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VINCENZO CAPONI
Ryerson University, Toronto, Canada
And
The Rimini Centre for Economics Analysis

MIANA PLESCA
University of Guelph

"POST-SECONDARY EDUCATION IN CANADA: CAN ABILITY BIAS EXPLAIN THE EARNINGS GAP BETWEEN COLLEGE AND UNIVERSITY GRADUATES?"

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The Rimini Centre for Economic Analysis
Legal address: Via Angherà, 22 – Head office: Via Patara, 3 - 47900 Rimini (RN) – Italy
www.rcfea.org - secretary@rcfea.org

Post-Secondary Education in Canada: Can Ability Bias Explain the Earnings Gap Between College and University Graduates?

Vincenzo Caponi
Ryerson University, Rimini Center for Economic Analysis and IZA

Miana Plesca
University of Guelph

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Post-Secondary Education in Canada: Can Ability Bias Explain the Earnings Gap Between College and University Graduates?*

Using the Canadian General Social Survey we compute returns to post-secondary education relative to high-school. Unlike previous research using Canadian data, our dataset allows us to control for ability selection into higher education. We find strong evidence of positive ability selection into all levels of post-secondary education for men and weaker positive selection for women. Since the ability selection is stronger for higher levels of education, particularly for university, the difference in returns between university and college or trades education decreases slightly after accounting for ability bias. However, a puzzling large gap persists, with university-educated men still earning over 20% more than men with college or trades education. Moreover, contrary to previous Canadian literature that reports higher returns for women, we document that the OLS hourly wage returns to university education are the same for men and women. OLS returns are higher for women only if weekly or yearly wages are considered instead, because university-educated women work more hours than the average. Nevertheless, once we account for ability selection into post-secondary education, we generally find higher returns for women than for men for all wage measures as a result of the stronger ability selection for men.

JEL Classification: J24, J31, I2, C31

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Corresponding author:

Vincenzo Caponi
Department of Economics
Ryerson University
350 Victoria St.
Toronto, Ontario M5B 2K3
Canada
E-mail: vcaponi@ryerson.ca

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1 Introduction

Canada spends a tremendous amount of resources on post-secondary education.[1] Consequently, the share of Canadian population with post-secondary education is the largest among OECD countries. Encompassed within this successful statistic is the fact that Canada also has the largest share of non-university post-secondary education such as trades and community colleges. This in turn raises the obvious question whether there are potential differences in the return to human capital investments between university and non-university post-secondary degrees.

The very small Canadian literature looking at returns to different types of post-secondary education reports large gaps between returns to university and trades or college education, with university degrees appearing to be much more rewarding than community college degrees or trade certificates.[2] However, this literature does not account for the possibility that the estimated returns to education may suffer from the selection bias that arises when the choice of education is related to unobserved characteristics, for example innate ability, which also affect earnings. Controlling for ability bias has a twofold importance. First of all, we need to have a better understanding of the true, unbiased returns to education. Second, we would like to know how much of any university-college earnings differential is due to ability selection and how much of the differential still persists even after controlling for ability.

The first major contribution of this paper is to provide selection-corrected estimates of the returns to schooling using a dataset rich in information on personal background, the 1994 Canadian General Social Survey (GSS). Our results show that, once we correct for selection bias, the returns for post-secondary education are lower than the OLS numbers would indicate, especially for men. Since we do find evidence of ability selection into all levels of post-secondary education, the gap between university and non-university post-secondary returns remains substantial even after accounting for ability selection.

While previous literature has investigated the returns to education for Canada (for instance Vaillancourt (1995) and Burbidge, Magee, and Robb (2002) among others), the only two

[1]Post-secondary education represents studies pursued beyond high-school graduation. We focus on three types of post-secondary education: non-university degrees − comprised of (i) trades certificates and (ii) community college diplomas −, and (iii) university degrees (Bachelor's or above).

[2]See Ferrer and Riddell (2002) and Boothby and Drewes (2006).

Canadian studies we are aware of that address the distinction between university and non-university post-secondary education are Ferrer and Riddell (2002) and Boothby and Drewes (2006).[3] Ferrer and Riddell (2002) use the 1996 Canadian Census to separate the effect of schooling measured as years spent in an educational institution from the effect of credentials measured as the type of degree obtained. Related to non-university post-secondary education, they find that trades and college degrees are characterized by returns which are not much higher than the returns to high school degrees, and lower than the returns to university degrees. Similar results are reported by Boothby and Drewes (2006) who use four waves of Census data spanning 1981 to 1996, to look at the trends in the returns to post-secondary education over this period.

In our study we use family background characteristics from the 1994 Canadian GSS to provide bias-corrected returns to different categories of post-secondary education. Because our data allow it, we use here both types of bias-correction methods commonly used in the literature – "selection on observables" and "selection on unobservables." Within the former category we implement propensity score matching estimators, and within the latter we implement both Heckman correction and instrumental variables (IV) estimators. Both for estimators assuming selection on observables and for those assuming selection on unobservables, the idea is to find some variables (instruments) such that, conditional on these variables, the assignment to education becomes random. While both approaches rely on the availability of good data, they differ in the properties these data need to satisfy for identification to be achieved. Propensity score matching relies on the availability of variables correlated with both ability and educational attainment. The IV estimator, and to some extent the Heckman correction estimator as well, rely on the availability of instruments which are orthogonal to ability and correlated with the education outcome. We provide arguments and some statistical evidence why, among the three methods proposed here, propensity score matching should be the preferred bias correction procedure, given our data characteristics and the selection mechanism into post-secondary education.

Once ability selection is accounted for by our propensity score matching procedure, the university returns relative to high-school decrease from 0.45 to 0.35 for men and from from 0.45

[3] For similar work for the U.S. see Keane and Rouse (1995).

to 0.41 for women.[4,5] Even after accounting for ability selection into post-secondary education, the gap between the returns to university and the returns to trades or college decreases only slightly. For instance, the gains from university education relative to college are reduced from 0.26 to 0.21 for men and from 0.24 to 0.21 for women after controlling for ability bias. While innate ability can thus account for some of the differential returns between college and university degrees, a large gap still remains.

The second contribution of this paper is related to the differential returns to education between men and women. We find not only that the ability correction is smaller for working women than it is for men, but also that it matters which definition of earnings is employed. In particular, we find that the widely accepted finding of higher OLS returns for university educated women holds only when the outcome is measured in terms of weekly or yearly earnings. If instead we use our preferred measure, hourly wages, there is no OLS differential in the returns to university between men and women.[6] The higher weekly wage returns for women, as documented for instance by Ferrer and Riddell (2002) and Boothby and Drewes (2006), result from a labour supply issue, since university educated women are the only demographic category working more hours per week and per year than the population average. Nevertheless, once we account for selection into education, the corrected returns are generally higher for women than for men for any measure of wages, including hourly wages. This results from the larger ability correction for men compared to women for all wage measures, together with the higher labour supply of university-educated women when looking at weekly or yearly wages.

The paper is organized as follows. Section 2 describes the GSS data we use in this analysis. Section 3 refers to the identifying assumptions and properties of the three bias correction procedures we implement here: propensity score matching, Heckman correction, and IV. Section 4 discusses our findings. We start by placing our OLS results within the rest of the litera-

[4]For college the returns drop from 0.19 to 0.14 for men and from 0.22 to 0.20 for women once ability selection is controlled for. For trades the returns change from 0.15 to 0.12 for men, and from 0.04 to 0.02 for women, for whom the small returns to trades are also not statistically significant.

[5]We report throughout returns as log wage differentials. Usually the log coefficients are a good approximation for percentage increases, but when the coefficients become larger this approximation is less accurate. The percentage difference can be exactly calculated as the exponentiated log coefficient minus 1. The uncorrected returns are from OLS estimation, while the corrected ones are from our preferred propensity score matching specification. The outcome of interest is log hourly wages.

[6]From our OLS computation, the returns to university education are 0.45 for both men and women when the outcome of interest is hourly wages, and 0.46 for men and 0.52 for women with weekly wages.

ture, and then we present returns to post-secondary education corrected for selection bias. We conclude in Section 5.

2 Data Characteristics

In this paper we use the General Social Survey (GSS) 1994 - Cycle 09. The GSS was established by Statistics Canada in 1985 with the purpose of gathering data on social issues and on the living conditions of Canadians over time. Every year Statistics Canada collects information on a cross section of individuals. The information collected varies year by year depending on the focus of the particular GSS Cycle. Examples of topics covered by the GSS are health, time use, victimization, education, work and retirement, family and friends, social support, access to and use of information technology. Usually the topics are repeated every six years; however, not all topics are repeated regularly, with some new topics added later on and others dropped. Unfortunately, the latter is the case for the survey cycles of interest for us, the GSS on Education, Work, and Retirement, which were conducted in 1989 (cycle 4) and 1994 (cycle 9) and then terminated.

