minority status. The magnitude of the association between segregation and wage growth falls by half when measured by ethnicity rather than place of birth, and lies inbetween the two when measured by mother tongue. The relationship is no longer statistically significant when affiliation is measured by visible minority group.

Hou and Picot (2003) also use Canadian census data from 1981 to 1996 to explore the relationship between exposure to one's visible minority group and three labour market outcomes: employment, earnings and occupational segregation. They analyze outcomes of different visible minority groups separately by city, focusing on the three largest Canadian cities: Toronto, Montreal and Vancouver. The index used to measure exposure to individuals belonging to the same visible minority group is a weighted sum of census tract level proportions of the given minority group, where the weights are the distances of other neighbourhoods to the census tract of residence. They find that increased exposure to members of one's own visible minority group is generally associated with lower probability of being employed, higher probability of working in a segregated occupation, and in general little association with annual earnings. These relationships are in most cases not statistically significant though, and the effect of exposure to own-group members appears to vary by city for the same group. Perhaps the most consistently negative and statistically significant relationship between exposure to own-group members and labour market outcomes exists in the case of Blacks, the least segregated group considered in the study, and the weakest association exists among Chinese immigrants, the most segregated group in the study. The choice of visible minority group as affiliation may be one reason why no consistent relationship was found between segregation and labour market outcomes, in light of the evidence in Warman (2005). The authors also test whether the correlation between exposure to co-ethnics and labour market outcomes is channeled through the economic conditions in the neighbourhood. They find no evidence in support of this hypothesis, at least not when neighbourhood economic conditions are represented by the unemployment rate.

Questions of social network formation and their implications are perhaps more commonly addressed in the sociology literature. Two Canadian studies in particular are the closest in content to the analysis in this chapter. Fong and Isajiw (2000) examine the determinants of the degree of interaction with own ethnic group and with the majority (British ancestry) group, measured by the ethnicity of a person's three closest friends. They find that immigrants and those employed in a co-ethnic business have more co-ethnic and fewer British close friends although duration of stay in Canada increases the likelihood of having British friends. Intermarriage and inter-ethnic friendships in childhood increase the likelihood of inter-ethnic friendships. Low-income status appears to have a negative association with both co-ethnic and inter-ethnic friendships. Education level and English proficiency imply less contact with co-ethnics but have no significant impact on contact with the majority group. Neighbourhood characteristics like the proportion of residents who are British or proportion immigrant and experience of discrimination have no significant effect on the level of contact with either co-ethnics or the majority group. The authors acknowledge the fact that some of the estimated relationships cannot be interpreted as causal because of endogeneity problems. The study is based on data from the Ethnic Pluralism Study collected in Toronto between 1978 and 1979. The data set contains information on 2,310 individuals from ten ethnic groups, only one of which is a visible minority group. In comparison, the Ethnic Diversity Survey used in my analysis is a recent (2002), Canada-wide survey with a sample size of over 40,000 that is very much representative of the ethnic diversity in Canadian society today.

The second study, Ooka and Wellman (2003), uses information on the ethnicity of individuals' three closest friends to establish a link between ethnicity of social networks, ethnicity of job contacts and earnings. This study too relies on data from the Ethnic Pluralism Study although only English, German, Italian, Jewish and Ukrainian groups were selected for analysis. The authors show that individuals with heterogeneous social networks were more likely to also have inter-ethnic job contacts. Inter-ethnic job contacts were associated with higher incomes, and the difference was bigger for women than men. Further, inter-ethnic job contacts benefited members of low-status ethnic groups (Italian and Ukrainian), while intra-ethnic contacts implied higher incomes for members of high status groups (English and German). While the study is not fully representative of the ethnic diversity in Canadian society today, it does highlight the importance of inter-ethnic social contacts.

The above studies examine the relationship between ethnic enclaves and the labour market outcomes of their immigrant inhabitants using different measures and concepts of exposure to co-ethnics. The goal in this chapter is to paint a more complete picture of that relationship by combining elements of these different papers into one study and further extending the analysis using a more direct measure of co-ethnic networks. Warman (2005) has already shown evidence of cohort effects in the relationship between exposure to co-ethnics and immigrant earnings. I extend his analysis by exploring whether the nature of these cohort effects varies by education level. Studies like Borjas (2000) in the US and Edin, Fredriksson, and Aslund (2003) in Sweden have shown in cross-sectional analyses that earnings of immigrants with different levels of education are influenced by the relative size of their co-ethnic community in different ways. None of the previous studies have shown whether there are education-level-specific cohort effects in the relationship between enclave size and immigrant earnings. This is the focus of the next section in this chapter. Characterizing the relationship between ethnic enclaves, immigrant education and labour market outcomes and particularly how this may have changed over time is essential to understanding what a cross-sectional estimate of the ethnic enclave effect represents. I use these results as a starting point for the cross-sectional analysis in the subsequent section of this chapter. This analysis focuses on drawing a distinction between exposure to co-ethnics and actual interaction with co-ethnics, a distinction that has been blurred in existing literature.

3.3 Cohort Effects and Educational Attainment

In this section, I take a closer look at the relationship between the proportion of co-ethnics in a city and the earnings of immigrants who belong to that ethnic group. The purpose of this exercise is to establish basic patterns in the data rather than estimate a causal relationship between exposure to co-ethnics and labour market outcomes - the analysis of causal impacts is left to the next section. My objective is to re-examine earlier findings that there is essentially no difference in mean earnings of immigrants across cities with different relative enclave sizes, while at the same time there is a difference in earnings growth rate, conditional on initial wages. It is possible that the path of post-migration earnings is different in enclaves, but that post-migration earnings in present value terms are roughly the same. On the other hand, post-migration earnings could be permanently lower or higher in enclaves for immigrants with different characteristics, e.g. education level, and/or across arrival cohorts.

3.3.1 Data and Estimation

For this part of the analysis I use the public Canadian Census files from 1986 to 2001, focusing on immigrants age 20 to 59 who arrived between 1980 and 1999. In contrast to most previous studies, I exclude immigrants who arrived before age 18 as the experiences of the children of immigrants are likely to vary substantially from those of their parents. The labour market outcome of interest is the log of weekly earnings, where earnings are measured as the sum of wages and salaries and self-employment income. I exclude individuals with weekly earnings of less than \$1.

I measure ethnic enclave size using the exposure index, i.e. the fraction of a city's population that belongs to a particular ethnic group. Since more than one ethnic ancestry can be reported on the Census, the counts used for the exposure index include only individuals who reported a single ethnic ancestry. I exclude immigrants from the British Isles and France for whom the concept of ethnic enclave is not as clear as in the case of minority ethnic groups. There are 17 remaining ethnic origin groups that are identified in the public use Census files.[1] I use ethnicity as a measure of affiliation rather than place of birth, which is perhaps more common in the literature. Warman (2005) compares the magnitude of ethnic enclave effects on earnings growth rate using both ethnicity and place of birth and finds that the former yields smaller estimates. The reason for choosing ethnicity rather than place of birth is to maintain consistency throughout this chapter; I am restricted to using ethnicity as group affiliation in the next section of this chapter.

I run an individual level earnings regression with the log of weekly earnings as the dependent variable and with the following controls: exposure index, a quadratic in years since migration (ysm), arrival cohort dummies, interactions between arrival cohort and ysm (linear term only), interaction between each of the latter three and the exposure index (interactions with the linear term of ysm only). Also included is a quadratic in age, educational attainment, detrended unemployment rate and dummies for broad ethnic origin groups. Unlike most studies I do not control for city or neighbourhood fixed effects. This is to keep the variation used for identification fairly similar throughout the study. These indicators are likely endogenous and finding a sufficient number of instruments presents a challenge. Thinking of city characteristics like ethnic composition as endogenous once we condition on the city itself is no longer reasonable. Although I do not attempt to identify a causal effect of enclaves on earnings in this section, this is the ultimate goal in the later sections, where I will use lagged values of the exposure index to instrument for its contemporaneous value.

3.3.2 Empirical Results

The coefficients from earnings regressions estimated for men and women separately are reported in Tables 3.1 and 3.2, respectively. For men, the strongest evidence of cohort effects in the relationship between the proportion of co-ethnics in the city of residence and earnings is present among immigrant men with a high school or lower education. Earnings appear higher in enclaves for newly arrived immigrants, although the intercept coefficients are not statistically significant. The earnings growth rate, however, is slower, especially for the most recent arrival cohort (1995-99). The proportion of co-ethnics in a city appears to have less impact on women's earnings. Although there is some evidence that entry earnings

[1] The index is calculated from tabulations published by Statistics Canada for 2001 and 1996. For the two earlier years, the index was calculated from the public use files.

Table 3.1: Earnings Regressions Using 1986-2001 Census Data - Men

	All education groups	HS or less	College	University
Exposure Index (EI)	0.188	1.694	-0.962	-0.004
	(0.981)	(1.323)	(2.232)	(0.974)
EI*1990-94	0.058	-0.258	0.063	-1.060
	(1.409)	(1.531)	(3.031)	(1.842)
EI*1984-89	1.945	-0.431	3.668	2.889
	(1.259)	(1.904)	(2.819)	(1.784)
EI*1980-83	1.114	-1.569	4.734*	0.919
	(1.692)	(1.825)	(2.544)	(3.096)
EI*YSM	-0.301*	-0.653**	0.057	-0.371
	(0.169)	(0.261)	(0.392)	(0.269)
EI*1990-94*YSM	0.267	0.469*	-0.031	0.541*
	(0.232)	(0.276)	(0.537)	(0.290)
EI*1984-89*YSM	0.162	0.648**	-0.291	0.069
	(0.170)	(0.264)	(0.453)	(0.283)
EI*1980-83*YSM	0.282	0.741***	-0.276	0.346
	(0.181)	(0.264)	(0.366)	(0.293)
YSM	0.056***	0.100***	0.0003	0.064**
	(0.017)	(0.026)	(0.039)	(0.028)
YSM sq.	-0.001**	0.00002	-0.002***	-0.001**
	(0.0003)	(0.0005)	(0.001)	(0.001)
1990-94	-0.092	0.090	-0.251	-0.149
	(0.118)	(0.155)	(0.248)	(0.178)
1984-89	0.143	0.396**	-0.150	0.057
	(0.102)	(0.153)	(0.233)	(0.144)
1980-83	0.193*	0.483***	-0.055	0.043
	(0.104)	(0.156)	(0.222)	(0.171)
1990-94 * YSM	-0.031*	-0.100***	0.045	-0.011
	(0.017)	(0.029)	(0.042)	(0.029)
1984-89 * YSM	-0.030*	-0.096***	0.048	-0.013
	(0.017)	(0.029)	(0.043)	(0.028)
1980-83 * YSM	-0.013	-0.068**	0.050	-0.006
	(0.020)	(0.028)	(0.046)	(0.032)
Age	0.073***	0.072***	0.076***	0.082***
	(0.006)	(0.007)	(0.011)	(0.012)
Age sq.	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
College	0.171***			
	(0.031)			
University	0.407***			
	(0.029)			
Observations	16862	7548	4461	4853
R-squared	0.09	0.06	0.05	0.07

Detrended unemployment rate and indicators for broad ethnic origin groups included in all regressions. Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.2: Earnings Regressions Using 1986-2001 Census Data - Women

	All education groups	HS or less	College	University
Exposure Index (EI)	-0.747	1.471	0.501	-3.065*
	(0.923)	(1.241)	(1.896)	(1.806)
EI*1990-94	2.426**	-0.459	2.322	3.651*
	(1.113)	(1.550)	(1.883)	(1.884)
EI*1984-89	1.418	-0.947	-0.341	4.615
	(1.886)	(1.896)	(2.648)	(2.925)
EI*1980-83	2.495*	1.748	-0.642	2.786
	(1.349)	(1.749)	(2.624)	(3.097)
EI*YSM	0.158	-0.330	-0.079	0.669
	(0.195)	(0.261)	(0.441)	(0.412)
EI*1990-94*YSM	-0.356*	0.171	-0.264	-0.687
	(0.215)	(0.289)	(0.423)	(0.426)
EI*1984-89*YSM	-0.135	0.334	0.196	-0.736*
	(0.216)	(0.285)	(0.435)	(0.427)
EI*1980-83*YSM	-0.186	0.255	0.152	-0.633
	(0.201)	(0.274)	(0.445)	(0.487)
YSM	0.044**	0.003	0.099**	0.056
	(0.021)	(0.035)	(0.042)	(0.045)
YSM sq.	-0.001*	0.0001	-0.001	-0.002**
	(0.0003)	(0.001)	(0.001)	(0.001)
1990-94	0.040	0.060	0.205	-0.172
	(0.118)	(0.163)	(0.219)	(0.219)
1984-89	0.267**	0.166	0.646***	-0.046
	(0.108)	(0.161)	(0.209)	(0.204)
1980-83	0.249*	0.183	0.669***	-0.180
	(0.142)	(0.203)	(0.222)	(0.249)
1990-94 * YSM	-0.021	-0.007	-0.081*	0.025
	(0.022)	(0.038)	(0.043)	(0.045)
1984-89 * YSM	-0.023	-0.001	-0.088**	0.017
	(0.021)	(0.036)	(0.043)	(0.044)
1980-83 * YSM	-0.008	0.005	-0.048	0.013
	(0.023)	(0.035)	(0.046)	(0.047)
Age	0.053***	0.057***	0.055***	0.051**
	(0.012)	(0.011)	(0.020)	(0.020)
Age sq.	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
College	0.198***			
	(0.014)			
University	0.411***			
	(0.021)			
Observations	16098	7268	4685	4145
R-squared	0.07	0.02	0.05	0.05

Detrended unemployment rate and indicators for broad ethnic origin groups included in all regressions. Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

were higher for women living in a relatively larger co-ethnic community in the early 1980s and 1990s, in regressions run separately by education level, most of the estimated ethnic enclave effects across cohorts are not statistically significant.

To present a clearer picture of the relationship between immigrant earnings profiles and the proportion of co-ethnics in a city, I carry out the following exercise. I predict two earnings profiles, both for an individual age 25 at arrival: one assumes that 3% of the city population is co-ethnic and the other, 0%. I then plot the difference between the two. Panel (a) in Figures 3.1 and 3.2 show plots for immigrant men and women, respectively. The plots suggest that immigrant men living in cities with a higher proportion of co-ethnics had higher entry earnings in the 1980s, but not in the 1990s. This advantage was fairly persistent for cohorts from the early 1980s, but declined with time since migration for those who arrived in the late 1980s. By early 1990s there was essentially no difference in either the level or the path of earnings. Finally, for the most recent arrival cohort, although entry earnings were comparable, immigrants in a city with 3% of co-ethnics face slower earnings growth rate than immigrants with essentially no other co-ethnics in the city. The difference in entry earnings of immigrant women does not appear to follow any particular pattern.

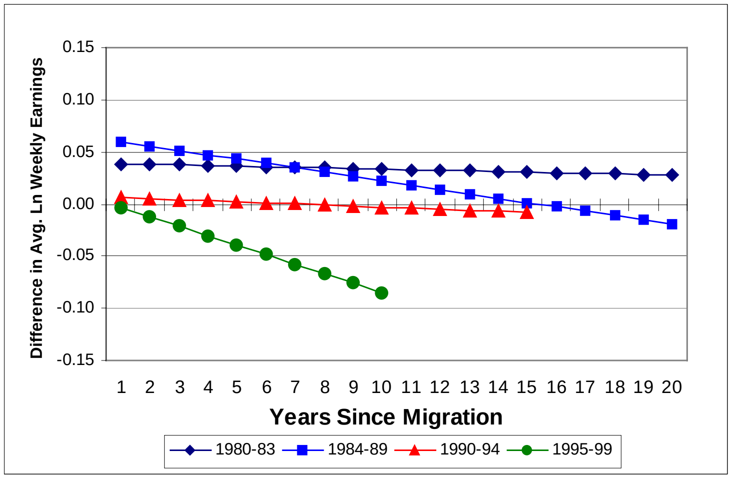
Panels (b)-(d) in Figures 3.1 and 3.2 show similar plots for three education groups separately: high school diploma or less, non-university post-secondary, and university degree. Immigrants with a high school education or less, both men and women, living in cities with a larger proportion of co-ethnics typically start out with somewhat higher entry earnings but the advantage appears to be declining across entry cohorts. There doesn't appear to be any discernible pattern across cohorts for college or university-educated men or women.

So far there appears to be variation across arrival cohorts in the relationship between the proportion of co-ethnics in the city and both the intercept and slope of immigrant earnings profiles but no particular pattern, except for immigrants with low levels of education. Perhaps a more informative way to judge these differences is to compare the present value of earnings across cohorts and different levels of exposure to co-ethnics. Following Green and Worswick (2004) I use predicted earnings 7 years after arrival to calculate the present value of post-migration earnings for an immigrant who arrived at age 25. Using the estimated coefficients in Tables 3.1 and 3.2, I find the predicted (level of) weekly earnings, multiply by 52 weeks to obtain annual earnings, and by (1-exp(-rT))/r to find the present value of earnings (PVE). T is the number of years an immigrant works after arrival, and is set to 40, r is the discount rate and is set to 0.1. I calculate the difference in PVE between immigrants living in a city where 3% of the population is co-ethnic and similar immigrants living in a city with no other co-ethnics. Results are reported in Table 3.3. The overall picture painted by these estimated PVEs is essentially one where immigrants who arrived in the 1980s and settled in cities with a larger proportion of co-ethnics have in general higher earnings in present value terms. This apparent advantage has turned into a disadvantage for immigrants who arrived in the 1990s, especially the late 1990s, and in particular immigrant men.

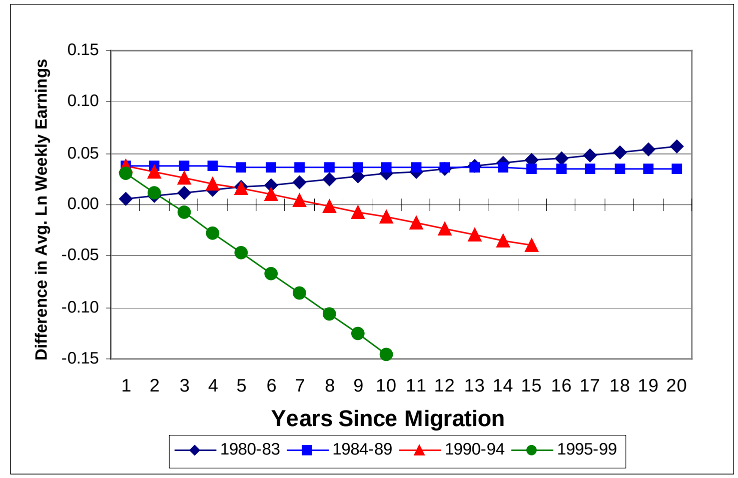
The estimated differences in PVE are for the most part not statistically significant. Neither are most of the estimated coefficients reported in Tables 3.1 and 3.2. The variation

Figure 3.1: Enclave – Non-Enclave Earnings Gap: Immigrant Men

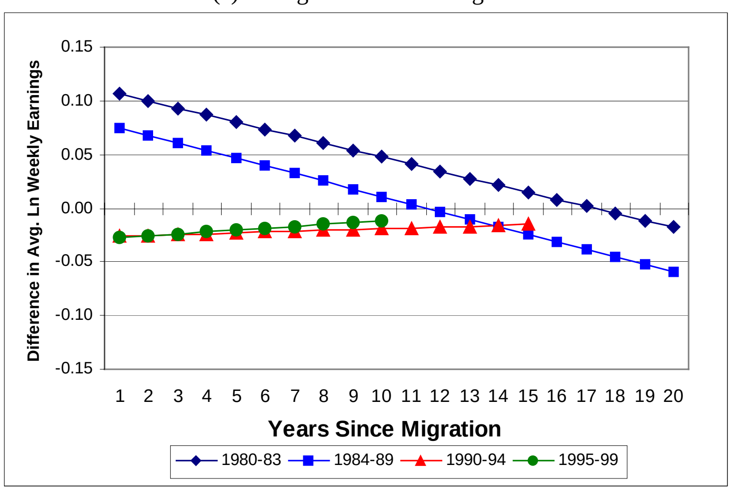
(a) Immigrant Men – All Education Groups



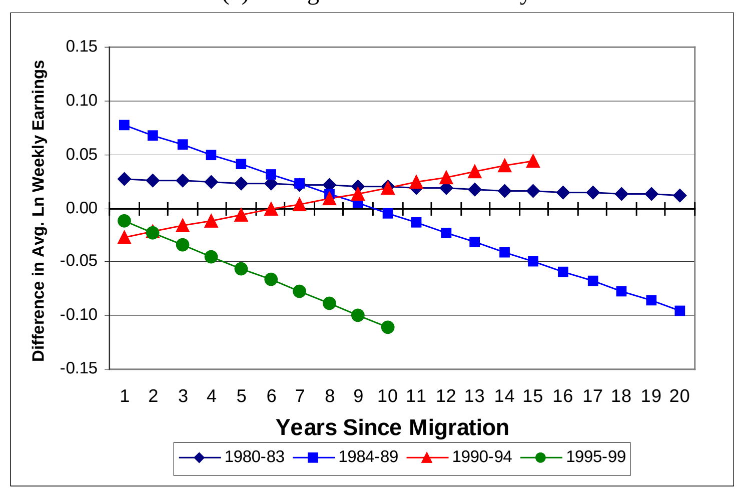
(b) Immigrant Men – High School or Less



(c) Immigrant Men – College

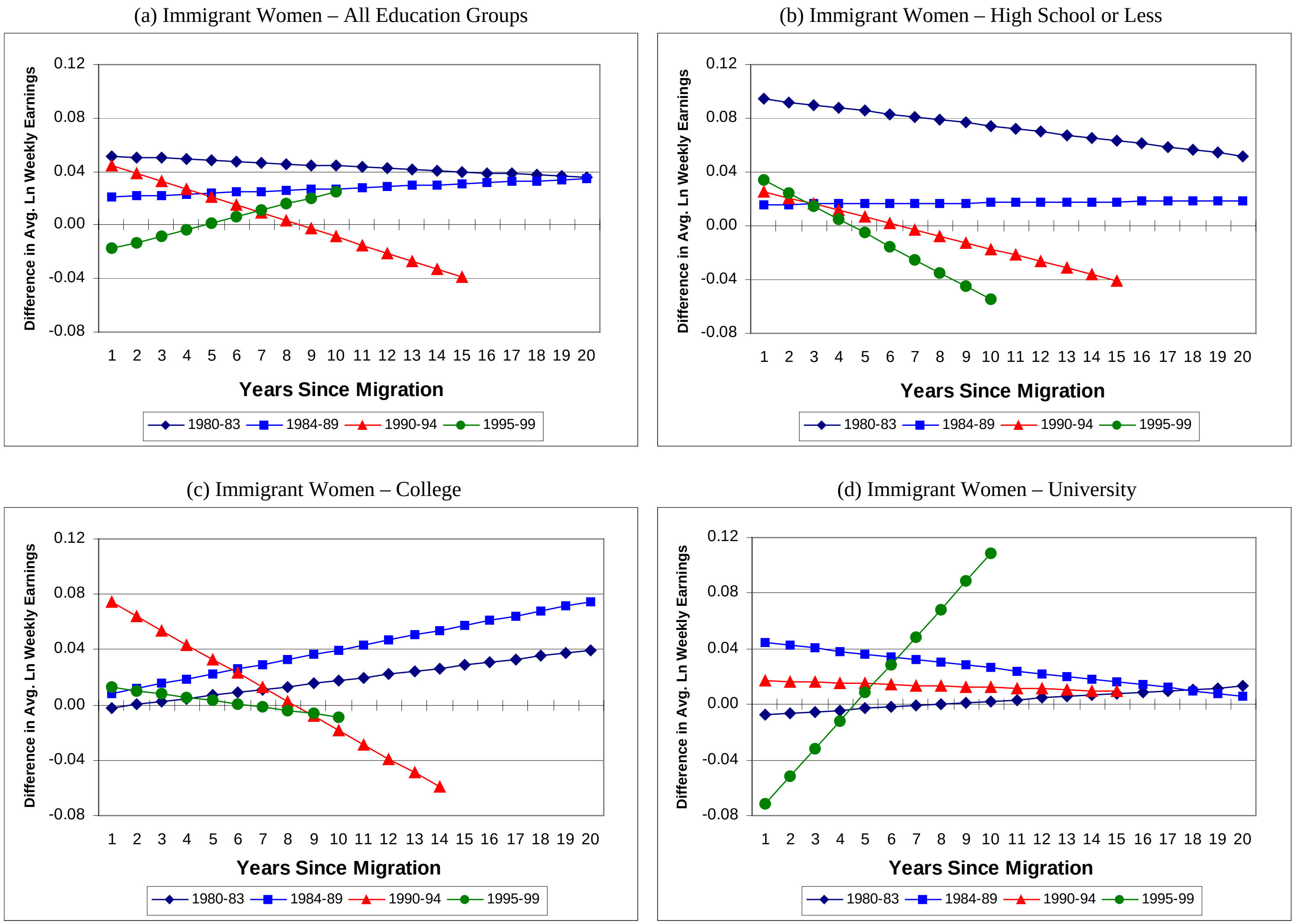


(d) Immigrant Men – University



The plotted lines represent the difference in fitted mean earnings of immigrants living in a city (more specifically a CA/CMA) with 3% of co-ethnics and a city with no co-ethnics for four arrival cohorts.

Figure 3.2: Enclave – Non-Enclave Earnings Gap: Immigrant Women



The plotted lines represent the difference in fitted mean earnings of immigrants living in a city (more specifically a CA/CMA) with 3% of co-ethnics and a city with no co-ethnics for four arrival cohorts.

Table 3.3: Enclave - Non-Enclave Gap in PVE

	Men			
	1980-83	1984-89	1990-94	1995-99
HS or less	6,713	10,527	1,099	-30,710***
	(8,494)	(7,198)	(3,307)	(10,896)
College	21,856	9,510	-5,710	-4,057
	(13,683)	(7,169)	(5,596)	(5,897)
University	9,039	9,422	1,303	-31,649*
	(22,666)	(8,672)	(5,397)	(16,691)
	Women			
	1980-83	1984-89	1990-94	1995-99
HS or less	14,048***	2,878	-462	-3,592
	(3,009)	(4,201)	(1,651)	(4,155)
College	2,332	5,731	2,084	-286
	(6,510)	(6,199)	(2,555)	(7,536)
University	-236	9,327	3,392	13,152
	(8,478)	(9,875)	(3,445)	(11,757)

Difference in fitted present value of earnings of immigrants living in a city (more specifically a CA/CMA) with 3% of co-ethnics and a city with no co-ethnics. Detrended unemployment rate and indicators for broad ethnic origin categories included in all regressions. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

used to estimate these enclave effects is at the ethnic group - city level. There are only 17 ethnic origin groups and 15 CMA's in the analysis, and the exposure index varies between 0 and 0.159, with a mean of 0.046. There may simply not be enough variation in the data to precisely estimate all the parameters of the model. As a robustness check, I reran the earnings regressions on the four pooled census cross sections using a simplified functional form – allowing a cohort-specific ethnic enclave effect which did not vary with time since arrival. Results presented in Tables 3.4 and 3.5 are to a large extent consistent with the patterns revealed by the PVE comparisons. Immigrants who arrived in the early 1980s do better in ethnic enclaves, with the biggest gains accruing to immigrants with a high school diploma or less, while those who arrived in the late 1990s do worse. This cross-cohort decline in the benefits associated with living in an ethnic enclave was most pronounced among immigrants with low education levels. It is easy to see how a single cross section of data can suggest that there is no statistically significant relationship between average immigrant earnings and the relative size of the co-ethnic community. When estimating an enclave effect common to immigrants of all education levels and arrival cohorts, the earnings disadvantage associated with living in an enclave for the immigrants of the late 1990s may well offset the higher earnings experienced in enclaves by earlier cohorts of immigrants with low educational attainment.

Table 3.4: Earnings Regressions Using Census Data (Simpler Specification) - Men

	All education groups	HS or less	College	University
EI*1995-99	-1.086**	-1.387**	-0.735	-1.430**
	(0.440)	(0.545)	(0.734)	(0.630)
EI*1990-94	0.016	0.219	-0.744	0.068
	(0.384)	(0.523)	(0.690)	(0.592)
EI*1984-89	0.807**	1.218*	0.533	-0.058
	(0.408)	(0.656)	(0.722)	(0.398)
EI*1980-83	1.009**	1.447**	0.483	0.497
	(0.437)	(0.558)	(0.748)	(0.784)
YSM	0.038***	0.061***	0.004	0.042***
	(0.010)	(0.015)	(0.019)	(0.016)
YSM sq.	-0.001**	0.0001	-0.002***	-0.001**
	(0.0003)	(0.0005)	(0.001)	(0.001)
1990-94	-0.158**	-0.016	-0.251*	-0.295**
	(0.079)	(0.114)	(0.136)	(0.134)
1984-89	0.117	0.225**	-0.065	0.101
	(0.076)	(0.109)	(0.129)	(0.107)
1980-83	0.125	0.263**	0.045	-0.035
	(0.092)	(0.119)	(0.154)	(0.157)
1990-94 * YSM	-0.013	-0.058***	0.037	0.011
	(0.012)	(0.019)	(0.024)	(0.021)
1984-89 * YSM	-0.017	-0.059***	0.037*	-0.004
	(0.011)	(0.018)	(0.022)	(0.018)
1980-83 * YSM	0.004	-0.040**	0.049**	0.026
	(0.011)	(0.018)	(0.021)	(0.021)
Age	0.073***	0.073***	0.078***	0.082***
	(0.006)	(0.007)	(0.011)	(0.012)
Age sq.	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
College	0.172***			
	(0.030)			
University	0.408***			
	(0.029)			
Observations	16862	7548	4461	4853
R-squared	0.09	0.06	0.05	0.06

Detrended unemployment rate and indicators for broad ethnic origin groups included in all regressions. Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.5: Earnings Regressions Using Census Data (Simpler Specification) - Women

	All education groups	HS or less	College	University
EI*1995-99	-0.074	0.016	0.172	-0.466
	(0.511)	(0.552)	(0.479)	(0.882)
EI*1990-94	0.381	-0.019	0.556	0.464
	(0.521)	(0.453)	(0.829)	(0.474)
EI*1984-89	0.910	0.573	1.318	0.850
	(0.711)	(0.666)	(0.856)	(0.857)
EI*1980-83	1.335***	2.110***	0.975*	0.242
	(0.378)	(0.431)	(0.550)	(0.898)
YSM	0.052***	-0.015	0.094***	0.092***
	(0.012)	(0.023)	(0.023)	(0.022)
YSM sq.	-0.001*	0.0001	-0.001	-0.002**
	(0.0003)	(0.001)	(0.0005)	(0.001)
1990-94	0.143*	0.036	0.290**	-0.026
	(0.078)	(0.120)	(0.136)	(0.125)
1984-89	0.295***	0.083	0.583***	0.121
	(0.075)	(0.120)	(0.127)	(0.149)
1980-83	0.301***	0.142	0.621***	-0.058
	(0.106)	(0.160)	(0.148)	(0.166)
1990-94 * YSM	-0.031**	0.009	-0.074***	-0.010
	(0.014)	(0.027)	(0.024)	(0.022)
1984-89 * YSM	-0.031**	0.018	-0.079***	-0.022
	(0.012)	(0.024)	(0.024)	(0.024)
1980-83 * YSM	-0.026**	0.016	-0.059**	-0.024
	(0.013)	(0.024)	(0.025)	(0.022)
Age	0.053***	0.057***	0.054***	0.051**
	(0.012)	(0.011)	(0.019)	(0.020)
Age sq.	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
College	0.198***			
	(0.014)			
University	0.411***			
	(0.021)			
Observations	16098	7268	4685	4145
R-squared	0.07	0.02	0.05	0.05

Detrended unemployment rate and indicators for broad ethnic origin groups included in all regressions. Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4 Exposure vs Interaction

The literature on ethnic enclave effects, and the broader literature on neighbourhood effects, often argues that social interaction is the key channel of transmission of such effects. The exposure index (or some version of it) has been used also as a proxy for social networks (Bertrand, Luttmer and Mullainathan (2000)). For lack of data on who an individual actually interacts with, previous studies rely on some combination of the following assumptions: social networks are strongest at the neighbourhood level and become weaker with distance; social networks are created along ethnic or racial lines in ethnically diverse societies; and higher supply of co-ethnics within a certain geographic area implies that any given member of that ethnic group residing in that geographic area has more interaction with co-ethnics relative to members of other ethnic groups. It is not clear, however, that increased exposure to co-ethnics necessarily crowds out interaction with members of other ethnic groups. This would certainly be true if friendships and social networks in general were formed randomly within the boundaries of a city for example. But this is not likely to be the case.

In this section I test the hypothesis that higher exposure to co-ethnics in fact implies more interaction with co-ethnics than members of other ethnic groups, so that in empirical analysis measures of exposure to or supply of co-ethnics capture an interaction effect. The proportion of co-ethnics could potentially influence immigrant labour market outcomes through several different channels. Social networks are the most commonly cited channel. Co-ethnic friends could be valuable job contacts for an immigrant unfamiliar with the workings of the host country labour market. To the extent that job opportunities available within an ethnic community are limited compared to the broader labour market, ethnically diverse networks could be valuable in providing access to other segments of the labour market. Co-ethnic social networks may also mean that an immigrant does not have the opportunity to acquire/improve host country language skills, and any other host country specific skills rewarded in the general labour market. However, there may be more to the ethnic enclave effects than social networks. Higher exposure to co-ethnics could be capturing preferences of employers for hiring members of their own group, preferences of immigrants to seek employment with co-ethnics rather than in the broader economy, or preferences of majority group employers for hiring immigrants of a particular origin group (to the extent that these vary with the fraction of a minority group in the city population). Introducing a more direct measure of co-ethnic social networks into an earnings regression in addition to the more traditional measure like the proportion of co-ethnics in the city, should drive the coefficient on the latter variable to zero if ethnic enclave effects are in fact just network effects.

3.4.1 Data and descriptive statistics

The analysis in this section is based on data from the Ethnic Diversity Survey (EDS), a Canadian post-censal survey conducted in 2002. The respondents for this survey were selected from among those who answered the long form of the 2001 Canadian Census. Their answers to some of the census questions are also provided in the EDS data set. This analysis makes use of both information collected during the EDS interview and on the 2001 Census questionnaire. The EDS is described in more detail in Section 2.4.1 of Chapter 2.

The sample is restricted to immigrants age 18 to 64 in 2001 who arrived in Canada at age 18 or older. As in the previous section, this age restriction is put in place to focus on the role of ethnic enclaves and co-ethnic networks in the adaptation process of immigrants who arrive as adults. Only immigrants who arrived between 1980 and 1999 are considered. I excluded observations for which ethnic ancestry is not precisely reported, e.g. European n.i.e. or Asian n.i.e.[2] and those who are French, American, Australian, New Zealander or from the British Isles as the concept of ethnic enclave is not as obvious in their case. This leaves 116 ethnic origins in the sample, although these are grouped into broader categories in regression analysis due to small sample sizes. Only individuals residing in Census Agglomerations (CAs) or Census Metropolitan Areas (CMAs) outside the Atlantic Provinces or the Territories are considered – there are 32 CA/CMAs in the sample.[3]

The key explanatory variables in this analysis are the exposure index and social segregation indicator. The exposure index, i.e. the fraction of a city population that belongs to a particular ethnic group, is defined as in the previous section. I match this variable to the city the respondent resided in at the time of selection for the EDS survey, rather than at the time the EDS was actually conducted, since the labour market outcomes explored in this section, earnings and employment, are based on information gathered during the 2001 Census and pertain to the year 2000.

The social segregation indicator chosen for this study is based on data on the proportion of a person's friends who share his or her ethnic ancestry collected during the EDS interview. Respondents could list up to eight different ethnic ancestries in the EDS and rated each in terms of its importance. I assign each person to the ethnic origin group they rated highest in importance.[4] Individuals were then asked what proportion of their friends also belong to the ethnic origin rated highest in importance.[5] The answers are reported in five categories: all, most, half, some, or none of the friends share the respondent's ethnic origin. Based on this information, I define a social segregation indicator which takes the value of 1 when most or all of a person's friends are co-ethnic, and zero otherwise.

Table 3.6 shows summary statistics by proportion of co-ethnic friends. Among immigrants who arrive as adults, 14-18% have friends only from their own ethnic group. A further 38-41% report that most of their friends are from their own ethnic group. Only about 5% of immigrants have no co-ethnic friends at all. Immigrants with mostly co-ethnic friends live in cities with a higher proportion of their co-ethnics; 4% compared to on average 2% for immigrants who report that half or fewer of their friends are co-ethnic.

[2]The exception are responses of 'Black', 'African Black n.i.e.' and 'Arab, n.i.e.' for which counts at the city level are reported in public Census data tabulations.

[3]For simplicity, I will refer to a CA/CMA as a city.

[4]When two ethnic ancestries were listed and given the same importance rating, I used the first-reported highest-rated ancestry.

[5]Respondents were asked this question about the two highest-rated ancestries, where more than one ancestry was reported. 'Canadian' was one of the responses accepted to the ancestry question, however, regardless of it's importance rating, respondents who reported 'Canadian' as at least one of their ancestries where not asked what proportion of their friends were 'Canadian'.

Table 3.6: Characteristics of Immigrants by Proportion of Co-ethnic Friends

	MEN					WOMEN				
Proportion of co-ethnic friends	all	most	half	some	none	all	most	half	some	none
% of population	14	38	23	21	5	18	41	18	18	5
Exposure Index (%)	4	4	3	2	1	4	4	2	2	2
Weekly earnings	811	798	1,031	934	841	498	569	637	684	711
% with High School or Less	68	42	32	36	43	65	48	36	41	42
% with College	19	30	29	31	28	20	27	35	34	32
% with University	13	28	39	33	29	15	25	29	25	26
Age	46	45	44	46	48	46	45	43	45	45
Age at Immigration	30	30	29	29	29	31	29	28	28	28
Canadian Experience	15	14	14	16	19	15	14	15	17	17
Foreign Experience	13	11	9	9	10	14	10	8	8	8
Years since migration	16	15	15	17	20	16	15	16	18	18
% English/French 1^{st} language	13	13	16	21	26	10	11	18	27	22
% English/French 2^{nd} language	71	82	83	79	73	73	82	79	72	71
% European	27	20	24	37	56	22	21	35	35	53
% with most or all co-ethnic childhood friends	97	94	83	74	53	96	93	80	70	55
Ethnic composition of networks by origin group (%)	all	most	half	some or none		all	most	half	some or none	
European	13	28	20	39		15	30	23	32	
E. and S.E. Asian	14	57	20	9		22	53	14	11	
South Asian	14	39	25	22		24	34	21	22	
Other origins	13	25	28	35		11	39	18	32	

Immigrants with more co-ethnic friends tend to have lower earnings. Immigrant men with most or all co-ethnic friends earn around \$800 a week, compared to between \$840 and \$1,030 among men with half or fewer co-ethnic friends. A similar pattern is observed among immigrant women. Although the EDS collected data on earnings referring to the 12 months prior to the survey date, the non-response rate is very high. Given the already small samples available, I chose to use earnings information reported by respondents on their Census questionnaire. I focus on weekly earnings rather than hourly earnings since usual hours worked are reported for the census reference week in 2001, while usual weeks worked and employment earnings for 2000. Both weeks worked and employment income reported in the census pertain to all jobs held in 2000. Therefore, I combine income from paid employment and self-employment in the analysis. I exclude individuals with weekly earnings of less than \$1 and annual earnings greater than \$350,000 as higher earnings are top-coded at that value.