Our choice to use the GSS on Education, Work, and Retirement, rather than another Canadian dataset with information on educational attainment, is motivated by the fact that it contains much richer information on individual and family characteristics than other data sets. Most importantly for our study, the GSS collects information on the educational and working history of individuals, the composition of their current family (spouses and children), the composition of their family of origin (parents and siblings) and the education and social status of parents.[7] As detailed in the next section, we can use this rich set of background information to characterize the educational choice of individuals and build a proper counterfactual of what would have been the labour market outcome for an individual, had he or she made different educational choices. This in turn will allow us to assess the bias in OLS estimates when factors outside of the econometrician's control, such as unobserved innate ability, influence both the educational choice and the labour market outcomes of an individual.

To define educational attainment, we use the survey variable "Highest degree, diploma

[7] The social status is given by the Blishen socio-economic index, a measure that assigns an ordinal importance to each occupation code.

or certificate completed". The categories considered in our analysis are high-school diploma ("High-school"), diploma or certificate from trade or vocational schools ("Trades"), diploma or certificate from community college ("College"), and bachelor degree or above ("University").[8] We drop from the sample individuals who report not having a high-school diploma. This includes a few individuals who, despite not having graduated from high-school, have acquired either trades or college education.[9]

The GSS cycle 9 collected information on 11,876 persons 15 years old or older, reporting for a population of about 22 million residents in the ten provinces of Canada. We restrict our analysis to the working age population, 17 to 65 years old, who have completed high school in Canada, are not currently attending any school, and report positive earnings (and are therefore employed) for at least part of the survey year. Considering these restrictions our sample reduces to a total of 3538 observations, 1746 for men and 1792 for women.

Table 1 summarizes the education data for men and women. The second column shows the number of observations in each schooling category, while the third reports the corresponding population equivalent. Each observation is weighted by sample survey weights to ensure the statistics are representative at the national level. The fourth column reports the share of each category in the total population. Our numbers are within the range of statistics reported by OECD (2005) for Canada using 2002 data, also reproduced in Riddell (2002) Table 5. For the full sample, the percentage attending respectively high-school, non-university post-secondary education (trades and college), and university are reported to be 34%, 41% and 24%. Our high-school percentage is slightly higher and the non-university post-secondary education slightly lower. There are two potential reasons for this: the first is that from 1994 to 2002 the percentage of individuals with trades and college degrees could have further increased; the second is that, while the OECD statistics include high-school drop-outs with trades or college degrees, we have eliminated them from our sample.

[8]Because of small sample sizes, we combine within the university category the following: bachelor's degree, first professional degree, university certificate or diploma above bachelors degree, masters degree, and earned doctorate. Due to their short length of study, we consider university diplomas below a bachelor's degree to belong to the college category.

[9]Unlike the U.S., for OECD statistics Canada includes such individuals within the post-secondary education group. We do not believe high-school drop-outs should belong to the post-secondary analysis and thus we drop them from the sample. There are 165 such individuals in the trades group, or 24.5% of all trades observations, and 91 individuals in the college group, or 10.4% of all college observations.

Table 1: Summary Statistics: Educational Attainment

	N obs.	Population	Share
Men			
High school	709	1,506,857	0.41
Trades	277	532,721	0.15
College	312	710,174	0.19
University	448	910,651	0.25
Total	1,746	3,660,403	1
Women			
High school	663	1,239,394	0.38
Trades	232	394,742	0.12
College	470	883,911	0.27
University	427	762,699	0.23
Total	1,792	3,280,746	1

Notes: Authors' calculation using GSS 1994 data. Referenced population: 17 to 65 years old, having completed high school in Canada, not currently attending any school, and reporting positive labour earnings for at least part of the survey year. Population totals are computed by applying GSS survey weights to sample observations.

For men, one third of high-school graduates decide to acquire non-university post-secondary education (trades or community college) after high-school, while one quarter continue to university. The fraction of women who participate in college or trades education is even higher than for men. However, while for men the enrollment rates in trades or college are not that dissimilar, many more women enroll in college education rather than trades. Moreover, unlike men, women in our data are more likely to choose community college over a university education.[10]

To some extent, the educational choices made by individuals can be better understood by looking at the earnings differences between trades, college, and university for women and for men. For all individuals we use the reported main working activity to derive three measures of labour earnings: hourly, weekly, and yearly wages. Because the survey allows people to choose how to report the frequency of their earnings (hourly, weekly, yearly, etc.), when the reported frequency is different from hourly or annually we compute wages using information

[10]We emphasize that we restrict our analysis to working individuals. As such, it may be possible that the educational attainment in the sample of working women differs from the educational attainment of women in general, to the extent that there could be systematic differences between the educational choices of women who are in the labour force compared to those out of the labour force.

on the number of weeks worked during the year and the usual number of hours worked in a week. Summary statistics on earnings data are reported in Table 2.

Table 2: Summary Statistics: Wages by Education Categories

	Hourly wage	Std. err.	Yearly wage	Std. err.
Men				
High school	15.07	0.28	33,495	682.3
Trades	17.76	0.46	39,705	918.4
College	17.52	0.43	38,636	979.9
University	24.70	0.54	55,543	1185.6
Women				
High school	11.82	0.22	21,878	499.3
Trades	12.11	0.34	20,696	786.9
College	14.74	0.33	26,192	642.0
University	18.82	0.44	36,902	932.8

Notes: Authors' calculation, see Table 1 notes.

Columns two and four report the average hourly wages and yearly earnings for each education category; the associated standard errors are in columns three and five. While the college versus trades differential is substantial for women (a college educated woman earns on average more than $\$5,000$ per year over what a trade educated one does), for men there is little difference. Thus it makes sense that women are more likely to get a college education rather than a trades one, while the proportions should be more similar for men. It is also apparent, even from these simple summary statistics, that university seems to be more rewarding than any other post-secondary educational alternative for both genders, even more so for men than for women. Nevertheless, the average unconditional financial gain is not the only factor that determines the education decision; if that were the case, everyone would opt for a university education. The focus of our paper is to disentangle the various factors that determine the choice of higher education and to correctly measure the monetary gain from higher education after accounting for selection into education on the basis of ability.

Our dataset provides relatively good information on the individual's working history. People were asked to report the date when they completed their highest degree and also when they started the first full-time job after graduation, as well as any full-time jobs they might have held prior to or during their studies. We use this information to build an experience variable that takes into account the time individuals spend looking for a job after graduation. This is a more precise measure than the often used potential experience one (which is age minus years of schooling minus 6).[11] We also have access to all the socio-economic variables usually used in Mincerian wage regressions, such as province of residence, union status, and family demographics.

Perhaps the most relevant feature of our dataset comes from a set of questions asking individuals about their family background. As detailed in Section 3, we use this information in two different ways to correct for selection bias, (i) selection on observables (propensity score matching) and (ii) selection on unobservables (Heckman correction and IV estimation). To successfully implement either methodology we need information on individuals that can explain their educational choice in such a way that, conditional on this information, the educational choice can be considered random.

For matching such information can be given by individual and family characteristics that can explain the likelihood of success in school as well as in the working place. In other words we look for those variables that represent a good proxy for the individual's ability, variables that are then correlated with the probability to attend a post-secondary education and also with their earnings once school is finished. Among these variables, we believe that parental education plays a crucial role, given that the intergenerational transmission of ability from parents to their children contributes substantially to define the ability of individuals.[12] It is also a well-established fact that parental education is highly correlated with children's education.

For the IV implementation (as well as for Heckman selection to some extent) we need to find variables that can give a good measure of how the cost of attending post-secondary education differs across individuals, so we can identify variation in participation that is independent of unobserved ability. Although the IV literature related to returns to education is huge, there is no obvious consensus on what a very good instrument should look like in this context. We believe that the province of high school attendance, the number of siblings, and the birth rank of the individual in the family could give a good approximation of exogenous conditions that

[11] Although our measure is a better approximation for overall job market experience, it still falls short of the true experience measure. While we expect that for men our measure is going to be very close to actual experience, we are aware that this may not be the case for women, who tend to move in and out of the labour force much more often than men do.

[12] See for example Plug and Vijverberg (2003) for evidence on genetic transmission of ability as measured by IQ performance. See also Solon (1999) for an overview of the literature about the correlation between parents' and children's earnings.

might affect the direct and the opportunity costs of attending post-secondary education after high school. Geographical variables could affect the cost of education because of policy differences across provinces. All provinces in Canada support post-secondary education directly, by financing post-secondary institutions, and indirectly, by supporting students who need to borrow to cover their expenses either through student loans or through grants. However, the extent of this support varies across provinces, and students might face different costs when residing in different places. Moreover, in more densely populated provinces such as Ontario, students are more likely to live in close proximity of education centres, compared with other provinces. Also, there may be differences in the quality of primary and secondary education across provinces, as well as in the high-school graduation rates.