Immigrants with more segregated social networks tend to have lower education levels. Around 68% of men and 65% of women with only co-ethnic friendships have completed at most a high school diploma, compared to between 32% and 48% of individuals with most or fewer co-ethnic friends. Only about 14% of immigrants who report having only co-ethnic friends have a university education, compared to at least 25% among the remaining groups. Respondents' educational attainment is measured by their responses in the Census rather than the EDS. The Census collects much more detailed information on education, and it also represents the attainment closest to the time at which labour market outcomes are measured. I control for the highest completed level of schooling in earnings and employment regressions rather than years of schooling. This is because immigrants in the sample would have completed most if not all of their education outside Canada in a variety of countries and therefore different education systems. The same level of schooling, say high school, could be completed in a different number of years depending on the country. I would like to eliminate students from the sample, however there is no variable in the data set that identifies individuals who were students in 2000 or during the census reference week in May 2001. My results are not affected if I restrict the sample to individuals age 25 and over in an attempt to eliminate potential students.

Immigrants who report having mostly co-ethnic friends tend to have arrived at a later age, 30 on average, compared to 28 or 29 among those with more friends from other ethnic groups. The same pattern is not reflected in average age however. Related to the age at arrival is the distribution of Canadian and foreign (potential) labour market experience. Immigrants with more segregated social networks have fewer years of Canadian labour market experience, 14 to 15 years compared to 17 to 19 years among immigrants with some or no co-ethnic friends, and more years of foreign experience, 10 to 14 years compared to 8 to 10 years.[6]

[6] Labour market experience is measured as potential rather than actual experience. Foreign experience equals (age at arrival - years of schooling - 6) and Canadian experience equals (age - age at arrival) when age at arrival is greater than years of schooling + 6.

One common assumption about why immigrants segregate in enclaves is that they don't have the necessary host language skills to integrate into the broader society. The information on language knowledge is that collected in the EDS. Upwards of 93% of individuals with at least some friends from other ethnic origin groups report being able to speak English or French, while only about 84% of those with all co-ethnic friends do.[7] Still, 84% of immigrants who choose to have only co-ethnic friends are in theory able to communicate with members of other ethnic groups. Furthermore, between 10-13% of them learned English or French as their first language.

Immigrants with segregated networks tend to belong to visible minority ethnic origin groups. Only between 20 to 27% of them are of European descent, compared to 24 to 56% of those with half or fewer co-ethnic friendships. There are important differences in the distribution of ethnic composition of networks across the visible minority groups (lower panel of Table 3.6). The biggest difference is in the categories 'most' and 'some', the smallest in the middle group. Nevertheless, it is the within ethnic origin group variation in the ethnic composition of networks that will be used to identify the effect of social segregation in regression analysis.[8] I use the more detailed information on ethnic origin collected in the EDS, rather than on the Census.

Given that visible minorities tend to have more ethnically segregated friendship networks than non-minorities, and that the ability to communicate with other ethnic groups is insufficient to induce individuals to diversify their social networks, it appears that the ethnic composition of social networks is anything but random, and is likely heavily influenced by preferences.[9] One way in which such preferences may have been shaped is through the availability of contacts with other ethnic groups in childhood. There appears to be a high positive correlation between the proportion of co-ethnic friendships in adulthood and having had mostly co-ethnic friends in childhood (up until age 15). Among individuals who report that most or all of their friends are co-ethnic, upwards of 93% had mostly co-ethnic friends in childhood as well. This proportion drops to between 53% and 80% among those with half or fewer co-ethnic friends.

It is evident from the summary statistics that women tend to form more ethnically segregated social networks than men. Around 59% of women report that most or all of their friends are co-ethnic, compared to 52% of men. These women also tend to be on average better educated than men with similar level of network segregation. This suggests that segregation may play a different role in men and women's post-migration labour market outcomes. I conduct all regression analysis separately by gender.

[7]The interviewers for EDS were instructed to record knowledge of a language if the respondent could carry on a conversation in that language on several topics. That ability was presumably self-reported. A respondent was also classified as able to speak a language if he or she answered the survey in that language.

[8]The categories 'some' and 'none' are collapsed in this part of the table due to small sample sizes in the 'none' category.

[9]Other explanations are possible, too, e.g. discrimination or fear thereof.

3.4.2 Exposure vs interaction

The summary statistics in Table 3.6 suggest a positive correlation between exposure to co-ethnics and the proportion of co-ethnic friends. However, the correlation between these two variables is only around 0.25. There is also a systematic relationship between social segregation and a number of standard socio-demographic characteristics, like education or host country language ability, etc. Most studies of ethnic enclave effects control for these characteristics. In order to find out how much correlation remains between these two variables after conditioning on a number of individual characteristics, I ran several descriptive regressions with the social segregation indicator as dependent variable. Results are presented in Table 3.7. In columns 1 and 2 the dependent variable takes the value 1 if most or all friends are co-ethnic. This is the definition chosen for the remaining analysis in this section. In columns 3 and 4 I explore a stricter definition of social segregation - the dependent variable takes the value 1 if all friends are co-ethnic, and zero otherwise.

The correlation between social segregation, measured by most or all friends being co-ethnic, and the exposure index is positive and statistically significant for both immigrant men and women, even after controlling for several standard socio-demographic characteristics. The relationship, however, is not very strong. The magnitude of the estimated marginal effect suggests that immigrants in cities where 1% of the population shares their ethnic ancestry are only about 1 percentage point more likely to report that most or all of their friends are co-ethnic, than are immigrants who live in cities where the proportion of co-ethnics is essentially zero. With a stricter definition of social segregation, the magnitude of the estimated relationship between exposure and interaction falls dramatically and is no longer statistically significant.

Immigrants who report that most of their childhood friends were of the same ancestry as them are on average 40 percentage points more likely to report that most or all of their friends in adulthood have the same ethnic background (column 2). Those with all co-ethnic childhood friends are on average 15 percentage points more likely to have all co-ethnic friends as adults (column 4). These results suggest that the ethnic composition of one's networks is anything but random. Note that since the immigrants in my sample arrived in Canada at age 18 or older, their childhood friendship would have been established in a different country. Judging by the strong correlation between the proportion of co-ethnic friends an immigrant had in childhood before arriving in Canada and has in Canada as an adult, preferences play an important role in determining the ethnic composition of post-migration social networks.

The correlation between some of the other individual characteristics and social segregation takes on a predictable sign. For example, immigrants who speak English or French, either as a mother tongue (first language) or as a second language, are more likely to form inter-ethnic friendships than those who don't. Also higher education is associated with a lower probability of social segregation. One result that is perhaps surprising is that the likelihood of segregation does not change very much with time spent in Canada.

Table 3.7: Marginal Effects on Social Segregation Indicators (from Probit Estimation)

	MEN				WOMEN			
Dependent variable	Most or all co-ethnic friends	Most or all co-ethnic friends	ALL co-ethnic friends	ALL co-ethnic friends	Most or all co-ethnic friends	Most or all co-ethnic friends	ALL co-ethnic friends	ALL co-ethnic friends
Exposure Index (EI)	0.868**	1.041**	0.379	0.302	1.431***	1.289**	0.102	0.010
	(0.407)	(0.415)	(0.245)	(0.217)	(0.487)	(0.522)	(0.291)	(0.287)
All or most co-ethnic childhood friends		0.386***				0.434***		
		(0.044)				(0.036)		
All co-ethnic childhood friends				0.138***				0.161***
				(0.016)				(0.017)
YSM	-0.003	-0.005**	-0.001	-0.0004	-0.005**	-0.005**	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Age	0.001	0.001	0.0001	-0.0003	0.004*	0.004*	0.004***	0.004**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
College	-0.096*	-0.112**	-0.079***	-0.075***	-0.152***	-0.178***	-0.088***	-0.081***
	(0.058)	(0.056)	(0.022)	(0.019)	(0.037)	(0.039)	(0.020)	(0.018)
University	-0.203***	-0.231***	-0.114***	-0.107***	-0.129***	-0.156***	-0.099***	-0.090***
	(0.038)	(0.038)	(0.017)	(0.015)	(0.042)	(0.044)	(0.025)	(0.022)
English/French 1^{st} language	-0.444***	-0.352***	-0.144***	-0.101***	-0.307***	-0.199*	-0.146***	-0.106***
	(0.069)	(0.082)	(0.026)	(0.028)	(0.084)	(0.102)	(0.024)	(0.027)
English/French 2^{nd} language	-0.392***	-0.366***	-0.249***	-0.194***	-0.120	-0.082	-0.141***	-0.118***
	(0.069)	(0.068)	(0.086)	(0.073)	(0.075)	(0.089)	(0.047)	(0.044)
Married	0.171***	0.172***	0.037	0.033	0.100***	0.090**	-0.023	-0.022
	(0.046)	(0.048)	(0.024)	(0.021)	(0.038)	(0.039)	(0.025)	(0.025)
Observations	1599	1599	1599	1599	1888	1888	1888	1888

Regressions include dummies for broad ethnic origin groups. Clustered standard errors in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.3 Addressing endogeneity

In order to estimate the causal impact of exposure to and interaction with co-ethnics, we must address the potential endogeneity concerns. First of all, ethnic enclaves may form in cities with favourable economic conditions. Thus we could see a positive relationship between enclave size and labour market outcomes which had nothing to do with the relative enclave size itself. On the other hand, immigrants who settle in established ethnic enclaves may not be a random draw from all incoming immigrants. For example, individuals who tend to settle in enclaves may be in general less able to secure employment and more likely to hold lower paying jobs because of characteristics, perhaps ability or skill, unobservable to the researcher. In this case, we might see a negative correlation between labour market outcomes of immigrants and the proportion of co-ethnics in the city, even if the causal impact were actually positive.

The ethnic composition of an immigrant's social network may also be endogenous in labour market outcome regressions. If immigrants who restrict their social networks to within their own ethnic group are also less able to successfully adapt to the host country labour market, then we might see a negative correlation between social segregation and earnings and/or employment even if no causal impact were present. Also, the ethnic composition of an immigrant's social network may itself be a function of the type of job the immigrant is able to secure and the ethnicity of his or her co-workers.

To address these endogeneity concerns, I use the lagged values of both the proportion of co-ethnics in the city of residence and in the ethnic composition of the immigrant's social network to instrument for the potentially endogenous exposure index and social segregation indicator. It is a well-documented phenomenon that many immigrants settle in pre-existing ethnic enclaves. Part of the reason may be that immigrants from particular countries settle in the part of the host country closest to the country of origin (i.e. easiest or cheapest to get to), hence we might expect for example East Indians to settle disproportionately in Western Canada while immigrants from the Caribbean to settle in the East. I use the relative size of an ethnic enclave in 1971 to instrument for its size in 2001. This instrument is meant to capture historical settlement patterns of different ethnic groups. As long as economic conditions in a particular city and within individual ethnic communities are not very persistent, this will be a valid instrument.

To instrument for social segregation I use self-reported information on the fraction of one's childhood friends, i.e. friends a person had until age 15, who shared his or her ethnic ancestry. Given that the immigrants in my sample arrived in Canada at age 18 or older, the childhood friendships would have been established in the country where the person was born and/or grew up in. The crucial assumptions made here are as follows. Exposure to members of other ethnic groups in childhood helps shape preferences towards other ethnic groups. These preferences persist into adulthood and in turn help determine the ethnic composition of social networks an immigrant chooses in the host country. Furthermore, the ethnicity of one's childhood friends is assumed to be independent of any unobservable individual characteristics (like ability) that may influence labour market outcomes in the host country. The supply of potential friends from other ethnic groups, particularly in ethnically homogeneous countries, however, may reflect socio-economic characteristics of the person's family, like education, income, size of the city the person grew up in etc. Since all of these factors could impact a person's future labour market outcomes, we should be controlling for such characteristics in the labour market outcome regressions in order to isolate the preference-based variation in the instrument. The only relevant individual-level information in the EDS is parental education. Controlling for parental education does not alter the results, however, and these variables are not statistically significant.

3.4.4 Estimating the 'enclave effect' from a single cross section of data

Data on the proportion of co-ethnic friends present a unique opportunity to study the relationship between exposure to and interaction with co-ethnics among immigrants. However, the data set presents a couple of problems. First of all, it is a single cross section. The analysis in the preceding section suggests that a cross-sectional estimate of the 'enclave effect' could be essentially zero because of the offsetting cohort effects in the relationship between immigrant earnings and the proportion of co-ethnics in the city over the period studied. These cross-sectional estimates should be interpreted with caution. Second, the sample sizes in the EDS are rather small.

In this subsection I estimate the association between the exposure index and immigrant earnings using both the public use 2001 Census data and the EDS to see whether the two data sets yield comparable estimates. I report results from two model specifications. In one I estimate a single ethnic enclave effect for all education groups. In the other I allow the effect of the proportion of co-ethnics in the city to vary by education group (but restrict the effect of the remaining regressors to be common to immigrants of all education levels). In Tables 3.8 and 3.9 I report the key coefficients from the two models respectively, estimated by both least squares and 2SLS. First stage regressions for the 2SLS estimation are reported in Appendix B, Tables B.1 to B.3.

In Table 3.8 the overall ethnic enclave effect is not statistically significant in either data set. In Table 3.9 the estimates based on the Census are also insignificant.[10] The EDS, on the other hand, shows a positive and statistically significant effect of exposure to co-ethnics on earnings of immigrant men with a non-university post-secondary education, and a positive significant effect, as estimated by least squares but not 2SLS, on earnings of immigrant women with a university education. In both cases, the coefficient estimated from EDS has the opposite sign to that estimated from the Census. Given the inconsistencies in estimates obtained from the two data sources, the analysis in the remainder of this section should be treated as primarily an exploration of the relationship between the proportion of co-ethnics in the city of residence and in an immigrant's social networks.

[10] In robustness checks I ran the regressions using Census data separately by education and controlling for individual ethnic origin categories, rather than groups of origins. In that specification the coefficient on the exposure index was negative and statistically significant for both men and women.

Table 3.8: Earnings Regressions: 2001 Census vs Ethnic Diversity Survey - Specification 1

	Census		EDS	
	least squares	2SLS	least squares	2SLS
		MEN		
EI	-0.446	-0.914	0.626	1.464
	(0.327)	(0.553)	(0.654)	(1.205)
YSM	0.038***	0.038***	0.024	0.024
	(0.007)	(0.007)	(0.023)	(0.023)
YSM sq.	-0.0008**	-0.0007**	0.0002	0.0002
	(0.0003)	(0.0003)	(0.001)	(0.001)
College	0.218***	0.216***	0.162**	0.162**
	(0.030)	(0.030)	(0.070)	(0.070)
University	0.458***	0.456***	0.562***	0.567***
	(0.026)	(0.026)	(0.077)	(0.077)
Observations	7986	7986	962	962
R-squared	0.07	0.07	0.12	0.12
		WOMEN		
EI	0.175	0.174	0.574	-0.618
	(0.525)	(0.695)	(0.691)	(1.458)
YSM	0.058***	0.058***	0.011	0.013
	(0.008)	(0.008)	(0.023)	(0.023)
YSM sq.	-0.001***	-0.001***	0.001	0.001
	(0.0003)	(0.0003)	(0.001)	(0.001)
College	0.217***	0.217***	0.211***	0.212***
	(0.021)	(0.021)	(0.071)	(0.070)
University	0.408***	0.408***	0.548***	0.539***
	(0.034)	(0.034)	(0.072)	(0.072)
Observations	7852	7852	963	963
R-squared	0.05	0.05	0.10	0.10

All regressions include dummies for broad ethnic origin groups. Clustered standard errors in brackets. In 2SLS estimation, the instrument for EI, proportion of co-ethnics in CA/CMA in 2001, is the corresponding proportion in 1971. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.5 Empirical framework

This section examines the effect of exposure to co-ethnics and social segregation on two labour market outcomes of immigrants, earnings and employment. I use the same model specification to analyze both of these outcomes. The empirical model is the following:

$$\begin{aligned} y_{ijk} = \alpha + \xi_1 EI_{jk} + \zeta_1 SI_{ijk} + educ_{ijk}\eta \\ [(EI_{jk} * educ_{ijk})\xi_2 + (SI_{ijk} * educ_{ijk})\zeta_2] + X_{1ijk}\beta + \tau_j + \epsilon_{ijk} \end{aligned} \quad (3.4.1)$$

where y_{ijk} is the labour market outcome (earnings or employment status) of individual i belonging to ethnic origin group j and residing in area k. 'SI' is the social segregation indicator and 'EI' the traditional exposure index, i.e. the number of co-ethnics living in

Table 3.9: Earnings Regressions: 2001 Census vs Ethnic Diversity Survey - Specification 2

	Census		EDS	
	LS	2SLS	LS	2SLS
		MEN		
EI*hs	-0.412	-0.656	0.613	-0.007
	(0.467)	(1.162)	(0.774)	(2.392)
EI*coll	-0.412	-2.085	1.961*	7.697*
	(0.650)	(1.407)	(1.056)	(4.469)
EI*univ	-0.508	-0.443	-0.579	-1.850
	(0.498)	(0.858)	(1.526)	(2.369)
YSM	0.038***	0.038***	0.021	0.012
	(0.007)	(0.007)	(0.023)	(0.024)
YSM sq.	-0.0008**	-0.0008**	0.0003	0.001
	(0.0003)	(0.0003)	(0.001)	(0.001)
College	0.218***	0.284***	0.120	-0.082
	(0.050)	(0.107)	(0.090)	(0.177)
University	0.463***	0.444***	0.595***	0.607***
	(0.051)	(0.087)	(0.098)	(0.120)
Observations	7986	7986	962	962
R-squared	0.07	0.07	0.13	0.10
		WOMEN		
EI*hs	0.171	0.592	0.278	-0.966
	(0.456)	(1.150)	(0.952)	(1.434)
EI*coll	0.487	-0.936	0.062	0.409
	(0.609)	(0.826)	(0.882)	(3.272)
EI*univ	-0.132	0.654	2.219**	-1.611
	(0.752)	(1.556)	(0.982)	(2.987)
YSM	0.058***	0.058***	0.011	0.014
	(0.008)	(0.008)	(0.023)	(0.023)
YSM sq.	-0.001***	-0.001***	0.001	0.001
	(0.0003)	(0.0003)	(0.001)	(0.001)
College	0.202***	0.292***	0.216**	0.166
	(0.032)	(0.070)	(0.097)	(0.146)
University	0.423***	0.407***	0.494***	0.552***
	(0.042)	(0.076)	(0.099)	(0.120)
Observations	7852	7852	963	963
R-squared	0.06	0.05	0.10	0.09

All regressions include dummies for broad ethnic origin groups. Clustered standard errors in brackets. In 2SLS estimation, the instruments for interactions between EI, proportion of co-ethnics in CA/CMA, and education are interactions between the corresponding proportion of co-ethnics in 1971 and education. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

area k divided by the total population of area k, where the area is a Census Agglomeration or a Census Metropolitan Area. 'Educ' is a vector of two education groups: college (non-university post-secondary) and university, with high school or less being the base category. X_1 represents personal characteristics: a quadratic in Canadian potential experience, a quadratic in foreign potential experience, an indicator for English or French being the first language learned, an indicator for English or French being the second language learned, and marital status. τ_j are the ethnic origin effects. The ethnic dummies absorb differences between ethnic groups in average labour market success and various unobservable characteristics so that the exposure and social segregation effects can be identified off of within ethnic group variation. In practice, due to small sample sizes, I group the individual origins into seven broad categories: European, West Asian, East and Southeast Asian, South Asian, African, Caribbean, and other. I estimate two versions of the model. The benchmark model restricts the effect of exposure and interaction with co-ethnics to be the same across education groups. The second (preferred) model includes interactions between the variables of interest (EI and SI) and education categories. The latter is the preferred specification in light of results in Section 3.3.

In the analysis of immigrant women's labour market outcomes, two things have to be accounted for: potential endogeneity of the exposure index and social segregation indicator and selection into the labour force. This problem can be written down in the following system of equations:

(1) the earnings regression:

$$y_1 = z_1\delta_1 + \lambda\varphi + y_3\kappa_1 + u \tag{3.4.2}$$

(2) the selection equation for whether the woman worked at some point in the year 2000 for pay or not:

$$y_2 = 1(z_2\delta_2 + y_3\kappa_2 + \upsilon > 0) \tag{3.4.3}$$

and (3) the linear projection of the potentially endogenous regressors on all independent variables in the system:

$$y_3 = z_3\delta_3 + v \tag{3.4.4}$$

The variables that enter the selection equation but not the earnings regression are indicators for the presence of children (a dummy for the presence of 1-2 children and a dummy for 3 or more children) and an indicator for any of the children being younger than 2 years. Both these variables could affect weekly earnings if women with children, particularly young children, are more likely to work part time. Since I do not know usual hours worked in 2000, but do know the hours worked in the Census reference week in 2001, I control for the latter instead.

I use a two-step approach to estimate the above system. The presence of the same endogenous variables in both the outcome and selection equations makes the estimation more complicated than the usual self-selection problem, especially that the selection equation is of interest in and of itself. In order to examine the employment decision of immigrant women, I first estimate the linear projection of the two endogenous variables on all exogenous regressors in the system. I obtain the predicted standard errors from these regressions and include them in the selection equation. This control function approach is also used to estimate the causal relationship between exposure to and/or interaction with co-ethnics and the probability of employment among immigrant men.

To estimate the earnings regression for immigrant women, I first run a probit of the employment indicator on all exogenous regressors in the system, i.e. including the proportion of co-ethnics in the city in 1971 and the proportion of co-ethnic childhood friends, rather than their potentially endogenous 2001 counterparts. Using the estimated coefficients, I form the fitted inverse Mills ratio, λ. Next I include the fitted inverse Mills ratio in the earnings regression and estimate it by 2SLS on the sample of women who report positive earnings for the year 2000.

The standard errors reported in Tables 3.10 to 3.17 are clustered at the ethnic group-CA/CMA level and adjusted to account for the sampling variation in the generated regressors (or more precisely the first stage estimates used to construct the said generated regressors), where applicable. The latter adjustment is necessary in estimating the tobit model for women's earnings due to the inclusion of the inverse Mills ratio[11], in accounting for the potential endogeneity of the key explanatory variables through 2SLS estimation in case of earnings analysis and the control function approach in case of employment outcomes (inclusion of standard errors predicted from first stage regressions in the probit model for employment).[12] The assumptions regarding the structure of the standard errors are as in Chapter 2 (see the last paragraph of Subsection 2.6.2).

3.4.6 Empirical Results

Least squares estimates from the benchmark earnings model for men and women are reported in columns 1, 3 and 5 of Tables 3.10 and 3.11, respectively. For both men and

[11]The variance-covariance matrix is assumed to take the following form: $Var = V + R_1 + R_2$. The matrix V is the clustered variance-covariance matrix that would be obtained if there were no generated regressors in the model. R_1 is the term necessary to correct for the inverse Mills ratio being a generated regressor. The matrix $R_1 = (\widehat{X}'\widehat{X})^{-1}\widehat{G_\gamma}\widehat{V_\gamma}\widehat{G_\gamma}'(\widehat{X}'\widehat{X})^{-1}$, where $\widehat{X}$ is the weighted data matrix, and $\widehat{G_\gamma} = \nabla_\gamma g(z_i, \widehat{\beta}, \widehat{\gamma})$ is the Jacobian with weighted data matrix z_i, $\widehat{\gamma} = (\widehat{\delta_2}, \widehat{\kappa_2})$ the probit estimator, $\widehat{\theta} = (\widehat{\delta_1}, \widehat{\varphi}, \widehat{\kappa_1})$ the tobit estimator, $\widehat{V_\gamma}$ is the probit estimator of the asymptotic error variance in the selection equation (Newey and McFadden (1994)). The matrix R_2 is the correction necessary when the enclave and/or social segregation variables are treated as endogenous (as in footnote 24 in Chapter 2). The matrix V and $V + R_2$ was provided by Stata software.

[12]The variance-covariance matrix is: $Var = V + (\pi'\Sigma_v\pi)(\widetilde{H}'\widetilde{\Sigma}\widetilde{H})^{-1}\widetilde{H}'\widetilde{\Sigma}\begin{pmatrix} \Sigma_{zz}^{-1} & 0 \\ 0 & 0 \end{pmatrix}\widetilde{\Sigma}\widetilde{H}(\widetilde{H}'\widetilde{\Sigma}\widetilde{H})^{-1}$, where $\widetilde{\Sigma} = \sum_i \left[\frac{w_i\phi(\widetilde{Z_i}'\widetilde{\delta}+v_i'\pi)}{\Phi(\widetilde{Z_i}'\widetilde{\delta}+v_i'\pi)[1-\Phi(\widetilde{Z_i}'\widetilde{\delta}+v_i'\pi)]} \begin{bmatrix} z_{3i} \\ v_i \end{bmatrix} \begin{bmatrix} z_{3i} \\ v_i \end{bmatrix}' \right]$, Σ_v is the variance of first stage residuals v, z_3 is the matrix of all exogenous regressors in the system, $\widetilde{H} = \begin{bmatrix} \delta_3 & J & 0 \\ I_m & 0 & I_m \end{bmatrix}$, δ_3 is the matrix of estimated coefficients from the set of first stage regressions (linear projections on the endogenous variables), J is a matrix such that Jz_3 gives the matrix of exogenous regressors other than the instrumental variables, w_i is the sample weight, Σ_{zz} is the covariance matrix of z_3 (Rivers and Vuong (1988)). In the absence of clustering, the matrix V would equal $(\widetilde{H}'\widetilde{\Sigma}\widetilde{H})^{-1}$; in the current problem, the standard errors are clustered.

women these cross-sectional estimates suggest a positive relationship between the proportion of co-ethnics in the city of residence and earnings, and a negative relationship between having mostly co-ethnic friends and earnings. Although the magnitude of these coefficients is nontrivial, they are not statistically significant. Note also that including more explanatory variables like experience and host language skills does not substantially change the magnitude of the estimated exposure coefficients compared to the estimates in Table 3.9.

Next, I test whether the enclave and social segregation variables are endogenous, as commonly hypothesized. There is no strong evidence that this is the case as we cannot reject the null hypothesis of exogeneity at conventional significance levels (test statistics are reported in the bottom panel of Tables 3.10 and 3.11). However, to err on the side of caution and ensure consistency, I estimate the earnings regressions by 2SLS; results are presented in columns 2, 4 and 6 of Tables 3.10 and 3.11. In most cases the estimated coefficients have the opposite sign to the least squares estimates, but once again none are significant. A note of caution is necessary at this point. The F-test statistics on the excluded instruments in the first stage (reported in the bottom panel of Tables B.4 and B.5 in Appendix B) suggest that while the instrument for the social segregation indicator is strong, the instrument for the exposure index is quite weak.[13]

In Tables 3.12 and 3.13 I report results from my preferred specification, where a separate 'impact' of exposure to and interaction with co-ethnics is estimated for each of the three education groups. In columns 1, 3 and 5, where the enclave and social segregation variables are treated as exogenous, the coefficients on the interaction terms in most cases have the same sign as the corresponding overall effect in Tables 3.10 and 3.11. One exception is the negative association between the exposure index and earnings of university-educated immigrant men. This negative association is relatively small in economic terms. Immigrants living in a city where 10% of the population is co-ethnic earn just over 4% more than those in cities where the proportion of co-ethnics is essentially zero, but note that the mean of the exposure index is only 0.046 or 4.6%. In contrast to men, university-educated immigrant women have significantly higher wages in cities with a higher proportion of their co-ethnics, 23% higher without controlling for social segregation and 27% with. Recall, however, that this positive and significant relationship was not present in the public use 2001 Census sample (see Table 3.9). There is still no compelling evidence of a significant relationship between ethnically segregated social networks and immigrant earnings.

When the exposure index and social interaction indicator are treated as endogenous in the preferred specification, the effect of exposure to co-ethnics on earnings of university-educated immigrant women changes from a substantial positive and significant one to an equally large negative impact which is no longer significant. It is however comparable in magnitude to the corresponding 2SLS estimate for immigrant men. Controlling for endogeneity in this specification with between three and six potentially endogenous variables becomes much more difficult with the available instruments. The instruments for the interaction terms are simply interactions between the relevant instrument and the education

[13] Following the rule of thumb offered by Staiger and Stock (1997) that an instrument is weak if the F-test statistic in the first stage is less than 10.

Table 3.10: Earnings Regressions – Men – Benchmark Model

	LS	2SLS	LS	2SLS	LS	2SLS
Exposure Index	0.776	1.535	0.858	1.506		
	(0.640)	(1.181)	(0.650)	(1.198)		
Social Segregation			-0.065	0.053	-0.059	0.048
			(0.060)	(0.193)	(0.059)	(0.195)
College	0.150**	0.148*	0.144*	0.153*	0.147*	0.156*
	(0.076)	(0.075)	(0.078)	(0.079)	(0.078)	(0.080)
University	0.553***	0.556***	0.542***	0.565***	0.541***	0.559***
	(0.078)	(0.078)	(0.081)	(0.080)	(0.081)	(0.080)
Cdn exp	0.031	0.031	0.030	0.031	0.031	0.032
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Cdn exp sq.	-0.0002	-0.0001	-0.0002	-0.0002	-0.0002	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
For exp	0.006	0.006	0.006	0.007	0.006	0.007
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
For exp sq.	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Eng/Fr 1^{st} language	0.204	0.212	0.189	0.224	0.182	0.207
	(0.204)	(0.196)	(0.203)	(0.205)	(0.212)	(0.217)
Eng/Fr 2^{nd} language	0.048	0.057	0.037	0.067	0.028	0.049
	(0.172)	(0.163)	(0.171)	(0.178)	(0.181)	(0.186)
Married	0.072	0.072	0.085	0.061	0.083	0.062
	(0.085)	(0.084)	(0.088)	(0.092)	(0.088)	(0.093)
West Asia	-0.390**	-0.385**	-0.402**	-0.375**	-0.408**	-0.387**
	(0.170)	(0.168)	(0.170)	(0.169)	(0.170)	(0.170)
E. & S.E. Asia	-0.238**	-0.276***	-0.228**	-0.286***	-0.186**	-0.211**
	(0.094)	(0.094)	(0.092)	(0.102)	(0.076)	(0.093)
South Asia	-0.043	-0.055	-0.039	-0.059	-0.025	-0.034
	(0.079)	(0.077)	(0.078)	(0.080)	(0.076)	(0.080)
Africa	-0.093	-0.085	-0.092	-0.085	-0.102	-0.101
	(0.102)	(0.102)	(0.101)	(0.103)	(0.101)	(0.101)
Caribbean	-0.229	-0.225	-0.227	-0.227	-0.231	-0.234
	(0.168)	(0.166)	(0.166)	(0.168)	(0.167)	(0.168)
Other origins	-0.098	-0.087	-0.112	-0.075	-0.124	-0.099
	(0.143)	(0.144)	(0.143)	(0.152)	(0.143)	(0.150)
R-squared	0.13	0.13	0.13	0.13	0.13	0.13
Exogeneity test						
F(#, #)		(1, 293)		(2, 293)		(1, 293)
test statistic		0.56		0.46		0.27
p-value		0.4545		0.6342		0.6020

The sample size is 962. Indicators for broad ethnic origin categories included in all regressions. Standard errors (in brackets) are clustered and (in 2SLS) adjusted for presence of generated regressors. In 2SLS estimation, the instrument for EI, proportion of co-ethnics in CA/CMA, is the corresponding proportion in 1971. The instrument for social segregation is social segregation in childhood (before age 15). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.11: Earnings Regressions – Women – Benchmark Model

	Tobit	2SLS	Tobit	2SLS	Tobit	2SLS
Exposure Index	0.560	-0.731	0.670	-0.714		
	(0.587)	(1.620)	(0.585)	(1.778)		
Social Segregation			-0.051	0.300	-0.048	0.282
			(0.080)	(0.365)	(0.081)	(0.359)
College	0.194**	0.199**	0.184**	0.216**	0.187**	0.212**
	(0.078)	(0.077)	(0.079)	(0.092)	(0.079)	(0.090)
University	0.534***	0.528***	0.520***	0.552***	0.517***	0.554***
	(0.076)	(0.075)	(0.078)	(0.091)	(0.077)	(0.090)
Cdn exp	0.005	0.006	0.0001	0.007	0.001	0.006
	(0.021)	(0.021)	(0.021)	(0.022)	(0.020)	(0.021)
Cdn exp sq.	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
For exp	-0.013	-0.013	-0.014	-0.011	-0.013	-0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
For exp sq.	0.0004	0.0004	0.0004	0.0003	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Eng/Fr 1^{st} language	0.418**	0.412**	0.407**	0.457***	0.404**	0.459**
	(0.168)	(0.162)	(0.166)	(0.174)	(0.164)	(0.175)
Eng/Fr 2^{nd} language	0.187	0.173	0.179	0.192	0.172	0.199
	(0.154)	(0.154)	(0.152)	(0.158)	(0.152)	(0.156)
Married	-0.021	-0.019	-0.018	-0.051	-0.017	-0.051
	(0.077)	(0.075)	(0.079)	(0.092)	(0.078)	(0.093)
West Asia	-0.135	-0.139	-0.136	-0.181	-0.138	-0.176
	(0.194)	(0.192)	(0.190)	(0.201)	(0.190)	(0.201)
E. & S.E. Asia	-0.136	-0.076	-0.138	-0.151	-0.107	-0.179
	(0.085)	(0.116)	(0.085)	(0.142)	(0.073)	(0.112)
South Asia	-0.141	-0.112	-0.152	-0.141	-0.137	-0.155
	(0.095)	(0.111)	(0.094)	(0.119)	(0.097)	(0.106)
Africa	-0.293*	-0.307*	-0.298*	-0.324*	-0.305*	-0.315*
	(0.159)	(0.157)	(0.157)	(0.173)	(0.156)	(0.171)
Caribbean	-0.332***	-0.337***	-0.324***	-0.405***	-0.327***	-0.398***
	(0.109)	(0.108)	(0.109)	(0.153)	(0.108)	(0.151)
Other origins	-0.227	-0.244	-0.237	-0.232	-0.245	-0.224
	(0.178)	(0.176)	(0.177)	(0.197)	(0.177)	(0.196)
Hours (May 2001)	0.011***	0.011***	0.009**	0.012**	0.009**	0.011**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Inv. Mills ratio	0.098	0.108	-0.014	0.109	-0.007	0.105
	(0.221)	(0.219)	(0.213)	(0.248)	(0.207)	(0.235)
R-squared	0.15	0.14	0.15	0.11	0.15	0.12
Exogeneity test						
F(#, #)		(1, 289)		(2, 289)		(1, 289)
test statistic		0.87		0.85		0.95
p-value		0.3526		0.4289		0.3309

The sample size is 963. Indicators for broad ethnic origin categories included in all regressions. Standard errors (in brackets) are clustered and corrected for presence of generated regressors. In 2SLS estimation, the instrument for EI, proportion of co-ethnics in CA/CMA, is the corresponding proportion in 1971. The instrument for social segregation is social segregation in childhood (before age 15). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.12: Earnings Regressions – Men – Preferred Specification

	LS	2SLS	LS	2SLS	LS	2SLS
EI*hs	0.910	0.119	0.868	0.123		
	(0.811)	(2.253)	(0.835)	(2.602)		
EI*coll	1.919*	7.765*	2.324**	8.569*		
	(1.071)	(4.534)	(1.042)	(4.565)		
EI*univ	-0.430	-1.953	-0.430	-2.504		
	(1.579)	(2.273)	(1.595)	(2.506)		
SI*hs			-0.019	-0.013	-0.011	-0.044
			(0.111)	(0.224)	(0.108)	(0.218)
SI*coll			-0.166*	-0.232	-0.128	-0.047
			(0.096)	(0.329)	(0.098)	(0.296)
SI*univ			-0.028	0.472	-0.050	0.405
			(0.108)	(0.482)	(0.111)	(0.491)
College	0.118	-0.092	0.175	-0.007	0.209*	0.153
	(0.093)	(0.181)	(0.130)	(0.216)	(0.124)	(0.180)
University	0.589***	0.601***	0.589***	0.415*	0.565***	0.359
	(0.098)	(0.118)	(0.127)	(0.232)	(0.120)	(0.230)
Cdn exp	0.029	0.020	0.029	0.026	0.032	0.036*
	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.020)
Cdn exp sq.	-0.0001	0.0003	-0.0001	0.0001	-0.0003	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
For exp	0.005	-0.001	0.005	-0.003	0.007	0.005
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)
For exp sq.	-0.0003	-0.0002	-0.0003	-0.0001	-0.0004	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Eng/Fr 1^{st} language	0.201	0.136	0.202	0.150	0.200	0.191
	(0.203)	(0.216)	(0.209)	(0.224)	(0.218)	(0.231)
Eng/Fr 2^{nd} language	0.047	-0.028	0.044	-0.042	0.044	0.016
	(0.172)	(0.187)	(0.175)	(0.188)	(0.182)	(0.197)
Married	0.070	0.075	0.080	0.060	0.080	0.057
	(0.085)	(0.086)	(0.087)	(0.100)	(0.087)	(0.098)
R-squared	0.13	0.11	0.14	0.08	0.13	0.11
Exogeneity test						
F(#, #)		(3, 293)		(6, 293)		(3, 293)
test statistic		1.54		1.06		0.32
p-value		0.2036		0.3886		0.8090

The sample size is 962. All regressions include dummies for broad ethnic origin groups. Standard errors (in brackets) are clustered and (in 2SLS) adjusted for presence of generated regressors. In 2SLS estimation, the instruments for interactions between EI, proportion of co-ethnics in CA/CMA, and education are interactions between the corresponding proportion of co-ethnics in 1971 and education. The instruments for interactions between SI, the social segregation indicator, and education are interactions between social segregation in childhood (before age 15) and education. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.13: Earnings Regressions – Women – Preferred Specification

	Tobit	2SLS	Tobit	2SLS	Tobit	2SLS
EI*hs	0.188	-0.891	0.090	-1.218		
	(0.901)	(1.653)	(0.914)	(1.530)		
EI*coll	0.052	0.844	0.109	1.003		
	(0.770)	(3.225)	(0.809)	(3.021)		
EI*univ	2.354**	-2.751	2.717**	-2.771		
	(1.033)	(3.369)	(1.093)	(3.912)		
SI*hs			0.030	0.677	0.031	0.626
			(0.135)	(0.448)	(0.133)	(0.448)
SI*coll			-0.094	-0.282	-0.096	-0.289
			(0.124)	(0.350)	(0.121)	(0.351)
SI*univ			-0.133	0.006	-0.102	-0.026
			(0.118)	(0.860)	(0.111)	(0.843)
College	0.197**	0.141	0.259**	0.721**	0.265**	0.764**
	(0.098)	(0.144)	(0.131)	(0.358)	(0.130)	(0.338)
University	0.475***	0.573***	0.547***	1.004**	0.599***	0.959**
	(0.098)	(0.127)	(0.139)	(0.450)	(0.140)	(0.468)
Cdn exp	0.004	0.007	-0.000	0.012	0.001	0.010
	(0.021)	(0.021)	(0.021)	(0.023)	(0.021)	(0.023)
Cdn exp sq.	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
For exp	-0.013	-0.014	-0.012	-0.010	-0.013	-0.010
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)
For exp sq.	0.0004	0.0004	0.0004	0.0003	0.0004	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Eng/Fr 1^{st} language	0.409**	0.416**	0.405**	0.481***	0.413**	0.478***
	(0.168)	(0.165)	(0.166)	(0.174)	(0.165)	(0.174)
Eng/Fr 2^{nd} language	0.172	0.183	0.173	0.249	0.183	0.248
	(0.155)	(0.155)	(0.153)	(0.160)	(0.151)	(0.160)
Married	-0.023	-0.015	-0.018	-0.032	-0.016	-0.034
	(0.078)	(0.076)	(0.080)	(0.100)	(0.079)	(0.101)
Hours (May 2001)	0.010***	0.011***	0.008**	0.010	0.008**	0.010
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
Inv. Mills ratio	0.080	0.122	-0.056	0.057	-0.033	0.051
	(0.224)	(0.220)	(0.215)	(0.280)	(0.205)	(0.268)
R-squared	0.15	0.14	0.15	0.09	0.15	0.11
Exogeneity test						
F(#, #)		(3, 289)		(6, 289)		(3, 298)
test statistic		1.76		1.73		1.02
p-value		0.1553		0.1137		0.3824

The sample size is 963. All regressions include dummies for broad ethnic origin groups. Standard errors (in brackets) are clustered and corrected for presence of generated regressors. In 2SLS estimation, the instruments for interactions between EI, proportion of co-ethnics in CA/CMA, and education are interactions between the corresponding proportion of co-ethnics in 1971 and education. The instruments for interactions between SI, the social segregation indicator, and education are interactions between social segregation in childhood (before age 15) and education. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

categories, and in all model specifications are weak. Since there is little evidence of endogeneity in the benchmark specification and the 2SLS estimates are likely biased, least squares estimation may be more appropriate in this case.