We also consider that the number or siblings and the rank at birth might affect the support that students could have from their families. In most cases parents support financially the education of their children, either directly or indirectly (for instance by facilitating borrowing). Families with more children might have greater difficulty in spreading their funds across all of their children, resulting in greater difficulty for all siblings in financing post-secondary education. It might also be the case that, in the presence of more children, the household decides to allocate more resources to children based on their birth rank - for example the first born might be privileged compared to subsequent siblings.[13]

While these seem like reasonable candidates for instruments for the methods that would solve the selection bias, ultimately it is up to statistical tests and data to let us know whether indeed they work well as instruments in our case. In what follows we go into greater detail about how the various econometric methods (propensity score matching, Heckman correction and IV models) implement the correction for selectivity bias.

[13]While family composition and income would likely influence an individual's post-secondary decisions, they might also influence early childhood investments in cognitive and non-cognitive skills, which would in turn correlate with the individual's outcomes even conditional on education. This line of reasoning, pioneered by Becker's work on children quantity-quality trade-off (e.g. Becker and Lewis (1973)), may cast some doubt on the appropriateness of family composition as instruments.

3 Estimation Methodologies

To identify the causal effect of education on earnings we use the standard wage equation framework, which accounts for observed characteristics that influence the productivity of a worker. We can summarize the wage equation by

$$Y = \beta X + \delta D + \epsilon,$$

where the left-hand side variable Y represents log earnings; X is a collection of individual characteristics which in our analysis include labor market experience, union status, province of residence, marital status, and the presence of kids at home; D is the education variable; and ϵ is an unobserved nuisance parameter. The focus of our research is on the coefficient δ as a measure of returns to education. In order to compare our results to the previous literature we first perform a multinomial analysis where D is a collection of three indicator variables, one for each education category on top of high-school: trades, college, and university.[14]

As well known in the returns to education literature (see e.g. Card (1999) for a review), a simple Ordinary Least Squares (OLS) regression may not identify the true returns to education δ. If any component of the unobservables ϵ (such as for instance innate ability) is correlated with both the education variable D and the earnings variable Y, the OLS coefficients will be biased and inconsistent. The main methods used in the literature to correct for selection bias, selection on observables (matching) and selection on unobservables (Heckman and IV) differ on the identification assumptions, and on how the selection correction is implemented. In what follows we detail these procedures.

3.1 Selection on Observables: Matching

The assumption here is that the researcher has access to some variables Z correlated with both ability and educational attainment, so that conditional on these variables assignment to education is random. Formally, this identification assumption, called Conditional Independence

[14]The multinomial analysis corresponds to a constrained wage equation which assumes that all the X's have the same effect on individuals with different educational levels (*i.e.* all the β's are constrained to be equal across educational groups). Running separate regressions for each education category relative to high-school would be equivalent to a multinomial analysis where the education indicators are interacted with all other productivity characteristics X, therefore allowing for heterogeneity in the returns to productivity characteristics by education.

Assumption (CIA) or strong unconfoundedness, states that $Y_1, Y_0 \perp D \mid Z$, where Y_1 is the treatment outcome (earnings for individuals with post-secondary education), Y_0 is the outcome without treatment (high-school earnings), D is the treatment indicator (education dummy) and Z is the set of variables that account for selection into education. In fact, this form of CIA is too strong for identification, and all that is needed to uncover unbiased returns to post-secondary education is the weaker, mean-independence assumption $E[Y_0|Z, D = 0] = E[Y_0|Z, D = 1]$. This assumption suffices to identify the returns to post-secondary education for the educated, or what the literature calls the "treatment on the treated" parameter:

$$\Delta^{TT} = E[Y_1|Z, D = 1] - E[Y_0|Z, D = 1].$$

Intuitively, what the mean CIA assumption gives us is the possibility to identify, conditional on the appropriate Z, the counterfactual of what would have been the earnings of post-secondary educated people had they stayed with a high-school education. This counterfactual can now be easily obtained from the observed outcomes of the high-school educated individuals.

The best example of Z from our dataset is parental education. Parental education is strongly correlated with the educational attainment of children: on the average, better educated parents produce better educated children. Better educated parents are higher-than-average ability individuals within their age cohort. Assuming intergenerational transfer of innate abilities, the children of higher-ability parents should also be higher-ability within their own age cohort. Therefore, parental education is also a good predictor for both children's education and children's innate ability. Because we have access to a dataset where we can control for parental education, using selection on observables to control for selection bias should make a very good methodological choice.

Within the class of selection on observables we use the widely-used propensity score matching models. The idea is to find, for each treated individual who attends post-secondary education $D_i = 1$, a very similar (in terms of Z) control individual $D_j = 0$ who did not attend post-secondary education, where $i \in D_1$ denotes post-secondary educated individuals (also referred to as "treatments" in this context) and $j \in D_0$ denotes high-school educated individuals ("controls"). By comparing the earnings of these two very similar individuals we can get a measure of the impact of post-secondary education for the educated individual $\Delta_i = E[Y_{1i} - Y_{0j}|Z]$.

Averaging these impacts across individuals who attended post-secondary education gives the treatment on the treated parameter

$$\Delta^{TT} = E[Y_1|Z, D = 1] - E[Y_0|Z, D = 1] = E[Y_1|Z, D = 1] - E[Y_0|Z, D = 0] = E[Y_{1i} - Y_{0j}|Z].$$

The intuitive procedure described here corresponds to cell matching, where individuals are paired according to a large vector of relevant characteristics Z. One reason for the current popularity of propensity score matching is due to Rosenbaum and Rubin (1983) who show that, if Z satisfies CIA, then rather than matching on the multi-dimensional vector Z, matching can be performed instead on a scalar index $P(Z)$. Such an index $P(Z)$ is the predicted probability of attending higher education conditional on the characteristics Z, $P(D = 1|Z)$. In nearest neighbour matching, for each higher-educated individual the counterfactual non-participation earnings come from the "closest" individual with no post-secondary education, where closest is defined in terms of the distance between propensity scores. More efficient versions of the propensity score matching estimator account for more than one closest nearest neighbour for each educated individuals. Our preferred propensity score matching estimator employs kernel matching, where each participant in post-secondary education is compared not just to a handful of closest neighbours, but to the entire sample of control observations, with each control receiving a weight corresponding to its propensity score distance from the treatment observation. In general, the propensity score matching estimator is given by:

$$\Delta = \frac{1}{n_1} \sum_{i \in D_1} \left[Y_{1i} - \sum_{j \in D_0} w(i, j) Y_{0j} \right]$$

where n_1 is the number of treated persons $i \in D_1$ (n_0 would be the number of untreated persons in $j \in D_0$) and $w(i, j)$ is the weight placed on the j^{th} observations in constructing the counterfactual for the i^{th} treated observation. For instance, in nearest neighbour matching the weight is $w(i, j) = 1$ if $j \in D_0$ is the closest neighbour of i and zero otherwise; for five nearest neighbours the weight is $w(i, j) = \frac{1}{5}$ for each of the five $j \in D_0$ that are closest to i in terms of $P(Z)$ and zero otherwise; for Kernel matching the weights are given by $w(i, j) = \frac{G_{ij}}{\sum_{k \in D_0} G_{ik}}$ where $G_{ik} = G\left(\frac{P(X_i) - P(X_k)}{a_n}\right)$ is a kernel with bandwidth parameter a_n.

Bandwidth selection is an important issue in kernel matching. We pick the functional form of the kernel G and the optimal bandwidth a_n in a cross-validation optimization procedure that minimizes root mean squared error (RMSE).[15] While our main results come from kernel matching estimators with optimal bandwidth, we also report sensitivity results to different bandwidths using the Epanechnikov kernel, as well as results from one, five, and ten nearest neighbours.

Although we cannot test the identification assumption that conditioning on the set of characteristics Z makes assignment to education random, we can test one implication of this assumption, namely whether conditional on the propensity score $P(Z)$ the Z have the same distribution in the treatment and in the control group. Such a test is called the balancing score test. The literature offers more variants for the balancing score test; because it is insensitive to the particular form of the matching estimator, we use here the polynomial version introduced by Smith and Todd (2005). For every possible Z we estimate a polynomial in $P(Z)$ and interactions between D and powers of $P(Z)$. Once we have conditioned by the polynomial in $P(Z)$, further conditioning by the treatment indicator D and interactions between D and the polynomial in $P(Z)$ should not be informative.[16]

One final concern regarding the biases that may arise when using propensity score matching (or other regression techniques such as OLS) is the issue of common support. To compare similar persons, the distribution of the propensity scores for people who go to post-secondary education and for those who do not should have overlapping support. We achieve common support by imposing a min-max condition where we drop observations with a propensity score below the maximum of the two minima or above the minimum of the two maxima of the propensity scores. This is the most commonly used, as well as the easiest, way to impose common support. [17]

[15]See Racine and Li (2005) for details. We are grateful to Dan Black for providing his Stata cross-validation code.

[16]While there is no guidance as for the order of the polynomial, we follow Smith and Todd (2005) by picking a quartic in $P(Z)$. Formally, for each component of the vector Z we can estimate the regression $Z_k = \beta_0 + \beta_1 \widehat{P(Z)} + \beta_2 \widehat{P(Z)}^2 + \beta_3 \widehat{P(Z)}^3 + \beta_4 \widehat{P(Z)}^4 + \beta_5 D + \beta_6 D\widehat{P(Z)} + \beta_7 D\widehat{P(Z)}^2 + \beta_8 D\widehat{P(Z)}^3 + \beta_9 D\widehat{P(Z)}^4 + \epsilon$. The variable Z_k is balanced if we do not reject the null $H_0 : \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0$.

[17]No overlapping common support creates less problems for kernel matching than for nearest neighbour matching or for OLS because observations outside the common support receive a very low weight in kernel matching anyway. We nevertheless impose common support in all non-parametric estimations, including kernel matching.

3.2 Selection on Unobservables: Heckman and IV

The second approach implemented here solves the selection problem by making explicit assumptions about the correlation between the endogenous regressor D and the error term ϵ. Methods belonging to this class of corrections are the Heckman correction model and the Instrumental Variables (IV) approach.

The success of either Heckman or, even more so, IV, hinges very strongly on the availability of a good instrument (or what the Heckman procedure refers to as an "exclusion restriction"), that is, a variable that determines participation in education but not the earnings outcome Y.[18] A good instrument is a variable Z that is correlated with the endogenous regressor D but uncorrelated with the error term (and thus uncorrelated with the outcome variable Y other than through D). The burden of proof usually falls on the researchers, who need to make a convincing argument for the appropriateness of the chosen instrument. In our analysis we use as instrument (or, exclusion restriction in the Heckman model) the number of siblings of an individual. As argued earlier, the number of siblings will influence educational attainment, since it is easier to finance post-secondary education for one child than for four. It is moreover conceivable that the number of siblings would not have a direct influence on the earnings outcome of the individual, conditional on educational attainment.[19]

The selection problem which biases OLS coefficients, $E[\epsilon|X, D] \neq 0$, is solved here by imputing the non-zero conditional mean of the error term as a missing variable. By adding and subtracting this term from the original wage equation we obtain

$$Y = \beta X + \gamma D + E[\epsilon|X, D] + (\epsilon - E[\epsilon|X, D]),$$

where the term in round brackets has now become a well-behaved mean-zero error term. Since, under different assumptions, the term $E[\epsilon|X, D]$ can be recovered as an added regressor with both Heckman and IV procedures, these are also referred to as "control function" methods. $E[\epsilon|X, D]$ represents the control function which, when added to the outcome equation, leads

[18] While identification in the Heckman correction model could rely solely on the non-linearity from a joint normality distribution assumption (discussed in more detail shortly), the ensuing literature has shown that without good exclusion restrictions the Heckman estimator is extremely sensitive to even tiny departures from the joint normality assumption, and the correction may not work.

[19] Parental education would make a poor instrument for exactly the reasons it is a good control in the matching procedure: it is correlated with both education and unobserved ability, thus with earnings potential even conditional on education.

to unbiased coefficient estimates. In what follows we detail the identification assumptions required by the two-stage Heckman and IV estimators, where the control function is estimated in a first-stage participation equation and is then added as an extra regressor in the second-stage outcome equation.

3.2.1 Heckman Correction Estimator

In the Heckman correction framework, the first-stage participation equation is given by: $D^* = \gamma Z + \eta$, where D^* is a latent variable (for instance, utility from education) such that we observe $D = 1$ when $D^* > 0$ and $D = 0$ otherwise. Z is assumed to be orthogonal on ϵ, and it can include any or all of the exogenous X. The extra term can be written as $E[\epsilon|X, D] = E[\epsilon|X, D, Z] = E[\epsilon|X, Z, D = 1]D + E[\epsilon|X, Z, D = 0](1 - D)$. The Heckman correction model further assumes joint normality for the distribution of the two error terms $(\epsilon, \eta)\tilde{\ }N(0, 0, \sigma, 1, \rho)$, where the variance of η is normalized to 1, and σ and ρ are the standard deviation of ϵ and the correlation of ϵ and η respectively. Then, $E[\epsilon|X, Z, D = 1] = E[\epsilon|X, Z, \eta > -\gamma Z)$, and using properties of the truncated normal mean $E[\epsilon|X, Z, D = 1] = \rho\sigma\lambda$, where $\lambda = \frac{\phi(Z\gamma)}{\Phi(Z\gamma)}$, with ϕ and Φ the p.d.f and the c.d.f of the standard normal distribution.[20] Similarly we obtain $E[\epsilon|X, Z, D = 0] = \rho\sigma\widetilde{\lambda}$, where $\widetilde{\lambda} = \frac{\phi(Z\gamma)}{1-\Phi(Z\gamma)}$. The Heckman procedure eliminates therefore the selection bias by imputing the extra term $\rho\sigma(\lambda D + \widetilde{\lambda}(1 - D))$, where $\lambda D + \widetilde{\lambda}(1 - D)$ is computed from the first-stage probit and $\rho\sigma$ is estimated as a coefficient in the second stage wage equation. The true impact of post-secondary education on earnings is computed from corrected wage equation as $\Delta = E[Y|D = 1] - E[Y|D = 0] = \delta + \rho\sigma(\lambda - \widetilde{\lambda})$.[21]

3.2.2 Instrumental Variables (IV) Estimator

In the first step education D is regressed on all exogenous variables X as well as on the instrument Z: $D = \gamma_1 Z + \gamma_2 X + u$. In the second step, the wage equation is estimated by replacing the education indicator D with its prediction $\widehat{D} = \widehat{\gamma}_1 Z + \widehat{\gamma}_2 X$ from the first stage, leading to: $Y = \beta X + \delta\widehat{D} + \epsilon$. Since by assumption the instruments are not correlated with

[20]The literature calls λ inverse Mills ratio, or selection hazard.

[21]While a more efficient one-step maximum likelihood version of the Heckman correction is available, we prefer the two-step procedure because it is slightly more stable when departures from the assumed joint normality occur.

the unobserved error ($Z \perp \epsilon$) and X is exogenous ($X \perp \epsilon$) $\Rightarrow \widehat{D} \perp \epsilon$. Note that the equivalent IV correction can be obtained as a the control function version by supplementing the second stage wage regressors X and D with the residual from the first stage regression, $Y = \beta X + \delta D + \pi \widehat{u} + \epsilon$.

Recent research has shown that a weak instrument, that is an instrument Z that is only weakly correlated with the education attainment variable D, is going to do more harm than good when trying to correct for the bias in the returns coefficient δ. To check whether the instrument Z is strongly correlated with education D, we test whether $\widehat{\gamma_1} = 0$. The R-squared from the first stage regression is also informative in this sense. Finally, we use the second stage regression to test whether the IV model is statistically different from the original OLS one, and therefore whether our selection-bias correction makes any quantitative difference. We do this by looking at the statistical significance of the added regressor $\widehat{u}$. If we cannot reject $H_0 : \widehat{\pi} = 0$ then basically there has been no IV correction.

Two observations apply to both selection on observables and selection on unobservables estimators. The first one regards standard errors. Other than OLS, obtaining correct standard errors is a non-trivial issue, because of the extra variation induced by the 2-stage estimation procedures. For IV we have closed-form standard errors that account for the variation due to the first-stage derived regressor. For matching and for the Heckman correction procedures we compute standard errors in a bootstrap procedure with 300 repetitions.

The second observation refers to the matching and Heckman bias-correction estimators that rely on first-stage estimations of probit models.We do not implement a multinomial procedure to compute joint probabilities. Instead, we get consistent marginal probabilities of attending one level of education versus another directly from the binary probability estimators.[22]

[22] For papers that extend binary correction models to the multinomial case see for instance Imbens (2000), Lechner (2001), or Plesca and Smith (2007).