The story looks somewhat different when we examine immigrants' employment outcomes. In Tables 3.14 and 3.15, columns 1, 3 and 5 where the exposure and interaction variables are treated as exogenous, there is a significant negative relationship between exposure to co-ethnics and the probability of employment for both men and women, comparable in size for both groups. The estimates in column 1 of Tables 3.14 and 3.15 suggest that an immigrant living in a city with 10% co-ethnic population is about 4.8 percentage points less likely to be employed than a similar immigrant living in a city with essentially no co-ethnics. Ethnically segregated social networks are associated with an approximately 9 percentage points higher probability of employment among women, but appear to be uncorrelated with the employment probability of immigrant men. There is some evidence that the exposure index is endogenous in the employment model for women (in this specification). Accounting for the endogeneity results in much larger, negative and statistically significant coefficients on the exposure index for women. The coefficient is only slightly larger but no longer precisely defined for men. The coefficient on the social segregation indicator is positive for both men and women but not significant for either group.

In the preferred specification, the relationship between relative enclave size and the probability of being employed is negative across education groups for both immigrant men and women (columns 1, 3, and 5 of Tables 3.16 and 3.17). Social segregation is still not significantly related to employment of immigrant men. There is a positive association between social segregation and employment of immigrant women which increases in magnitude with education. When potential endogeneity is taken into account, the proportion of co-ethnics in the city of residence has a much larger negative effect on the employment probability of immigrant women and university-educated immigrant men than the least squares estimates suggest, although the effect is not precisely estimated for the university educated. In contrast, having mostly co-ethnic friends has a positive and significant effect on the probability of employment of immigrant men and women with a university education. Ethnically segregated social networks do not appear to significantly impact employment outcomes of immigrants with a high school or lower education, regardless of the estimator chosen. Note that as before, accounting for potential endogeneity of the enclave and social segregation variables in the preferred specification becomes quite problematic with the available instrumental variables.

The main goal of this analysis, as set out at the beginning of this chapter, was to establish whether the 'ethnic enclave' effect as measured by the proportion of co-ethnics in the city of residence in fact captures an 'interaction with co-ethnics' effect, as commonly assumed. This does not appear to be the case. A comparison of columns 1 and 3 in Tables 3.10 to 3.17 reveals that controlling for the ethnic composition of social networks generally does not affect the magnitude (or significance) of the estimated coefficients on the exposure index. In addition, in most of the estimated earnings and employment models above, the two effects have the opposite sign. Based on these results and the definition of social interaction with

Table 3.14: Marginal Effects on Probability of Employment – Men – Benchmark Model

	Probit	Control Function	Probit	Control Function	Probit	Control Function
Exposure Index	-0.476*	-0.570	-0.476*	-0.513		
	(0.271)	(0.549)	(0.271)	(0.534)		
Social Segregation			-0.002	0.108	-0.002	0.116
			(0.030)	(0.090)	(0.030)	(0.093)
College	0.044*	0.044*	0.044*	0.049**	0.045*	0.051
	(0.026)	(0.024)	(0.026)	(0.024)	(0.026)	(0.032)
University	0.080***	0.080***	0.080***	0.095***	0.084***	0.100**
	(0.025)	(0.023)	(0.025)	(0.023)	(0.024)	(0.040)
Cdn exp	0.032***	0.032***	0.032***	0.033***	0.031***	0.033**
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.013)
Cdn exp sq.	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.000)	(0.001)
For exp	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
For exp sq.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Eng/Fr 1^{st} language	0.094***	0.094***	0.094***	0.109***	0.092***	0.109**
	(0.030)	(0.026)	(0.029)	(0.024)	(0.029)	(0.048)
Eng/Fr 2^{nd} language	0.142*	0.141*	0.142*	0.181*	0.142*	0.185
	(0.082)	(0.077)	(0.082)	(0.095)	(0.079)	(0.121)
Married	0.089**	0.089**	0.089**	0.065	0.089**	0.063
	(0.040)	(0.038)	(0.041)	(0.043)	(0.042)	(0.046)
West Asia	-0.205***	-0.206***	-0.205***	-0.177**	-0.200***	-0.170**
	(0.074)	(0.072)	(0.076)	(0.075)	(0.075)	(0.076)
E. & S.E. Asia	0.017	0.022	0.018	-0.008	-0.012	-0.043
	(0.039)	(0.044)	(0.038)	(0.049)	(0.034)	(0.052)
South Asia	-0.050	-0.048	-0.050	-0.060	-0.060	-0.073
	(0.047)	(0.044)	(0.047)	(0.045)	(0.049)	(0.056)
Other origins	0.020	0.019	0.020	0.021	0.025	0.027
	(0.040)	(0.037)	(0.040)	(0.036)	(0.039)	(0.046)
Fitted residuals from first stage regressions:						
Exposure Index		0.125		0.075		
		(0.684)		(0.662)		
Social Segregation				-0.119		-0.127
				(0.086)		(0.131)
Exogeneity test						
$\chi(\#)$		(1)		(2)		(1)
test statistic		0.03		1.51		1.67
p-value		0.867		0.4707		0.1959

The sample size is 1087. All regressions include dummies for broad ethnic origin groups. Standard errors (in brackets) are clustered and (in the control function approach) adjusted for presence of generated regressors. In the control function approach, the instrument for EI, proportion of co-ethnics in CA/CMA, is the corresponding proportion in 1971. The instrument for social segregation is social segregation in childhood (before age 15). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.15: Marginal Effects on Probability of Employment – Women – Benchmark Model

	Probit	Control Function	Probit	Control Function	Probit	Control Function
Exposure Index	-0.483*	-1.876**	-0.552*	-1.941***		
	(0.286)	(0.747)	(0.296)	(0.726)		
Social Segregation			0.090**	0.311	0.087**	0.255
			(0.042)	(0.205)	(0.042)	(0.204)
College	0.069**	0.074***	0.074**	0.088***	0.070**	0.077**
	(0.028)	(0.027)	(0.029)	(0.030)	(0.028)	(0.031)
University	0.093***	0.088***	0.093***	0.097***	0.094***	0.100***
	(0.034)	(0.033)	(0.033)	(0.031)	(0.033)	(0.030)
Cdn exp	0.036***	0.038***	0.036***	0.038***	0.036***	0.036***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Cdn exp sq.	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
For exp	0.001	0.002	0.001	0.003	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
For exp sq.	-0.0001	-0.0002	-0.0002	-0.0002**	-0.0001	-0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Eng/Fr 1^{st} language	0.025	0.014	0.047	0.066	0.049	0.070
	(0.085)	(0.085)	(0.082)	(0.078)	(0.082)	(0.077)
Eng/Fr 2^{nd} language	0.017	-0.005	0.025	0.014	0.034	0.044
	(0.085)	(0.078)	(0.089)	(0.085)	(0.091)	(0.090)
Married	0.024	0.030	0.019	0.013	0.017	0.007
	(0.051)	(0.050)	(0.050)	(0.045)	(0.050)	(0.044)
West Asia	0.050	0.044	0.038	-0.000	0.040	0.017
	(0.050)	(0.051)	(0.052)	(0.056)	(0.052)	(0.052)
E. & S.E. Asia	0.098*	0.158***	0.076	0.079	0.049	0.001
	(0.051)	(0.048)	(0.049)	(0.062)	(0.044)	(0.058)
South Asia	0.122***	0.139***	0.115***	0.117***	0.108***	0.095***
	(0.037)	(0.032)	(0.037)	(0.030)	(0.038)	(0.034)
Africa	0.073	0.059	0.068	0.045	0.073	0.067
	(0.065)	(0.069)	(0.064)	(0.069)	(0.063)	(0.061)
Caribbean	0.020	0.012	-0.006	-0.078	-0.003	-0.048
	(0.103)	(0.103)	(0.107)	(0.133)	(0.106)	(0.123)
Other origins	0.112*	0.102	0.114**	0.099	0.117**	0.113**
	(0.059)	(0.062)	(0.057)	(0.060)	(0.057)	(0.053)
Hours (May 2001)	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Kids age$\leqslant$2	0.039	0.027	0.039	0.045	0.044	0.056
	(0.043)	(0.045)	(0.041)	(0.042)	(0.041)	(0.040)
# kids 1-2	-0.021	-0.016	-0.030	-0.048	-0.035	-0.052
	(0.040)	(0.038)	(0.039)	(0.038)	(0.040)	(0.039)
# kids$\geqslant$3	-0.120**	-0.113**	-0.138**	-0.166***	-0.143**	-0.171***
	(0.055)	(0.053)	(0.057)	(0.063)	(0.058)	(0.063)

Table 3.15: cont'd

	Probit	Control Function	Probit	Control Function	Probit	Control Function
Fitted residuals from first stage regressions:						
Exposure Index		1.729*		1.665*		
		(0.910)		(0.879)		
Social Segregation				-0.212		-0.164
				(0.183)		(0.188)
Exogeneity test						
$\chi(\#)$		(1)		(2)		(1)
test statistic		3.04		5.63		0.83
p-value		0.0810		0.0600		0.3635

The sample size is 1334. All regressions include dummies for broad ethnic origin groups. Standard errors (in brackets) are clustered and (in the control function approach) adjusted for presence of generated regressors. In the control function approach, the instrument for EI, proportion of co-ethnics in CA/CMA, is the corresponding proportion in 1971. The instrument for social segregation is social segregation in childhood (before age 15). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.16: Marginal Effects on Probability of Employment – Men – Preferred Specification

	Probit	Control Function	Probit	Control Function	Probit	Control Function
EI*hs	-0.631	-0.654	-0.766*	-0.646		
	(0.413)	(0.880)	(0.432)	(0.868)		
EI*coll	-0.122	1.157	-0.061	0.852		
	(0.430)	(1.141)	(0.446)	(1.363)		
EI*univ	-0.426	-1.045*	-0.343	-1.100*		
	(0.374)	(0.592)	(0.396)	(0.604)		
SI*hs			0.049	0.026	0.041	0.019
			(0.030)	(0.092)	(0.034)	(0.095)
SI*coll			-0.060	0.129***	-0.052	0.134***
			(0.064)	(0.041)	(0.060)	(0.042)
SI*univ			-0.041	0.113*	-0.034	0.120**
			(0.055)	(0.065)	(0.052)	(0.058)
College	0.028	-0.008	0.071**	-0.106	0.085***	-0.060
	(0.035)	(0.056)	(0.031)	(0.078)	(0.029)	(0.089)
University	0.074**	0.086**	0.106***	0.037	0.116***	0.024
	(0.033)	(0.039)	(0.034)	(0.073)	(0.030)	(0.072)
Cdn exp	0.031***	0.030***	0.031***	0.032***	0.031***	0.033***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Cdn exp sq.	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
For exp	-0.002	-0.003	-0.001	-0.003	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
For exp sq.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Eng/Fr 1^{st} language	0.091***	0.086*	0.098***	0.090***	0.099***	0.093***
	(0.031)	(0.029)	(0.028)	(0.031)	(0.028)	(0.031)
Eng/Fr 2^{nd} language	0.133	0.119*	0.145*	0.129	0.158*	0.145
	(0.081)	(0.077)	(0.086)	(0.092)	(0.085)	(0.096)
Married	0.090**	0.091**	0.080**	0.071**	0.079**	0.070
	(0.040)	(0.038)	(0.038)	(0.043)	(0.040)	(0.044)
First Stage fitted residuals:						
EI*hs		0.033		-0.112		
		(1.060)		(1.013)		
EI*coll		-1.710		-1.209		
		(1.376)		(1.600)		
EI*univ		0.794		0.969		
		(0.709)		(0.721)		
SI*hs				0.035		0.031
				(0.101)		(0.097)
SI*coll				-0.312**		-0.321**
				(0.143)		(0.153)
SI*univ				-0.221		-0.234
				(0.181)		(0.172)

Table 3.16: cont'd

	Probit	Control Function	Probit	Control Function	Probit	Control Function
Exogeneity test						
$\chi(\#)$		(3)		(6)		(3)
test statistic		3.56		10.33		6.56
p-value		0.3136		0.1114		0.0872

The sample size is 1087. All regressions include dummies for broad ethnic origin groups. Standard errors (in brackets) are clustered and (in the control function approach) adjusted for presence of generated regressors. In the control function approach, the instruments for interactions between EI, proportion of co-ethnics in CA/CMA, and education are interactions between the corresponding proportion of co-ethnics in 1971 and education. The instruments for interactions between SI, the social segregation indicator, and education are interactions between social segregation in childhood (before age 15) and education. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.17: Marginal Effects on Probability of Employment – Women – Preferred Specification

	Probit	Control Function	Probit	Control Function	Probit	Control Function
EI*hs	-0.576*	-1.128**	-0.550	-0.610		
	(0.344)	(0.554)	(0.338)	(0.738)		
EI*coll	-0.395	-3.374*	-0.400	-3.377*		
	(0.562)	(1.837)	(0.590)	(1.981)		
EI*univ	-0.354	-0.935	-0.776	-2.248		
	(0.618)	(1.500)	(0.533)	(1.460)		
SI*hs			0.053	0.031	0.049	-0.005
			(0.041)	(0.130)	(0.041)	(0.131)
SI*coll			0.084	0.132	0.085*	0.127
			(0.052)	(0.182)	(0.049)	(0.186)
SI*univ			0.118**	0.369***	0.111*	0.366***
			(0.057)	(0.142)	(0.060)	(0.140)
College	0.063	0.138**	0.045	0.072	0.043	-0.052
	(0.040)	(0.058)	(0.051)	(0.177)	(0.049)	(0.210)
University	0.087**	0.089	0.053	-0.546	0.051	-0.618
	(0.044)	(0.059)	(0.072)	(0.461)	(0.071)	(0.433)
Cdn exp	0.036***	0.037***	0.036***	0.033***	0.036***	0.032***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Cdn exp sq.	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
For exp	0.001	0.002	0.001	-0.001	0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
For exp sq.	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Eng/Fr 1^{st} language	0.024	0.022	0.048	0.050	0.049	0.042
	(0.086)	(0.084)	(0.082)	(0.083)	(0.081)	(0.084)
Eng/Fr 2^{nd} language	0.015	0.0001	0.022	-0.023	0.029	-0.016
	(0.085)	(0.082)	(0.089)	(0.085)	(0.090)	(0.085)
Married	0.024	0.029	0.021	-0.013	0.019	-0.018
	(0.051)	(0.050)	(0.050)	(0.042)	(0.050)	(0.041)
Hours (May 2001)	0.015***	0.015***	0.015***	0.016***	0.015***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Kids age$\leqslant$2	0.039	0.023	0.040	0.054	0.043	0.067*
	(0.044)	(0.046)	(0.041)	(0.043)	(0.040)	(0.039)
# kids 1-2	-0.022	-0.022	-0.035	-0.087*	-0.039	-0.090*
	(0.039)	(0.038)	(0.038)	(0.048)	(0.039)	(0.048)
# kids$\geqslant$3	-0.121**	-0.114**	-0.141**	-0.138**	-0.145**	-0.142**
	(0.055)	(0.053)	(0.057)	(0.064)	(0.058)	(0.065)

Table 3.17: cont'd

	Probit	Control Function	Probit	Control Function	Probit	Control Function
First Stage fitted residuals:						
EI*hs		0.736		0.276		
		(0.839)		(0.960)		
EI*coll		3.489*		3.499		
		(2.023)		(2.136)		
EI*univ		0.820		1.637		
		(1.521)		(1.631)		
SI*hs				0.029		0.062
				(0.155)		(0.147)
SI*coll				-0.091		-0.067
				(0.299)		(0.300)
SI*univ				-0.961		-0.953
				(0.590)		(0.588)
Exogeneity test						
$\chi(\#)$		(3)		(6)		(3)
test statistic		3.11		9.48		3.27
p-value		0.3743		0.1482		0.3515

The sample size is 1334. All regressions include dummies for broad ethnic origin groups. Standard errors (in brackets) are clustered and (in the control function approach) adjusted for presence of generated regressors. In the control function approach, the instruments for interactions between EI, proportion of co-ethnics in CA/CMA, and education are interactions between the corresponding proportion of co-ethnics in 1971 and education. The instruments for interactions between SI, the social segregation indicator, and education are interactions between social segregation in childhood (before age 15) and education. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

co-ethnics adopted in this study, it would be misleading to interpret the overall ethnic enclave effect as an interaction effect.

3.5 Conclusions

This chapter is aimed at re-assessing the Canadian literature on the relationship between ethnic enclaves and labour market outcomes of immigrants. It examines how this relationship varies with the immigrants' educational attainment and across arrival cohorts. Further, it provides a preliminary test of the common assumption that the ethnic enclave effect is channelled through increased interaction with co-ethnics relative to the majority population (or other ethnic minorities).

Using pooled data from four Canadian Censuses, I find that immigrants who arrived in the 1980s have higher mean earnings in cities with a larger proportion of co-ethnics. This apparent benefit has turned into a disadvantage for immigrants who arrived in the late 1990s. The cross-cohort decline was largest among immigrants with low education levels. These results may explain why the relationship between the proportion of co-ethnics in a city and earnings estimated from a single cross section of data are typically very small and not statistically significant.

The correlation between the proportion of co-ethnics in a city and the proportion of co-ethnic friends, a more direct measure of the relative amount of interaction an immigrant has with co-ethnics, is much lower than we might have believed a priori. The traditional geography-based measures of exposure to co-ethnics capture more than just network effects. In fact, network and ethnic enclave effects appear to offset one another at least to some extent. Conditional on the relative size of the ethnic enclave, having a higher share of co-ethnic friends generally appears to improve employment opportunities, particularly among immigrants with post-secondary education. Living in a city with a higher proportion of co-ethnics, on the other hand, appears to have a negative impact on employment. The effect of ethnic enclave size on earnings is not precisely estimated with the EDS. Small sample sizes and cohort effects are likely responsible for the lack of robustness in the estimated relationship. Neither is there any strong evidence that a larger proportion of co-ethnic friends is associated with systematically higher or lower earnings. The results presented in this chapter suggest that in general co-ethnic friends may help immigrants, particularly well-educated immigrants, find employment, but not necessarily better (or worse) employment as measured by earnings.

Chapter 4

Cognitive Skills and Immigrant Earnings

4.1 Introduction

Considerable research effort has been devoted to understanding earnings differences between immigrant and native-born (i.e. Canadian-born) workers (see, for example, Chiswick (1978), Borjas (1985, 1995) for the U.S., and Baker and Benjamin (1994), Bloom, Grenier and Gunderson (1995), and Grant (1999) for Canada). These studies clearly establish that immigrants typically earn less than native-born workers with the same amount of education and work experience. The low earnings of immigrants are often attributed to the specificity of human capital to the country where it originates. Skills generated through education or work experience in the source country cannot be directly transferred to the host country, resulting in apparently well qualified immigrants holding low paying jobs. Of course, this is not the only potential explanation for lower immigrant earnings. Another possibility is that employers in the host country discriminate against immigrants, that is, pay immigrant workers less than equally productive native-born workers. Investigating these issues would be straightforward if we had access to direct measures of skill. In that case, we could compare native-born and immigrant workers with the same levels of measured education and experience to see whether the immigrants in fact have lower skill levels, supporting the first hypothesis. Alternatively, we could observe whether immigrants get a lower return to their observed skills, supporting the second hypothesis. In this study, we take advantage of the rich data provided by the Canadian component of the International Adult Literacy and Skills Survey (IALSS)[1] which includes both standard demographic and labour market information for the native born and immigrants and results from tests of literacy, numeracy and problem-solving skills. Interpreting the test scores as direct measurements of cognitive skills, we are able to provide a closer examination of explanations for low immigrant earnings than has previously been possible. In addition, the data include more precise information on where education was obtained and age of migration than is available in most

[1] The IALSS study is known internationally as the Adult Literacy and Life Skills Survey (ALL).

previous studies, further refining our ability to scrutinize immigrant-native born earnings differentials. The primary goal of the chapter is to provide answers to four questions related to immigrants' skills. First, do the cognitive skills of immigrants differ from those of the native born and, if so, in what way? Second, do immigrant - native born skill differences depend on where immigrant human capital was acquired? Third, do immigrants receive different returns to these skills than observationally similar native-born workers? Fourth, can differences in levels and returns to these skills explain differences in earnings between immigrant and native-born workers?

Recent contributions stress the need to account carefully for where education and experience was acquired in examining immigrant earnings. Using Israeli Census data, Friedberg (2000) finds that lower immigrant earnings compared to native-born workers with similar education and experience can be explained almost entirely by lower returns to experience acquired outside of Israel. This is true in particular for non-European immigrants. Similarly, Green and Worswick (2002) find zero returns to foreign experience for recent immigrant cohorts but show that, in Canada's case, this is a change from the early 1980s when immigrants earned returns to foreign experience that were similar to what the native born were earning for domestically acquired experience. Much of this change over time is related to changes in the source country composition of the inflow. Using data on immigrants to Ontario, Ferrer, Green and Riddell (2006) also find that low returns to foreign experience play a major role in the immigrant - native born earnings gap, especially among the university-educated. Schaafsma and Sweetman (2001) and Ferrer and Riddell (2003) examine the issue of lower returns to foreign acquired education in a somewhat indirect way by using age at immigration.[2] Both papers find that returns to foreign education, while lower than those to Canadian education, are still substantial. In this study we provide additional evidence on the importance of where education and experience was acquired. This additional evidence is particularly valuable because the data used in this chapter has definite advantages over the data used in previous studies. Part of the contribution of this chapter is to re-examine issues about returns to foreign experience and education raised in earlier papers with better data.

This study also builds on work by Green and Riddell (2003) and Ferrer, Green and Riddell (2006) that uses, respectively, the International Adult Literacy Survey (IALS) and the Ontario Immigrant Literacy Survey (OILS) to examine the role of cognitive skills in earnings patterns of native-born and immigrant workers. Like the IALSS, the IALS and OILS data contain both standard survey questions and literacy and numeracy tests. Green and Riddell (2003) argue that the types of literacy questions asked in the IALS are particularly conducive to using the literacy test scores as measures of cognitive skills possessed by the respondent at the time of the survey. Based on this assumption, they argue that much can be learned about how these basic skills influence earnings from an analysis of interactions of the literacy measures and other standard human capital variables. In that

[2]The Canadian Census of Population – the data used in most previous immigration studies - has no information about the origin of human capital. In addition, the age of arrival variable is coded in bracketed intervals. This enormously complicates the imputation of measures of pre- and post-migration experience.

analysis they use an hedonic model in which observed earnings are directly determined by the basic skills an individual possesses and the implicit prices of those skills. We adopt a similar interpretative framework in this chapter.

The results imply that the answer to our first main question - Do immigrant literacy skills differ from those of the native born? - is Yes. The native born test score distributions dominate those for immigrants and immigrants have lower average test scores than observationally equivalent native-born workers. An important part of the gap stems from a set of immigrants unable to complete the tests, and who were therefore assigned low scores. We also find strong evidence that skill differences depend on where human capital was acquired. Immigrants who completed their education prior to arrival in Canada have significantly lower skills than otherwise similar immigrants who obtained some or all of their education in Canada. Regardless of these differences in skill levels and acquisition, however, we clearly reject the hypothesis that immigrants receive lower returns to cognitive skills than the native born. Indeed, an important group of immigrants benefit more than do natives from higher skill levels. We argue that this is evidence against a discrimination explanation for differences in earnings between immigrant and native-born workers.

Our earnings regression results support findings in earlier papers that returns to both foreign acquired education and experience for immigrants are lower than returns to education and experience obtained in Canada by either immigrants or native-born workers. This pattern in returns to experience does not change once we control for cognitive skills, indicating that the root of the problem does not lie in foreign experience generating lower cognitive skills. Cognitive skills themselves affect earnings significantly with a 100-point increase in the average skill score generating an earnings increase of almost 30 percent.[3] The combination of this return to skills and the lower skill levels of immigrants explain part of the immigrant earnings differential. We estimate that raising immigrant average skill levels to the native born level would almost eliminate the earnings disadvantage of high school educated male immigrants relative to similarly educated native-born men, and would produce a substantial earnings advantage among high school educated female immigrants. Among the university educated, for whom the earnings differential is larger, raising immigrant skill levels to the native born level would reduce the male earnings gap by more than 50 percent and would more than eliminate the female earnings gap, turning the immigrant disadvantage into an advantage.

The chapter is organized as follows. In the next section we present a framework for considering what we might learn from introducing cognitive skills measures into a standard earnings equation. In the third section, we discuss our data and present basic data patterns. The fourth section examines whether immigrants have different skill levels from the native born. The fifth section contains the analysis of immigrant earnings. The final section concludes.

[3]The mean of the average literacy score (average of prose literacy, document literacy, numeracy and problem-solving scores) among native-born males with a high school diploma is 282, compared to 317 among university graduates - that's a 35-point difference. The corresponding difference among native-born women is around 41 points (these gaps are not conditional on any other factors).

4.2 A Framework for Discussing Earnings Generation

This section sets out a simple framework for considering earnings generation and its relationship to cognitive skills. This will prove useful in understanding the role of these skills in immigrant and native born earnings. The framework is based on the one used by Green and Riddell (2003) in a discussion of literacy and earnings among non-immigrants. They distinguish among attributes (personal characteristics that can be acquired by the worker and enhance individual earnings), skills (personal characteristics that aid in productivity in specific tasks and which can be acquired by the worker) and abilities (innate, productive characteristics). In this taxonomy, skills are a subset of attributes, where the former focus on facility with specific tasks while the latter also includes characteristics such as persistence and willingness to follow orders. Abilities are similar to attributes but are innate while attributes are acquirable. In this study, we group together attributes and skills and refer to them simply as skills. Thus, the key distinction is that between skills and abilities.

Assume, for the moment, there are three skills a worker can possess, and workers can possess them in varying amounts. We begin with three skills because it allows us to emphasize key points. The framework can easily be extended to address the more likely scenario that there are more than three. Individual earnings are determined according to some function of the skills an individual possesses and puts into use, as follows:

$$E_i = f(G_{1i}, G_{2i}, G_{3i}) + e_i \tag{4.2.1}$$

where E_i are earnings for individual i, G_{ki} is the amount of skill k that person i sells in the market, and e_i is a disturbance term that is independent of the skills. The disturbance term captures either measurement error in earnings or individual idiosyncratic events that are independent of the skill levels. The earnings generation function f(.) can be viewed as derived ultimately from marginal product conditions related to an overall production function that is separable in other (non-skill) inputs. Alternatively, it can be seen as representing worker capacities to capture rents from firms (e.g. Bowles, Gintis and Osborne, 2001). We remain agnostic on which interpretation is correct. In either case, by characterizing the f(.) function, we can learn about the importance of the various skills and how they interact in earnings generation. To help focus ideas, we will think of G_1 as cognitive skills of the type measured in literacy, numeracy and problem-solving tests, G_2 as other (perhaps manual) skills that are not captured in such tests and that might be acquired through work experience, and G_3 as non-cognitive characteristics such as persistence.

The earnings function in equation (4.2.1) is quite general. However, it will prove easier to work with a more specific functional form. In our empirical investigations, we find that the data is well characterized by first or second order polynomials in observable variables. Thus, for empirical purposes we work with:

$$\begin{aligned} E_i = {} & \gamma_0 + \gamma_{11} G_{1i} + \gamma_{21} G_{2i} + \gamma_{31} G_{3i} + \gamma_{12} G_{1i}^2 + \gamma_{22} G_{2i}^2 + \gamma_{32} G_{3i}^2 \\ & + \delta_{12} G_{1i} G_{2i} + \delta_{13} G_{1i} G_{3i} + \delta_{23} G_{2i} G_{3i} + e_i \end{aligned} \tag{4.2.2}$$

We are interested in characterizing the f(.) function and obtaining estimates of the γ and δ parameters. Doing so will provide information about the relative importance of the various skills in earnings generation and whether the skills are complements or substitutes in generating earnings.

Characterizing the earnings function would be relatively straightforward if we observed the skills, G_{ki}. Typically, of course, we do not observe them. What we do observe are some of the inputs used in generating the skills. To see how they enter our framework, consider a set of skill production functions:

$$G_i = h_k(edn_i, exp_i, \theta_{ki}) \tag{4.2.3}$$

where k indexes the skill type, edn corresponds to a set of dummy variables representing different levels of formal schooling, exp is years of work experience and θ_k is an ability specific to the production of the k-th skill. Of course, an h function could be constructed such that a skill corresponds one for one with an ability (e.g. persistence may be an innate characteristic rather than something that can be produced).

As with the f(.) function, our discussion of the features of the $h_k(.)$ functions is simplified by considering a quadratic version:

$$\begin{aligned} G_{ki} = {} & \alpha_{ks1} edn_i + \alpha_{ke1} exp_i + \alpha_{ke2} exp_i^2 + \alpha_{k\theta_1} \theta_{ki} + \alpha_{k\theta 2} \theta_i^2 \\ & + \alpha_{ks2} edn_i * exp_i + \alpha_{ks\theta} edn_i * \theta_{ki} + \alpha_{ke\theta} exp_i * \theta_{ki} \end{aligned} \tag{4.2.4}$$

where the e, s and θ subscripts on the α's correspond to experience, schooling and ability variables, respectively. Note that edn corresponds to a vector of education dummy variables and thus the α's correspond to either scalar parameters or vectors of parameters as appropriate.

If we do not observe the G_{ki}'s directly, we can obtain an estimating equation by substituting equation (4.2.3) into (4.2.1). This yields a reduced form specification for earnings as a function of schooling and experience. The ability variables are unobserved and thus end up in the error term. An inspection of equations (4.2.2) and (4.2.4) makes it clear that the coefficient on an observable variable such as educational attainment in the reduced form earnings equation will consist of a combination of the α, γ and δ parameters. More specifically, such a coefficient reflects the combination of how that covariate contributes to production of each of the skills and how those skills contribute to earnings generation.

We are interested in how much we can learn about the structure of the functions in equations (4.2.1) and (4.2.3) when we observe some but not all of the skills. Labelling the set of observed skills G_1, and using it to refer to a vector of cognitive skills, we obtain a quasi-reduced form earnings regression that includes G1 (the observed cognitive skills), experience and schooling variables. Thus, our general estimating regression is of the form:

$$
\begin{aligned}
E_i = \beta_0 + \beta_1 edn_i + \beta_2 exp_i + \beta_3 exp_i^2 + \beta_4 edn_i * exp_i \\
+ \beta_5 G_{1i} + \beta_6 G_{1i}^2 + \beta_7 G_{1i} * edn_i + \beta_8 G_{1i} * exp_i + u_i
\end{aligned}
\tag{4.2.5}
$$

where G_{1i} corresponds to our measures of cognitive skills, edn is again a vector of education dummy variables, the β's are either scalars or vectors of parameters as appropriate and u is an error. Notice that the error term will include interactions of the ability variables and the observables. This means that some type of random coefficients estimator may be appropriate. As a first step, we will ignore this latter complication and present results based on mean regression (though we do correct the standard errors for general forms of heteroskedasticity). Given the model set out above, these estimates are not fully efficient and can provide only part of the story of how the various skills interact. Nonetheless, as we shall see, there is still a great deal we can learn from mean regressions, and they have the advantage of being easy to interpret and compare to the existing literature.

The framework set out to this point could be considered the relevant earnings generation model for a native-born individual. We assume that immigrants use the same sets of skills to generate earnings in the Canadian labour market. Immigrants could differ from the native born in both of the main building blocks of the model: in the returns they obtain from a given set of skills (i.e. immigrants could have a different f(.) function); and in the production functions for creating individual skills (i.e. immigrants could have different h(.) functions).

Differences in the f(.) function between immigrants and the native born correspond to discrimination in this model since they represent differences in earnings between immigrant and native-born workers who are in fact equally productive. Thus, if we could directly observe all relevant skills, we could determine whether shortfalls in earnings for immigrants relative to the native born arise from discrimination. It is tempting to think that differences between immigrants and the native born in the coefficients on the non-interacted G_{1i} terms (i.e. β_5 and β_6) can provide direct evidence on whether discrimination exists (i.e. on whether immigrant and native-born workers with the same observed cognitive skills are paid differently). However, if interactions of G_{1i} with the exp and edn variables are significant then this interpretation need not hold. A non-zero interaction of, for example, exp and G_{1i} would imply both that the f(.) function involves an interaction of G_{1i} and some other skill (say, G_{2i}) and that exp helps to produce G_{2i}. In that case, the return to G_{1i} is a complicated function that varies with different levels of exp and β_5 and β_6 represent the effect of G_{1i} on earnings at the base level for experience. Consequently, one could observe different coefficients related to G_{1i} between immigrants and the native born because exp is differentially productive in creating other skills for the two groups rather than because of discrimination. Thus, the coefficients β_5 and β_6 provide information about discrimination only if the coefficients on the interactions of G_{1i} and other variables (i.e. β_7 and β_8) are zero.

Given results in earlier research both in Canada and in other countries, it seems very likely that the skill production functions differ between immigrants and the native born.

Thus, for immigrants, we rewrite these production functions as:

$$G_{ki} = h_k^I(edn_i, exp_i, \theta_{ki}, fedn_i, fexp_i) \tag{4.2.6}$$

where edn and exp correspond to education and experience obtained in Canada, while $fedn$ and $fexp$ represent foreign acquired education and experience. A standard claim in the immigrant earnings literature is that credentials recognition problems and mismatches in technological requirements imply that education and experience obtained in most other countries will not be as productive in Canada as Canadian education and experience. If this is not true, then equation (4.2.6) collapses to equation (4.2.3) and differences in earnings between immigrants and the native born arise either because they have different levels of schooling, experience and ability or because there is discrimination. Often, studies do not have particularly good measures of $fedn$ and $fexp$ so it is difficult to check directly for differences in returns on these skill inputs. However, the IALSS data contains direct questions on education obtained abroad and permits calculation of age at arrival as a continuous variable. This means we can construct reliable versions of both $fedn$ and $fexp$. With this information the immigrant earnings specification, with G_{1i} included, becomes:

$$\begin{aligned}
E_i = {} & \beta_0^I + \beta_1^I edn_i + \beta_2^I exp_i + \beta_3^I exp_i^2 + \beta_4^I edn_i * exp_i \\
& + \beta_5^I G_{1i} + \beta_6^I G_{1i}^2 + \beta_7^I G_{1i} * edn_i + \beta_8^I G_{1i} * exp_i \\
& + \beta_9^I fedn_i + \beta_{10}^I fexp_i + \beta_{11}^I G_{1i} * fedn_i + \beta_{12}^I G_{1i} * fexp_i \\
& + \beta_{13}^I fexp_i * fexp_i + \beta_{14}^I exp_i * fexp_i + u_i
\end{aligned} \tag{4.2.7}$$

Equation (4.2.7) includes a wide variety of interactions of $fexp$ and $fedn$ with each other and other variables.[4] Thus, the specification allows for complex interactions among foreign obtained inputs in the production of skills. For example, the interaction of $fexp$ and exp represents the possibility that immigrants are better able to translate their source country experience into earnings after they have more experience in Canada. A key conclusion of the previous literature on immigrant earnings in Canada is that more recent cohorts of immigrants have poorer earnings when compared to both earlier immigrants and native-born workers with the same measured levels of education and experience. In our framework, that would arise either because of an increase in discrimination against more recent cohorts (for example, because they have a larger visible minority component) or because more recent cohorts have lower skills. With a single cross section, we cannot separate effects of changes across immigrant cohorts from the effects of gradual adaptation to the Canadian labour market by new immigrants. The Canadian experience coefficients we estimate for immigrants will effectively combine true assimilation effects and the impact on earnings of differences across cohorts. Although this means we cannot distinguish between these features of immigrant adaptation, we are still able to learn much about the immigrant experience and how it relates to measured skills.

[4] We have, however, left out further interactions of Canadian obtained education with source country variables since they turn out not to be important in our empirical analysis.

Cognitive skills play an important role in this analysis. As stated earlier, we assume that the IALSS test scores provide direct measures of these skills and thus we can examine G_{1i} and its interactions with inputs such as experience and education to learn about the role of various skills in earnings generation. In equation (4.2.7), the interactions of cognitive skills with $fexp$ and $fedn$ are of special importance. Nonzero coefficients on these interactions may reflect impacts of cognitive skills in helping immigrants translate their foreign obtained human capital into the Canadian labour market. Note that in our framework, such an effect would amount to improved cognitive skills leading to more production of G_{2i} and G_{3i} with given levels of $fexp$ and $fedn$ and would be captured by including G_{1i} in the G_{2i} and G_{3i} skill production functions.

To this point we have not mentioned a key component of the immigrant assimilation experience: language skills. Using a variety of approaches to address potential endogeneity and measurement error issues, papers by Chiswick (1991), Chiswick and Miller (1995), Dustmann and Fabbri (2003), and Berman, Lang, and Siniver (2003) find substantial effects of host country language acquisition on immigrant earnings. In our framework, fluency in the host country language can enter either as a skill in its own right (i.e. we would add G_{4i} to equation (4.2.1)) and/or as an input to the generation of other skills. In the latter case, employers care only about the usable amounts of each skill that a worker possesses. Thus, an engineer who is well trained but cannot communicate with his or her employer or fellow employees would be counted as having zero usable engineering skills. Language ability in French or English then enters as an input into the production of usable skills, with greater language ability leading to higher usable skills for any given level of other inputs. Both Chiswick (1991) and Dustmann and Fabbri (2003) include self-reported reading skills along with host country fluency in earnings regressions, interpreting the reading and speaking fluencies as separate skills. Chiswick (1991), using a sample of illegal immigrants to the US, finds that reading fluency has a much stronger effect on earnings than speaking fluency when both are included. Dustmann and Fabbri (2003), using UK immigrant data, find that reading fluency is a more important determinant of employment but speaking fluency is a more important determinant of earnings. Following these and other authors, we control for language proficiency in our analysis.

Finally, the framework is useful for considering endogeneity issues. In either equation (4.2.6) or (4.2.7), the error term will contain ability factors and, potentially, the interaction of those factors with skill inputs such as education and experience. As in standard analyses of the endogeneity of schooling, if those ability factors are also inputs into choices about levels of schooling and skills then G_{1i} and edn_i are endogenous. It is interesting to consider the assumptions under which such an endogeneity problem does not exist. Assume that cognitive ability is only an input into generating cognitive skills (i.e. it enters the G_{1i} production function but not those for G_{2i} and G_{3i}) and other types of ability do not help produce cognitive skills. Thus, for example, social ability does not help produce cognitive skills and cognitive ability does not help produce social skills. In that case, θ_{1i} does not enter the error term - it is fully captured by the included G_{1i} variable. Then, assuming the various types of ability are uncorrelated is sufficient to imply that G_{1i} is exogenous. Further, if schooling choices are related only to generation of cognitive skills (e.g. schooling may help create social skills but that is not why people choose to go to school) then education is also exogenous. These assumptions are strong but no stronger than what is assumed when researchers include measures of ability in earnings regressions to address the schooling endogeneity problem, and we do not view them as completely unreasonable.

4.3 Data and Basic Patterns

The main data set we use in this investigation is the International Adult Literacy and Skills Survey (IALSS), the Canadian component of the Adult Literacy and Life Skills Survey (ALL). Statistics Canada carried out this survey in 2003 to study the skills of Canadians. The IALSS data contain the results of literacy, numeracy and problem-solving tests as well as information on labour market variables such as income, education and labour force status. The survey covers individuals age 16 and over, and this is also the age range we focus on in our analysis. We drop individuals who list their main activity as "student" in order to focus on the effect of completed schooling and what happens subsequently to individual skills. We also drop the over-sampled aboriginal population, reserving a careful analysis of these individuals for a separate study. Finally, we drop observations when we do not have information on age at arrival or education, and in the earnings analysis we also drop observations with missing earnings information. Although much of the immigration literature focuses on males, we analyse both male and female immigrants. We use the sample weights in our analysis, so all summary statistics and regression estimates are nationally representative. In regression analysis, we also use the Jackknife replicate weights provided in the data set to account for the complex survey design in computing standard errors for the coefficient estimates.

Our combined immigrant and native born sample has 18,373 observations of which 3,709 are immigrants. However, when we turn our attention to the impact of cognitive skills on individual earnings, we restrict the sample by eliminating the self-employed and workers with weekly earnings that are less than or equal to \$50 and over \$20,000. The latter restriction eliminates the unemployed and individuals not in the labour force. It also cuts out a small number of workers with earnings that are significant outliers relative to the rest of the sample. We exclude the self-employed because we wish to assess the way skills are rewarded in the labour market, and earnings from self-employment reflect both returns to skills and returns to capital.

For the earnings analysis our dependent variable is weekly earnings. In the IALSS respondents are first asked about their standard pay period and then asked about typical earnings in that pay period. Using these responses we construct a weekly earnings measure for each paid worker. Thus, for example, in the case of individuals who report that they are paid monthly we divide their usual monthly earnings by 4.333.

The main objective, and major advantage, of the IALSS survey is to provide measures of four skills: Prose literacy, Document literacy, Numeracy and Problem Solving. The test questions do not attempt to measure abilities such as those in mathematics and reading but rather try to assess capabilities in applying skills to circumstances that arise in everyday life. Thus, the Document questions, which are intended to assess capabilities in locating and using information in various forms, range from identifying percentages in categories in a pictorial graph to assessing an average price by combining several pieces of information. The Numeracy component ranges from simple addition of pieces of information on an order form to calculating the percentage of calories coming from fat in a Big Mac based on a nutritional table. Thus, the questions are related to implementation and use of skills in the real world and are intended not just to elicit current capacities but also adaptability to answering questions in other contexts (Murray, Clermont and Binkley, 2005).[5] This is an important point for the interpretation of our results since we want to interpret the test results as revealing job relevant skills at the time of the interview rather than inherent abilities. It is worth emphasizing that these skills are essentially cognitive in nature.

The survey was administered by first asking respondents to complete a limited set of "core tasks." The majority of respondents then completed the survey and a set of "main tasks" that were randomly drawn from a large pool of potential tasks. Those unable to complete the "core tasks" because of language difficulties or other limitations remain in the sample but have their skill test scores imputed. In our empirical analysis we control for this group, usually by including a dummy variable for "those unable to complete main skill tasks."

A salient feature of the data is the strong correlation among the various cognitive skill measures. The correlation between the Prose literacy and Document literacy scores is 0.96, that between Prose literacy and Numeracy is 0.90, and the correlation between Prose literacy and Problem Solving is 0.93. Further, a principal components analysis indicated only two principal components with the first being vastly more important and placing equal weight on all four scores. Thus a simple average of the four scores captures much of the information available in the skill measures. This is the skill measure that we use in much of the analysis.

The other main variables in our analysis are standard human capital measures plus variables related to language ability in English or French. The survey asked respondents their number of years of completed schooling, so we are able to construct the standard Mincer measure of potential experience (i.e. age - years of schooling - 6). Since we know the age at which immigrants entered Canada, we are able to divide experience of immigrants into foreign experience and Canadian experience.[6] We examine educational impacts using both years of completed schooling and highest level of educational attainment. For the latter, we employ four categories: less than completed high school, high school graduates, non-university post-secondary graduates, and those with a Bachelor's or higher university

[5]The IALSS builds on the IALS survey that was carried out in several countries during the period 1994 to 1998. Two of the skill domains - prose literacy and document literacy - are defined and measured in the same manner in IALS and IALSS.

[6]Foreign experience = age at arrival - foreign years of schooling - 6 if positive, zero otherwise. Canadian experience = age - age at arrival - (total years of schooling - foreign years of schooling) if positive and age at arrival $\geqslant 6$. Canadian experience = age - total years of schooling - 6 if age at arrival<6.

degree.[7] As mentioned earlier, a major advantage of the IALSS data is its detailed questions on where immigrants obtained their education. In particular, respondents are asked about their total years of completed schooling as well as their years of schooling completed outside of Canada. The survey also asks whether the respondent completed his/her highest level of education in Canada. We make use of this information in what follows by dividing our analysis between immigrants who completed their education in Canada versus those who completed it abroad. This turns out to be an important distinction and is one that cannot be made very precisely in data sets such as the Census.

The survey also includes a series of questions on language ability in English or French, all of which are self-reported. We use one that asks respondents about their first language spoken. We create a dummy variable that equals one if the first language spoken is other than English or French. Finally, we include dummy variables corresponding to the country of origin. One variable corresponds to immigrants from the U.S. or U.K., a second to immigrants from continental Europe, and a third to immigrants from Asia, with the rest of the world forming the omitted category in the estimation.[8] Much of the earlier literature on immigrants indicates that there are strong source country effects and that immigrants from the U.S. and U.K. adapt particularly well to the Canadian economy.

Tables 4.1 and 4.2 display summary statistics for the main variables of interest. Both male and female immigrants are, on average, four years older and, correspondingly, have four more years of labour market experience than their native-born counterparts. Immigrant men report one more year of schooling than do native-born men, but immigrant women report one year less education than Canadian born women. This gender difference in the immigrant - native born educational attainment gap is also evident when we look at the highest level of education attained. Among males, the distribution of formal education among immigrants is very different than, and generally superior to, that for the native born. The fraction of native-born men with no postsecondary education is 57%, versus 46% among immigrants. Additionally, a much larger fraction of male immigrants has a university degree (31%) compared to native-born men (18%). In contrast, the fraction of native-born women with no post-secondary education is the same as that for immigrant women (57%) and the fraction of immigrant women that did not complete high school (26%) is higher than that of native-born women (23%). At the top of the educational distribution, a larger proportion of immigrant women has a university degree (21%) than is the case for native-born women (17%), but the gap between immigrants and natives is much smaller than that for males. Another evident difference between immigrants and natives is their levels of cognitive skills, as assessed in English or French. The average skill levels of immigrant men range from 241 to 252, whereas these range from 274 to 281 for native Canadian men. The largest gaps are in prose literacy and problem solving and the smallest are in numeracy. Across the four domains, male immigrant skill levels are 9% to 12% lower than those of native-born males. The immigrant - native born skill gaps are generally even larger for

[7]Individuals with some but not completed post-secondary education are classified as high school graduates.

[8]We also examined finer breakdowns of the source country but these had little effect on the results.

females, ranging from a gap of 31 points for problem-solving to 44 points for prose literacy. The largest gaps are in prose literacy and document literacy and the smallest is in problem solving. Across the four domains, female immigrant skill levels are 11% to 16% below those of natives.

Table 4.1: Summary Statistics for Immigrants and the Native Born – Males

	Immigrant			Native Born
	Cdn Educ	No Cdn Educ	All	
Age	45	52	49	44
Experience	25	33	29	25
Canadian	21	20	20	-
Foreign	5	13	10	-
Years of Schooling	14	13	14	13
% Less than HS	17	25	21	27
% HS	28	22	25	30
Foreign	-	22	12	-
Canadian	28	-	12	-
% Non-Univ PS	24	23	23	25
Foreign	-	23	13	-
Canadian	24	-	11	-
% University	31	31	31	18
Foreign	-	31	17	-
Canadian	31	-	14	-
Years Since Migration	29	20	24	-
Age at Immigration	16	32	25	-
% with First Language not English or French	66	77	72	5
% with US or UK Origin	16	13	14	-
% with European Origin	26	23	24	-
% with Asian Origin	24	35	30	-
% Did Not Complete Main Skill Tasks	16	30	24	13
Prose Literacy	264	231	245	278
Document Literacy	271	238	252	281
Numeracy	269	240	252	277
Problem Solving	258	228	241	274
Observations	750	981	1,731	6,711

Sample: Males, age 16 and older, excluding students and observations with missing information on age at immigration or highest level of schooling.

An interesting fact arising from Tables 4.1 and 4.2 is the substantial fraction of immigrants who acquire some education in Canada. Columns 1 and 2 separate immigrants between those who report obtaining some or all of their schooling in Canada and those who did not acquire any education in Canada. It is immediately apparent that these two groups have very different characteristics. Both male and female immigrants with Canadian education are much younger, have less work experience, but at least as much experience in the Canadian labour market. They arrived in Canada at a substantially younger age, and have been in the country much longer, despite being substantially younger than immigrants educated abroad. In terms of educational attainment, immigrants with Canadian education

Table 4.2: Summary Statistics for Immigrants and the Native Born – Females

	Immigrant			Native Born
	Cdn Educ	No Cdn Educ	All	
Age	45	53	50	46
Experience	26	35	31	27
Canadian	21	21	21	-
Foreign	5	14	10	-
Years of Schooling	13	12	12	13
% Less than HS	19	31	26	23
% HS	32	29	31	34
Foreign	-	29	17	-
Canadian	32	-	13	-
% Non-Univ PS	26	20	22	26
Foreign	-	20	12	-
Canadian	26	-	11	-
% University	22	20	21	17
Foreign	-	20	12	-
Canadian	22	-	9	-
Years Since Migration	29	22	25	-
Age at Immigration	16	31	25	-
% with First Language not English or French	64	75	71	5
% with US or UK Origin	19	15	16	-
% with European Origin	22	23	22	-
% with Asian Origin	24	36	31	-
% Did Not Complete Main Skill Tasks	17	36	28	13
Prose Literacy	261	224	239	283
Document Literacy	259	223	238	276
Numeracy	247	215	228	261
Problem Solving	252	218	232	273
Observations	826	1152	1,978	7,953

Sample: Females, age 16 and older, excluding students and observations with missing information on age at immigration or highest level of schooling.

have more years of completed schooling, are much less likely to be high school dropouts, but equally likely to be university graduates as immigrants without Canadian education. Perhaps the most striking differences are those relating to measured skills. Immigrants with Canadian education have skill levels somewhat below those of the native born, but much higher than those of immigrants without Canadian education. The skills gap between foreign-educated immigrants and natives is especially large for women. Relative to native-born men, the gap in average skills for those educated outside of Canada ranges from 13% for numeracy to 17% for prose literacy and problem solving, whereas for male immigrants with some Canadian education the average skills gap ranges from 3% for numeracy to 6% for problem solving. Among female immigrants educated in Canada the skills gap is somewhat larger than for men - ranging from 5% for numeracy to 8% for prose literacy and problem solving. Among female immigrants educated prior to arrival the skills gap is huge - approximately 20% across all four skill domains. These differences suggest that controlling

Table 4.3: Summary Statistics for Immigrant and Native-Born Workers – Males

	Immigrant			Native Born
	Cdn Educ	No Cdn Educ	All	
Annual Earnings*				
Mean	49,408	39,146	44,060	44,484
Median	40,000	31,200	35,100	41,000
Weekly Earnings				
Mean	972	780	872	895
Median	788	626	702	808
Hours*	41	42	42	42
Weeks*	49	50	50	49
Age	38	44	41	38
Experience	17	24	21	18
Canadian	14	13	13	-
Foreign	4	12	8	-
Years of Schooling	15	14	14	13
% Less than HS	11	14	12	18
% HS	32	25	29	35
Foreign	-	25	13	-
Canadian	32	-	15	-
% Non-Univ PS	27	23	24	29
Foreign	-	23	12	-
Canadian	27	-	13	-
% University	31	38	35	18
Foreign	-	38	20	-
Canadian	31	-	15	-
Years Since Migration	23	13	18	-
Age at Immigration	15	31	23	-
% with First Language not English or French	64	79	72	5
% with US or UK Origin	15	9	12	-
% with European Origin	22	18	20	-
% with Asian Origin	27	40	34	-
% Did Not Complete Main Skill Tasks	11	25	18	11
Prose Literacy	273	241	256	289
Document Literacy	282	249	265	293
Numeracy	280	250	264	289
Problem Solving	267	236	251	285
Observations	417	500	917	3,634

Sample: Males, age 16 and older, excluding students and observations with missing information on age at immigration or highest level of schooling and with weekly earnings greater than $50 and less than or equal to $20,000. Annual earnings and weeks worked (annual) are based on slightly smaller samples due to missing information. Hours worked (weekly) are based on a smaller sample in case of the native born only.

Table 4.4: Summary Statistics for Immigrant and Native-Born Workers – Females

	Immigrant			Native Born
	Cdn Educ	No Cdn Educ	All	
Annual Earnings*				
Mean	33,091	27,545	30,401	31,182
Median	29,900	25,000	27,040	27,196
Weekly Earnings				
Mean	747	546	649	641
Median	577	485	525	540
Hours*	37	36	37	35
Weeks*	49	49	49	49
Age	40	43	41	38
Experience	20	24	22	19
Canadian	16	14	15	-
Foreign	4	9	6	-
Years of Schooling	14	14	14	14
% Less than HS	12	16	14	12
% HS	33	26	30	37
Foreign	-	26	13	-
Canadian	33	-	17	-
% Non-Univ PS	29	24	27	29
Foreign	-	24	12	-
Canadian	29	-	15	-
% University	27	34	30	22
Foreign	-	34	16	-
Canadian	27	-	14	-
Years Since Migration	25	15	20	-
Age at Immigration	14	28	21	-
% with First Language not English or French	63	77	70	6
% with US or UK Origin	16	12	14	-
% with European Origin	18	21	20	-
% with Asian Origin	27	41	34	-
% Did Not Complete Main Skill Tasks	11	23	17	9
Prose Literacy	274	246	260	300
Document Literacy	273	247	260	294
Numeracy	260	239	250	278
Problem Solving	262	237	250	289
Observations	437	433	870	4,133

Sample: Females, age 16 and older, excluding students and observations with missing information on age at immigration or highest level of schooling and with weekly earnings greater than $50 and less than or equal to $20,000. Annual earnings and weeks worked (annual) are based on slightly smaller samples due to missing information. Hours worked (weekly) are based on a smaller sample in case of the native born only.

for the origin of education may indeed be important for understanding immigrant labour market outcomes. They also suggest that there may be gender differences in immigrant outcomes relative to those of natives.

We explore these differences further in Tables 4.3 and 4.4, which reports summary statistics for our sample of earners - individuals currently employed as paid workers. The substantial differences in the characteristics of the two groups of immigrants are also evident in the sample of earners. Compared to the native born, immigrants without Canadian education are older, have more work experience, and less experience in the Canadian labour market. These generalizations hold for both men and women, although the differences between immigrants without Canadian education and natives are more modest among women. As before, one dimension on which there are gender differences is that relating to educational attainment gaps between immigrants and natives. Immigrant men educated abroad report higher attainment than natives at both the bottom and the top of the educational distribution. For example, 38% are university graduates versus 18% among native-born men. In contrast, immigrant women without Canadian education have a more dispersed educational distribution than that of natives, being both more likely to be high school dropouts and more likely to be university graduates.

The apparent advantage in education and experience among immigrant men does not translate into higher income. Average annual and weekly earnings of native-born men are substantially higher than those of immigrants without Canadian education, and the gap in median earnings is even greater. In contrast, mean earnings of immigrants with some Canadian education exceed earnings of the native born, although median earnings are modestly lower than those of natives. Among women both mean and median earnings of foreign-educated immigrants are below those of natives, whereas mean and median earnings of Canadian-educated immigrants exceed those of natives. One possible explanation for the puzzle of lower earnings of immigrants without Canadian education, despite their generally reporting more experience and education, is that the Canadian labour market may place a different value on the experience and education obtained outside of Canada than on that obtained after arrival in Canada. Another possible explanation for lower earnings is that the skills of immigrants educated abroad are much lower than those of native Canadians, despite their higher levels of educational attainment and greater amount of total labour market experience. We explore both of these explanations further in what follows.

4.4 Do Immigrant and Native Born Cognitive Skills Differ?

Figures 4.1(a) and 4.2(a) plot the kernel density functions of the individual averages of the four cognitive skill scores for males and females, respectively.[9] For both men and women the cumulative distribution function (CDF) for native born scores lies to the right of the immigrant CDF throughout the sample range and stochastically dominates the immigrant

[9]We estimate the kernel density functions with the kdensity function in Stata, using the Epanechnikov kernel and Stata's default bandwidth formula.

CDF at conventional significance levels.[10] The differences between immigrants and natives are especially large at the low end of the skill distribution. For example, among women the immigrant-native born gap is over 50 points at the 10^{th} percentile, 38 points at the median, and 25 points at the 90^{th} percentile. The skill gaps for men are smaller but follow the same pattern - a differential of 42 points at the 10^{th} percentile, 30 points at the 50^{th} percentile, and 14 points at the 90^{th} percentile. Figures 4.1(b) and 4.2(b) plot the cognitive skill distributions with the respondents who did not complete the main tests removed. The immigrant literacy distributions now appear more similar, though still inferior, to the native born distributions.

Panels (c) and (d) of these figures show the skills distributions for immigrants with and without Canadian education relative to that of the native born. The skill distributions of both immigrant groups are inferior to those of the Canadian born, and the difference between the respective distributions is largest for immigrants educated outside of Canada.[11] There is also less dispersion in the cognitive skills of immigrants who completed their education in Canada than is the case for those educated outside of Canada. In addition, for immigrant men educated in Canada the upper tail of the distribution is similar to that for Canadian born men, whereas this is not the case for male immigrants who were educated prior to arrival in Canada, nor is it the case for either group of female immigrants. For both men and women a noteworthy difference between immigrants who obtained some or all of their education in Canada and those that did not is the relative absence of individuals with high skill levels in the latter group.

The final two panels, (e) and (f), compare the skills distributions of the two immigrant groups to those of the native born after removing individuals who did not complete the main cognitive skill tasks. Doing so makes little difference to the distributions for immigrants with Canadian education, but makes a substantial difference to the distributions for immigrants without Canadian education. A significant number of those with low skill levels are evidently in this group.

Figures 4.3 to 4.10 provide further evidence of differences in the distribution of skills among native Canadians and the two immigrant groups. These figures recreate Figures 4.1 and 4.2 for each of the four individual skills. For both men and women the immigrant distributions are clearly inferior to those of the native born. The immigrant-native born skill gaps are most evident for prose literacy and least evident for numeracy. This latter pattern may reflect the tendency for numeracy to be less language dependent. As was the case with the average scores, separating immigrants into two sub-samples delineated by where they obtained their education reveals substantial differences between the two groups. For each of the four cognitive skills and both genders the distributions for immigrants

[10]More precisely, we cannot reject the null hypothesis that the native born CDF first order stochastically dominates the immigrant CDF at conventional significance levels.

[11]For example, the median skill score of female immigrants without Canadian education is 54 points below that of natives, while that of female immigrants with Canadian education is 16 points below that of natives. The story for males is similar: a differential in the median skill score of 45 points between foreign-educated immigrants and native Canadians versus a differential of 17 points between Canadian-educated immigrants and natives.