4 Estimation Results

4.1 Comparing our OLS Results to the Previous Literature

Since we use different data from Ferrer and Riddell (2002) and Boothby and Drewes (2006), we first check to what extent the choice of the dataset drives the difference between our results and those in the previous literature. In Table 3 we summarize the results obtained by Boothby and Drewes (2006) (first column) and by Ferrer and Riddell (2002) (second column) and we compare them with our own results from two different specifications. Reported throughout are log wage coefficients. Column 3 reports results from an OLS analysis where we impose restrictions trying to get as close as possible to the OLS specification and sample restrictions as in Ferrer and Riddell (2002) and Boothby and Drewes (2006). Like in their analysis, we restrict the sample to men and women working full time and full year (FTFY) , we use potential experience (age minus years of schooling minus 6) rather than our more accurate experience measure, and we use as dependent variable log weekly wages. Column 4 has results from our preferred OLS specification, which does not impose FTFY, uses our better experience measure, and looks at log hourly wages as a more direct measure of human capital.

Table 3: Comparison of OLS Returns to Post-Secondary Education in Canada

Log wage coefficient	Boothby *et al.*[a]	Ferrer *et al.*[b]	Restricted[c]	Unrestricted[d]
Men				
Trades	0.108		0.114	0.160
College	0.156		0.135	0.190
Trades and College	0.142	0.125	0.125	0.176
University	0.377	0.373	0.418	0.444
Women				
Trades	0.034		0.016	0.026
College	0.184		0.158	0.208
Trades and College	0.153	0.158	0.107	0.145
University	0.473	0.494	0.486	0.444

[a] Boothby and Drewes (2006), Table 4, Census data 1995. Results reported in log-differences rather than percentage for consistency.

[b] Authors' calculation from Ferrer and Riddell (2002), Census data 1995. Results from specifications (3) and (4) in Table 3, using average education duration from Table 1.

[c] Authors' estimation based on GSS 1994. Log-weekly wages; potential experience used instead of actual experience; sample restricted to FTFY workers ($\geq$ 30 hours/week, $\geq$ 48 weeks/year).

[d] Authors' estimation based on GSS 1994. Log-hourly wages; GSS-defined measure of experience; full sample as defined in Table 1.

Not surprisingly, if we define our sample and variables to be similar to the sample and variables used in Ferrer and Riddell (2002) and Boothby and Drewes (2006), we obtain similar results. However, small differences remain, such as higher returns to university for men, or lower returns to trades and college combined for women.[23] Nevertheless, when we use our preferred unrestricted specification, we depart slightly from the original results. For men our returns are higher at every level of education, although the relative differences remain stable, and for women the returns to university are lower.

While we do not have a conclusive explanation for the larger observed returns for men, we conjecture it could be our more precise measure of experience, which accounts for gaps in experience until the first full-time job is obtained. The potential experience measure used in Ferrer and Riddell (2002) and Boothby and Drewes (2006) considers the initial time spent looking for the first job after graduation as full-time experience, even when this is not the case, and this could potentially account for higher returns to experience at the expense of lower returns to schooling in their specification.

For women our lower returns to university are clearly driven by the different measure of earnings employed. In our preferred specification we focus on hourly wages, while Ferrer and Riddell (2002) and Boothby and Drewes (2006) both use weekly wages. There is little variation in hours worked by men, but women with university education have a higher labour supply than the average. As such, when looking at returns to weekly or yearly wages, we also capture the effect of extra hours worked. This effect is not present when hourly wages are used instead.[24] To bring support to the labour supply assertion, Table 4 presents the hours worked by men and women by education level during a typical week and throughout the year. In Appendix Table A1 we also report statistics on the hours worked in the restricted sample of full-time full-year (FTFY) workers as imposed by Ferrer and Riddell (2002) and Boothby and Drewes (2006).

The hours worked on average by men vary very little across education levels. This is true

[23]Given the order of magnitude of our standard errors, the difference may be simply due to random errors.

[24]As far as OLS results are concerned, contrary to previous findings in the Canadian literature, we find that men and women have similar returns to a university education when looking at hourly wages. Higher OLS results for women can be obtained for weekly or yearly wages, as a result of labour supply differences. We investigate this issue in further detail later on, using our preferred specification and focusing on three different outcome measures: hourly, weekly, and yearly wages.

Table 4: Summary Statistics: Labour Supply by Education Categories

	Weekly Hours			Yearly Hours		
	Mean	Std.Dev.	N.Obs.	Mean	Std.Dev.	N.Obs.
Men						
High-school	44.6	12.0	648	2158.0	766.4	648
Trades	43.5	9.5	252	2105.5	622.8	251
College	44.7	11.1	288	2174.9	727.3	287
University	44.6	11.8	410	2232.2	718.7	409
Total	44.5	11.4	1598	2171.8	726.7	1595
Women						
High-school	35.7	11.4	560	1723.5	688.0	559
Trades	36.4	13.1	203	1766.2	728.4	203
College	35.9	11.9	417	1725.5	681.1	416
University	39.5	12.8	384	1966.8	730.5	380
Total	36.8	12.2	1564	1788.9	708.8	1558

Notes: Authors' calculation, full sample. See notes from Table 1.

for both hours worked per week and hours worked per year; similar results are given by the FTFY analysis reported in Appendix Table A1. For women the picture changes dramatically. There is little difference between average hours worked among high-school, trades, and college educated women, while university graduates work on average almost 4 hours a week more than all other women, and about 240 hours a year more. Although the differences in hours worked are slightly lower for FTFY women than for the unrestricted sample, they are still substantive (see Table A1).

Overall the information in Table 3 indicates that, although we use a different dataset and a close but different year in our estimation, our results can be reconciled with the results obtained by previous literature using Census data. In this sense we are confident that the use of our dataset, which is significantly richer in personal and family information than the Census, provides comparable results that can be generalized to the whole Canadian population.

4.2 Bias-Corrected Returns to Education

Table 5 summarizes the main results of our analysis, separately for men and women. We start with the multinomial OLS results (which were already presented in the last column of Table 3). The second column of Table 5 reports returns to post-secondary schooling using the same simple OLS procedure but performing separate regressions for each level of schooling above high-school relative to high-school only.[25, 26] The returns to schooling from the three separate regressions are very close to the multinomial case, lending further support to the bivariate analysis. It is more convenient for us to focus on separate regressions by education groups in order to easily implement the procedures which correct for selection bias and compare their results with OLS.

Table 5: Returns to Education using Log Hourly Wages

	Men			**Women**		
	M-OLS[a]	2x2-OLS[b]	Matching[c]	M-OLS[a]	2x2-OLS[b]	Matching[c]
Trades	0.160	0.145	0.115	0.026	0.043	0.016
	(0.032)	(0.032)	(0.035)	(0.032)	(0.032)	(0.041)
College	0.190	0.191	0.141	0.208	0.217	0.201
	(0.031)	(0.031)	(0.035)	(0.026)	(0.027)	(0.034)
University	0.444	0.450	0.352	0.444	0.454	0.409
	(0.028)	(0.029)	(0.041)	(0.027)	(0.029)	(0.034)

Standard errors in parenthesis.
[a] Multinomial OLS: one single OLS regression with dummies for each educational level. Reference group is high-school graduates;
[b] Two by two OLS: three OLS regressions, each comparing one level of post-secondary education with high-school;
[c] Matching: three estimation procedures, each comparing one level of post-secondary education with high-school. Kernel matching with optimal bandwidths.

Given the very rich information on family background and the identifying assumptions for the three correction procedures, we believe our dataset to be best suited for the matching correction for selectivity. This is further confirmed by the statistical properties of matching, Heckman, and IV estimators, as resulting from the first and second stage estimations, properties which will be further discussed in Sections 4.2.1 and 4.3.1. We focus therefore our discussion on the bias-corrected returns to education as obtained from the propensity score matching correction method. The main results come from kernel matching with optimal kernel

[25]This method differs from the multinomial one only by allowing the coefficients on all the X to vary from one regression to the other, while in the multinomial specification all explanatory factors except for education are constrained to have the same coefficient across different education groups.

[26]The full regression coefficients and R-square statistics for the multinomial OLS regressions are provided in Appendix Table A2. Similar details for the separate OLS regression analysis for men and for women are available from Appendix Tables A3 and A4 respectively.

and bandwidth as reported in Appendix Table A5.[27]

We provide returns to education corrected for ability selection bias in column 3 of Table 5 for men and in column 6 for women. The bias correction procedure decreases the returns to post-secondary education when compared to OLS returns, indicating a positive ability selection into higher education. Just like in the OLS case, with the exception of women with trades education, the results are all statistically significant.

For men the bias corrected returns go down to .352 compared to the .452 OLS returns, while college returns go down to .141 compared to the .191 OLS returns. Accounting for selection bias not only lowers the returns for post-secondary education, but, because the ability selection into university is the highest, it also decreases to some extent the puzzlingly large gap between returns to university and college education. However, even taking into account the bias, there is still a 23% difference between the earnings of the two educational groups.This gap seems still too high to justify the preference that many Canadians show for trades or college education over university.