Figure 4.1: Distribution of Average Skill Score - Males

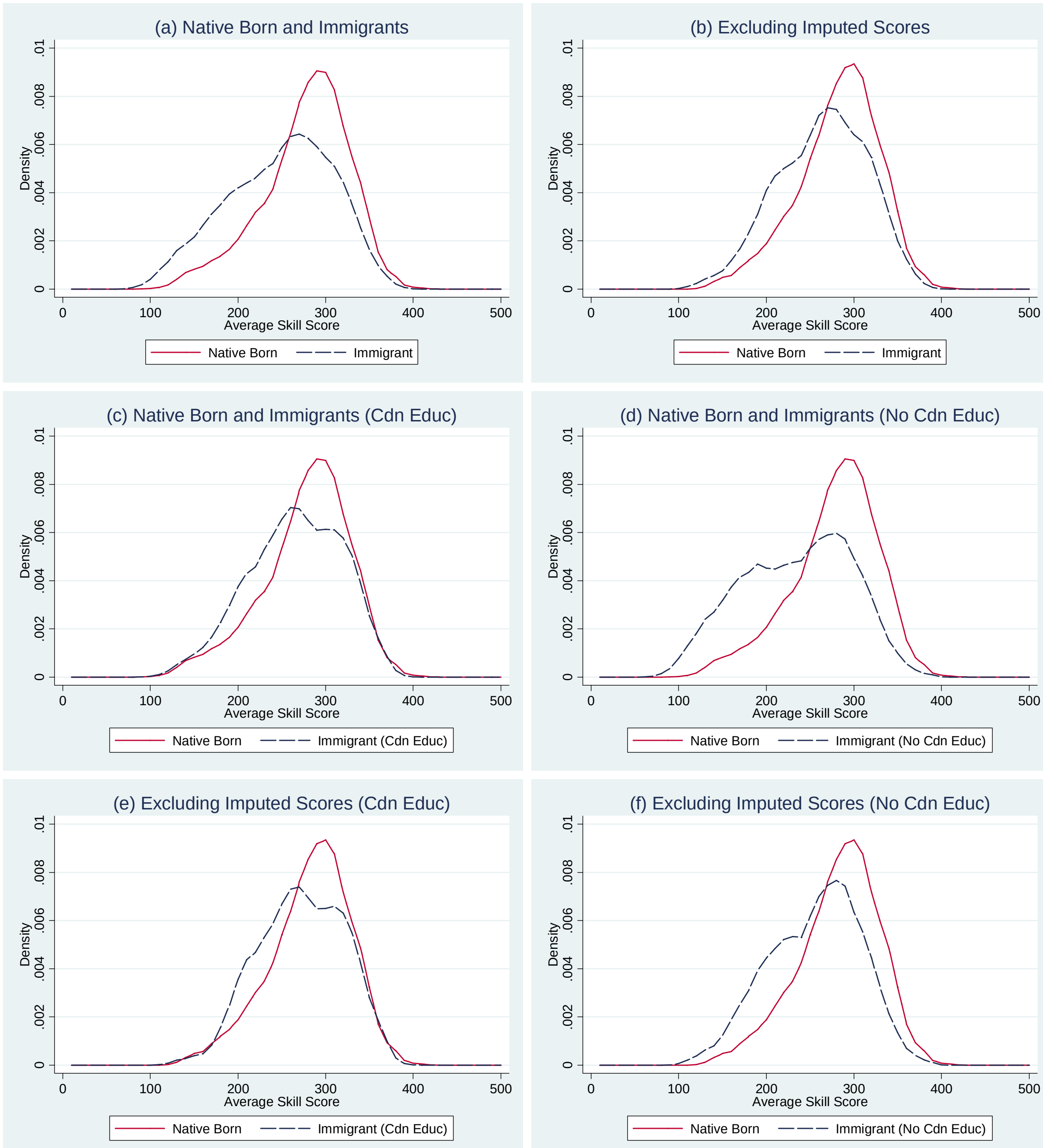


Figure 4.2: Distribution of Average Skill Score - Females

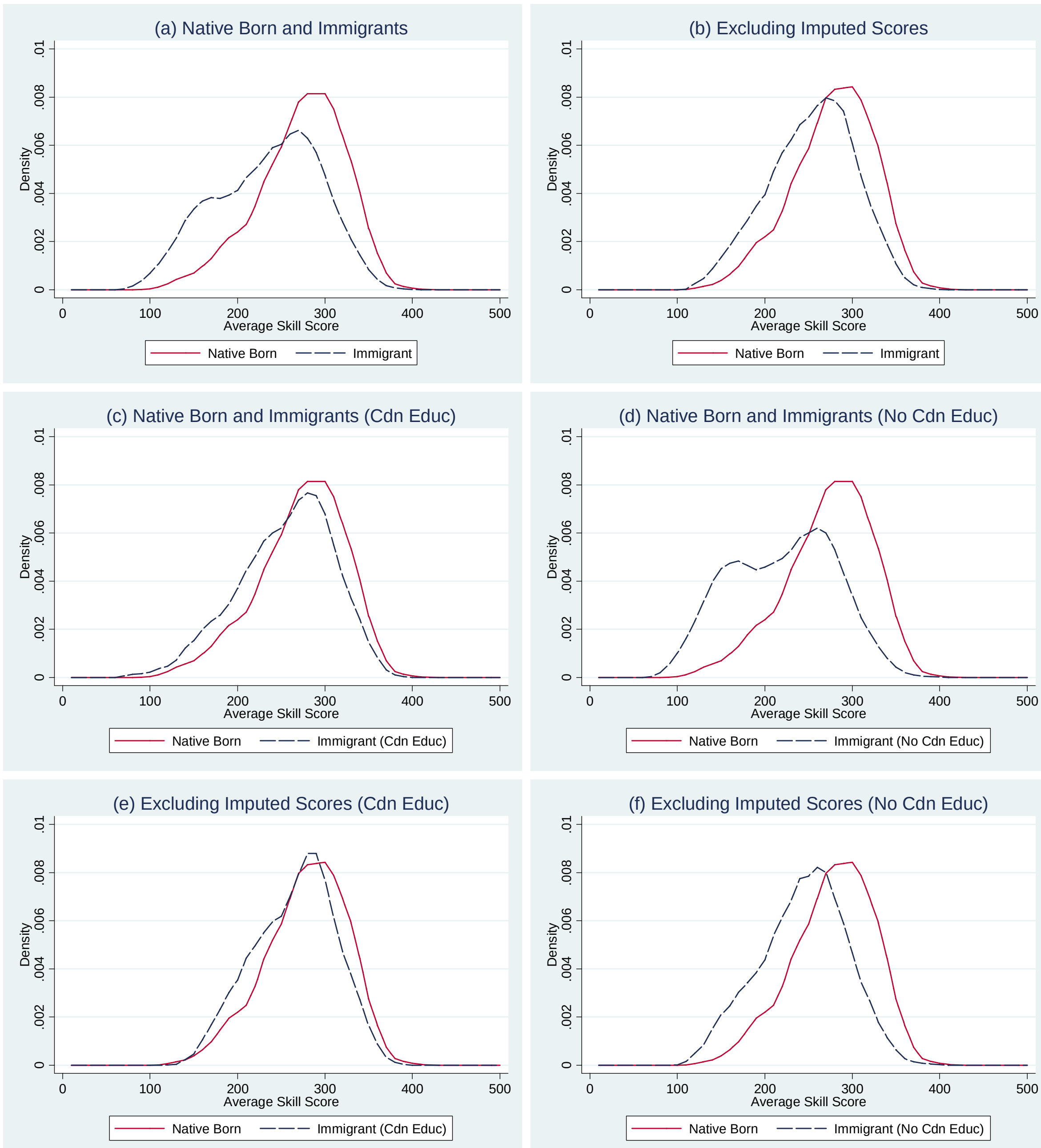


Figure 4.3: Distribution of Prose Literacy Score - Males

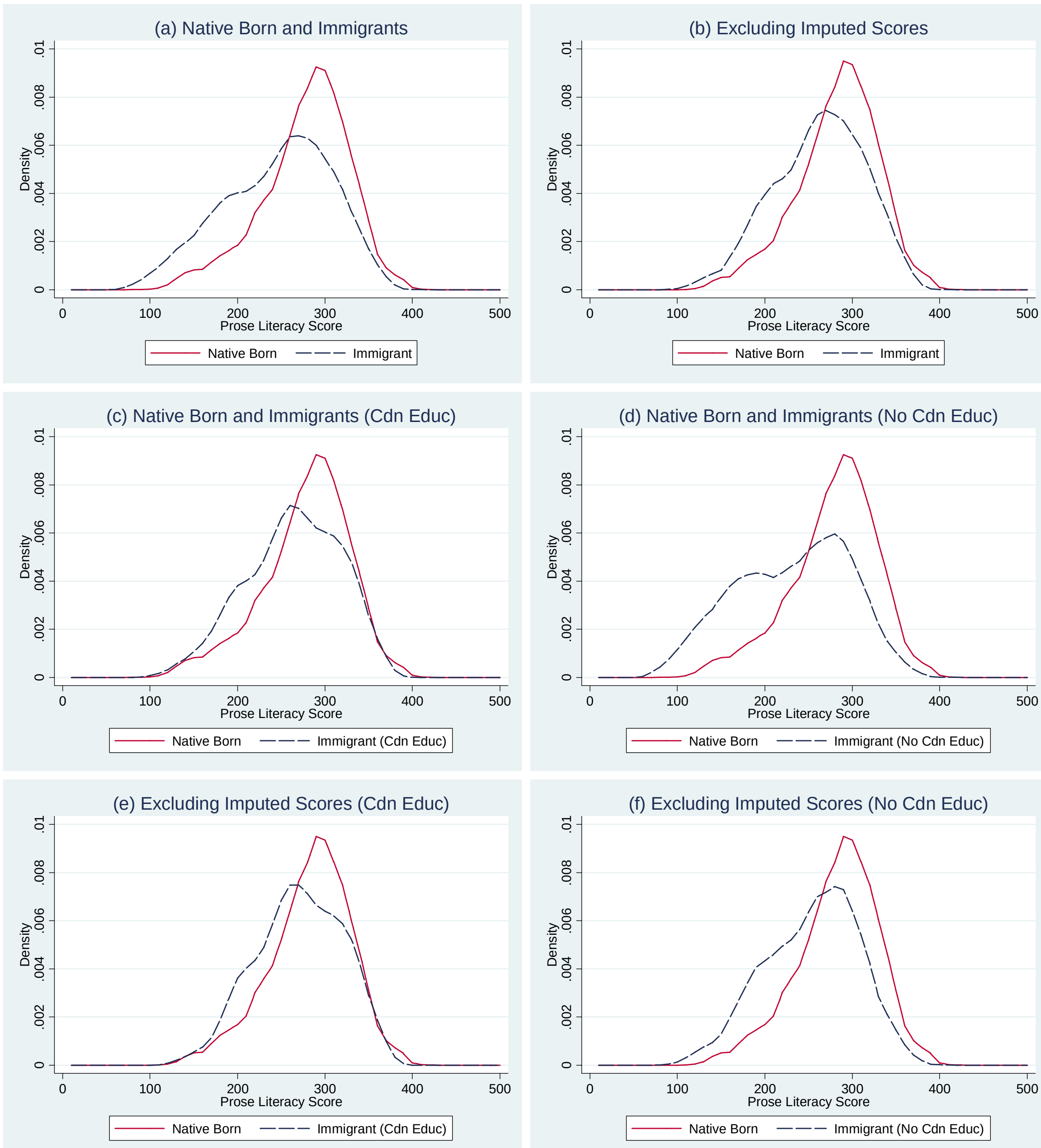


Figure 4.4: Distribution of Prose Literacy Score - Females

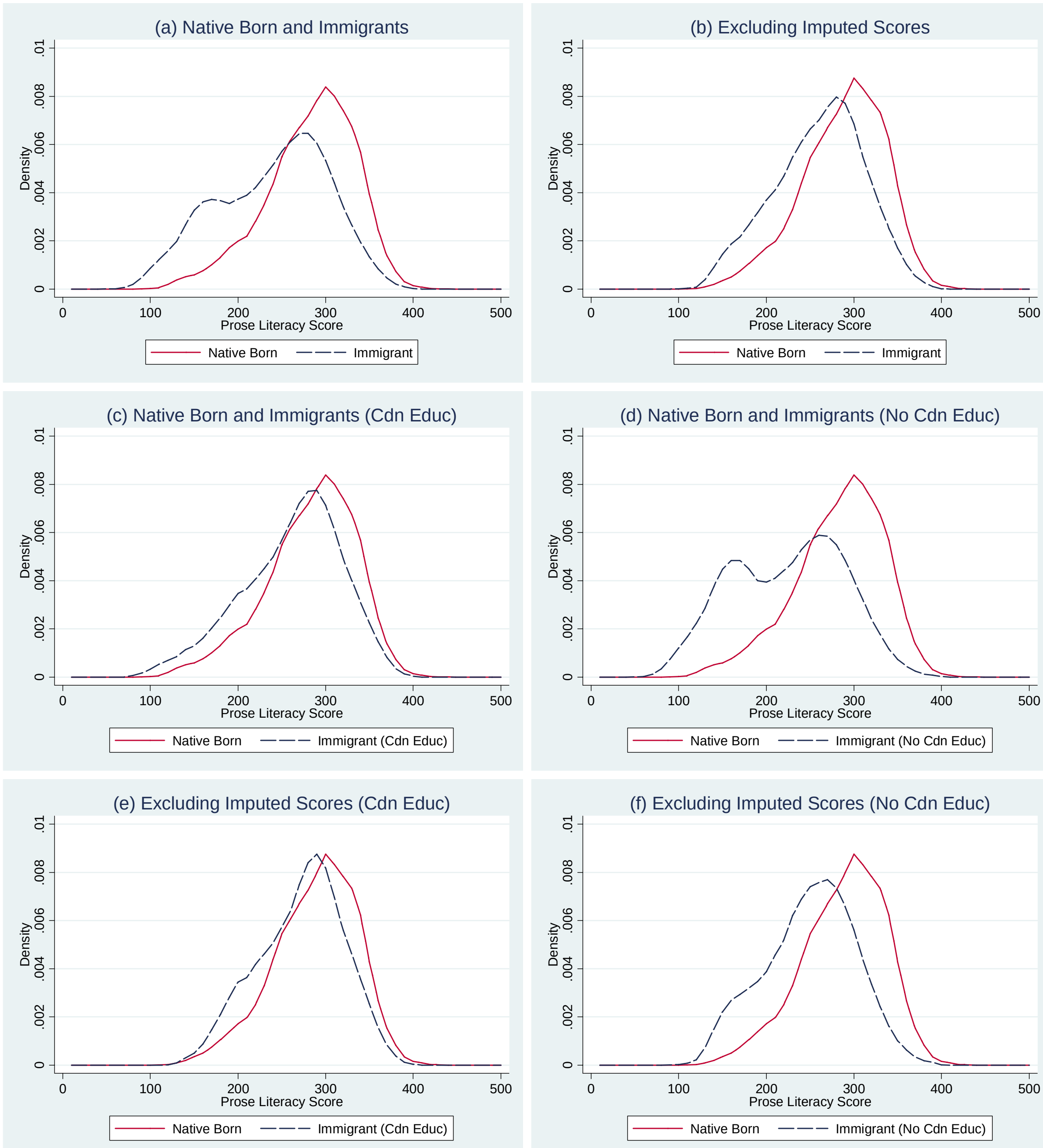


Figure 4.5: Distribution of Document Literacy Score - Males

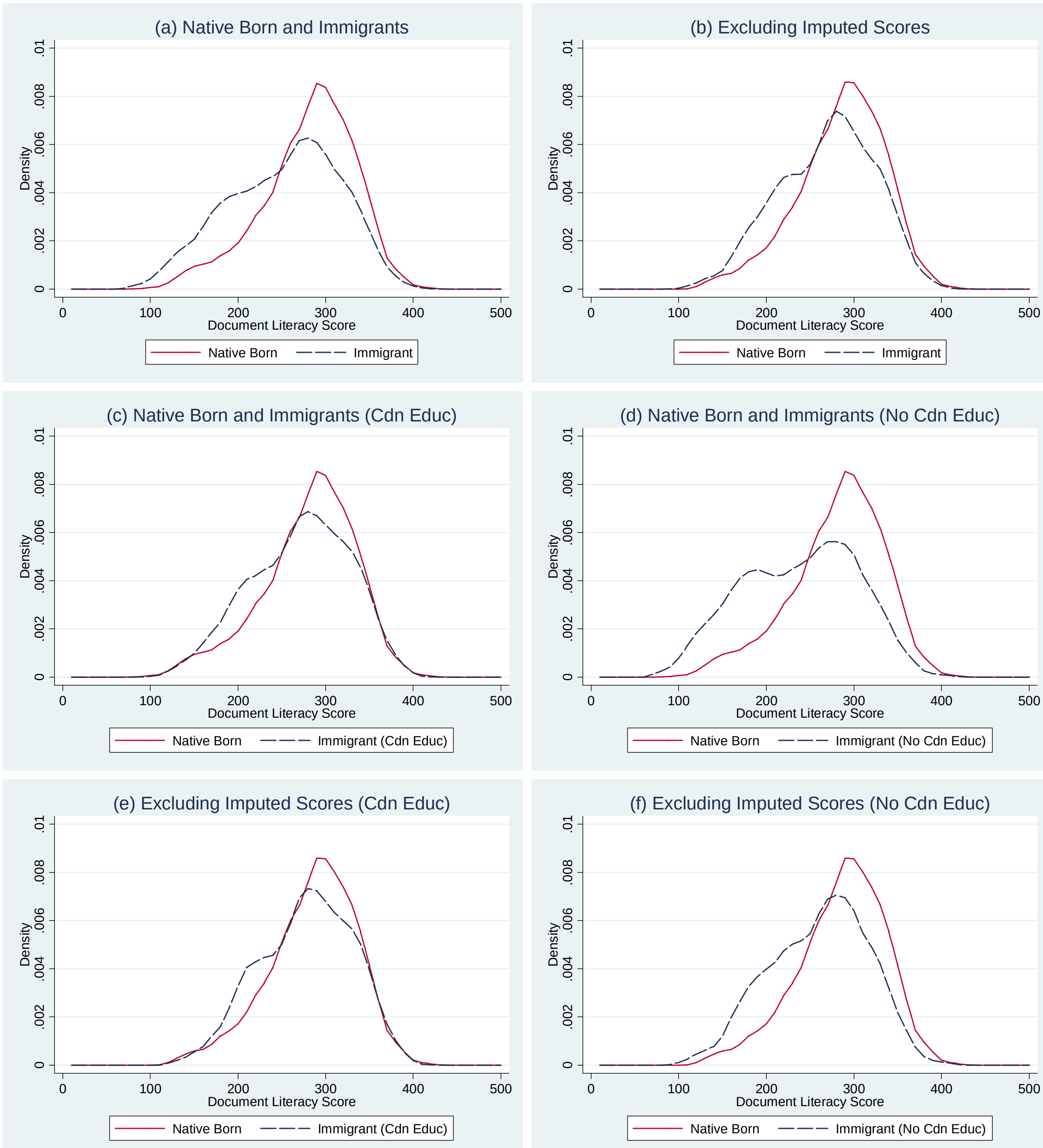


Figure 4.6: Distribution of Document Literacy Score - Females

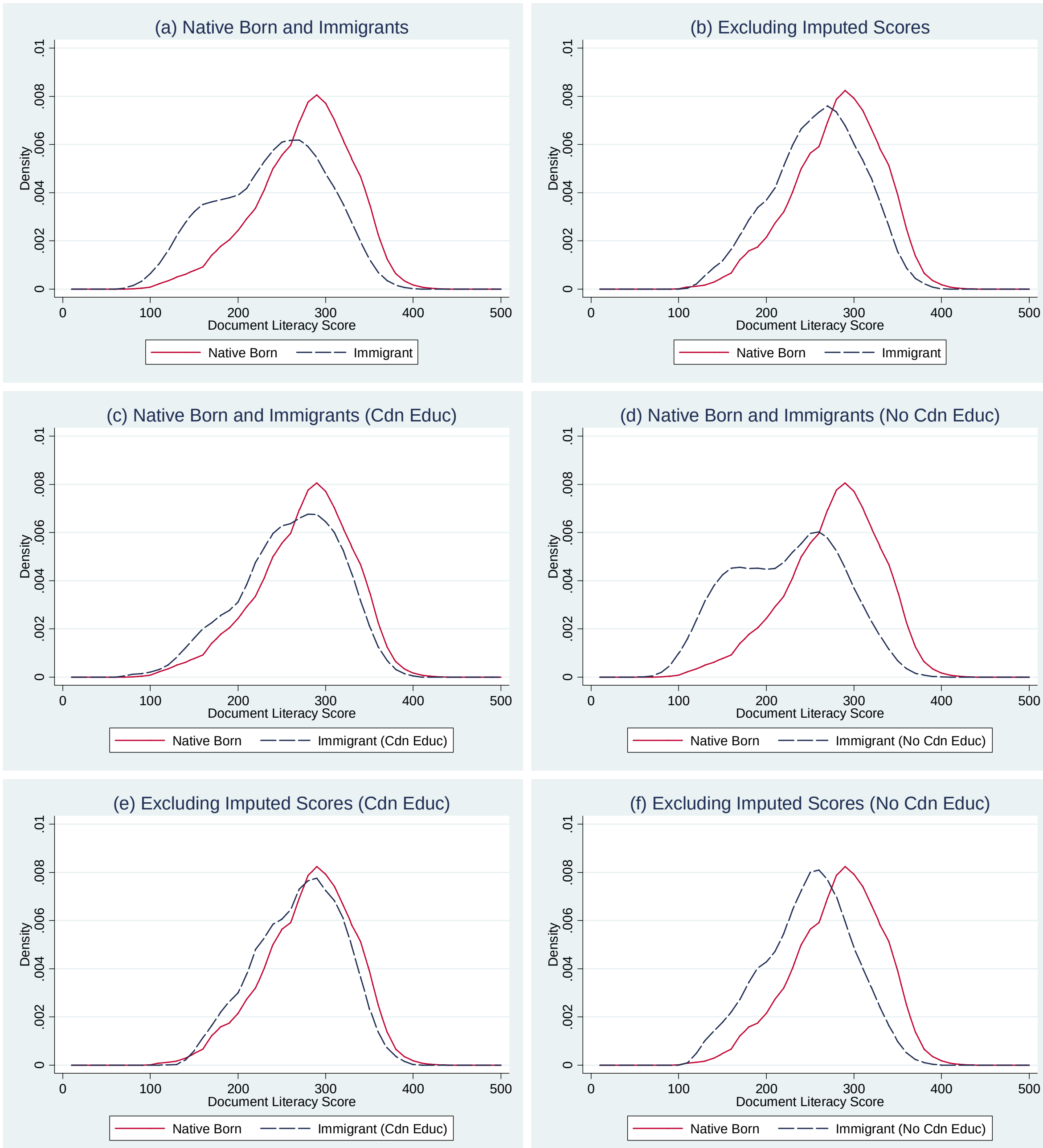


Figure 4.7: Distribution of Numeracy Score - Males

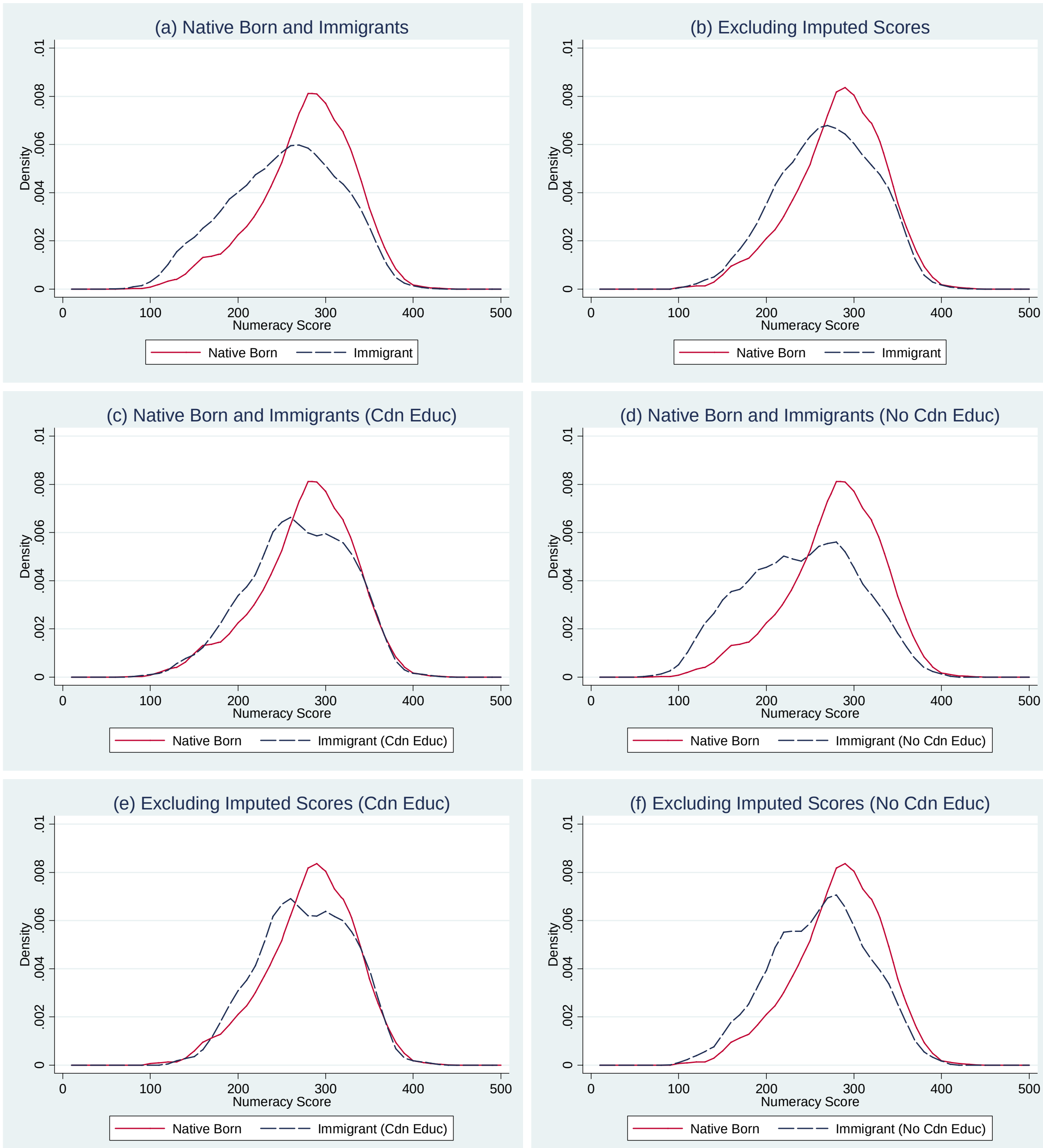


Figure 4.8: Distribution of Numeracy Score - Females

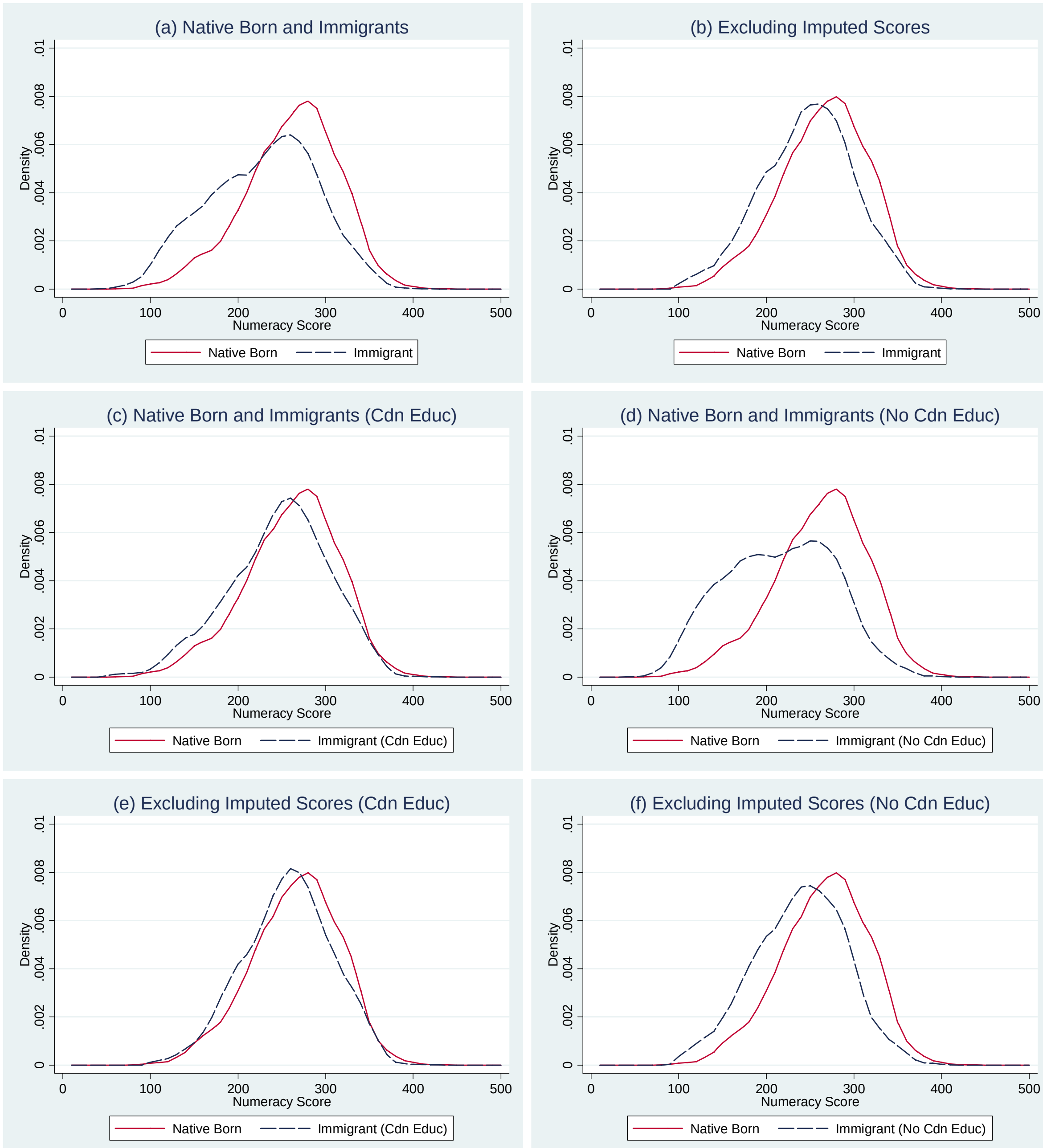


Figure 4.9: Distribution of Problem Solving Score - Males

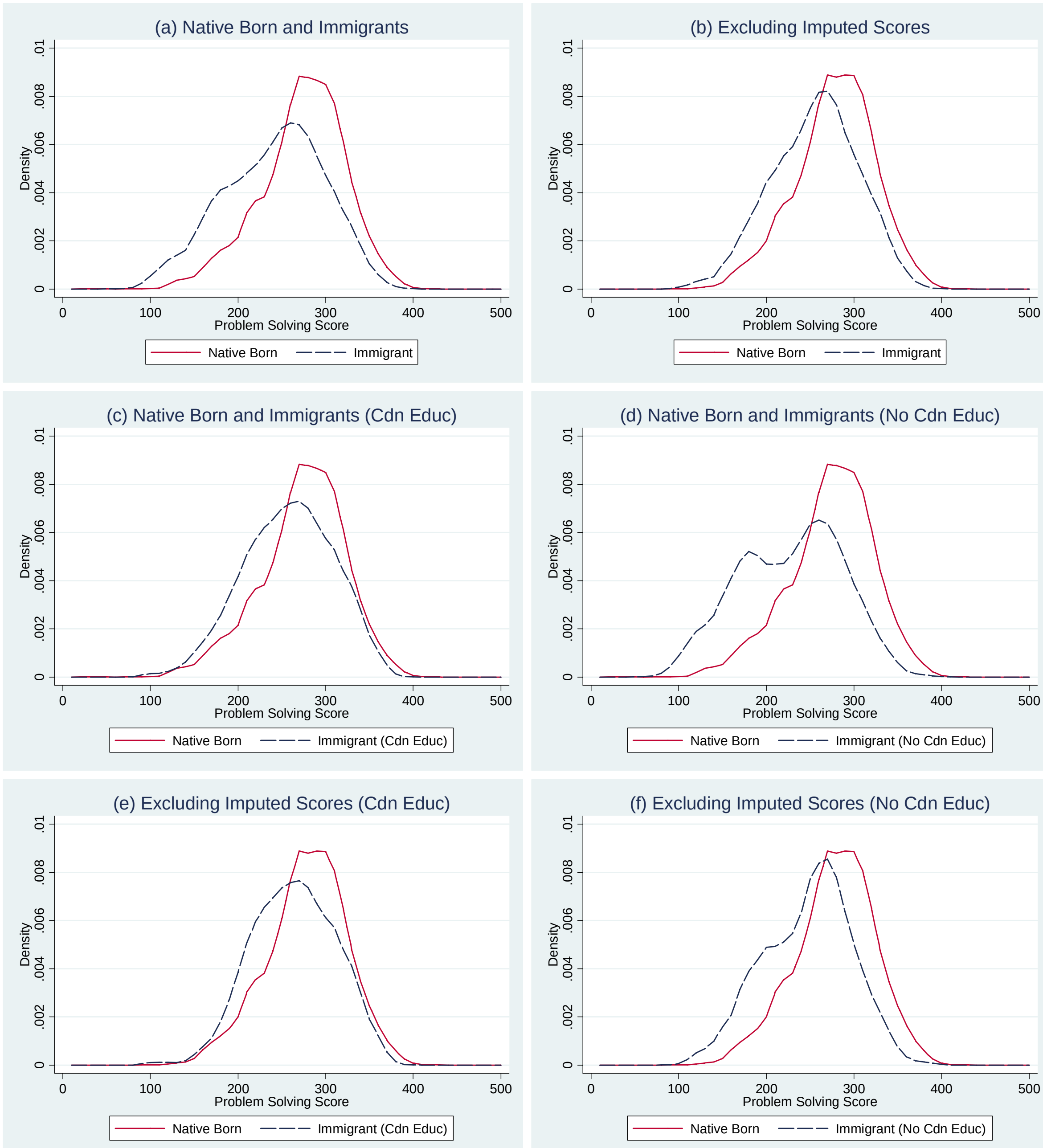
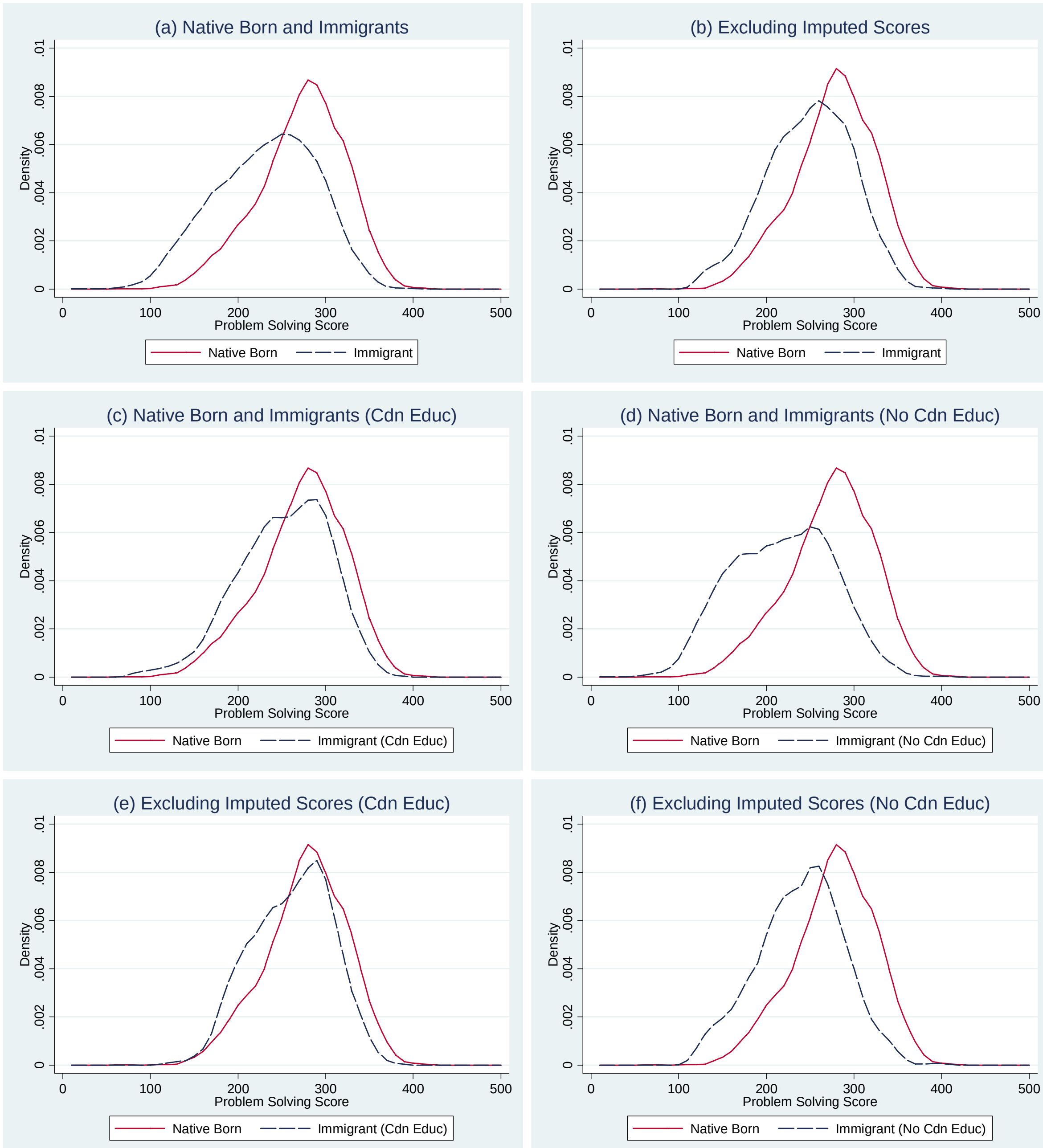


Figure 4.10: Distribution of Problem Solving Score - Females



educated in Canada have lower dispersion than those for foreign-educated immigrants and proportions of individuals with high skill levels that are closer to those observed among the native born. This similarity at the top of the skill distribution is especially evident for males. Both immigrant groups have larger proportions of their respective distributions with low skill levels (scores below 200) than is the case for the Canadian born. This concentration in the lower tail of the distribution is especially pronounced for immigrants who completed their education prior to arriving in Canada.

Given the impact on skill distribution of removing individuals who had their skill scores imputed, particularly in the case of immigrants, it is informative to look at the characteristics of those who did and did not complete the main skill tasks. In Table C.1 (see Appendix C) we report the results of this comparison for our sample of immigrant workers, given that most of the analysis in this chapter focuses on the earners sample. Immigrant workers who did not complete the main tasks were on average older at the time of migration than those who did, have on average lower educational attainment and are roughly half as likely to have English or French as a first language. Around 75% of immigrants who did not complete the main skill tasks speak English on a regular basis at work. About the same proportion reports believing they have sufficient reading skills in English to do their job well, although about 10% fewer report being satisfied with their English writing skills. Literacy use at work is also much lower among immigrants who did not complete the main skill tasks. For example, about half report rarely using writing skills in English at work, compared to only about 20% among immigrants who did complete the main skill tasks. Finally, immigrant workers who did not complete the main skill tasks receive around 70%-80% of the average annual earnings received by immigrants who did, although those earnings are still fairly high ($31,435 for men and $25,134 for women). The principal objective of this study is to examine the relationship between cognitive skills and the labour market outcomes experienced by immigrants and native-born Canadians. However, because of its relevance to our analytical framework we also examine the determinants of individual skills, with particular focus on the relationship between cognitive skills and human capital variables like education and age or experience. Table 4.5 reports the results from regressions of the average skill score on age and education plus parents' education, language proficiency, source country, and province of residence (not reported). The dependent variable is the log of the average skill score, so the coefficients can be interpreted as showing the percentage effect of a unit change in the variable of interest on the average score. We also include a dummy variable to control for the individuals who did not complete the main tasks, and whose test scores were therefore imputed. We do not view this regression as representing a causal story of how cognitive skills are generated. Instead, we interpret the coefficients as revealing partial correlations that are useful for summarizing skill patterns in the population.

Regression results are reported separately for males and females as some of the determinants of skills vary by gender. We also allow the effects of age and education to differ across the three groups - natives, immigrants with Canadian education, and immigrants who completed their education prior to arrival. Columns 1 and 3 allow the age profiles (as well as education effects) to differ across the three groups, while columns 2 and 4 also include a "years since migration" variable that allows the immigrant age profile after arrival to differ from that prior to arrival. For ease of interpretation, the age and education variables used in the Table 4.5 estimation are defined in such a way that the immigrant coefficients stand on their own; that is, they are not defined relative to the native born coefficients.

In the Table 4.5 regressions the omitted category consists of native Canadians with less than high school education, whose mothers and fathers also had not completed secondary school, whose first language is English or French and who completed the main skill tasks. Relative to these natives, the skills of immigrants with Canadian education are 8% to 11% lower, although the estimate associated with this immigrant dummy is imprecise and not significantly different from zero. Foreign-educated immigrants have much lower skills than the reference group - in the order of 20% lower for females and more than 30% lower for males. These estimates are statistically significant. A further reduction of 11-12% is associated with inability to complete the main skill tasks.

The age profiles reported in columns 1 and 3 are similar for men and women. For all three groups there is a positive partial correlation between age and skills, but one that is small in magnitude and diminishes with increased age. The estimated impact is about the same for natives and Canadian-educated immigrants - about 1/2 of 1% per year at early ages, diminishing to zero by age 25 to 30. For foreign-educated immigrants the magnitudes of the estimated coefficients are similar to those for the other two groups but the estimates are imprecise and not significantly different from zero. These results suggest that among adults (i.e. after about age 20) there is essentially no relationship between age (or experience) and the individual's skills. This conclusion is consistent with Green and Riddell (2003) who find that years of experience are essentially uncorrelated with the individual's skill level across various specifications in the IALS data that is predominantly made up of adult workers. Adding controls for years since arrival provides some evidence suggesting that years in Canada matter more than years abroad, especially for immigrants with Canadian education. Nonetheless the main message is the small effect of age on an individual's skills.

On the other hand, there is a strong relationship between education and cognitive skills for all three groups. Canadian-born high school graduates have skills that are approximately 13% higher than those of high school dropouts, while university graduates have average skill scores that are 22-24% higher than individuals who have not completed high school. University graduates also have dramatically higher skills than graduates from other post-secondary institutions.

Among Canadian-educated immigrants the impact of educational attainment on skills is similar to that of native Canadians - gains of 10-11% associated with secondary school, somewhat larger gains associated with non-university post-secondary, and skill gains in the order of 26% associated with university education. In contrast, the educational gradients are much larger for immigrants who obtained their education abroad - estimated skill gains of 18% for high school and approximately 35% for university education.

In summary, for all three groups there are substantial gains in skills associated with higher educational attainment.[12] The skill gains associated with higher education are great-

[12] As noted previously these estimates should not be given a causal interpretation. The positive association

Table 4.5: Estimated Coefficients from Regressions with Log of Average Cognitive Skill Score as the Dependent Variable

	Males		Females	
	(1)	(2)	(3)	(4)
Age (Native Born)	0.005***	0.005***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Age Sq / 100 (Native Born)	-0.008***	-0.008***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Immigrant (Cdn Educ)	-0.079	-0.091	-0.100	-0.105
	(0.055)	(0.061)	(0.071)	(0.074)
Age (Immig Cdn Educ)	0.005*	0.003	0.007*	0.004
	(0.002)	(0.003)	(0.003)	(0.003)
Age Sq / 100 (Immig Cdn Educ)	-0.007***	-0.009**	-0.011***	-0.011***
	(0.002)	(0.004)	(0.004)	(0.004)
YSM (Immig Cdn Educ)		0.004*		0.005*
		(0.002)		(0.003)
YSM Sq / 100 (Immig Cdn Educ)		0.0002		-0.002
		(0.003)		(0.004)
Immigrant (No Cdn Educ)	-0.310**	-0.374**	-0.208**	-0.152
	(0.120)	(0.138)	(0.094)	(0.110)
Age (Immig No Cdn Educ)	0.005	0.008	0.003	-0.0005
	(0.005)	(0.006)	(0.004)	(0.005)
Age Sq / 100 (Immig No Cdn Educ)	-0.006	-0.008	-0.005	-0.003
	(0.004)	(0.005)	(0.004)	(0.005)
YSM (Immig No Cdn Educ)		-0.003*		0.004
		(0.002)		(0.003)
YSM Sq / 100 (Immig No Cdn Educ)		0.004		-0.003
		(0.004)		(0.005)
High School (Native Born)	0.131***	0.131***	0.127***	0.127***
	(0.009)	(0.009)	(0.007)	(0.007)
Non-Univ Post-Sec (Native Born)	0.153***	0.154***	0.156***	0.155***
	(0.008)	(0.009)	(0.009)	(0.009)
University (Native Born)	0.237***	0.238***	0.223***	0.223***
	(0.010)	(0.010)	(0.009)	(0.009)
High School (Immig Cdn Educ)	0.107***	0.113***	0.097***	0.106***
	(0.032)	(0.031)	(0.026)	(0.025)
Non-Univ Post-Sec (Immig Cdn Educ)	0.143***	0.161***	0.172***	0.179***
	(0.030)	(0.030)	(0.027)	(0.025)
University (Immig Cdn Educ)	0.256***	0.273***	0.237***	0.246***
	(0.027)	(0.026)	(0.032)	(0.029)

Table 4.5: cont'd

	Males		Females	
	(1)	(2)	(3)	(4)
High School (Immig No Cdn Educ)	0.175***	0.178***	0.183***	0.182***
	(0.037)	(0.037)	(0.028)	(0.029)
Non-Univ Post-Sec (Immig No Cdn Educ)	0.243***	0.245***	0.282***	0.289***
	(0.030)	(0.029)	(0.026)	(0.026)
University (Immig No Cdn Educ)	0.349***	0.346***	0.325***	0.338***
	(0.032)	(0.031)	(0.026)	(0.026)
Father's Education				
High School	0.027**	0.027**	0.020***	0.021***
	(0.011)	(0.011)	(0.006)	(0.006)
Non-Univ Post-Secondary	0.030***	0.028***	0.028***	0.028***
	(0.009)	(0.009)	(0.007)	(0.007)
University	0.031***	0.031***	0.045***	0.046***
	(0.010)	(0.010)	(0.011)	(0.011)
None Reported	-0.008	-0.008	-0.013	-0.014
	(0.015)	(0.015)	(0.010)	(0.010)
Mother's Education				
High School	0.035***	0.034***	0.029***	0.030***
	(0.008)	(0.008)	(0.006)	(0.006)
Non-Univ Post-Secondary	0.036***	0.036***	0.044***	0.044***
	(0.011)	(0.012)	(0.007)	(0.007)
University	0.053***	0.052***	0.051***	0.051***
	(0.016)	(0.016)	(0.011)	(0.011)
None Reported	-0.029	-0.028	-0.055***	-0.055***
	(0.021)	(0.021)	(0.015)	(0.015)
First Language not English or French	-0.024	-0.023	-0.025**	-0.023*
	(0.014)	(0.014)	(0.012)	(0.012)
US or UK Origin	0.093***	0.083***	0.107***	0.089***
	(0.022)	(0.024)	(0.018)	(0.019)
European Origin	0.021	0.016	0.022	0.011
	(0.028)	(0.027)	(0.019)	(0.019)
Asian Origin	-0.014	-0.014	-0.057***	-0.042***
	(0.021)	(0.021)	(0.014)	(0.013)
Did Not Complete Main Skill Tasks	-0.115***	-0.114***	-0.110***	-0.107***
	(0.008)	(0.008)	(0.009)	(0.008)
Observations	8442	8442	9931	9931
R-squared	0.54	0.55	0.61	0.62

Specifications (1) and (3) do not differentiate between the time immigrants spent in Canada and abroad. Specifications (2) and (4) also include a "years since migration" variable that allows the immigrant age profile after arrival to differ from that prior to arrival in Canada. Robust standard errors in brackets. Regressions include indicators for province of residence. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

est for immigrants without Canadian education, and similar in size for the native born and immigrants with Canadian education. Combining the negative immigrant dummies with the positive effects of higher education, foreign-educated male immigrants with a university degree have an average cognitive skill score that is 20-25% lower than that for a university-educated native-born male. In contrast, among male high school dropouts the skills gap between these two groups is approximately 30-40%. The comparable estimates for females are approximately 5-10% and 15-20%, respectively. For both genders a university education narrows the skills gap relative to high school dropouts by approximately 10 percentage points.

Parents' education is also positively associated with the child's cognitive skills, but the estimated impacts are relatively modest. Among men the key factor is having a father or mother with at least a high school education; beyond this level there is little additional impact of the father's education. Among women there is a clear gradient, with the estimated effect of either parent being a university graduate being approximately double that of either parent being a high school graduate. Nonetheless for both men and women the estimated impacts are small relative to the effects of one's own education. The estimates imply that if both parents are university graduates the average skills of men are 8% higher than if both parents are high school dropouts, while those of women are 10% higher.

These results indicate that, for foreign-educated immigrants, there is a substantial skills deficiency relative to the native born and that deficiency declines somewhat with education. In contrast, for immigrants who obtained some of their education in Canada the skills disadvantage relative to natives is much smaller but that disadvantage is not reduced at higher education levels. Notice that in obtaining these results we control for region of origin and that immigrants from the U.S. or U.K. do not face as large a skills disadvantage. These differences in measured skills could arise because of differences in the quality of education across source countries or because immigrants not from the U.S. or U.K. have some difficulties in English or French.

4.5 The Effect of Education and Cognitive Skills on Earnings

4.5.1 Results without cognitive skill variables

In this section, we use our sample of paid workers to estimate earnings regressions with and without controlling for individual skills. The dependent variable is the log of weekly earnings. As a first step, we estimate a specification that includes a quadratic in experience, the education dummy variables specified earlier, a dummy for immigrant status, a quadratic in years since entering Canada for immigrants, and a dummy for first language other than English or French. This specification is similar to immigrant - native born earnings equations estimated with cross-sectional data that have been reported in previous studies.

between education and skills may (or may in part) arise because education exerts a causal influence on skill formation. However, the association could also arise because both educational attainment and cognitive skills are correlated with unobserved factors such as innate ability.

The first column in Tables 4.6 (males) and 4.7 (females) presents these results. They reflect commonly observed patterns. In particular, male returns to experience are approximately 7% per year just after leaving school but decline to zero by 29 years later. As is typically found to be the case, female returns to experience are lower, 5.4% per year early in the career and also declining to zero by 25-30 years later. There are also substantial returns to education that are on the order of those found in earlier studies, with women experiencing much higher returns to schooling than men. Male immigrants receive weekly earnings that are over 50% less than earnings of native-born workers with the same level of total experience and education. For female immigrants the magnitude of this negative entry effect is somewhat lower, but the gap is still a substantial one - approximately 44 percent. Immigrant earnings then rise at rates of approximately 2.5% (males) and 2.8% (females) more per year compared to similar native-born workers in the years just after the immigrant enters Canada. As indicated by the negative coefficients on the years-since-migration (YSM) squared variables, this rate of catch-up to the native born diminishes over time. If male and female immigrant earnings actually follow these "years since migration" profiles, then their earnings would equal those of a comparable native-born worker after approximately 28 years in Canada. This, however, is a big "if". As Borjas (1985) points out, if immigrants arriving in different years (i.e. in different cohorts) face different entry earnings and/or years since migration earnings profiles, then a cross-sectional years since migration profile will represent a combination of actual profiles and the effects of shifts across cohorts. Thus, the cross-sectional profile is not necessarily the relevant earnings assimilation profile for any set of immigrants. With only a single cross section of IALSS data, there is no way to address this problem. The immigrant dummy variable and years since migration profile summarize a combination of cohort effects and assimilation profiles rather than a profile that bears behavioural interpretation. Since our focus is on effects of cognitive skills rather than cohort patterns, this is not a central concern. It is only important that we control for the combination of cohort and assimilation effects, not that we can separately identify them.[13]

The specification in column 1 imposes equal returns to education and experience for immigrants and the native born but allows immigrants to have separate entry earnings and an earnings progression with years since arrival. However, the latter YSM effects can be difficult to interpret even in the absence of the cohort effect complication just described. For individuals arriving in Canada after they have completed their education, YSM corresponds to experience in the Canadian labour market. For individuals completing their education in Canada, YSM will equal years of experience in the Canadian labour market plus the number of years between arrival and entry into the labour market. Since the latter years may include time when the migrant is quite young, their impact on earnings is likely quite different from that of labour market experience. For that reason, we implement an adjusted specification (reported in column 2) that allows the immigrant entry effects and Canadian experience effects to differ between immigrants who arrive after completing their education

[13]In future work we plan to examine cohort effects using the 1998 OILS data and the Ontario observations in the 2003 IALSS data.

and immigrants who obtain some or all of their education in Canada. Differences between these two groups of immigrants in the coefficients on Canadian experience variables could represent some combination of differential returns to experience and differential cohort effects.

The adjusted specification in column 2 includes both the separate immigrant experience variables described above and three dummy variables corresponding to immigrants whose source country was either: 1) the US or UK; 2) any continental European country; or 3) Asia. We include these variables because previous studies have placed a great deal of emphasis on region of origin effects in explaining immigrant earnings patterns (e.g. Baker and Benjamin, 1994). In interpreting the estimates reported in column 2 note that the various experience coefficients are reported so that they can be read directly rather than as comparisons to, say, the Canadian experience variables.

Although the results for males and females share many common features, there are also some noteworthy gender differences. We therefore discuss the male results (Table 4.6) and female results (Table 4.7) separately. The estimated coefficients relating to the Canadian experience of male immigrants who obtained some of their education in Canada and the overall male experience coefficient (which corresponds mainly to the experience effects for the native born) are extremely similar in size, and tests of the hypothesis that they are equal to each other cannot be rejected at conventional significance levels. In contrast, male immigrants without Canadian education receive significantly greater returns to Canadian work experience. The intercept coefficients for the two groups of immigrants are both negative and significantly different from zero. Nonetheless, the implication from the coefficients is that immigrants who complete their education abroad have earnings that are almost 65% lower than comparable native-born workers, whereas those with some Canadian education receive earnings that are about 16% lower than otherwise comparable natives. These estimates apply to the base category, those whose first language spoken was French or English and who are not from the US, the UK, Europe, or Asia. For those whose first language was other than English or French, average weekly earnings are another 3% to 5% lower, although this effect is not precisely estimated and is not significantly different from zero. Finally, the source region coefficients suggest that immigrants from continental Europe have earnings that are over 20% higher than those of other immigrants. Immigrants from the US/UK also receive higher earnings than the base group, although these estimated effects are smaller than for Europe (about 12%) and are not precisely estimated. Immigrants from Asia have earnings that are slightly lower than the base group, although this effect is also not statistically significant.

Table 4.7 reports the results for females. As was the case for men, the negative entry effect experienced by foreign-educated immigrants is much larger than that for immigrants with Canadian education. However, both entry effects are smaller (in absolute value) than the corresponding estimates for male immigrants, and the coefficient associated with Canadian-educated female immigrants is not significantly different from zero. Another feature common to both male and female immigrants is the result that foreign-educated immigrants experience substantially higher returns to Canadian experience than do natives.

Table 4.6: Earnings Regressions without Skill Effects – Males

	Basic 1	Basic 2	Basic 3	Preferred
Immigrant	-0.528***			
	(0.066)			
Immigrant (Cdn Educ)		-0.157	0.032	-0.003
		(0.092)	(0.115)	(0.094)
Immigrant (No Cdn Educ)		-0.643***	0.020	0.628***
		(0.117)	(0.107)	(0.134)
YSM	0.025***			
	(0.004)			
YSM Sq / 100	-0.019**			
	(0.008)			
Experience	0.070***	0.072***		
	(0.003)	(0.003)		
Experience Sq / 100	-0.122***	-0.125***		
	(0.007)	(0.007)		
Cdn Exp (Native Born)			0.075***	0.092***
			(0.004)	(0.005)
Cdn Exp Sq / 100 (Native Born)			-0.132***	-0.144***
			(0.008)	(0.008)
Cdn Exp (Immig Cdn Educ)		0.072***	0.062***	0.076***
		(0.009)	(0.011)	(0.013)
Cdn Exp Sq / 100 (Immig Cdn Educ)		-0.109***	-0.098***	-0.092***
		(0.021)	(0.027)	(0.030)
Foreign Exp (Immig Cdn Educ)				-0.003
				(0.017)
Foreign Exp Sq / 100 (Immig Cdn Educ)				0.046
				(0.060)
Cdn Exp (Immig No Cdn Educ)		0.099***	0.058***	0.047***
		(0.013)	(0.011)	(0.011)
Cdn Exp Sq / 100 (Immig No Cdn Educ)		-0.152***	-0.104***	-0.088**
		(0.039)	(0.030)	(0.033)
Foreign Exp (Immig No Cdn Educ)				-0.008
				(0.009)
Foreign Exp Sq / 100 (Immig No Cdn Educ)				0.005
				(0.023)
Foreign Exp			0.002	
			(0.009)	
Foreign Exp Sq / 100			-0.005	
			(0.028)	

Table 4.6: cont'd

	Basic 1	Basic 2	Basic 3	Preferred
High School	0.200***	0.200***	0.207***	
	(0.047)	(0.048)	(0.047)	
Non-Univ Post-Sec	0.402***	0.402***	0.412***	
	(0.040)	(0.040)	(0.038)	
University	0.719***	0.731***	0.739***	
	(0.043)	(0.042)	(0.040)	
HS (NB & Immig Cdn Educ)				0.422***
				(0.080)
PS (NB & Immig Cdn Educ)				0.816***
				(0.072)
Univ (NB & Immig Cdn Educ)				1.223***
				(0.082)
High School (Immig No Cdn Educ)				0.117
				(0.097)
Non-Univ Post-Sec (Immig No Cdn Educ)				0.364***
				(0.102)
University (Immig No Cdn Educ)				0.477***
				(0.090)
HS * Cdn Exp (NB & Immig Cdn Educ)				-0.010***
				(0.003)
PS * Cdn Exp (NB & Immig Cdn Educ)				-0.021***
				(0.003)
Univ * Cdn Exp (NB & Immig Cdn Educ)				-0.026***
				(0.004)
First Language not English or French	-0.049	-0.028	-0.023	-0.049
	(0.043)	(0.052)	(0.055)	(0.052)
US or UK Origin		0.119	0.121	0.123
		(0.092)	(0.103)	(0.102)
European Origin		0.234***	0.231***	0.229***
		(0.082)	(0.081)	(0.078)
Asian Origin		-0.042	-0.021	-0.005
		(0.063)	(0.058)	(0.049)
Observations	4551	4551	4551	4551
R-squared	0.39	0.40	0.40	0.43

Specification (1) is the most basic one. Specification (2) distinguishes between immigrants with and without Canadian education and allows separate returns to experience for the native born and the two immigrant groups. Specification (3) further distinguishes between experience acquired in Canada and foreign experience. Column (4) contains our preferred specification. Robust standard errors in brackets. Regressions include indicators for province of residence. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.7: Earnings Regressions without Skill Effects – Females

	Basic 1	Basic 2	Basic 3	Preferred
Immigrant	-0.436***			
	(0.096)			
Immigrant (Cdn Educ)		-0.046	0.090	0.153**
		(0.093)	(0.079)	(0.069)
Immigrant (No Cdn Educ)		-0.387***	-0.072	0.639**
		(0.118)	(0.149)	(0.247)
YSM	0.028***			
	(0.007)			
YSM Sq / 100	-0.035***			
	(0.012)			
Experience	0.054***	0.054***		
	(0.005)	(0.006)		
Experience Sq / 100	-0.102***	-0.102***		
	(0.012)	(0.013)		
Cdn Exp (Native Born)			0.057***	0.072***
			(0.006)	(0.005)
Cdn Exp Sq / 100 (Native Born)			-0.108***	-0.114***
			(0.014)	(0.013)
Cdn Exp (Immig Cdn Educ)		0.066***	0.058***	0.072***
		(0.007)	(0.007)	(0.006)
Cdn Exp Sq / 100 (Immig Cdn Educ)		-0.120***	-0.109***	-0.113***
		(0.019)	(0.018)	(0.016)
Foreign Exp (Immig Cdn Educ)				-0.022
				(0.013)
Foreign Exp Sq / 100 (Immig Cdn Educ)				0.105**
				(0.051)
Cdn Exp (Immig No Cdn Educ)		0.076***	0.054***	0.040**
		(0.015)	(0.016)	(0.015)
Cdn Exp Sq / 100 (Immig No Cdn Educ)		-0.126***	-0.099**	-0.078**
		(0.036)	(0.038)	(0.034)
Foreign Exp (Immig No Cdn Educ)				0.026
				(0.017)
Foreign Exp Sq / 100 (Immig No Cdn Educ)				-0.079
				(0.047)
Foreign Exp			0.003	
			(0.008)	
Foreign Exp Sq / 100			0.015	
			(0.027)	

Table 4.7: cont'd

	Basic 1	Basic 2	Basic 3	Preferred
High School	0.342***	0.341***	0.354***	
	(0.060)	(0.059)	(0.059)	
Non-Univ Post-Sec	0.569***	0.570***	0.580***	
	(0.066)	(0.067)	(0.066)	
University	0.967***	0.971***	0.983***	
	(0.079)	(0.080)	(0.080)	
HS (NB & Immig Cdn Educ)				0.604***
				(0.085)
PS (NB & Immig Cdn Educ)				1.028***
				(0.119)
Univ (NB & Immig Cdn Educ)				1.430***
				(0.083)
High School (Immig No Cdn Educ)				0.143
				(0.127)
Non-Univ Post-Sec (Immig No Cdn Educ)				0.290**
				(0.130)
University (Immig No Cdn Educ)				0.411***
				(0.141)
HS * Cdn Exp (NB & Immig Cdn Educ)				-0.010***
				(0.003)
PS * Cdn Exp (NB & Immig Cdn Educ)				-0.020***
				(0.004)
Univ * Cdn Exp (NB & Immig Cdn Educ)				-0.020***
				(0.003)
First Language not English or French	-0.049	-0.046	-0.044	-0.064
	(0.044)	(0.052)	(0.051)	(0.052)
US or UK Origin		-0.067	-0.085	-0.072
		(0.103)	(0.117)	(0.132)
European Origin		-0.052	-0.038	-0.081
		(0.077)	(0.076)	(0.075)
Asian Origin		-0.078	-0.072	-0.083
		(0.072)	(0.070)	(0.072)
Observations	5003	5003	5003	5003
R-squared	0.33	0.33	0.34	0.36

Specification (1) is the most basic one. Specification (2) distinguishes between immigrants with and without Canadian education and allows separate returns to experience for the native born and the two immigrant groups. Specification (3) further distinguishes between experience acquired in Canada and foreign experience. Column (4) contains our preferred specification. Robust standard errors in brackets. Regressions include indicators for province of residence. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

However, in contrast to the results for men, female immigrants with Canadian education also obtain higher returns to Canadian experience than the native born, albeit lower than those obtained by their foreign-educated counterparts. Finally, although the estimated consequences of having a first language other than English or French are similar to those for men, the earnings differences associated with alternative source countries are very different. In particular, after controlling for other factors, female immigrants from the US/UK and Europe do not experience higher earnings than those from other source regions, in contrast to the situation for male immigrants.

The adjusted basic specification is still, potentially, too restrictive. In particular, it restricts the returns to foreign experience (in terms of earnings in Canada) to be the same as returns to Canadian experience for the native born. The specification in the third column of Tables 4.6 and 4.7 permits a separate return to foreign experience. This is important because Friedberg (2000) finds, using Israeli data, that negative immigrant entry earnings effects can be completely explained by a lower return to foreign experience than native experience. For immigrants from some countries, she found that foreign experience was worth zero in the Israeli labour market. These results are replicated for Canada by Alboim et al. (2003) and Ferrer, Green and Riddell (2006). Green and Worswick (2002) study this further and show that this is a recent phenomenon for Canada since immigrant cohorts in the early 1980s earned returns on foreign experience that were similar to the returns the native born earned for Canadian experience. Similar to results in those papers, when we introduce foreign experience variables in column 3, the immigrant entry effect coefficients are no longer significantly different from zero; indeed, three of the four estimated coefficients are positive. At the same time, for both men and women the returns to Canadian experience for the two immigrant groups are not significantly different from those for the native born. Finally, note that introducing the foreign experience effect does not change the returns to education, language impacts, and country of origin effects.

Among both male and female immigrants the return to foreign experience itself is essentially zero. It is this low rate of return on foreign experience that is the source of the negative immigrant entry effects in the first two columns of the table. Comparing immigrant earnings to those of native-born workers with the same total number of years of experience shows that immigrant earnings are significantly lower. This occurs because the immigrants are obtaining zero returns to some of those years of experience. Once we control for foreign experience, we are effectively comparing immigrants to native-born workers with the same number of years of Canadian experience and it turns out that immigrant and native-born workers have earnings that are much more similar when compared on that basis. This does not negate the fact that immigrants have lower earnings. However, it does help us understand that a major source of those lower earnings is an inability to transfer human capital acquired in a foreign labour market to Canada. It is worth noting, as well, that foreign experience does not suffer from the same interpretation difficulties as Canadian experience for immigrants. That is, there is no cohort dimension to the number of years an immigrant worked before arriving. Immigrants arriving in recent cohorts and cohorts from decades ago could all have the same distribution of foreign experience before arriving. The same is not true of Canadian experience: those arriving in earlier cohorts necessarily have more. This means that we can give the coefficient on foreign experience a standard human capital acquisition interpretation much as we have given to Canadian experience.[14]

The final column of Tables 4.6 and 4.7 contains our preferred specification which we reach by first allowing a complete set of interactions among all immigrant, experience and education variables and then eliminating sets of interactions where testing indicates it is appropriate. Thus, for example, we allowed for different returns to education for immigrants who obtained some education in Canada. For both males and females we could not reject the restriction that the differences between these returns and those for the native born were zero at any conventional significance level. However, we do find that returns to education are significantly lower for male and female immigrants without Canadian education. We also allowed for the possibility that each type of experience (whether foreign or Canadian-acquired) might interact with each type of education. We do find evidence of significant interactions of Canadian experience with education for the native born and immigrants who obtained some education after arrival. These interaction coefficients are negative for both men and women, and increase (in absolute value) with educational attainment. Thus among the native born and immigrants with Canadian education the positive impact of experience on earnings diminishes as educational attainment rises. However, there is no evidence of similar interactions between experience and education for immigrants educated before arrival.

To aid in interpretation of the results in the last column of Tables 4.6 and 4.7, we present in Table 4.8 fitted average earnings for a set of specific cases characterized by differing levels of education and experience. To generate the entries in this table, we formed fitted average log earnings values for a base case person who is a native-born worker who has not graduated from high school and has no Canadian experience. We also formed average log earnings for native-born and immigrant workers with differing levels of Canadian and foreign experience and education. For the immigrants, we formed the fitted averages such that they are relevant for an individual who completed schooling outside Canada, who is not from the US, the UK, Europe or Asia, and whose first language is English or French. The various fitted earnings are differenced relative to those of the base case native-born individual.

[14]However, Green and Worswick (2002) point out that native born earnings can also be organized in a cohort format and that doing so provides insights into the cross-cohort patterns in immigrant cohorts. In particular, they find that approximately 60% of the cross-cohort decline in immigrant earnings in the 1980s can be attributed to general declines across cohorts of new entrants of all kinds into the Canadian labour market.

Table 4.8: Fitted Returns to Immigrants and Native Born by Experience and Education Without Skill Effects

	Males			Females		
	Canadian Exp = 0	Canadian Exp = 10	Canadian Exp = 20	Canadian Exp = 0	Canadian Exp = 10	Canadian Exp = 20
Native Born (Less Than High School)	0.00	0.77	1.26	0.00	0.60	0.98
	-	(0.04)	(0.07)	-	(0.04)	(0.06)
Immigrant (Less Than High School)						
Foreign Experience = 0	0.63	1.01	1.22	0.64	0.96	1.13
	(0.13)	(0.11)	(0.10)	(0.25)	(0.18)	(0.15)
Foreign Experience = 10	0.55	0.93	1.14	0.82	1.14	1.31
	(0.14)	(0.13)	(0.12)	(0.21)	(0.13)	(0.11)
Native Born (High School)	0.42	1.1	1.48	0.60	1.11	1.38
	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)
Immigrant (Foreign High School)						
Foreign Experience = 0	0.74	1.13	1.33	0.78	1.10	1.27
	(0.13)	(0.10)	(0.09)	(0.17)	(0.11)	(0.12)
Foreign Experience = 10	0.67	1.05	1.26	0.96	1.28	1.45
	(0.12)	(0.10)	(0.09)	(0.14)	(0.09)	(0.11)
Native Born (University)	1.22	1.73	1.96	1.43	1.83	2.00
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Immigrant (Foreign University)						
Foreign Experience = 0	1.10	1.49	1.69	1.05	1.37	1.54
	(0.12)	(0.10)	(0.09)	(0.20)	(0.16)	(0.17)
Foreign Experience = 10	1.03	1.41	1.62	1.23	1.55	1.72
	(0.12)	(0.11)	(0.11)	(0.14)	(0.11)	(0.14)

Estimates are fitted log weekly earnings based on the parameter estimates in the final column of Tables 4.6 and 4.7, respectively, and differenced relative to the base group. The base group consists of English or French speaking native-born workers with less than a high school education, and experience normalized to zero.

An examination of the table entries corresponding to native born and foreign-educated immigrants who have not graduated from high school (the 1^{st} and 2^{nd} rows in the first and fourth columns, respectively) indicates that low educated immigrants earn considerably more than similarly educated native-born workers when they first enter the Canadian labour market. By moving along the first and second rows, we can see the effects of increasing Canadian experience for low educated workers. The larger increase as we move along the first row rather than the second arises because foreign-educated immigrants receive a lower return to Canadian experience than do native Canadians. Thus, the immigrant advantage right out of school is whittled away by the fact that the native born get a higher return to Canadian experience than do immigrants.[15]

Moving across rows 1, 4 and 7 shows the effects of greater Canadian experience for native-born workers with different levels of education. Earnings increase with experience for all three education categories, but the magnitude of the increase is smaller among well educated workers than among the poorly educated.

It is also instructive to move down each column to see the impacts of increased educational attainment for a given level of Canadian experience. Comparing rows 1, 4 and 7 to rows 2, 5 and 8 within each column illustrates the higher estimated returns to education for native born compared to foreign-educated immigrant workers.

Finally, a noteworthy feature of the immigrant - native born differences is that the patterns are very similar for men and women.

4.5.2 Results with literacy variables

Foreign-educated immigrants earn on average 7% less than native-born workers (this is true for both men and women, although the gap is not statistically significant for the latter). In contrast, Canadian-educated immigrant men earn about 2% more than native-born men (although this gap is not statistically significant), while immigrant women earn over 10% more. In column 1 of Tables 4.9 and 4.10 we show how controlling for average skill score affects these gaps in a simple regression with no other controls. Conditional on literacy skills, both Canadian and foreign-educated immigrants earn more than native-born workers. The disadvantage of foreign-educated immigrants turns into an advantage of 11% for men and 16% for women. Canadian-educated immigrant men earn 7% more, although the gap is still not statistically significant, while the gap doubles to almost 22% for women.

In the remaining columns of Tables 4.9 and 4.10, we use the preferred specification from Tables 4.6 and 4.7 but include the average skill score. A comparison of the second column in Tables 4.9 (males) and 4.10 (females), where we simply add the skill variable without any interactions, and the last column in Tables 4.6 and 4.7 respectively reveals the direct impact of cognitive skills and their indirect impacts on other returns. The returns to skills are substantial, with a 100-point increase in cognitive skills raising earnings by almost 30 percent.[16] The impact of skills on earnings is remarkably similar for men and women.

[15]Note that all of these statements are based on interpreting coefficients on Canadian experience as reflecting true returns to experience rather than cohort effects.

[16]However, these estimated returns to skills are lower than those obtained in our previous research for

As in Green and Riddell (2003), there is little, if any, change in the experience effects or experience interactions when we control for skills. However, estimated returns to education for natives and Canadian-educated immigrants decline to a significant extent, indicating that an important component of conventional estimates of the return to schooling arises from the impact of education on skills and the value placed on skills in the labour market.[17] With the inclusion of controls for cognitive skills, estimated returns to foreign-educated immigrants decline even more than was the case for the native born. Indeed, for men returns to education fall by about 50%; for women the decline is even greater, and, after controlling for skills, the remaining returns to education are no longer significantly different from zero. Thus, cognitive skills constitute a significant amount of what foreign education seems to deliver - at least in terms of the skills that are valued by Canadian employers.

As discussed earlier, a major question of interest is whether returns to skills are lower for immigrants. To investigate this issue we report in column 3 estimates based on a specification that allows the returns to skills to differ between immigrants and natives, but does not allow interactions between skills and human capital inputs like education and experience. As discussed previously, in the absence of such interaction effects differences in the coefficient on the average skill measure between immigrants and the native born can be interpreted as a clear measure of discrimination. The estimates in column 3 provide no evidence of discrimination in the sense of immigrants receiving a lower return to cognitive skills. Indeed, male immigrants receive a rate of return that is about 50% greater than that experienced by native-born men (earnings gains for immigrants of 37% associated with a 100 point increase in cognitive skills, versus 24% for native Canadians) while female immigrants receive returns equal to those of natives - earnings gains of approximately 28%.

In column 4 we report a more general specification that allows returns to skills to differ across the three groups, again estimated without interactions with skills. Among males, foreign-educated immigrants receive the largest returns to skills, followed by immigrants with Canadian education, and natives receive the lowest (although still substantial) returns. The differences in returns between natives and foreign-educated immigrants are statistically significant, but the pair-wise differences between the other two groups (natives versus Canadian-educated immigrants, Canadian-educated versus foreign-educated immigrants) are not statistically significant at conventional levels. A test of the hypothesis that all three coefficients equal each other cannot be rejected at the 10% level. Among females, foreign-educated immigrants also experience the greatest returns, followed by native Canadians, with Canadian-educated immigrants receiving the lowest returns. The three coefficients are also not significantly different from each other at the 10% level. However, in a pairwise comparison of Canadian and foreign-educated immigrants, we can reject equality of earnings impacts at the 10% level.

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native-born workers with the IALS data (Green and Riddell (2003)) and for immigrants with the OILS data (Ferrer, Green and Riddell (2006)). These differences warrant further investigation.

[17] For example, the earnings gain associated with a university education (relative to less than high school) falls by 18 percentage points for men and 15 percentage points for women.

Table 4.9: Earnings Regressions with Skill Effects – Males

	(1)	(2)	(3)	(4)	(5)
Avg Skill Score /100	0.414***	0.281***			
	(0.036)	(0.033)			
Avg Skill Score /100 (Native Born)			0.244***	0.241***	0.108
			(0.051)	(0.050)	(0.093)
Avg Skill Score /100 (Immigrants)			0.368***		
			(0.045)		
Avg Skill Score /100 (Immig Cdn Educ)				0.317***	0.267***
				(0.076)	(0.085)
Avg Skill Score /100 (Immig No Cdn Educ)				0.408***	0.279***
				(0.056)	(0.098)
Avg Skill Score /100 * Exp (Native Born)					0.007**
					(0.003)
Avg Skill Score /100 * Foreign Exp (Immigrants)					0.011*
					(0.006)
Immigrant (Cdn Educ)	0.077	0.068	-0.288	-0.152	-0.416
	(0.048)	(0.085)	(0.246)	(0.308)	(0.427)
Immigrant (No Cdn Educ)	0.114**	0.814***	0.541*	0.458*	0.439
	(0.054)	(0.157)	(0.276)	(0.268)	(0.409)
Cdn Exp (Native Born)		0.092***	0.092***	0.092***	0.071***
		(0.005)	(0.005)	(0.005)	(0.012)
Cdn Exp Sq / 100 (Native Born)		-0.140***	-0.141***	-0.140***	-0.134***
		(0.008)	(0.008)	(0.008)	(0.009)
Cdn Exp (Immig Cdn Educ)		0.076***	0.075***	0.076***	0.079***
		(0.013)	(0.012)	(0.012)	(0.013)
Cdn Exp Sq / 100 (Immig Cdn Educ)		-0.087***	-0.085***	-0.086***	-0.089***
		(0.029)	(0.028)	(0.028)	(0.030)
Foreign Exp (Immig Cdn Educ)		0.004	0.006	0.004	-0.027
		(0.016)	(0.015)	(0.015)	(0.025)
Foreign Exp Sq / 100 (Immig Cdn Educ)		0.036	0.031	0.034	0.053
		(0.053)	(0.052)	(0.052)	(0.055)

Table 4.9: cont'd

	(1)	(2)	(3)	(4)	(5)
Cdn Exp (Immig No Cdn Educ)		0.049***	0.050***	0.050***	0.054***
		(0.011)	(0.011)	(0.012)	(0.012)
Cdn Exp Sq / 100 (Immig No Cdn Educ)		-0.091***	-0.092***	-0.092***	-0.101***
		(0.032)	(0.032)	(0.032)	(0.033)
Foreign Exp (Immig No Cdn Educ)		-0.010	-0.010	-0.010	-0.041*
		(0.009)	(0.008)	(0.009)	(0.021)
Foreign Exp Sq / 100 (Immig No Cdn Educ)		0.014	0.016	0.016	0.036
		(0.020)	(0.020)	(0.019)	(0.025)
HS (NB & Immig Cdn Educ)		0.356***	0.363***	0.365***	0.393***
		(0.087)	(0.085)	(0.085)	(0.078)
PS (NB & Immig Cdn Educ)		0.719***	0.730***	0.732***	0.774***
		(0.076)	(0.077)	(0.077)	(0.073)
Univ (NB & Immig Cdn Educ)		1.042***	1.050***	1.058***	1.124***
		(0.084)	(0.083)	(0.086)	(0.081)
High School (Immig No Cdn Educ)		0.020	-0.016	-0.034	-0.074
		(0.088)	(0.090)	(0.087)	(0.082)
Non-Univ Post-Sec (Immig No Cdn Educ)		0.207**	0.152	0.125	0.082
		(0.098)	(0.101)	(0.100)	(0.093)
University (Immig No Cdn Educ)		0.267***	0.194**	0.158	0.147
		(0.084)	(0.090)	(0.093)	(0.099)
HS * Cdn Exp (NB & Immig Cdn Educ)		-0.011***	-0.011***	-0.011***	-0.012***
		(0.003)	(0.003)	(0.003)	(0.003)
PS * Cdn Exp (NB & Immig Cdn Educ)		-0.021***	-0.021***	-0.021***	-0.023***
		(0.003)	(0.003)	(0.003)	(0.003)
Univ * Cdn Exp (NB & Immig Cdn Educ)		-0.026***	-0.026***	-0.026***	-0.029***
		(0.004)	(0.004)	(0.004)	(0.004)
First Language not English or French		-0.027	-0.021	-0.018	-0.020
		(0.045)	(0.046)	(0.045)	(0.044)
Did Not Complete Main Skill Tasks		0.098***	0.104***	0.106***	0.110***
		(0.026)	(0.026)	(0.026)	(0.026)
US or UK Origin		0.031	-0.003	-0.004	0.004
		(0.099)	(0.094)	(0.094)	(0.094)
European Origin		0.173**	0.159*	0.161*	0.155*
		(0.080)	(0.082)	(0.083)	(0.084)
Asian Origin		-0.015	-0.024	-0.022	-0.030
		(0.050)	(0.052)	(0.052)	(0.057)
Observations	4551	4551	4551	4551	4551
R-squared	0.07	0.45	0.45	0.45	0.45

Specification (1) adds our measure of cognitive skills to a regression with separate intercepts for immigrants with and without Canadian education. The mean earnings for the native born and the two groups of immigrants without controlling for skills are reported in the first paragraph of Subsection 4.5.2. Specification (2) adds our measure of cognitive skills to the preferred specification from Table 4.6. Specification (3) estimates separate returns to skills for all immigrants relative to the native born. Specification (4) estimates separate returns to skills for the two groups of immigrants relative to the native born. Column (5) contains our preferred specification with skills controls. Regressions include indicators for province of residence. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4.10: Earnings Regressions with Skill Effects – Females

	(1)	(2)	(3)	(4)	(5)
Avg Skill Score /100	0.485***	0.281***			
	(0.038)	(0.038)			
Avg Skill Score /100			0.281***	0.278***	0.125
(Native Born)			(0.045)	(0.046)	(0.099)
Avg Skill Score /100			0.283***		
(Immigrants)			(0.041)		
Avg Skill Score /100				0.196***	0.192***
(Immig Cdn Educ)				(0.064)	(0.064)
Avg Skill Score /100				0.373***	-0.077
(Immig No Cdn Educ)				(0.064)	(0.234)
Avg Skill Score /100 * Experience					0.008*
(Native Born)					(0.004)
Avg Skill Score /100 * High School					0.515**
(Immig No Cdn Educ)					(0.202)
Avg Skill Score /100 * Non-Univ PS					0.345
(Immig No Cdn Educ)					(0.266)
Avg Skill Score /100 * University					0.708**
(Immig No Cdn Educ)					(0.314)
Immigrant (Cdn Educ)	0.218***	0.197**	0.189	0.428*	-0.036
	(0.049)	(0.078)	(0.163)	(0.210)	(0.269)
Immigrant (No Cdn Educ)	0.161***	0.842***	0.836***	0.654***	1.033**
	(0.057)	(0.245)	(0.267)	(0.234)	(0.501)
Cdn Exp (Native Born)		0.074***	0.074***	0.074***	0.049***
		(0.005)	(0.005)	(0.005)	(0.013)
Cdn Exp Sq / 100 (Native Born)		-0.114***	-0.114***	-0.114***	-0.106***
		(0.013)	(0.013)	(0.013)	(0.013)
Cdn Exp (Immig Cdn Educ)		0.074***	0.074***	0.074***	0.078***
		(0.007)	(0.007)	(0.007)	(0.007)
Cdn Exp Sq / 100 (Immig Cdn Educ)		-0.113***	-0.113***	-0.115***	-0.118***
		(0.018)	(0.018)	(0.017)	(0.018)
Foreign Exp (Immig Cdn Educ)		-0.010	-0.010	-0.015	-0.016
		(0.012)	(0.011)	(0.012)	(0.013)
Foreign Exp Sq / 100 (Immig Cdn Educ)		0.084*	0.084*	0.094**	0.099**
		(0.043)	(0.041)	(0.046)	(0.046)

Table 4.10: cont'd

	(1)	(2)	(3)	(4)	(5)
Cdn Exp (Immig No Cdn Educ)		0.040**	0.040**	0.040***	0.041***
		(0.015)	(0.015)	(0.014)	(0.014)
Cdn Exp Sq / 100 (Immig No Cdn Educ)		-0.079**	-0.079**	-0.079**	-0.083**
		(0.033)	(0.033)	(0.033)	(0.032)
Foreign Exp (Immig No Cdn Educ)		0.031*	0.031*	0.033*	0.035*
		(0.016)	(0.016)	(0.016)	(0.017)
Foreign Exp Sq / 100 (Immig No Cdn Educ)		-0.081*	-0.081*	-0.083*	-0.099*
		(0.046)	(0.046)	(0.046)	(0.049)
HS (NB & Immig Cdn Educ)		0.546***	0.546***	0.551***	0.581***
		(0.088)	(0.088)	(0.088)	(0.084)
PS (NB & Immig Cdn Educ)		0.938***	0.938***	0.946***	0.979***
		(0.129)	(0.129)	(0.130)	(0.132)
Univ (NB & Immig Cdn Educ)		1.280***	1.280***	1.289***	1.355***
		(0.083)	(0.083)	(0.084)	(0.090)
High School (Immig No Cdn Educ)		-0.0001	-0.001	-0.049	-1.007***
		(0.132)	(0.133)	(0.153)	(0.346)
Non-Univ Post-Sec (Immig No Cdn Educ)		0.092	0.090	0.025	-0.514
		(0.144)	(0.142)	(0.166)	(0.446)
University (Immig No Cdn Educ)		0.179	0.178	0.101	-1.402*
		(0.139)	(0.139)	(0.165)	(0.701)
HS * Cdn Exp (NB & Immig Cdn Educ)		-0.011***	-0.011***	-0.011***	-0.013***
		(0.003)	(0.003)	(0.003)	(0.003)
PS * Cdn Exp (NB & Immig Cdn Educ)		-0.021***	-0.021***	-0.021***	-0.023***
		(0.005)	(0.005)	(0.005)	(0.005)
Univ * Cdn Exp (NB & Immig Cdn Educ)		-0.021***	-0.021***	-0.021***	-0.025***
		(0.003)	(0.003)	(0.003)	(0.004)
First Language not English or French		-0.048	-0.048	-0.049	-0.048
		(0.052)	(0.051)	(0.051)	(0.051)
Did Not Complete Main Skill Tasks		0.015	0.015	0.018	0.010
		(0.041)	(0.041)	(0.041)	(0.042)
US or UK Origin		-0.119	-0.119	-0.129	-0.131
		(0.126)	(0.126)	(0.125)	(0.131)
European Origin		-0.100	-0.100	-0.101	-0.101
		(0.074)	(0.074)	(0.075)	(0.078)
Asian Origin		-0.063	-0.063	-0.054	-0.038
		(0.067)	(0.067)	(0.067)	(0.071)
Observations	5003	5003	5003	5003	5003
R-squared	0.09	0.38	0.38	0.38	0.38

Specification (1) adds our measure of cognitive skills to a regression with separate intercepts for immigrants with and without Canadian education. The mean earnings for the native born and the two groups of immigrants without controlling for skills are reported in the first paragraph of Subsection 4.5.2. Specification (2) adds our measure of cognitive skills to the preferred specification from Table 4.7. Specification (3) estimates separate returns to skills for all immigrants relative to the native born. Specification (4) estimates separate returns to skills for the two groups of immigrants relative to the native born. Column (5) contains our preferred specification with skills controls. Regressions include indicators for province of residence. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Once we allow the impact of cognitive skills on earnings to differ across the three groups, returns to education decline markedly for foreign-educated immigrants, and remain much smaller than for the native born. Indeed, for both male and female foreign-educated immigrants the coefficients on educational attainment are no longer significantly different from zero. Immigrants who finished their education prior to arrival in Canada receive substantially greater returns to skills than do natives but lower returns to formal education after we control for skills. Within our analytical framework, the implication is that education acquired abroad produces cognitive skills such as literacy, numeracy and problem solving skills (since the educational attainment coefficients change substantially with the introduction of the skill variable) but does not produce other skills that are valued in the Canadian labour market (since the educational attainment coefficients are not significantly different from zero once we control for skills).

In summary, when we allow the impacts of skills on earnings to differ across the three groups, we find no evidence that the returns to skills for natives exceed those for Canadian-educated or foreign-educated immigrants. Indeed, among foreign-educated immigrant men the earnings gains associated with additional skills are significantly greater than those for native Canadians, while those for Canadian-educated immigrants are not significantly different from those for natives. Among women the skills-related earnings gains received by natives are not significantly different from those received by Canadian-educated or foreign-educated immigrants. Thus these estimates provide no evidence of discrimination in the sense of employers paying immigrants less for the same skills as native-born workers. It is worth emphasizing that this result refers to what we call "usable" skills. Immigrants may have higher cognitive skill scores if tested in their native language and one could argue that those skills are being undervalued. But immigrants are receiving returns to skills as measured in English or French that are no worse than those obtained by native-born workers.

The last specification in column 5 is the result of a specification search involving interactions of average skill scores with education and experience. The results indicate some interaction of skills with experience for native-born men and women and for male (but not female) immigrants. The two immigrant groups are pooled in this case because the (foreign) experience-skills interaction effects of the two groups were not significantly different from each other. These interaction effects are positive, suggesting that immigrant men and native-born men and women with higher skill levels receive greater returns to work experience. The interaction effects are moderate in size; for example, an extra 25 skill points raises the returns to experience by about 2 percentage points. For men the interaction is somewhat larger among immigrants than natives, but this is not the case for women as there is no evidence of an interaction between experience (Canadian or foreign) and skills for immigrant women.

Perhaps the most interesting implication from the last column is the strong evidence of a positive interaction between education and skills for female immigrants educated outside Canada. The magnitude of this effect is largest at the university level, followed by the high school graduate level. Including these interaction terms results in the coefficient on the average skill score of foreign-educated female immigrants falling to zero. This implies that women with less than a high school education receive zero returns to additional skills, while women with at least a high school education experience earnings gains from a 100-point increase in skills in the order of 35% to 71%. However, returns to skills do not vary with educational attainment for native-born women and Canadian-educated immigrant women. The interaction terms between education and skills were also not statistically significant among men. The reasons for these differences between foreign-educated immigrants and the other two groups in the way skills and education interact in influencing earnings - and the differences in the nature of these interactions between men and women - warrant further analysis.

Finally, the dummy variable corresponding to men whose skill scores were imputed indicates that inability (or unwillingness) to complete the main test is positively associated with earnings. These men, many of whom are immigrants, earn approximately 10% more than one would anticipate given their imputed skill scores and other characteristics. This positive coefficient is consistent with results in other studies indicating the importance of immigrant enclaves in allowing immigrants to do better than expected when they do not acquire the host country language (Edin et al. (2003)). However, the result does not hold for females, for whom there is no difference in earnings associated with not completing the main tasks.

Tables C.2 and C.3 in Appendix C reproduce the results in Tables 4.9 and 4.10 with a different specification, one in which the average skills score enters the regression in log form rather than linearly. The main differences in conclusions drawn about the relationship between literacy and earnings pertain to interaction effects with experience and education (column 5 of Tables C.2 and C.3). For immigrant men, we no longer find a significant interaction effect between foreign experience and skills. We do, however, find evidence of an interaction with Canadian education. The estimated interaction effects are positive, suggesting that native-born men and Canadian-educated immigrant men with higher skill levels receive greater returns to higher education. The impacts of cognitive skills are largest at the post-secondary level. Note that these effects are only marginally significant and not very stable. When estimated separately for native-born and Canadian-educated immigrant men, the coefficients on the interaction terms with some post-secondary and university education are significant at the 10% level for both groups. Since we cannot reject the hypothesis that the effects are different for the two groups, they are pooled in the preferred specification. Now, however, the interaction term with university education is no longer significant. In the women's sample, we no longer find a significant interaction between skills and experience for the native born. Our key finding that returns to skills are not significantly different for the three groups remains unchanged. In fact, we cannot reject equality of returns in either a joint test nor in pairwise comparisons, for both men and women.

Table 4.11: Fitted Returns to Immigrants and Native Born by Experience and Education With Skill Effects

	Males			Females		
	Canadian Exp = 0	Canadian Exp = 10	Canadian Exp = 20	Canadian Exp = 0	Canadian Exp = 10	Canadian Exp = 20
Native Born (Less Than High School)	0.31	1.08	1.59	0.35	0.97	1.38
	(0.26)	(0.28)	(0.29)	(0.28)	(0.29)	(0.29)
Immigrant (Less Than High School)						
Foreign Experience = 0	1.23	1.66	1.90	0.81	1.14	1.30
	(0.33)	(0.30)	(0.30)	(0.44)	(0.40)	(0.39)
Foreign Experience = 10	1.16	1.59	1.82	1.06	1.39	1.54
	(0.33)	(0.31)	(0.31)	(0.39)	(0.36)	(0.35)
Native Born (High School)	0.70	1.35	1.74	0.93	1.43	1.71
	(0.28)	(0.30)	(0.30)	(0.30)	(0.30)	(0.31)
Immigrant (Foreign High School)						
Foreign Experience = 0	1.15	1.59	1.82	1.26	1.59	1.75
	(0.32)	(0.29)	(0.29)	(0.33)	(0.31)	(0.31)
Foreign Experience = 10	1.08	1.52	1.75	1.51	1.84	1.99
	(0.32)	(0.30)	(0.30)	(0.32)	(0.30)	(0.30)
Native Born (University)	1.43	1.92	2.13	1.71	2.08	2.23
	(0.26)	(0.27)	(0.28)	(0.26)	(0.28)	(0.30)
Immigrant (Foreign University)						
Foreign Experience = 0	1.38	1.81	2.04	1.42	1.74	1.90
	(0.31)	(0.29)	(0.29)	(0.35)	(0.33)	(0.34)
Foreign Experience = 10	1.30	1.74	1.97	1.66	1.99	2.15
	(0.32)	(0.31)	(0.31)	(0.32)	(0.30)	(0.31)

Estimates are fitted log weekly earnings based on the parameter estimates in the final column of Tables 4.9 and 4.10, respectively, and differenced relative to the base case. The base group consists of English or French speaking native-born workers with average skill score, less than high school education, and experience normalized to zero.

To aid in the interpretation of the results in the last column of Tables 4.9 and 4.10, we repeat the exercise of forming fitted average log earnings for various types of workers but, in this case, holding the average skill score constant at 283 (the sample weighted average value for men and women). The results are contained in Table 4.11. Comparing these results to those in Table 4.8, one sees patterns similar to those when skills are not held constant.

One interesting question arising out of these estimates is the relative importance of lower immigrant skill levels in explaining immigrant-native born earnings differentials. To investigate this, we constructed a series of fitted average earnings differentials, all based on the last column in Tables 4.9 and 4.10. We first construct an estimate of average log earnings for immigrants and the native born separately using the estimated coefficients in conjunction with the appropriate average values for the regressors.[18] Those estimates imply an overall average immigrant earnings disadvantage of 11 log points over the native born among high school educated men and an immigrant advantage of 1 log point among high school educated women. The corresponding estimates among those with university education imply an immigrant disadvantage of 22 log points for men and 19 log points for women. We next repeated this exercise but gave immigrants the same return to foreign experience as the native born receive for their Canadian experience. The result is a shift from the immigrant disadvantage of 11 log points to an advantage of 46 log points for high school educated men - a net change of 57 percentage points in the earnings gap - and a shift from the immigrant advantage of 1 log point to an immigrant advantage of 13 log points for high school educated women - a net change of 12 percentage points. Among the university educated the immigrant disadvantage changes from 22 log points to an immigrant advantage of 28 log points for men - a net change of 50 percentage points in the earnings gap, and from an immigrant disadvantage of 19 log points to a disadvantage of 8 log points for women, a net change of 11 percentage points. These estimates fit with results in earlier papers, described above, indicating that lower returns to foreign experience play an important role in understanding immigrant-native born earnings differentials, especially for men. The importance of low returns to foreign experience is much more important for men than for women, but for each gender is similar across education groups.