For women, unlike in the OLS case, the returns to university are higher for women than for men once selection bias is accounted for by matching. This result is consistent with the trend in higher enrollment in university for women relative to men which has started by the mid-nineties, as document for instance in Christofides, Hoy, and Yang (2006). Once men's selection is corrected by the matching procedure, the returns to college education become higher for women than for men.[28] The higher returns might explain the higher enrollment in college education for women relative to men as indicated in Table 1. Nevertheless, like in the men's case, even after accounting for the selection bias, a difference of 23% between unioversity and college earnings still remains. Finally, the returns to trades education are very low, which raises the question of why so many women choose this type of education at all.

The education ability bias, as measured by the difference between OLS and matching-corrected estimates, is lower for women compared to men. One possible explanation can come from the labour supply side. Participation rates for high-school educated women are lower than those for other education categories, especially university educated women, presumably

[27] A more detailed discussion on kernel and bandwidth choice and sensitivity to different bandwidths appears in Section 4.2.1.

[28] Matching results indicate that there is virtually no selection into this type of education for women.

because women of higher ability face a higher opportunity cost of not participating in the labour market. It is plausible then that high-school educated women who do not participate in the labour force are on the average of lower ability. For the university-educated women this effect is mitigated both by the smaller fraction who do not participate in the labour force and by assortative mating arguments.[29] Therefore, it may be the case that there is an ability differential between high-school and university educated women coming through the labour participation channel that we do not account for. If that were indeed the case, then the OLS returns for women would be higher than our sample estimate, and the bias correction would also be larger and closer to the correction for men. Since we do not correct for selection into the labour force, we can only conjecture what the results would be for the entire women population. Still, we can make a strong case for the returns in the subpopulation of working women we observe in our sample.

The results for log weekly wages reported in Table 6 are consistent with the story told so far. For men, for whom the hours worked do not vary much across education, there are very few differences between the returns to log weekly wages and the log hourly wage results as reported in Table 5. The same positive ability selection is identified, resulting in smaller returns relative to the OLS ones. For women with university education, because of their higher labour supply relative to the rest of women, returns to weekly wages are higher compared to the returns to log hourly wages, both for OLS and for the bias-corrected matching estimator. The analysis for log yearly wages, reported in Appendix Table A6, further reinforces these conclusions. For men the returns to log yearly wages are similar to the returns to hourly and weekly wages, while for women they are larger than the returns to weekly wages, which are in turn larger than the returns to hourly wages. For any measure of wages: hourly, weekly, or yearly, the matching-corrected returns to university and college are higher for women than for men.

[29] Assortative mating suggests that highly educated women marry highly educated men. As a result, these women have higher family incomes because of their spouses, which may in turn decrease their work incentives.

Table 6: Returns to Education using Log Weekly Wages

	Men			Women		
	M-OLS[a]	2x2-OLS[b]	Matching[c]	M-OLS[a]	2x2-OLS[b]	Matching[c]
Trades	0.175	0.156	0.099	0.027	0.038	0.017
	(0.037)	(0.037)	(0.037)	(0.048)	(0.049)	(0.065)
College	0.213	0.212	0.144	0.199	0.218	0.158
	(0.035)	(0.035)	(0.038)	(0.039)	(0.041)	(0.044)
University	0.455	0.464	0.334	0.527	0.520	0.480
	(0.031)	(0.034)	(0.043)	(0.041)	(0.042)	(0.049)

[a] Multinomial OLS: one single OLS regression with dummies for each educational level. Reference group is high-school graduates;

[b] Two by two OLS: three OLS regressions, each comparing one level of post-secondary education with high-school;

[c] Matching: three estimation procedures, each comparing one level of post-secondary education with high-school. Kernel matching with optimal bandwidths.

4.2.1 Statistical Properties of Matching Estimators

We can rely on statistical tests to verify, to a certain extent, the appropriateness of each correction method. For matching, the first step requires computing the propensity score which combines in an index measure the covariates Z conditional on which assignment to education can be considered random. This is done in a probit estimation reported in Appendix Tables A7 and A8 for men and women respectively. Besides the role of the probit model in providing the metric to compare participants and non-participants, the probit results are relevant from a substantive point as well, by giving us an idea about what determines selection into post-secondary education. For both men and women, parental education matters especially for the decision whether to attend university or not. Individuals whose mothers have less than high-school education or whose fathers have any other education than university are less likely to participate in university education.[30] Having more sisters and brothers decreases the probability of a university education for men; the same story applies to men with trades or college education, and to women in all post-secondary education categories, but the coefficients are

[30] For other education categories the parental education coefficients are not significant, except for men who are more likely to enroll in trades or college education if their fathers also had a trades or college education, all else equal.

not statistically significant (except for women with trades education, where the sister dummies are once again significant). In general, living in any other province than Ontario increases the probability of a trades education, and, with few exceptions (not statistically significant) decreases the probability of college or university education for both men and women.

Related to the first stage probit analysis, we can observe that common support does not seem to pose a major problem. Very few observations (ranging from none for men with trades or college education, up to at most 1.5% for women with university education) are lost due to lack of common support. Moreover, the results from the polynomial version of the balancing score test, presented in Appendix Tables A9 and A10, indicate that balancing is almost always achieved in our specification.[31]

One final relevant thing for the matching procedure is the bandwidth selection in the kernel estimation, or, similarly, the number of neighbours in the nearest neighbour estimation in the second stage of the propensity score matching procedure. The main numbers we report in matching come from kernel estimation where the kernel and bandwidth have been selected in a leave-one-out cross-validation procedure that minimizes the root mean squared error (RMSE).[32] The optimal kernel and bandwidth choice for each education category are reported in Appendix Table A5. While the propensity score matching literature has documented in some instances significant sensitivity to the bandwidth choice, this is not the case in our estimation. Appendix Table A11 reports returns to education results from kernel propensity score matching with different bandwidth choices in kernel, as well as different number of neighbours in nearest neighbour matching. All results are remarkably close to those from kernel matching with optimal bandwidths. Matching overall appears to be a stable and appropriate bias correction procedure.

4.3 Sensitivity to Heckman and IV Corrections

Sensitivity results from using selection on unobservables correction methods, Heckman and IV, are reported in Table 7. Compared to the biased OLS, the Heckman correction procedure

[31] Since for each covariate Z the null hypothesis tested is that extra conditioning on the participation variable should provide no further information, a successful balancing score should show a small F test statistic and a large P-value, preferably more than 0.10.

[32] Details on the candidate kernels and the corresponding RMSE are available from the authors upon request, but for reasons of space we omit them here.

indicates, just like matching, a positive ability selection into post-secondary education. The bias correction is larger for men with trades education and for women with all levels of post-secondary education, and it appears negligible for men with college education. The correction also appears negligible for men with university education in the case of hourly wage outcome only.[33] As a consequence of the small ability bias detected by the Heckman procedure for men, the returns to college are smaller for women than for men when Heckman correction is applied. Moreover, for hourly wages only, the ability-corrected returns to university are smaller for women than for men.

The results from the IV procedure are more puzzling. While not statistically significant, the IV returns indicate a very large negative ability selection bias for men into college education, and, to a lesser extent, for women into university education (for whom returns are also statistically significant).

One should keep in mind that the IV procedure, and also the Heckman correction to some extent, only work if the right set of instruments is available.[34] While we may have compelling arguments in favour of our instruments, one could also find arguments against their validity, for instance that the number of siblings may be still correlated with ability through early childhood intervention effects. We proceed now to investigate the statistical properties of these estimators.

4.3.1 Statistical Properties of Heckman and IV Estimators

Like in matching, the first step in the Heckman correction procedure is a probit model for education choice.[35] Appendix Tables A12 and A13 report in the top panel the first stage probit regression and in the bottom panel the second stage log hourly wage regression corrected for

[33] Statistical properties of the Heckman estimator, discussed later on, confirm the bias correction is not significant only for men with college or university education for the hourly wage outcome. Results not reported here also show that for the weekly and yearly wage outcomes the correction is significant for all education groups except for men with college education.

[34] Because, unlike IV, the Heckman procedure also exploits the non-linearity embedded in the joint normality assumption, good instruments (exclusion restrictions) are still important for the Heckman correction but less crucial than for the IV case.

[35] While in matching probit is only one of the options available in the first step estimation - for instance, logit is also a popular choice to which matching results are not sensitive - the Heckman correction relies on the normality assumption embedded in the probit.