In our next counterfactual, we set the returns to foreign experience back to their original values but gave immigrants the average skill scores observed for native-born workers with the same level of education. For high school educated men, this reduces the immigrant disadvantage from the 11 log points mentioned above to an advantage of 5 log points, a net change of 16 percentage points, and among high school educated women it increases the immigrant advantage from 1 log point to 14 log points, a net change of 13 percentage points. For the university educated, it reduces the immigrant disadvantage from 22 log points to 11 log points for males and from 19 log points to 1 log point for females, net changes of 11 and 18 percentage points respectively. Again, the changes in the earnings differential are similar across the two education groups. Low skills thus appear to be an important factor

[18]We constructed fitted average earnings separately for the two immigrant groups; the estimates for immigrants as a whole are weighted averages of the fitted earnings for immigrants with and without Canadian education.

for understanding male immigrant earnings differentials, though not nearly as important as low returns to foreign experience. However, for females low skills are a somewhat more important factor in explaining immigrant - native born earnings differences than are low returns to foreign experience.

4.6 Conclusions

At the outset of the chapter, we posed four questions related to immigrant skills and earnings. First, do the cognitive skills of immigrants differ from those of the native born? Second, do immigrant - native born skill differences depend on where immigrant human capital was acquired? Third, do immigrants receive a different return to those skills than observationally equivalent native-born workers? Fourth, can differences in levels and returns to cognitive skills help explain differences in earnings between immigrant and native-born workers? Based on an examination of data that include both earnings and skill test scores for immigrants and the native born, the answer to the first question is clearly yes. The native-born literacy distributions first order stochastically dominate the distributions for immigrants. This is not just a reflection of differences in observable characteristics such as education since immigrants have lower average test scores than observationally equivalent native-born workers. These differences in measured skills may partially reflect host country language proficiency. As a result, the test scores should be interpreted as reflecting cognitive skills that are "usable" in the Canadian economy.

The answer to the second question is clearly Yes. We find substantial differences in behaviour and outcomes between immigrants who obtained their education prior to arrival in Canada and immigrants with Canadian education. Foreign-educated immigrants have much lower skills and earnings than immigrants with Canadian education. Indeed, the latter group is in many respects more similar to the native born than to foreign-educated immigrants.

The answer to the third question is a resounding No. There is no evidence that immigrants receive a lower return to the types of cognitive skills measured in IALSS than otherwise equivalent native-born workers. If we rely on Becker's notion of discrimination (i.e. equally productive workers being paid unequally) this indicates that immigrant-native born earnings differentials cannot be explained by discrimination, at least in this dimension.

Cognitive skills have a significant impact on earnings. A 100-point increase in the literacy score (equivalent to approximately one and a half standard deviations in the literacy distribution) raises earnings of men and women by almost 30 percent. Introducing the average skill score into a standard earnings regression reduces estimated education differentials by about 10-20 percent for the native born, and by substantially more for foreign-educated immigrants.

The result that cognitive skills have a significant impact on earnings implies that lower immigrant skill levels may help in understanding immigrant-native born earnings differentials. This is indeed the case. If immigrants had the same average skills as the native born, the earnings differential between high school educated immigrants and natives would narrow by about 13-16 percentage points. This change would turn the 11% earnings disadvantage of immigrant men with high school education into a 5% advantage, and would raise the advantage of high school educated female immigrants to almost three times that magnitude. Similarly, this change would reduce by half the immigrant earnings disadvantage among university educated men and would eliminate the 19 percentage point disadvantage among university educated women. It is worth noting, as well, that controlling for cognitive skills does not affect the relative patterns of returns to foreign and Canadian acquired experience. Thus, this important dimension of immigrant earnings patterns is not related to workers' cognitive skills.

Chapter 5

Concluding Remarks

This dissertation uses new information available in Canadian survey data to address some new issues like the determinants of educational attainment of second-generation immigrants, and re-assess answers to some older questions regarding determinants of labour market outcomes of first generation immigrants. The goal in this thesis was to test several commonly held assumptions, hypotheses and/or arguments regarding the immigrant adaptation experience in order to better understand the causes and consequences of those experiences.

In Chapter 2 I show that there is more to the gap in educational attainment between children of immigrants and their native-born counterparts than simply parental education and cultural preferences. I offer evidence in support of the presence of tradeoffs in human capital investments between immigrant parents and their children, particularly in families where the parents have low education levels. These tradeoffs lead to higher educational outcomes among immigrant children from low-education backgrounds than their native-born counterparts. The evidence of tradeoffs in immigrant families with well-educated parents is weak, but to the extent that such tradeoffs exist, they could work to the disadvantage of the children. In view of the results in this chapter, the deteriorating labour market outcomes (at least in terms of entry earnings) of the increasingly well-educated immigrants to Canada is cause for concern. The response of immigrants to poor labour market outcomes may have consequences that persist for several generations, and it will take many more years before we will be able to observe the actual consequences in the data.

In Chapter 3 I draw on results from existing international studies to re-assess the evidence on the association between ethnic enclaves and labour market outcomes of immigrants in Canada. I find that immigrant cohorts from the 1980s have higher earnings in cities with a higher proportion of co-ethnics. That positive correlation is no longer evident among the more recent cohorts. The enclave effect is still very much a black box and may be capturing the effect of any number of factors. Only one is referred to consistently in the literature, namely more social interaction with co-ethnics in larger ethnic enclaves. Data from the Ethnic Diversity Survey on the proportion of co-ethnic friends allow me to construct a more direct measure of social interaction with co-ethnics and for the first time provide some evidence on the relationship between social networks and the overall ethnic enclave effect.

The relationship turns out not to be as strong as commonly believed. This has implications particularly for studies that use geography-based measures of supply of potential networks to proxy for actual networks. The effects that such geography-based measures are capturing appear to have little to do with networks. In fact, they offset the very network effects researchers are trying to measure. There are several possible extensions to this study. The first is to reproduce the results using the master files of the Canadian census to obtain better estimates of the proportion of co-ethnics in an immigrant's city of residence. The 20% census samples will also allow a robustness check where the exposure index is measured as the proportion of co-ethnics in an immigrant's neighbourhood of residence (census tract), allowing more variation in the exposure index variable. Further, the analysis can be expanded to examine the effects of ethnic enclaves and social networks across the earnings distribution, rather than just at the mean. Another possible extension would be to account for some notion of ethnic enclave quality, e.g. co-ethnic friends will be more helpful as job contacts if they themselves are employed. Finally, results in this chapter suggest that there may be a link between the disappearance of the earnings advantage associated with living in ethnic enclaves and the observed cross-cohort decline in immigrant entry earnings, given their timing. This possibility is perhaps also worth pursuing in future research.

In Chapter 4 we provide strong evidence against the argument that immigrants earn lower wages than native-born workers with similar education and experience because of discrimination by employers. Data on literacy test scores from the IALSS allow us to construct a measure of cognitive skills with which to test this hypothesis and data on the origin of the immigrants' highest level of education allow us to examine whether Canadian and foreign education generate comparable levels of cognitive skills (as measured in English or French). We find that immigrants, particularly the foreign-educated, do indeed have lower cognitive skills which can explain much of the observed gap in earnings. Contrary to the discrimination argument, they face similar if not higher returns to their cognitive skills than comparable native-born workers. My co-authors and I hope to extend this study and examine cohort effects in the cognitive skills of immigrants to Canada. This analysis could shed light on the observed decline in entry earnings across successive and increasingly well-educated immigrant cohorts.

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Appendix A

Appendix to Chapter 2

Comparative Statics with Borrowing

In the benchmark model, where individuals can borrow at an interest rate r against future earnings, the comparative statics are given by:

$$\frac{\partial t^*}{\partial \tau_p} = \frac{\delta_2}{(1-\delta_1)\tau_p} t^* > 0 \tag{A.0.1}$$

$$\frac{\partial t^*}{\partial \tau_{m1}} = -\frac{1}{(1-\delta_1)\tau_{m1}} t^* < 0 \tag{A.0.2}$$

$$\frac{\partial S^*}{\partial \tau_p} = \frac{\beta\alpha\xi}{p(1+\beta+\beta\alpha\xi)} \left(\frac{\delta_2}{(1-\delta_1)\tau_p}\right) \left[\frac{a\gamma_p(\tau_p H_p)^{\delta_2} t^{*\delta_1}}{1+r} - a\tau_{m1} H_p t^*\right] > 0 \tag{A.0.3}$$

$$\begin{aligned} \frac{\partial S^*}{\partial \tau_{m1}} &= \frac{\beta\alpha\xi}{p(1+\beta+\beta\alpha\xi)} \left[a H_p(1-t^*) + a\tau_{m1} H_p t^* \frac{1}{(1-\delta_1)\tau_{m1}}\right] \\ &- \frac{\beta\alpha\xi}{p(1+\beta+\beta\alpha\xi)} \left[\frac{a\gamma_p(\tau_p H_p)^{\delta_2} t^{*\delta_1}}{1+r} \frac{\delta_1}{(1-\delta_1)\tau_{m1}}\right] \gtreqless 0 \end{aligned} \tag{A.0.4}$$

The sign of $\frac{\partial S^*}{\partial \tau_p}$ depends on the relationship between the total costs (foregone period 1 earnings, $a\tau_{m1}H_p t^*$ or $w_{min}t^*$ for individuals with low human capital) of parental investment in their own human capital and the present value of total benefits (period 2 earnings resulting from such investments). At the optimum, total benefits will exceed total costs, making $\frac{\partial S^*}{\partial \tau_p} > 0$.

Signing $\frac{\partial S^*}{\partial \tau_{m1}}$ is not as straightforward. The sign depends on whether a fraction of the present value of total benefits of investment in parental human capital is smaller than the total costs plus the first period earnings that a native-born worker would earn at the optimal level of investment of an equivalent immigrant. Although the answer depends on the model's parameter values, this comparative static is likely to be positive.

Comparative Statics with Extreme Credit Constraints

Under the assumption of extreme credit constraints, where individuals can neither save nor borrow, a closed form solution cannot be obtained for optimal investment in parental human capital with the specific functional form chosen. The first order condition for optimal investment in parental human capital is given by:

$$\frac{a\tau_{m1}H_p}{a\tau_{m1}H_p(1-t)-pS}-\frac{\beta a\gamma_p(\tau_pH_p)^{\delta_2}\delta_1}{(a\tau_{m2}H_p+a\gamma_p(\tau_pH_p)^{\delta_2}t^{\delta_1})t^{1-\delta_1}}=0 \tag{A.0.5}$$

By taking total derivatives of the above with respect to τ_p, the degree to which foreign human capital transfers to the production of host country specific human capital, we obtain the following expression:

$$\frac{\partial t^*}{\partial \tau_p}=\frac{(a\tau_{m1}H_p)(a\gamma_p\delta_2\tau_p^{\delta_2-1}H_p^{\delta_2}t^*)\left(\frac{\beta\delta_1}{1+\beta\alpha\xi}\frac{1-t^*}{t^*}-1\right)}{\left(1+\frac{\beta\delta_1}{1+\beta\alpha\xi}\right)(a\tau_{m1}H_p)(a\gamma_p(\tau_pH_p)^{\delta_2})+(a\tau_{m1}H_p)(a\tau_{m2}H_p)(1-\delta_1)t^{*\delta_1}} \tag{A.0.6}$$

The denominator in the above expression is positive. The sign of the comparative static is therefore determined by the numerator. The numerator is positive when $\frac{\beta\delta_1}{1+\beta\alpha\xi}\frac{1-t^*}{t^*}>1$. For this to occur, $\frac{1-t^*}{t^*}$ must be sufficiently greater than one, since $\frac{\beta\delta_1}{1+\beta\alpha\xi}<1$. That is, when the fraction of time parents devote to investments in their own human capital versus working in period 1 is sufficiently less than 1/2, then $\frac{\partial t^*}{\partial\tau_p}>0$.

The marginal effect of τ_{m1}, the degree to which foreign human capital transfers to the production of host labour market, on the optimal amount of time parents spend investing in their own human capital is given by:

$$\frac{\partial t^*}{\partial \tau_{m1}}=\frac{aH_pt^*\left(a\gamma_p(\tau_pH_p)^{\delta_2}t^{*\delta_1}(\frac{\beta\delta_1}{1+\beta\alpha\xi}\frac{1-t^*}{t^*}-1)-a\tau_{m2}H_p\right)}{(1-\delta_1)a\tau_{m1}H_p(a\tau_{m2}H_p)+\left(\frac{\beta\delta_1}{1+\beta\alpha\xi}+1\right)(a\tau_{m1}H_p)(a\gamma_p(\tau_pH_p)^{\delta_2}t^{*\delta_1})} \tag{A.0.7}$$

The denominator of the above expression is positive. The sign of the numerator and therefore the entire expression depends on (1) the optimal fraction of time devoted to investments in parental human capital, and (2) the relative magnitude of period 2 earnings in the absence of any human capital investments, $a\tau_{m2}H_p$, and the additional earnings resulting from the optimal human capital investments, $a\gamma_p(\tau_pH_p)^{\delta_2}t^{*\delta_1}$.

The optimality condition for investment in children's schooling takes the following form:

$$S^*=\frac{\beta\alpha\xi}{p(1+\beta\alpha\xi)}a\tau_{m1}H_p(1-t^*) \tag{A.0.8}$$

The marginal effect of τ_p on the optimal amount of expenditure on children's schooling is given by:

$$\frac{\partial S^*}{\partial\tau_p}=-\frac{\beta\alpha\xi}{p(1+\beta\alpha\xi)}a\tau_{m1}H_p\frac{\partial t^*}{\partial\tau_p} \tag{A.0.9}$$

The direction of the effect of τ_p on the amount of investment in child's human capital is the opposite to its effect on the amount of investment in parental human capital. That is if $\frac{\partial t^*}{\partial\tau_p}>0$, then $\frac{\partial S^*}{\partial\tau_p}<0$.

The marginal effect of τ_{m1} on the optimal amount of investment in children's schooling is given by:

$$\frac{\partial S^*}{\partial \tau_{m1}} = \frac{\beta\alpha\xi}{p(1+\beta\alpha\xi)} a H_p (1-t^*) - \frac{\beta\alpha\xi}{p(1+\beta\alpha\xi)} a \tau_{m1} H_p \frac{\partial t^*}{\partial \tau_{m1}} \tag{A.0.10}$$

If $\frac{\partial t^*}{\partial \tau_{m1}} < 0$, then $\frac{\partial S^*}{\partial \tau_{m1}} > 0$ as in the case with no credit constraints. If $\frac{\partial t^*}{\partial \tau_{m1}} > 0$, $\frac{\partial S^*}{\partial \tau_{m1}}$ could be negative.

Appendix B

Appendix to Chapter 3

Table B.1: First Stage for 2SLS in Table 3.8

	2001 Census pumf			EDS	
	Men	Women		Men	Women
Dependent Variable	EI	EI		EI	EI
EI71	1.629**	1.568**	EI71	1.109**	1.164**
	(0.660)	(0.680)		(0.062)	(0.530)
YSM /100	0.066**	0.019	YSM /100	0.049	0.095
	(0.035)	(0.058)		(0.082)	(0.081)
YSM sq./100	-0.005***	-0.003	YSM sq./100	-0.004	-0.005
	(0.002)	(0.003)		(0.004)	(0.004)
College	-0.005**	-0.004*	College	0.0002	-0.001
	(0.003)	(0.001)		(0.003)	(0.003)
University	-0.005	-0.006**	University	-0.003	-0.007**
	(0.003)	(0.002)		(0.003)	(0.003)
East Indian	0.070***	0.073***	West Asia	0.001	0.009
	(0.019)	(0.020)		(0.006)	(0.006)
East Asian	0.070***	0.070**	E.&S.E. Asia	0.054***	0.051***
	(0.019)	(0.021)		(0.016)	(0.015)
Other origins	0.032*	0.038**	South Asia	0.031**	0.037***
	(0.018)	(0.019)		(0.014)	(0.013)
			Africa	0.002	0.004
				(0.007)	(0.006)
			Caribbean	0.008	0.013*
				(0.008)	(0.007)
			Other origins	0.001	0.002
				(0.007)	(0.006)
R-squared	0.52	0.48	R-squared	0.53	0.50
F-test on excluded instruments					
F(#, #)	(1, 159)	(1, 156)		(1, 282)	(1, 278)
	6.08	5.32		5.54	4.82
p-value	1.0147	0.0224		0.0193	0.0290

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.2: First Stage for 2SLS in column 2 of Table 3.9

	2001 Census pumf - Men			2001 Census pumf - Women		
Dependent variable	EI*hs	EI*coll	EI*univ	EI*hs	EI*coll	EI*univ
EI71*hs	1.384*	0.098	0.120	1.461*	0.134*	0.122**
	(0.729)	(0.080)	(0.089)	(0.755)	(0.070)	(0.059)
EI71*coll	0.245***	0.916	0.236***	0.228***	0.907	0.169***
	(0.075)	(0.591)	(0.076)	(0.064)	(0.570)	(0.054)
EI71*univ	0.251**	0.200***	1.491*	0.269***	0.232***	1.237
	(0.101)	(0.075)	(0.840)	(0.083)	(0.071)	(0.771)
YSM/100	0.047*	0.020	-0.007	0.009	0.018	-0.015
	(0.028)	(0.013)	(0.024)	(0.022)	(0.021)	(0.031)
YSM sq./100	-0.003**	-0.001**	0.00003	-0.001	-0.001	-0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College	-0.040***	0.037***	0.0003	-0.039***	0.039***	0.001
	(0.006)	(0.006)	(0.001)	(0.006)	(0.006)	(0.001)
University	-0.044***	-0.003**	0.038***	-0.043***	-0.002*	0.038***
	(0.005)	(0.001)	(0.007)	(0.006)	(0.001)	(0.006)
East Indian	0.026***	0.021***	0.024***	0.029***	0.025***	0.020***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)
East Asian	0.026***	0.021***	0.024***	0.027***	0.025***	0.018***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)	(0.006)
Other origins	0.008	0.009	0.014*	0.013**	0.011	0.013**
	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
R-squared	0.63	0.56	0.63	0.63	0.55	0.60
F-test on excluded instruments						
F(#, #)	(3, 157)	(3, 157)	(3, 157)	(3, 154)	(3, 154)	(3, 154)
	7.51	6.93	4.9	5.83	4.32	3.55
p-value	0.0001	0.0002	0.0028	0.0009	0.0059	0.0160

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.3: First Stage for 2SLS in column 4 of Table 3.9

	EDS - Men			EDS - Women		
	EI*hs	EI*coll	EI*univ	EI*hs	EI*coll	EI*univ
EI71*hs	1.022*	-0.004	0.005	2.270**	-0.127	-0.038
	(0.569)	(0.053)	(0.071)	(0.940)	(0.149)	(0.105)
EI71*coll	-0.061	1.316*	0.001	-0.010	1.353*	0.017
	(0.119)	(0.077)	(0.096)	(0.073)	(0.749)	(0.066)
EI71*univ	-0.062	-0.039	1.254	0.037	0.048	0.576*
	(0.119)	(0.086)	(0.766)	(0.030)	(0.031)	(0.339)
YSM/100	-0.026	0.107**	-0.037	0.069	0.009	0.025
	(0.067)	(0.048)	(0.050)	(0.047)	(0.046)	(0.067)
YSM sq./100	0.0004	-0.005***	0.001	-0.004*	-0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
College	-0.024***	0.022***	0.001	-0.021***	0.023***	0.001*
	(0.007)	(0.006)	(0.001)	(0.006)	(0.006)	(0.001)
University	-0.025***	0.001	0.021***	-0.022***	0.0005	0.023***
	(0.007)	(0.001)	(0.006)	(0.006)	(0.001)	(0.005)
West Asia	-0.002	0.005	-0.001	0.004	0.006*	-0.0003
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
E. & S.E. Asia	0.018**	0.017***	0.018***	0.015***	0.020***	0.013***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)
South Asia	0.008	0.010**	0.012**	0.011**	0.013***	0.014***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
Africa	0.001	0.0001	0.001	0.001	0.004	0.0002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
Caribbean	-0.003	0.004	0.008**	0.002	0.007*	0.007***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Other origins	-0.004	0.0002	0.005	-0.005	0.004	0.006**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
R-squared	0.49	0.52	0.48	0.63	0.52	0.42
F-test on excluded instruments						
F(#, #)	(3, 280)	(3, 280)	(3, 280)	(3, 276)	(3, 276)	(3,276)
	1.4	2.32	1.39	3.90	2.79	2.44
p-value	0.2437	0.0755	0.2469	0.0093	0.0407	0.0650

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.4: First Stage for 2SLS in Table 3.10
(Earnings, Men, Benchmark)

	EI	EI	SI	SI
Exposure Index 1971 (EI71)	1.098**	1.099**	0.908	
	(0.454)	(0.456)	(1.159)	
Childhood Social Segregation (CSI)		0.001	0.362***	0.360***
		(0.003)	(0.053)	(0.054)
College	0.002	0.002	-0.099**	-0.099**
	(0.003)	(0.003)	(0.049)	(0.049)
University	-0.001	-0.001	-0.188***	-0.190***
	(0.003)	(0.003)	(0.044)	(0.044)
Cdn exp /100	0.059	0.059	-1.347	-1.330
	(0.087)	(0.087)	(1.201)	(1.196)
Cdn exp sq./100	-0.005	-0.005	0.034	0.033
	(0.004)	(0.004)	(0.055)	(0.055)
For exp /100	-0.004	-0.003	-0.036	-0.034
	(0.037)	(0.038)	(0.574)	(0.573)
For exp sq./100	0.001	0.001	0.003	0.003
	(0.001)	(0.001)	(0.016)	(0.016)
Eng/Fr 1^{st} language	-0.009	-0.009	-0.148**	-0.150**
	(0.013)	(0.013)	(0.065)	(0.063)
Eng/Fr 2^{nd} language	-0.007	-0.007	-0.173***	-0.177***
	(0.012)	(0.012)	(0.051)	(0.049)
Married	0.002	0.002	0.193***	0.191***
	(0.005)	(0.005)	(0.053)	(0.052)
West Asia	0.001	0.001	-0.184**	-0.191***
	(0.006)	(0.006)	(0.072)	(0.070)
E. & S.E. Asia	0.053***	0.053***	0.187***	0.184***
	(0.015)	(0.015)	(0.052)	(0.052)
South Asia	0.031**	0.031**	0.080	0.068
	(0.014)	(0.014)	(0.061)	(0.057)
Africa	0.003	0.002	-0.050	-0.061
	(0.007)	(0.007)	(0.078)	(0.076)
Caribbean	0.011	0.011	-0.029	-0.042
	(0.009)	(0.009)	(0.114)	(0.111)
Other origins	-0.0001	-0.0001	-0.199**	-0.211**
	(0.007)	(0.007)	(0.093)	(0.090)
R-squared	0.54	0.54	0.21	0.21
F-test on excluded instruments				
F(#,#)	(1, 277)	(2, 276)	(2, 276)	(1, 277)
	5.84	3.52	24.2	44.87
p-value	0.0163	0.0308	0.0000	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.5: First Stage for 2SLS in Table 3.11
(Earnings, Women, Benchmark)

	EI	EI	SI	SI
Exposure Index 1971 (EI71)	1.146**	1.139**	0.647	
	(0.532)	(0.513)	(0.953)	
Childhood Social Segregation (CSI)		0.010**	0.328***	0.351***
		(0.004)	(0.052)	(0.054)
College	0.0005	0.001	-0.118*	-0.079*
	(0.003)	(0.003)	(0.043)	(0.045)
University	-0.005*	-0.004**	0.179**	-0.121**
	(0.003)	(0.003)	(0.050)	(0.053)
Cdn exp/100	0.068	0.142	-3.724	-1.012
	(0.066)	(0.080)	(1.312)	(1.137)
Cdn exp sq./100	-0.005	-0.009	0.175	0.037
	(0.004)	(0.005)	(0.060)	(0.063)
For exp/100	0.026	0.027	-0.444	-0.510
	(0.037)	(0.036)	(0.546)	(0.571)
For exp sq./100	-0.001	-0.001	0.032*	0.027*
	(0.001)	(0.001)	(0.013)	(0.014)
Eng/Fr 1^{st} language	-0.006	-0.002	-0.082	-0.050
	(0.008)	(0.008)	(0.086)	(0.093)
Eng/Fr 2^{nd} language	-0.007	-0.006	-0.076	-0.050
	(0.007)	(0.007)	(0.060)	(0.061)
Married	0.0001	0.0002	0.071**	0.088**
	(0.002)	(0.002)	(0.040)	(0.039)
West Asia	0.009	0.010	0.094	0.132
	(0.006)	(0.006)	(0.082)	(0.086)
E. & S.E. Asia	0.050***	0.050***	0.192***	0.234***
	(0.015)	(0.015)	(0.063)	(0.052)
South Asia	0.037***	0.040***	0.035*	0.105*
	(0.014)	(0.014)	(0.063)	(0.059)
Africa	0.003	0.004	-0.011	0.034
	(0.006)	(0.007)	(0.101)	(0.096)
Caribbean	0.013	0.012	0.163	0.169
	(0.008)	(0.008)	(0.116)	(0.109)
Other origins	0.002	0.002	-0.129	-0.097
	(0.007)	(0.007)	(0.114)	(0.122)
Hours (May 2001)	0.0001	0.0004	-0.018***	-0.006***
	(0.0001)	(0.0002)	(0.003)	(0.002)
Inv. Mills ratio	0.005	0.023	-0.865*	-0.205*
	(0.006)	(0.010)	(0.120)	(0.119)
R-squared	0.50	0.51	0.17	0.17
F-test on excluded instruments				
F(#, #)	(1, 271)	(2, 270)	(2, 270)	(1, 271)
	4.64	3.79	21.09	41.92
p-value	0.0321	0.0237	0.0000	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.6: First Stage for 2SLS in columns 2 and 6 of Table 3.12
(Earnings, Men, Preferred)

Dependent Variable	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	0.992**	0.002	0.012			
	(0.504)	(0.048)	(0.057)			
EI71*coll	-0.066	1.291*	0.008			
	(0.118)	(0.700)	(0.096)			
EI71*univ	-0.062	-0.030	1.253			
	(0.108)	(0.082)	(0.763)			
CSI*hs				0.468***	-0.022	0.0001
				(0.084)	(0.021)	(0.016)
CSI*coll				-0.006	0.400***	-0.037*
				(0.016)	(0.091)	(0.022)
CSI*univ				-0.015	-0.0002	0.266***
				(0.020)	(0.013)	(0.064)
College	-0.022***	0.022***	0.0001	-0.183**	0.131	0.026
	(0.006)	(0.006)	(0.001)	(0.074)	(0.082)	(0.020)
University	-0.023***	0.001	0.020***	-0.188***	-0.014	0.178***
	(0.006)	(0.001)	(0.006)	(0.068)	(0.021)	(0.056)
Cdn exp/100	-0.021	0.104***	-0.027	-1.056	0.686	-1.061
	(0.071)	(0.040)	(0.039)	(0.760)	(0.731)	(0.702)
Cdn exp sq./100	0.0003	-0.005***	0.0002	0.036	-0.021	0.023
	(0.003)	(0.002)	(0.002)	(0.038)	(0.033)	(0.032)
For exp/100	-0.067	0.064**	-0.003	-0.645*	0.185	0.433
	(0.041)	(0.030)	(0.023)	(0.362)	(0.300)	(0.323)
For exp sq./100	0.003*	-0.001*	-0.0001	0.023**	-0.004	-0.017**
	(0.002)	(0.001)	(0.001)	(0.011)	(0.007)	(0.008)
Eng/Fr 1^{st} language	-0.020	0.008***	0.003	-0.204***	0.070*	-0.004
	(0.016)	(0.003)	(0.003)	(0.067)	(0.036)	(0.045)
Eng/Fr 2^{nd} language	-0.022	0.009***	0.005*	-0.223***	0.034	0.025
	(0.016)	(0.002)	(0.003)	(0.064)	(0.022)	(0.040)
Married	0.006	-0.002	-0.002	0.098***	0.029	0.059*
	(0.004)	(0.001)	(0.002)	(0.032)	(0.027)	(0.033)
West Asia	-0.003	0.005*	-0.001	-0.084	-0.017	-0.096**
	(0.003)	(0.003)	(0.003)	(0.054)	(0.035)	(0.041)
E. & S.E. Asia	0.016***	0.018***	0.019***	0.036	0.061***	0.095***
	(0.006)	(0.005)	(0.005)	(0.036)	(0.024)	(0.032)
South Asia	0.007	0.012***	0.013**	0.005	0.060**	0.008
	(0.005)	(0.004)	(0.005)	(0.032)	(0.027)	(0.030)
Africa	0.001	0.001	0.001	-0.032	-0.045	0.027
	(0.003)	(0.003)	(0.003)	(0.034)	(0.045)	(0.049)
Caribbean	-0.003	0.005	0.009**	-0.006	-0.051	0.018
	(0.005)	(0.004)	(0.004)	(0.074)	(0.049)	(0.036)
Other origins	-0.006*	0.001	0.005	-0.063	-0.157***	0.043
	(0.003)	(0.003)	(0.003)	(0.068)	(0.059)	(0.050)
R-squared	0.5258	0.5271	0.485	0.5959	0.4797	0.393
F-test on excluded instruments						
F(3,275)	1.64	2.20	1.45	12.16	6.87	10.59
p-value	0.1797	0.0883	0.2283	0.0000	0.0002	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.7: First Stage for 2SLS in column 4 of Table 3.12
(Earnings, Men, Preferred)

Dependent Variable	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	0.994**	-0.002	0.013	-0.357	0.002	0.091
	(0.502)	(0.048)	(0.057)	(1.500)	(0.275)	(0.452)
EI71*coll	-0.062	1.299*	0.004	-0.489	3.682**	-0.649
	(0.113)	(0.697)	(0.095)	(0.528)	(1.035)	(0.687)
EI71*univ	-0.070	-0.042	1.257	-0.418	-0.077	2.166
	(0.109)	(0.084)	(0.766)	(0.533)	(0.329)	(2.589)
CSI*hs	0.007	-0.001	-0.0004	0.468***	-0.019	0.001
	(0.008)	(0.002)	(0.002)	(0.084)	(0.020)	(0.016)
CSI*coll	-0.003	0.010	-0.004	-0.006	0.406***	-0.039*
	(0.003)	(0.010)	(0.003)	(0.015)	(0.089)	(0.022)
CSI*univ	-0.005*	-0.004*	0.002	-0.016	-0.002	0.275***
	(0.003)	(0.002)	(0.005)	(0.021)	(0.013)	(0.062)
College	-0.014	0.012	0.003	-0.183**	0.101	0.035*
	(0.011)	(0.011)	(0.003)	(0.074)	(0.085)	(0.020)
University	-0.013	0.003	0.018**	-0.188***	-0.008	0.159***
	(0.010)	(0.002)	(0.007)	(0.069)	(0.020)	(0.049)
Cdn exp/100	-0.028	0.105***	-0.027	-1.047	0.583	-1.022
	(0.070)	(0.038)	(0.038)	(0.763)	(0.718)	(0.705)
Cdn exp sq./100	0.001	-0.005***	0.0002	0.036	-0.016	0.021
	(0.003)	(0.002)	(0.002)	(0.038)	(0.032)	(0.032)
For exp/100	-0.065	0.060**	-0.002	-0.643*	0.108	0.478
	(0.040)	(0.028)	(0.023)	(0.364)	(0.289)	(0.321)
For exp sq./100	0.003*	-0.001*	-0.0002	0.023**	-0.002	-0.018**
	(0.002)	(0.001)	(0.001)	(0.011)	(0.007)	(0.008)
Eng/Fr 1^{st} language	-0.019	0.008***	0.003	-0.205***	0.069*	-0.006
	(0.015)	(0.003)	(0.003)	(0.068)	(0.036)	(0.044)
Eng/Fr 2^{nd} language	-0.021	0.009***	0.005	-0.224***	0.029	0.025
	(0.015)	(0.002)	(0.003)	(0.065)	(0.021)	(0.039)
Married	0.006	-0.002	-0.002	0.097***	0.027	0.060*
	(0.004)	(0.002)	(0.002)	(0.032)	(0.022)	(0.033)
West Asia	-0.003	0.005*	-0.001	-0.088	-0.006	-0.095**
	(0.003)	(0.003)	(0.003)	(0.054)	(0.034)	(0.042)
E. & S.E. Asia	0.016***	0.018***	0.019***	0.035	0.066***	0.094***
	(0.006)	(0.005)	(0.005)	(0.036)	(0.022)	(0.032)
South Asia	0.008	0.011***	0.013**	-0.00003	0.075***	0.013
	(0.005)	(0.004)	(0.005)	(0.034)	(0.027)	(0.032)
Africa	0.001	0.00004	0.002	-0.037	-0.028	0.031
	(0.003)	(0.003)	(0.003)	(0.035)	(0.045)	(0.051)
Caribbean	-0.003	0.005	0.009**	-0.012	-0.036	0.021
	(0.005)	(0.004)	(0.004)	(0.075)	(0.050)	(0.037)
Other origins	-0.004	-0.0004	0.005	-0.069	-0.138**	0.035
	(0.004)	(0.004)	(0.003)	(0.069)	(0.057)	(0.055)
R-squared	0.529	0.5326	0.4858	0.5962	0.4867	0.3957
F-test on excluded instruments						
F(6,272)	1.54	1.61	0.96	6.55	5.12	6.82
p-value	0.1650	0.1439	0.4555	0.0000	0.0001	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.8: First Stage for 2SLS in columns 2 and 6 of Table 3.13
(Earnings, Women, Preferred)

Dependant Variable	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	2.231**	-0.139	-0.015			
	(0.939)	(0.149)	(0.098)			
EI71*coll	-0.015	1.357*	-0.004			
	(0.076)	(0.754)	(0.073)			
EI71*univ	0.029	0.042	0.578*			
	(0.026)	(0.031)	(0.333)			
CSI*hs				0.479***	-0.010	-0.005
				(0.083)	(0.014)	(0.015)
CSI*coll				0.003	0.350***	-0.022
				(0.017)	(0.097)	(0.018)
CSI*univ				0.007	-0.049*	0.219**
				(0.025)	(0.027)	(0.088)
College	-0.020***	0.023***	0.001	-0.251***	0.261***	0.021
	(0.006)	(0.006)	(0.001)	(0.075)	(0.096)	(0.021)
University	-0.020***	0.001	0.023***	-0.272***	0.036*	0.361***
	(0.006)	(0.001)	(0.005)	(0.077)	(0.020)	(0.085)
Cdn exp/100	0.058	0.017	0.015	-0.758	0.201	-0.324
	(0.041)	(0.044)	(0.057)	(0.684)	(0.661)	(0.937)
Cdn exp sq./100	-0.004**	-0.002	0.0004	0.021	0.004	0.005
	(0.002)	(0.002)	(0.003)	(0.033)	(0.033)	(0.042)
For exp/100	0.024	0.014	-0.027	-0.481*	-0.217	0.201
	(0.023)	(0.019)	(0.017)	(0.257)	(0.316)	(0.332)
For exp sq./100	-0.0002	-0.001	0.001	0.019**	0.007	-0.0003
	(0.001)	(0.001)	(0.0004)	(0.007)	(0.008)	(0.008)
Eng/Fr 1^{st} language	-0.007	0.001	0.002	-0.057	-0.041	0.049
	(0.007)	(0.003)	(0.002)	(0.052)	(0.043)	(0.043)
Eng/Fr 2^{nd} language	-0.009	-0.002	0.005***	-0.084*	-0.008	0.050***
	(0.006)	(0.003)	(0.001)	(0.048)	(0.030)	(0.016)
Married	0.001	-0.001	0.001	0.016	0.024	0.049**
	(0.001)	(0.002)	(0.001)	(0.023)	(0.025)	(0.023)
West Asia	0.004*	0.005*	-0.000003	0.038	0.071	0.015
	(0.002)	(0.003)	(0.002)	(0.031)	(0.056)	(0.048)
E. & S.E. Asia	0.014***	0.020***	0.014***	0.038	0.091***	0.105***
	(0.004)	(0.007)	(0.004)	(0.026)	(0.028)	(0.030)
South Asia	0.011**	0.013***	0.015***	0.017	0.016	0.074**
	(0.005)	(0.005)	(0.004)	(0.041)	(0.029)	(0.030)
Africa	-0.00003	0.003	0.001	0.053	0.050	-0.063
	(0.003)	(0.004)	(0.003)	(0.035)	(0.048)	(0.059)
Caribbean	0.001	0.005	0.008**	-0.033	0.134***	0.072**
	(0.004)	(0.004)	(0.004)	(0.077)	(0.047)	(0.033)
Other origins	-0.005	0.003	0.007**	-0.215**	0.014	0.095**
	(0.004)	(0.004)	(0.003)	(0.090)	(0.054)	(0.037)

Table B.8: cont'd

Dependant Variable	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
Hours (May 2001)	0.0001	0.00002	0.0001	-0.0002	-0.002**	-0.004**
	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.002)
Inv. Mills' ratio	0.001	0.001	0.007	0.004	-0.096*	-0.130*
	(0.003)	(0.004)	(0.004)	(0.067)	(0.053)	(0.067)
R-squared	0.643	0.521	0.433	0.630	0.538	0.520
F-test on excluded instruments						
F(3, 269)	3.25	2.23	1.62	12.13	6.23	3.04
p-value	0.0224	0.0849	0.1840	0.0000	0.0004	0.0294

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.9: First Stage for 2SLS in column 4 of Table 3.13
(Earnings, Women, Preferred)

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	2.198**	-0.145	-0.015	-0.641	-0.559	-0.394
	(0.925)	(0.151)	(0.098)	(1.683)	(0.735)	(0.899)
EI71*coll	-0.015	1.359*	0.007	-0.414	-0.993	0.364
	(0.075)	(0.754)	(0.072)	(0.452)	(1.727)	(0.604)
EI71*univ	0.029	0.045	0.591*	0.139	0.237	1.189
	(0.028)	(0.032)	(0.339)	(0.214)	(0.226)	(1.516)
CSI*hs	0.010**	0.002	0.001	0.481***	-0.009	-0.003
	(0.005)	(0.002)	(0.001)	(0.083)	(0.013)	(0.014)
CSI*coll	0.0004	-0.004	0.00002	0.004	0.351***	-0.023
	(0.002)	(0.005)	(0.002)	(0.018)	(0.096)	(0.018)
CSI*univ	0.002	0.002	0.007	0.010	-0.049*	0.225**
	(0.002)	(0.002)	(0.008)	(0.025)	(0.028)	(0.090)
College	-0.012	0.028***	0.002	-0.250***	0.267***	0.018
	(0.008)	(0.008)	(0.002)	(0.076)	(0.098)	(0.021)
University	-0.013*	0.0004	0.017**	-0.277***	0.032	0.348***
	(0.008)	(0.002)	(0.007)	(0.078)	(0.020)	(0.091)
Cdn exp	0.066	0.014	-0.005	-0.749	0.152	-0.365
	(0.040)	(0.044)	(0.056)	(0.685)	(0.660)	(0.940)
Cdn exp sq.	-0.004**	-0.001	0.001	0.021	0.006	0.007
	(0.002)	(0.002)	(0.003)	(0.033)	(0.033)	(0.043)
For exp	0.027	0.014	-0.026	-0.471*	-0.211	0.210
	(0.023)	(0.019)	(0.016)	(0.261)	(0.324)	(0.329)
For exp sq.	-0.0004	-0.001	0.001	0.019**	0.007	-0.001
	(0.001)	(0.001)	(0.0004)	(0.007)	(0.008)	(0.008)
Eng/Fr 1^{st} language	-0.006	0.001	0.003	-0.057	-0.042	0.048
	(0.007)	(0.003)	(0.002)	(0.052)	(0.044)	(0.043)
Eng/Fr 2^{nd} language	-0.008	-0.002	0.005***	-0.085*	-0.009	0.051***
	(0.006)	(0.003)	(0.001)	(0.048)	(0.030)	(0.016)
Married	0.001	-0.001	0.0005	0.016	0.023	0.047**
	(0.001)	(0.002)	(0.001)	(0.024)	(0.025)	(0.023)
West Asia	0.004	0.005	-0.0001	0.036	0.067	0.021
	(0.002)	(0.003)	(0.002)	(0.031)	(0.055)	(0.049)
E. & S.E. Asia	0.014***	0.020***	0.014***	0.039	0.091***	0.109***
	(0.004)	(0.007)	(0.004)	(0.026)	(0.027)	(0.030)
South Asia	0.012**	0.013***	0.015***	0.014	0.011	0.080***
	(0.005)	(0.005)	(0.004)	(0.042)	(0.029)	(0.031)
Africa	-0.0002	0.002	0.001	0.050	0.046	-0.056
	(0.003)	(0.004)	(0.003)	(0.036)	(0.048)	(0.059)
Caribbean	0.001	0.006	0.008**	-0.038	0.127***	0.078*
	(0.004)	(0.004)	(0.003)	(0.078)	(0.048)	(0.034)
Other origins	-0.007*	0.003	0.007**	-0.219**	0.007	0.100***
	(0.004)	(0.004)	(0.003)	(0.090)	(0.055)	(0.038)

Table B.9: cont'd

Dependant Variable	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
Hours (May 2001)	0.0001	0.00002	0.00004	-0.0001	-0.003**	-0.004***
	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.001)
Inv. Mills' ratio	0.002	0.001	0.004	0.009	-0.099*	-0.132**
	(0.004)	(0.003)	(0.005)	(0.066)	(0.052)	(0.065)
R-squared	0.647	0.522*	0.434	0.630	0.539	0.521
F-test on excluded instruments						
F(6, 266)	4.59	1.44	1.32	7.01	4.42	2.31
p-value	0.0002	0.1982	0.2468	0.0000	0.0003	0.0342

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.10: First Stage for Control Fn in Table 3.14
(Employment, Men, Benchmark)

	EI	EI	SI	SI
Exposure Index 1971 (EI71)	1.075**	1.077**	0.301	
	(0.058)	(0.451)	(0.885)	
Childhood Social Segregation (CSI)		0.001	0.376***	0.375***
		(0.004)	(0.047)	(0.047)
College	-0.000005	-0.00003	-0.051	-0.052
	(0.003)	(0.003)	(0.052)	(0.051)
University	-0.005	-0.005	-0.167***	-0.167***
	(0.003)	(0.003)	(0.040)	(0.040)
Cdn exp/100	0.065	0.064	-2.005*	-2.000*
	(0.083)	(0.083)	(1.071)	(1.069)
Cdn exp sq./100	-0.006	-0.006	0.065	0.065
	(0.004)	(0.004)	(0.049)	(0.049)
For exp/100	-0.013	-0.013	-0.100	-0.102
	(0.028)	(0.028)	(0.454)	(0.455)
For exp sq./100	0.001	0.001	0.007	0.007
	(0.001)	(0.001)	(0.011)	(0.012)
Eng/Fr 1^{st} language	-0.003	-0.003	-0.197***	-0.197***
	(0.010)	(0.010)	(0.071)	(0.070)
Eng/Fr 2^{nd} language	-0.005	-0.005	-0.215***	-0.215***
	(0.009)	(0.009)	(0.052)	(0.051)
Married	0.003	0.003	0.160***	0.159***
	(0.006)	(0.006)	(0.051)	(0.050)
West Asia	0.001	0.001	-0.154**	-0.157**
	(0.006)	(0.006)	(0.073)	(0.071)
E. & S.E. Asia	0.056***	0.056***	0.202***	0.201***
	(0.016)	(0.015)	(0.050)	(0.050)
South Asia	0.031**	0.031**	0.074	0.070
	(0.013)	(0.013)	(0.056)	(0.052)
Other origins	0.004	0.003	-0.071	-0.075
	(0.007)	(0.007)	(0.063)	(0.060)
R-squared	0.55	0.55	0.22	0.22
F-test on excluded instruments				
F(#, #)	(1, 309)	(2, 309)	(1, 309)	(1, 309)
	5.73	3.00	32.59	63.33
p-value	0.0173	0.0512	0.0000	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.11: First Stage for Control Fn in Table 3.15
(Employment, Women, Benchmark)

	EI	EI	SI	SI
Exposure Index 1971 (EI71)	0.807*	0.806*	0.422	
	(0.449)	(0.447)	(0.496)	
Childhood Social Segregation (CSI)		0.008**	0.361***	0.361***
		(0.004)	(0.045)	(0.045)
College	0.0001	-0.0003	-0.076**	-0.074**
	(0.002)	(0.002)	(0.035)	(0.035)
University	-0.004	-0.005*	-0.073*	-0.072*
	(0.003)	(0.003)	(0.042)	(0.042)
Cdn exp	0.082	0.077	-0.340	-0.359
	(0.068)	(0.066)	(1.034)	(1.035)
Cdn exp sq.	-0.006*	-0.006*	-0.002	-0.0002
	(0.004)	(0.004)	(0.046)	(0.047)
For exp	0.005	0.005	-0.546	-0.528
	(0.032)	(0.032)	(0.424)	(0.420)
For exp sq.	-0.001	-0.001	0.024**	0.024**
	(0.001)	(0.001)	(0.011)	(0.011)
Eng/Fr 1^{st} language	-0.006	-0.004	-0.072	-0.073
	(0.008)	(0.008)	(0.075)	(0.075)
Eng/Fr 2^{nd} language	-0.012*	-0.011*	-0.024	-0.026
	(0.007)	(0.007)	(0.060)	(0.061)
Married	0.001	0.001	0.058	0.059
	(0.003)	(0.003)	(0.038)	(0.037)
West Asia	0.007	0.007	0.176***	0.170***
	(0.006)	(0.006)	(0.065)	(0.064)
E. & S.E. Asia	0.054***	0.054***	0.322***	0.320***
	(0.018)	(0.017)	(0.048)	(0.047)
South Asia	0.033**	0.033***	0.133**	0.127**
	(0.013)	(0.013)	(0.052)	(0.050)
Africa	0.0004	0.0003	0.070	0.064
	(0.005)	(0.005)	(0.089)	(0.088)
Caribbean	0.009	0.008	0.242***	0.235***
	(0.008)	(0.007)	(0.088)	(0.086)
Other origins	0.001	-0.0004	-0.013	-0.019
	(0.006)	(0.006)	(0.108)	(0.107)
Hours (May 2001)	-0.00001	-0.00001	-0.001	-0.001
	(0.00005)	(0.00005)	(0.001)	(0.001)
Kids age$\leqslant$2	-0.008*	-0.009*	-0.108	-0.109
	(0.005)	(0.005)	(0.070)	(0.070)
# kids 1-2	0.006**	0.006**	0.119***	0.118***
	(0.003)	(0.003)	(0.033)	(0.033)
# kids$\geqslant$3	0.008*	0.008	0.127**	0.126**
	(0.005)	(0.005)	(0.052)	(0.052)
R-squared	0.47	0.47	0.20	0.20
F-test on excluded instruments				
F(#, #)	(1, 354)	(2, 354)	(2, 354)	(1, 354)
	3.23	2.94	33.32	64.60
p-value	0.0732	0.0540	0.0000	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.12: First Stage for Control Fn in columns 2 and 6 of Table 3.16
(Employment, Men, Preferred)

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	0.934*	-0.004	0.011			
	(0.486)	(0.048)	(0.054)			
EI71*coll	-0.097	1.434*	-0.015			
	(0.155)	(0.755)	(0.100)			
EI71*univ	-0.089	-0.028	1.322*			
	(0.136)	(0.078)	(0.790)			
CSI*hs				0.473***	-0.007	-0.018
				(0.075)	(0.017)	(0.014)
CSI*coll				-0.021	0.415***	-0.028**
				(0.017)	(0.084)	(0.014)
CSI*univ				-0.032	0.004	0.311***
				(0.021)	(0.012)	(0.056)
College	-0.024***	0.021***	0.0003	-0.152**	0.153**	0.014
	(0.006)	(0.006)	(0.001)	(0.067)	(0.082)	(0.015)
University	-0.026***	0.001	0.019***	-0.162***	-0.007	0.142***
	(0.007)	(0.001)	(0.006)	(0.062)	(0.019)	(0.047)
Cdn exp/100	-0.013	0.096***	-0.025	-1.116	0.175	-1.136*
	(0.071)	(0.035)	(0.035)	(0.722)	(0.669)	(0.630)
Cdn exp sq./100	-0.001	-0.004***	0.0004	0.039	-0.002	0.032
	(0.003)	(0.002)	(0.002)	(0.035)	(0.030)	(0.031)
For exp/100	-0.065***	0.054***	-0.005	-0.796***	0.210	0.487*
	(0.024)	(0.021)	(0.020)	(0.305)	(0.246)	(0.273)
For exp sq./100	0.003***	-0.001**	-0.0001	0.028***	-0.005	-0.016**
	(0.001)	(0.0005)	(0.0004)	(0.009)	(0.006)	(0.006)
Eng/Fr 1^{st} language	-0.016	0.008***	0.004	-0.195***	0.058*	-0.051
	(0.011)	(0.002)	(0.003)	(0.057)	(0.033)	(0.041)
Eng/Fr 2^{nd} language	-0.020*	0.008***	0.007**	-0.203***	0.015	-0.019
	(0.011)	(0.002)	(0.003)	(0.054)	(0.017)	(0.036)
Married	0.006	-0.002	-0.003	0.105***	0.016	0.032
	(0.005)	(0.002)	(0.002)	(0.030)	(0.027)	(0.027)
West Asia	-0.002	0.004	-0.0004	-0.108**	0.013	-0.068**
	(0.003)	(0.003)	(0.003)	(0.049)	(0.038)	(0.034)
E. & S.E. Asia	0.020***	0.018***	0.018***	0.057	0.054***	0.096***
	(0.007)	(0.005)	(0.005)	(0.039)	(0.020)	(0.027)
South Asia	0.008	0.011***	0.012**	0.003	0.052**	0.020
	(0.006)	(0.004)	(0.005)	(0.032)	(0.024)	(0.027)
Other origins	-0.002	0.002	0.004	-0.008	-0.084***	0.026
	(0.003)	(0.003)	(0.003)	(0.037)	(0.031)	(0.033)
R-squared	0.55	0.53	0.49	0.60	0.49	0.41
F-test on excluded instruments						
F(3, 309)	1.55	2.04	1.36	17.57	8.53	17.37
p-value	0.2020	0.1086	0.2563	0.0000	0.0000	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.13: First Stage for Control Fn in column 4 of Table 3.16
(Employment, Men, Preferred)

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	0.949**	-0.008	0.011	-0.335	-0.043	0.027
	(0.482)	(0.049)	(0.055)	(1128)	(0.285)	(0.524)
EI71*coll	-0.091	1.439*	-0.019	-0.771	2.971*	-0.813
	(0.149)	(0.756)	(0.099)	(0.665)	(1.671)	(0.744)
EI71*univ	-0.098	-0.040	1.332*	-0.658	-0.169	1.946
	(0.134)	(0.080)	(0.795)	(0.656)	(0.297)	(2.160)
CSI*hs	0.011	-0.001	-0.001	0.471***	-0.005	-0.017
	(0.011)	(0.002)	(0.002)	(0.076)	(0.018)	(0.015)
CSI*coll	-0.003	0.005	-0.003**	-0.022	0.421***	-0.030**
	(0.003)	(0.006)	(0.002)	(0.017)	(0.083)	(0.014)
CSI*univ	-0.006*	-0.004*	0.004	-0.035	0.003	0.319***
	(0.003)	(0.002)	(0.006)	(0.022)	(0.012)	(0.054)
College	-0.012**	0.016*	0.003	-0.150**	0.128	0.023
	(0.013)	(0.009)	(0.002)	(0.069)	(0.089)	(0.015)
University	-0.012	0.003**	0.015*	-0.160**	-0.004	0.125***
	(0.012)	(0.002)	(0.009)	(0.064)	(0.019)	(0.041)
Cdn exp/100	-0.023	0.096***	-0.024	-1.099	0.087	-1.099*
	(0.070)	(0.034)	(0.036)	(0.724)	(0.666)	(0.634)
Cdn exp sq./100	-0.001	-0.004***	0.0003	0.038	0.002	0.031
	(0.003)	(0.002)	(0.002)	(0.036)	(0.030)	(0.031)
For exp/100	-0.063***	0.053***	-0.004	-0.796***	0.163	0.530*
	(0.024)	(0.017)	(0.018)	(0.308)	(0.245)	(0.273)
For exp sq./100	0.003***	-0.001***	-0.0001	0.028***	-0.004	-0.017***
	(0.001)	(0.0004)	(0.0005)	(0.009)	(0.006)	(0.006)
Eng/Fr 1^{st} language	-0.014	0.008***	0.004	-0.195***	0.056*	-0.052
	(0.010)	(0.002)	(0.003)	(0.057)	(0.033)	(0.041)
Eng/Fr 2^{nd} language	-0.019*	0.008***	0.007**	-0.202***	0.011	-0.019
	(0.011)	(0.002)	(0.003)	(0.054)	(0.015)	(0.035)
Married	0.006	-0.002	-0.002	0.105***	0.012	0.033
	(0.004)	(0.002)	(0.002)	(0.030)	(0.027)	(0.023)
West Asia	-0.002	0.004	-0.0001	-0.113**	0.023	-0.068*
	(0.003)	(0.003)	(0.003)	(0.049)	(0.037)	(0.035)
E. & S.E. Asia	0.020***	0.018***	0.018***	0.056	0.057***	0.094***
	(0.007)	(0.005)	(0.004)	(0.039)	(0.019)	(0.028)
South Asia	0.009*	0.011***	0.012**	-0.004	0.062**	0.024
	(0.005)	(0.004)	(0.005)	(0.034)	(0.025)	(0.029)
Other origins	-0.001	0.002	0.004	-0.015	-0.073**	0.028
	(0.003)	(0.003)	(0.003)	(0.039)	(0.031)	(0.034)
R-squared	0.56	0.54	0.49	0.60	0.50	0.42
F-test on excluded instruments						
F(6, 309)	1.57	1.87	1.27	9.33	5.30	11.08
p-value	0.1555	0.0862	0.2698	0.0000	0.0000	0.0000

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.14: First Stage for Control Fn in cols 2 and 6 of Table 3.17
(Employment, Women, Preferred)

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	2.007**	-0.196	-0.048			
	(0.912)	(0.174)	(0.084)			
EI71*coll	0.019	0.527	0.027*			
	(0.029)	(0.329)	(0.014)			
EI71*univ	0.007	0.008	0.789			
	(0.043)	(0.051)	(0.490)			
CSI*hs				0.450***	-0.009	0.003
				(0.060)	(0.011)	(0.011)
CSI*coll				-0.012	0.343***	-0.011
				(0.015)	(0.091)	(0.014)
CSI*univ				-0.007	-0.017	0.261***
				(0.015)	(0.018)	(0.068)
College	-0.021***	0.029***	0.001	-0.261***	0.260***	0.032*
	(0.006)	(0.009)	(0.001)	(0.061)	(0.088)	(0.018)
University	-0.021***	0.0004	0.022***	-0.265***	0.022	0.346***
	(0.006)	(0.001)	(0.006)	(0.056)	(0.019)	(0.072)
Cdn exp/100	0.074	0.007	-0.004	-0.539	-0.030	0.262
	(0.066)	(0.035)	(0.033)	(0.646)	(0.523)	(0.613)
Cdn exp sq./100	-0.004	-0.002	0.0005	0.016	0.003	-0.022
	(0.003)	(0.002)	(0.001)	(0.030)	(0.025)	(0.027)
For exp/100	0.010	0.011	-0.025**	-0.517**	-0.196	0.194
	(0.020)	(0.016)	(0.012)	(0.215)	(0.266)	(0.251)
For exp sq./100	-0.0003	-0.0004	0.0005*	0.021***	0.006	-0.004
	(0.001)	(0.0005)	(0.0003)	(0.006)	(0.006)	(0.006)
Eng/Fr 1^{st} language	-0.007	0.001	0.001	-0.053	-0.030	0.013
	(0.006)	(0.003)	(0.002)	(0.048)	(0.035)	(0.033)
Eng/Fr 2^{nd} language	-0.010**	-0.003	0.005***	-0.055	0.0003	0.038***
	(0.004)	(0.004)	(0.001)	(0.049)	(0.026)	(0.013)
Married	0.002	-0.0003	-0.001	0.022	0.007	0.030
	(0.002)	(0.002)	(0.001)	(0.025)	(0.021)	(0.017)
West Asia	0.002	0.004*	0.002	0.033	0.081*	0.050
	(0.003)	(0.002)	(0.002)	(0.041)	(0.042)	(0.036)
E. & S.E. Asia	0.017***	0.019**	0.015***	0.093***	0.112***	0.117***
	(0.004)	(0.008)	(0.005)	(0.027)	(0.023)	(0.026)
South Asia	0.012**	0.010***	0.013***	-0.005	0.037	0.096***
	(0.006)	(0.004)	(0.004)	(0.033)	(0.024)	(0.028)
Africa	-0.001	-0.001	0.003	0.059	0.010	-0.003
	(0.003)	(0.003)	(0.002)	(0.045)	(0.050)	(0.046)
Caribbean	0.001	0.001	0.009**	0.030	0.111***	0.096***
	(0.005)	(0.003)	(0.004)	(0.054)	(0.042)	(0.034)
Other origins	-0.005	0.002	0.006**	-0.174**	0.066	0.086*
	(0.004)	(0.003)	(0.003)	(0.081)	(0.042)	(0.045)

Table B.14: cont'd

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
Hours (May 2001)	0.00004	0.000003	-0.00005*	-0.0003	0.0001	-0.001**
	0.00003)	(0.00002)	(0.00003)	(0.001)	(0.0004)	(0.0004)
Kids age⩽2	-0.004**	-0.005*	0.002	-0.035	-0.032	-0.040
	(0.002)	(0.003)	(0.002)	(0.034)	(0.029)	(0.025)
# kids 1-2	0.002	0.001	0.002	0.020	0.051**	0.051**
	(0.002)	(0.001)	(0.002)	(0.022)	(0.020)	(0.021)
# kids⩾3	0.005*	0.003	0.0002	0.065*	0.056*	0.001
	(0.003)	(0.002)	(0.001)	(0.034)	(0.033)	(0.024)
R-squared	0.60	0.45	0.45	0.62	0.53	0.53
F-test on excluded instruments						
F(3, 354)	2.98	2.19	4.21	19.83	5.12	5.46
p-value	0.0313	0.0889	0.0061	0.0000	0.0018	0.0011

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B.15: First Stage for Control Fn in column 4 of Table 3.17
(Employment, Women, Preferred)

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
EI71*hs	1.993**	-0.198	-0.050	1.057	-0.881	-0.942
	(0.893)	(0.175)	(0.086)	(1.340)	(0.697)	(0.635)
EI71*coll	0.020	0.528	0.027**	-0.063	0.316	0.120
	(0.029)	(0.329)	(0.013)	(0.277)	(0.508)	(0.181)
EI71*univ	0.007	0.008	0.792	-0.099	0.074	1.279
	(0.045)	(0.052)	(0.490)	(0.363)	(0.372)	(1.598)
CSI*hs	0.013**	0.001	0.001	0.449***	-0.008	0.004
	(0.006)	(0.001)	(0.001)	(0.060)	(0.010)	(0.011)
CSI*coll	0.001	-0.002	-0.001	-0.011	0.341***	-0.012
	(0.003)	(0.005)	(0.002)	(0.015)	(0.090)	(0.014)
CSI*univ	0.00003	0.001	0.003	-0.007	-0.017	0.266***
	(0.002)	(0.002)	(0.004)	(0.015)	(0.019)	(0.068)
College	-0.011	0.032***	0.003**	-0.256***	0.254***	0.027
	(0.008)	(0.010)	(0.001)	(0.061)	(0.090)	(0.018)
University	-0.011	0.001	0.021***	-0.259***	0.017	0.329***
	(0.008)	(0.002)	(0.005)	(0.057)	(0.019)	(0.072)
Cdn exp/100	0.071	0.005	-0.007	-0.530	-0.022	0.228
	(0.062)	(0.035)	(0.033)	(0.652)	(0.520)	(0.611)
Cdn exp sq./100	-0.004*	-0.002	0.001	0.016	0.002	-0.021
	(0.003)	(0.002)	(0.001)	(0.030)	(0.025)	(0.028)
For exp/100	0.011	0.011	-0.025**	-0.535**	-0.189	0.211
	(0.020)	(0.016)	(0.012)	(0.222)	(0.272)	(0.251)
For exp sq./100	-0.0004	-0.0005	0.0005*	0.021***	0.006	-0.004
	(0.001)	(0.0005)	(0.0003)	(0.006)	(0.006)	(0.006)
Eng/Fr 1^{st} language	-0.004	0.001	0.002	-0.051	-0.031	0.010
	(0.006)	(0.005)	(0.001)	(0.048)	(0.035)	(0.032)
Eng/Fr 2^{nd} language	-0.009*	-0.003	0.005***	-0.051	-0.003	0.035***
	(0.005)	(0.004)	(0.001)	(0.048)	(0.027)	(0.013)
Married	0.002	-0.0004	-0.001	0.022	0.007	0.029
	(0.002)	(0.002)	(0.001)	(0.025)	(0.021)	(0.020)
West Asia	0.001	0.004	0.002	0.036	0.081	0.053
	(0.003)	(0.002)	(0.002)	(0.042)	(0.042)	(0.037)
E. & S.E. Asia	0.017***	0.019**	0.015***	0.091***	0.115***	0.122***
	(0.004)	(0.008)	(0.005)	(0.028)	(0.023)	(0.026)
South Asia	0.013**	0.010***	0.013***	-0.001	0.035	0.098***
	(0.006)	(0.004)	(0.004)	(0.035)	(0.025)	(0.029)
Africa	-0.001	-0.001	0.003	0.061	0.010	0.0004
	(0.003)	(0.003)	(0.003)	(0.046)	(0.050)	(0.046)
Caribbean	-0.0001	0.001	0.009**	0.033	0.110**	0.097***
	(0.004)	(0.003)	(0.004)	(0.056)	(0.043)	(0.034)
Other origins	-0.006*	0.001	0.006*	-0.170**	0.064	0.087*
	(0.003)	(0.003)	(0.003)	(0.081)	(0.042)	(0.045)

Table B.15: cont'd

	EI*hs	EI*coll	EI*univ	SI*hs	SI*coll	SI*univ
Hours (May 2001)	0.00003	0.000003	-0.00005*	-0.0003	0.00007	-0.001**
	(0.00003)	(0.00002)	(0.00003)	(0.001)	(0.0004)	(0.0004)
Kids age⩽2	-0.004**	-0.005*	0.002	-0.034	-0.033	-0.040
	(0.002)	(0.003)	(0.002)	(0.034)	(0.029)	(0.039)
# kids 1-2	0.002	0.001	0.002	0.019	0.052**	0.052**
	(0.002)	(0.001)	(0.002)	(0.022)	(0.020)	(0.021)
# kids⩾3	0.005*	0.003	0.0001	0.066*	0.056*	0.001
	(0.003)	(0.002)	(0.001)	(0.034)	(0.033)	(0.024)
R-squared	0.60	0.45	0.45	0.62	0.53	0.53
F-test on excluded instruments						
F(6, 354)	2.98	1.44	2.80	10.01	3.60	4.88
p-value	0.0075	0.1998	0.0112	0.0000	0.0018	0.0001

Clustered standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix C

Appendix to Chapter 4

Table C.1: Summary Statistics by Imputed and Non-imputed Skill Scores for Immigrant Workers

	Males		Females	
	Completed Main Skill Tasks	Did Not Complete Main Skill Tasks	Completed Main Skill Tasks	Did Not Complete Main Skill Tasks
Annual Earnings*				
Mean	46,377	33,662	31,435	25,134
Median	37,128	31,200	29,120	21,008
Weekly Earnings				
Mean	916	673	679	502
Median	740	650	575	408
Age	40	44	41	43
Experience	20	26	21	25
Canadian	13	14	16	15
Foreign	7	13	6	10
Years of Schooling	15	12	14	12
% High School	27	34	29	31
Foreign	12	20	11	19
Canadian	16	13	18	12
% Non-Univ Post-Sec	25	23	27	26
Foreign	11	15	12	12
Canadian	14	8	15	14
% University	39	15	33	14
Foreign	21	13	18	10
Canadian	17	2	15	4
Years Since Migration	18	16	21	18
Age At Immigration	22	28	20	25
% First Language English/French	32	14	33	19
% US or UK Origin	13	6	15	10
% European Origin	18	28	19	20
% Asian Origin	35	31	32	42
% Speak English Regularly At Work	91	74	88	75
% Satisfied With Own Skills: (a)				
Read English	98	70	96	75
Write English	96	62	94	65
Math Skills	96	79	94	84
% With Low Skill Use At Work: (b)				
Reading*	10	31	6	35
Writing*	22	50	20	53
Numeracy*	6	14	9	17
Observations	768	149	727	143

*Statistics in some cases based on a slightly smaller sample than the number of observations reported, due to missing information. (a) Respondents were asked whether they strongly agree, agree, disagree or strongly disagree that they have the reading and writing skills in English as well as the math skills they need to do their main job well. The table reports the percentage of immigrant workers who reported that they strongly agree or agree in each of the three cases. (b) Percentage of workers who report rarely or never performing any of the literacy tasks asked about. Respondents were asked about 6 different reading tasks, 5 writing tasks and 6 mathematical tasks.

Table C.2: Earnings Regressions with Skill Effects – Males – Ln Skills

	(1)	(2)	(3)	(4)	(5)
Ln Avg Skill Score /100	1.015***	0.718***			
	(0.092)	(0.083)			
Ln Avg Skill Score /100			0.654***	0.651***	-0.080
(Native Born)			(0.138)	(0.135)	(0.409)
Ln Avg Skill Score /100			0.825***		
(Immigrants)			(0.102)		
Ln Avg Skill Score /100				0.754***	0.322
(Immig. Cdn Educ)				(0.199)	(0.344)
Ln Avg Skill Score /100				0.863***	0.857***
(Immig. Foreign Educ)				(0.123)	(0.122)
Ln Avg Skill Score*Exp /100					0.017*
(Native Born)					(0.010)
Ln Avg Skill Score * HS /100					0.317
(NB & Immig. Cdn Educ)					(0.326)
Ln Avg Skill Score * PS /100					0.794**
(NB & Immig. Cdn Educ)					(0.387)
Ln Avg Skill Score * Univ /100					0.666
(NB & Immig. Cdn Educ)					(0.437)
Immigrant (Educ after arrival)	0.075	0.064	-0.898	-0.518	-2.233
	(0.049)	(0.087)	(1.104)	(1.599)	(2.111)
Immigrant (Educ before arrival)	0.123**	0.869***	-0.045	-0.260	-4.322*
	(0.057)	(0.163)	(1.112)	(1.042)	(2.503)
Cdn Exp (Native Born)		0.092***	0.092***	0.092***	-0.004
		(0.005)	(0.005)	(0.005)	(0.056)
Cdn Exp2/100 (Native Born)		-0.140***	-0.141***	-0.141***	-0.133***
		(0.008)	(0.008)	(0.008)	(0.009)
Cdn Exp (Immig. Cdn Educ)		0.076***	0.076***	0.076***	0.076***
		(0.013)	(0.013)	(0.013)	(0.013)
Cdn Exp2/100 (Immig. Cdn Educ)		-0.088***	-0.087***	-0.088***	-0.087***
		(0.029)	(0.029)	(0.029)	(0.030)
Foreign Exp (Immig Cdn Educ)		0.003	0.004	0.003	0.004
		(0.016)	(0.016)	(0.016)	(0.016)
Foreign Exp Sq / 100 (Immig Cdn Educ)		0.038	0.036	0.038	0.039
		(0.053)	(0.053)	(0.053)	(0.053)

Table C.2: cont'd

	(1)	(2)	(3)	(4)	(5)
Cdn Exp (Immig. Foreign Educ)		0.050***	0.050***	0.050***	0.050***
		(0.011)	(0.011)	(0.011)	(0.011)
Cdn Exp2/100 (Immig. Foreign Educ)		-0.092***	-0.093***	-0.093***	-0.093***
		(0.031)	(0.031)	(0.031)	(0.031)
Foreign Exp (Immig No Cdn Educ)		-0.010	-0.011	-0.011	-0.011
		(0.008)	(0.008)	(0.008)	(0.008)
Foreign Exp Sq / 100 (Immig No Cdn Educ)		0.016	0.017	0.017	0.017
		(0.019)	(0.018)	(0.018)	(0.018)
HS (NB & Immig. Cdn Educ)		0.361***	0.366***	0.367***	-1.371
		(0.087)	(0.085)	(0.085)	(1.810)
PS (NB & Immig. Cdn Educ)		0.727***	0.734***	0.735***	-3.708
		(0.076)	(0.077)	(0.077)	(2.189)
Univ (NB & Immig. Cdn Educ)		1.063***	1.069***	1.073***	-2.641
		(0.083)	(0.083)	(0.085)	(2.486)
High School (Immig. Foreign Educ)		-0.023	-0.047	-0.056	-0.056
		(0.086)	(0.089)	(0.088)	(0.088)
Non-Univ Post Sec (Immig. Foreign Educ)		0.155	0.120	0.107	0.108
		(0.094)	(0.096)	(0.096)	(0.096)
University (Immig. Foreign Educ)		0.218**	0.175*	0.158*	0.159*
		(0.086)	(0.089)	(0.092)	(0.092)
HS * Cdn Exp (NB & Immig. Cdn Educ)		-0.011***	-0.011***	-0.011***	-0.011***
		(0.003)	(0.003)	(0.003)	(0.003)
PS * Cdn Exp (NB & Immig. Cdn Educ)		-0.021***	-0.021***	-0.021***	-0.021***
		(0.003)	(0.003)	(0.003)	(0.003)
Uni * Cdn Exp (NB & Immig. Cdn Educ)		-0.026***	-0.026***	-0.026***	-0.027***
		(0.004)	(0.004)	(0.004)	(0.004)
Unable to answer literacy		0.105***	0.108***	0.109***	0.107***
		(0.026)	(0.026)	(0.026)	(0.027)
US or UK origin		0.032	0.015	0.016	0.024
		(0.100)	(0.097)	(0.097)	(0.097)
European origin		0.169**	0.162*	0.163*	0.164*
		(0.081)	(0.082)	(0.082)	(0.081)
Asian origin		-0.017	-0.021	-0.020	-0.019
		(0.052)	(0.054)	(0.053)	(0.052)
First Language not Eng. or Fr.		-0.024	-0.021	-0.020	-0.022
		(0.045)	(0.045)	(0.045)	(0.045)
Observations	4551	4551	4551	4551	4551
R-squared	0.06	0.45	0.45	0.45	0.45

Specification (1) adds our measure of cognitive skills to a regression with separate intercepts for immigrants with and without Canadian education. The mean earnings for the native born and the two groups of immigrants without controlling for skills are reported in the first paragraph of subsection 4.5.2. Specification (2) adds our measure of cognitive skills to the preferred specification from Table 4.6. Specification (3) estimates separate returns to skills for all immigrants relative to the native born. Specification (4) estimates separate returns to skills for the two groups of immigrants relative to the native born. Column (5) contains our preferred specification with skills controls. Regressions include indicators for province of residence. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.3: Earnings Regressions with Skill Effects – Females – Ln Skills

	(1)	(2)	(3)	(4)	(5)
Ln Avg Skill Score / 100	1.201***	0.713***			
	(0.091)	(0.091)			
Ln Avg Skill Score /100			0.766***	0.761***	0.134
(Native Born)			(0.120)	(0.121)	(0.392)
Ln Avg Skill Score /100			0.605***		
(Immigrants)			(0.093)		
Ln Avg Skill Score /100				0.465***	0.321
(Immig. Cdn Educ)				(0.157)	(0.422)
Ln Avg Skill Score /100				0.714***	-0.434
(Immig. Foreign Educ)				(0.148)	(0.567)
Ln Avg Skill Score * High School /100					1.106***
(Immig. Foreign Educ)					(0.364)
Ln Avg Skill Score * Non-Univ Post Sec /100					0.822
(Immig. Foreign Educ)					(0.496)
Ln Avg Skill Score * University /100					1.689**
(Immig. Foreign Educ)					(0.741)
Immigrant (Educ after arrival)	0.214***	0.191**	1.104	1.866*	-0.894
	(0.049)	(0.078)	(0.777)	(0.992)	(1.635)
Immigrant (Educ before arrival)	0.169***	0.884***	1.753**	1.156	3.655
	(0.058)	(0.251)	(0.775)	(0.940)	(3.408)
Cdn Exp (Native Born)		0.074***	0.074***	0.074***	-0.029
		(0.005)	(0.005)	(0.005)	(0.069)
Cdn Exp2/100 (Native Born)		-0.114***	-0.114***	-0.113***	-0.106***
		(0.013)	(0.013)	(0.013)	(0.013)
Cdn Exp (Immig. Cdn Educ)		0.074***	0.074***	0.075***	0.148**
		(0.007)	(0.007)	(0.007)	(0.069)
Cdn Exp2/100 (Immig. Cdn Educ)		-0.113***	-0.114***	-0.115***	-0.120***
		(0.018)	(0.018)	(0.017)	(0.019)
Foreign Exp (Immig Cdn Educ)		-0.009	-0.011	-0.015	-0.052
		(0.012)	(0.011)	(0.012)	(0.088)
Foreign Exp Sq / 100 (Immig Cdn Educ)		0.083*	0.087**	0.094**	0.107**
		(0.042)	(0.041)	(0.045)	(0.048)

Table C.3: cont'd

	(1)	(2)	(3)	(4)	(5)
Cdn Exp (Immig. Foreign Educ)		0.040***	0.040***	0.040***	-0.022
		(0.014)	(0.015)	(0.014)	(0.078)
Cdn Exp2/100 (Immig. Foreign Educ)		-0.079**	-0.079**	-0.079**	-0.081**
		(0.033)	(0.033)	(0.033)	(0.030)
Foreign Exp (Immig No Cdn Educ)		0.031*	0.030*	0.031*	0.001
		(0.016)	(0.016)	(0.016)	(0.085)
Foreign Exp Sq / 100 (Immig No Cdn Educ)		-0.077*	-0.077*	-0.077*	-0.096*
		(0.045)	(0.045)	(0.045)	(0.049)
HS (NB & Immig. Cdn Educ)		0.552***	0.551***	0.554***	-0.389
		(0.088)	(0.088)	(0.088)	(1.860)
PS (NB & Immig. Cdn Educ)		0.945***	0.944***	0.949***	-1.593
		(0.128)	(0.128)	(0.129)	(1.793)
Univ (NB & Immig. Cdn Educ)		1.298***	1.294***	1.300***	-1.248
		(0.083)	(0.083)	(0.084)	(2.829)
High School (Immig. Foreign Educ)		-0.036	-0.009	-0.038	-5.828***
		(0.136)	(0.137)	(0.156)	(1.851)
Non-Univ Post Sec (Immig. Foreign Educ)		0.050	0.086	0.048	-4.186
		(0.148)	(0.145)	(0.168)	(2.530)
University (Immig. Foreign Educ)		0.134	0.175	0.131	-8.931**
		(0.145)	(0.145)	(0.172)	(4.049)
HS * Cdn Exp (NB & Immig. Cdn Educ)		-0.011***	-0.011***	-0.011***	-0.012***
		(0.003)	(0.003)	(0.003)	(0.003)
PS * Cdn Exp (NB & Immig. Cdn Educ)		-0.021***	-0.021***	-0.021***	-0.022***
		(0.005)	(0.005)	(0.005)	(0.005)
Uni * Cdn Exp (NB & Immig. Cdn Educ)		-0.022***	-0.022***	-0.022***	-0.023***
		(0.003)	(0.003)	(0.003)	(0.004)
Unable to answer literacy		0.018	0.015	0.017	0.013
		(0.041)	(0.041)	(0.041)	(0.042)
US or UK origin		-0.119	-0.109	-0.113	-0.124
		(0.126)	(0.127)	(0.127)	(0.143)
European origin		-0.101	-0.099	-0.099	-0.089
		(0.074)	(0.074)	(0.074)	(0.076)
Asian origin		-0.066	-0.065	-0.060	-0.044
		(0.066)	(0.067)	(0.067)	(0.071)
First Language not Eng. or Fr.		-0.048	-0.049	-0.050	-0.049
		(0.052)	(0.051)	(0.051)	(0.051)
Observations	5003	5003	5003	5003	5003
R-squared	0.08	0.38	0.38	0.38	0.38

Specification (1) adds our measure of cognitive skills to a regression with separate intercepts for immigrants with and without Canadian education. The mean earnings for the native born and the two groups of immigrants without controlling for skills are reported in the first paragraph of subsection 4.5.2. Specification (2) adds our measure of cognitive skills to the preferred specification from Table 4.7. Specification (3) estimates separate returns to skills for all immigrants relative to the native born. Specification (4) estimates separate returns to skills for the two groups of immigrants relative to the native born. Column (5) contains our preferred specification with skills controls. Regressions include indicators for province of residence. Robust standard errors in brackets. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix D

Notes on Publication

Chapter 4 was co-written with Professor David Green (Thesis Supervisor, UBC) and Professor Craig Riddell (UBC). My contribution to the production of this chapter is outlined below:

Data analysis - I conducted all of the econometric analysis, in consultation with Craig Riddell and David Green.

Manuscript preparation - I assisted in the preparation of the manuscript to a small extent.