Table 7: Returns to Education Heckman and IV Bias Correction

	Men		Women	
	Heckman	IV	Heckman	IV
Outcome: Log-Hourly Wage				
Trades	0.111	-0.226	-0.002	0.104
	(0.038)	(0.414)	(0.039)	(0.306)
College	0.188	0.406	0.164	-0.018
	(0.033)	(0.333)	(0.035)	(0.390)
University	0.428	0.406	0.383	0.515
	(0.039)	(0.151)	(0.039)	(0.183)
Outcome: Log-Weekly Wage				
Trades	0.094	-0.360	-0.043	0.282
	(0.042)	(0.485)	(0.075)	(0.423)
College	0.205	0.034	0.146	0.132
	(0.038)	(0.361)	(0.055)	(0.557)
University	0.406	0.445	0.419	0.718
	(0.046)	(0.173)	(0.055)	(0.285)

Notes: Authors' calculation. Standard errors in parenthesis. Reference group: high-school graduates. Data as defined in Table 1.

selection, for men and women respectively.[36] While we argued that the number of siblings can work as exclusion restriction (or instrument) and therefore must be part of the probit in the Heckman correction, other variables such as parental education may determine both the post-secondary education decision and the wage outcome, and are not good exclusion restrictions, but may be nevertheless part of the probit participation model.[37] For all specifications the estimated coefficient $\rho\sigma$ in front of the correction term $\lambda D + \widetilde{\lambda}(1 - D)$ is negative, indicating therefore a positive ability selection into all categories of post-secondary education for both men and women. While it is significant for men with trades education and for women with all

[36]For reasons of space, we do not present here first and second stage regression output for weekly and yearly log wages. These estimation results are available form the authors.

[37]A specification which did not include parental education in the first step produced very similar results.

categories of post-secondary education, it is not significant for men with college or university education. This is consistent with the Heckman corrected results reported in Table 5 which indicate a substantial correction for the returns of men with trades education and for women with all levels of post-secondary education, but little change in the returns of men with college and university education compared to the biased OLS results.[38]

The full results from the IV estimations are reported in Appendix Tables A14 and A15.[39] The first stage equation regresses the endogenous education variable on instruments and on all other exogenous X from the second stage wage equation.[40] The F test for the joint significance of instruments in the first stage estimation indicates we have a weak instruments problem for all education categories except for men and women with university education. Since weak instruments may do more harm then good, we should feel very reluctant to put any emphasis on the IV returns to trades or college education. Indeed, looking at the IV corrected returns for these specifications, they are statistically insignificant. Furthermore, the endogeneity test rejects statistical differences between the OLS estimation and the IV in all cases, including the university returns. While the IV correction for men with university education is in line with the matching and Heckman results, for women it is not: the matching and Heckman procedures identify positive ability selection into university, while IV finds the opposite. Given that statistical tests indicate the IV correction is not particularly successful, we prefer to focus on the other correction results when interpreting the ability selection into post-secondary education.

4.4 The Rate of Return to Post-Secondary Education

We also calculate the internal rate of return to college and university education in a similar fashion to Drewes (2006). The internal rate of return is given by the value of the discount rate

[38] Also note that the coefficient on the education dummy from the second stage wage equation does not represent the returns to education, which should instead be computed as $E[Y|D=1] - E[Y|D=0] = \delta + \rho\sigma(\lambda - \widetilde{\lambda})$.

[39] Like with the Heckman correction, for reasons of space we only present here full estimation coefficients for log hourly wages.

[40] Since province of residence is among the exogenous regressors in the wage equation, we could not also use the province of high-school education as an instrument because of collinearity between the province of residence and the province of high-school education. Instead, we used as instrument an indicator whether the province of high-school education is the same as the province of residence.

that makes the relative gain from post-secondary education as compared to high-school equal to its costs, that is, the r that solves

$$\sum_{t=0}^{45} \frac{E_t^i - E_t^h}{(1+r)^t} - C = 0 \tag{1}$$

where E_t^i are the expected earnings at time t by persons with education $i = c, u$ for college and university respectively, and C is the direct cost of education, mainly fees.[41] In Table 8 we report the internal rates of return to college and university education for men and women as implied by our OLS and matching corrected regressions.

Table 8: Simulated Internal Rates of Returns to College and University

		Men		Women	
		College	University	College	University
Drewes (2006)[a]		0.1180	0.1140	0.1140	0.1280
LSE[b]	OLS	0.1143	0.1323	0.1265	0.1507
	Matching	0.0839	0.1032	0.1171	0.1384
NO-LSE[c]	OLS	0.1096	0.1225	0.1258	0.1148
	Matching	0.0790	0.0932	0.1164	0.1025

[a] Drewes (2006), Table 8;
[b,c] Authors' calculation based on equation 1. Lifelong earnings path of individuals computed based on OLS coefficients from the regressions reported in Tables A3 and A4 for men and women respectively. Hourly wages by level of education and experience are calculated first, then expected yearly earnings are computed by multiplying hourly wages by total hours worked. Labour supply effects are embedded in total hours worked as follows:
[b] Labor Supply Effects: hourly wages times average hours worked by education level;
[c] No-Labor Supply Effects: hourly wages times total average hours worked.

While Drewes (2006), whose results we reproduce in the beginning of our table, finds that the rate or return for college and university are not very dissimilar and therefore might explain the high enrollment in college education in Canada, we find a larger difference between the two. When we account for the effect of post-secondary education on labour supply, we find that the OLS internal rate of return for college education is 11.43% for men and 12.65% for women, while for university it is 13.23% for men and 15.07% for women.[42] The matching internal

[41]Our computation differs from the one made by Drewes (2006) in that we explicitly discount the costs, so that $C = \sum_{t=0}^{n} \frac{c_t}{(1+r)^t}$ with $n = 2$ for college and $n = 4$ for university.

[42]If we do not account for the effect of education on labour supply and focus instead on the returns to

rates of return are much lower than the OLS ones for men, and somewhat lower for women, consistent with matching accounting for selection bias into education. Nevertheless, the gap between the internal rate or return to college and the internal rate of return to university remains substantial, at about 2% for both men and women, even after taking into account ability selection into education.

5 Conclusion

Using a dataset rich in information on personal background, the 1994 Canadian General Social Survey (GSS), we provide selection-corrected estimates of the return to schooling. We perform the estimation separately for men and women to allow for a different selection mechanism and wage process for each gender. Among the three estimators implemented to correct for selection bias, propensity score matching, Heckman correction, and IV, we find propensity score matching to be the most reliable one, given identification assumptions and available data. We find the IV estimator to perform rather poorly, despite the fact that ex-ante the instruments had seemed plausible enough.[43]

Substantively, our results show positive ability selection into post-secondary education, especially for men. In other words, part of what the OLS estimator identifies as returns to education actually represents returns to innate ability. Once we correct for ability selection bias, the returns to post-secondary education are lower than the OLS numbers would indicate. For women, propensity score matching indicates a bias correction of a smaller magnitude than for men, which we conjecture may be related to women's selection into labour force participation.

Moreover, we use different labour earnings measures: hourly, weekly, and yearly, in order to separate the effects of education on human capital from those on labour supply. We document that the widely accepted finding of higher OLS returns to university for women holds only when the outcome is measured in terms of weekly or yearly earnings, because university-

productivity, we find substantively lower internal rates of returns for university educated women, given their labour supply response to university education.

[43] Since the Heckman estimator relies less heavily on the availability of good instruments, especially if departures from joint normality are small, the Heckman estimator has worked better than the IV in the context of correcting for post-secondary self-selection bias using the Canadian GSS.

educated women work more than the high-school educated ones (while this is not the case for men). When we use our preferred measure of hourly wages instead, there is no significant OLS differential in the returns to university between men and women. Nevertheless, once we account for the ability selection into post-secondary education, because we identify a larger selection bias for working men than for working women, the bias-corrected returns are higher for women than for men for all wage measures, including the hourly one.

Once we correct for ability selection bias, the university returns relative to high-school decrease slightly more than the returns to college or trades, for both genders. Because we find evidence of ability selection into all levels of post-secondary education, albeit of different magnitudes, the gap between the returns to trades or college and university decreases only slightly once ability selection is corrected for. Therefore, ability selection can account only for some of the differential returns between a university and non-university post-secondary education degrees. The large gap that remains may be perhaps due to differences in human capital technology between community colleges and universities.

We also compute internal rates of return to education, and we find somewhat lower rates or return for college compared to university, even after accounting for ability differences. We conclude that the high enrollment in community colleges in Canada represents a puzzle not justified by the lower returns generated by a non-university post-secondary education. Moreover, while internal rates of return can be illustrative of the education investment decisions faced by individuals, the computation is very sensitive to more or less ad-hoc constraints imposed by researchers, in particular relating to the duration of study and the direct costs of education.

To consistently explain how students select themselves into different educational programs, and how human capital gets accumulated, we need the discipline brought on by a full estimation of a structural model. Such a model should account for the present value of costs and benefits of human capital accumulation in a heterogeneous population. This is our next line of research.

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Table A1: Summary Statistics: Labour Supply by Education Categories - FTFY

	Weekly Hours			Yearly Hours		
	Mean	Std. Dev.	N. Obs.	Mean	Std. Dev.	N. Obs.
Men						
High-school	46.2	11.1	521	2,401.4	575.8	521
Trades	44.0	8.3	210	2,287.8	431.5	209
College	45.6	11.0	242	2,370.3	570.9	241
University	46.2	10.7	358	2,403.1	557.1	357
Total	45.7	10.6	1,331	2,378.3	550.5	1,328
Women						
High-school	40.4	7.6	385	2,100.4	395.1	384
Trades	40.4	9.8	146	2,100.3	507.2	146
College	40.2	7.9	280	2,088.3	413.4	279
University	43.1	10.0	292	2,244.5	522.5	291
Total	41.1	8.8	1,103	2,135.4	456.0	1,100

Notes: Authors' calculations, see notes on Table 1. Sample further restricted to workers working full time full year (FTFY).

Table A2: OLS Multinomial Analysis, Log Hourly Wages

Wage equation	Men		Women	
	Coef.	Std. Err.	Coef.	Std. Err.
Trades	0.1601	0.0322	0.0261	0.0325
College	0.1905	0.0310	0.2076	0.0262
University	0.4444	0.0276	0.4443	0.0275
Marital status: married	0.1333	0.0315	0.0748	0.0261
Marital status: div./wd./sep.	0.0395	0.0452	0.0847	0.0344
Province: NFL	-0.3078	0.0512	-0.2349	0.0480
Province: PEI	-0.3316	0.0748	-0.1859	0.0627
Province: NS	-0.1802	0.0464	-0.2446	0.0429
Province: NB	-0.2180	0.0520	-0.2286	0.0430
Province: QUE	-0.0994	0.0334	-0.0638	0.0315
Province: MAN	-0.2032	0.0476	-0.1350	0.0442
Province: SAS	-0.1824	0.0504	-0.1949	0.0450
Province: ATA	-0.0692	0.0390	-0.1293	0.0357
Province: BC	-0.0537	0.0373	0.0048	0.0362
Immigrant	-0.0414	0.0461	0.0259	0.0442
Experience	0.0321	0.0034	0.0326	0.0032
Experience squared	-0.0006	0.0001	-0.0007	0.0001
Children at home: 1	-0.0218	0.0370	-0.0384	0.0283
Children at home: 2	0.0095	0.0339	0.0264	0.0303
Children at home: 3 or more	0.0456	0.0470	0.0734	0.0472
Union/Collective agreement	0.2233	0.0221	0.2598	0.0211
Constant	2.2426	0.0372	2.0553	0.0350
N. Obs.		1591		1588
R-squared		0.311		0.355

Table A3: OLS Analysis, Men, Log Hourly Wages

	Trades		College		University	
Wage equation	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Education dummy	0.1449	0.0322	0.1906	0.0310	0.4501	0.0289
Marital status married	0.1450	0.0429	0.1745	0.0414	0.1089	0.0409
Marital status div./wd./sep.	0.1005	0.0580	0.1581	0.0606	-0.0058	0.0575
Province NFL	-0.2650	0.0624	-0.3235	0.0676	-0.3477	0.0677
Province PEI	-0.2238	0.1060	-0.2525	0.1031	-0.3260	0.0896
Province NS	-0.1503	0.0615	-0.1388	0.0614	-0.1678	0.0610
Province NB	-0.1756	0.0694	-0.1878	0.0602	-0.2070	0.0690
Province QUE	-0.0755	0.0461	-0.0525	0.0426	-0.0614	0.0421
Province MAN	-0.1504	0.0606	-0.1577	0.0592	-0.1951	0.0561
Province SAS	-0.1094	0.0631	-0.1674	0.0650	-0.1527	0.0622
Province ATA	-0.0469	0.0525	-0.0837	0.0499	-0.0240	0.0499
Province BC	0.0362	0.0493	-0.0109	0.0491	-0.0458	0.0466
Immigrant	-0.0436	0.0669	-0.0004	0.0666	-0.0631	0.0576
Experience	0.0317	0.0044	0.0318	0.0044	0.0372	0.0043
Experience squared	-0.0006	0.0001	-0.0006	0.0001	-0.0007	0.0001
Children at home 1	-0.0229	0.0484	-0.0350	0.0482	0.0129	0.0492
Children at home 2	-0.0015	0.0442	-0.0290	0.0447	0.0068	0.0443
Children at home 3 or more	0.0144	0.0629	-0.0387	0.0625	0.0570	0.0597
Union/Collective agreement	0.2792	0.0288	0.2594	0.0286	0.2023	0.0281
Constant	2.1832	0.0474	2.1892	0.0455	2.2083	0.0449
N. Obs.		901		929		1051
R-squared		0.276		0.272		0.350

Note: The reference group is High School graduates for each estimation.

Table A4: OLS Analysis, Women, Log Hourly Wages

	Trades		College		University	
Wage equation	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Education dummy	0.0429	0.0320	0.2166	0.0269	0.4536	0.0287
Marital status married	0.0596	0.0371	0.0661	0.0337	0.0945	0.0339
Marital status div./wd./sep.	0.0542	0.0484	0.1095	0.0429	0.0807	0.0455
Province NFL	-0.3860	0.0729	-0.2891	0.0637	-0.2413	0.0729
Province PEI	-0.1887	0.0821	-0.1826	0.0736	-0.2109	0.0830
Province NS	-0.2636	0.0606	-0.2804	0.0609	-0.2697	0.0522
Province NB	-0.2040	0.0668	-0.2490	0.0512	-0.2231	0.0590
Province QUE	-0.0970	0.0471	-0.0844	0.0392	-0.0733	0.0418
Province MAN	-0.1494	0.0619	-0.1778	0.0532	-0.1710	0.0562
Province SAS	-0.2262	0.0560	-0.2453	0.0565	-0.2300	0.0569
Province ATA	-0.0587	0.0505	-0.1397	0.0449	-0.1136	0.0453
Province BC	0.0148	0.0484	0.0452	0.0454	-0.0295	0.0444
Immigrant	0.0762	0.0669	0.0044	0.0561	-0.0128	0.0566
Experience	0.0299	0.0044	0.0344	0.0040	0.0339	0.0041
Experience squared	-0.0005	0.0001	-0.0007	0.0001	-0.0007	0.0001
Children at home 1	-0.0087	0.0391	-0.0229	0.0358	-0.0144	0.0374
Children at home 2	-0.0051	0.0427	-0.0037	0.0375	0.0214	0.0404
Children at home 3 or more	0.0990	0.0642	0.0196	0.0615	0.1189	0.0610
Union/Collective agreement	0.2768	0.0311	0.2540	0.0273	0.2346	0.0281
Constant	2.0543	0.0472	2.0570	0.0419	2.0466	0.0430
N. Obs.		786		1011		965
R-squared		0.270		0.305		0.403

Note: The reference group is High School graduates for each estimation.

Table A5: Optimal Kernel and Bandwidth Choice

	Log hourly wage		Log weekly wage		Log yearly wage	
	Kernel type	Bandwidth	Kernel type	Bandwidth	Kernel type	Bandwidth
			MEN			
Trades	Tricube	0.056	Epanechnikov	0.019	Epanechnikov	0.021
College	Epanechnikov	0.053	Epanechnikov	0.033	Tricube	0.044
University	Epanechnikov	0.060	Epanechnikov	0.055	Epanechnikov	0.055
			WOMEN			
Trades	Epanechnikov	0.034	Epanechnikov	0.031	Epanechnikov	0.031
College	Epanechnikov	0.016	Epanechnikov	0.143	Epanechnikov	0.130
University	Tricube	0.132	Epanechnikov	0.109	Epanechnikov	0.109

Notes: The optimal kernel function and bandwidth are chosen in a leave-one-out cross-validation procedure that minimizes the RMSE.

Table A6: Returns to Education using Log yearly Earnings

	Multinomial OLS	OLS	Matching	Heckman	IV
Men					
Trades	0.180	0.161	0.130	0.105	-0.439
	(0.045)	(0.048)	(0.056)	(0.058)	(0.828)
College	0.206	0.210	0.134	0.206	0.006
	(0.043)	(0.046)	(0.051)	(0.047)	(0.481)
University	0.490	0.494	0.353	0.417	0.517
	(0.038)	(0.039)	(0.046)	(0.045)	(0.211)
Women					
Trades	0.022	0.038	0.035	-0.022	-0.152
	(0.060)	(0.060)	(0.070)	(0.082)	(0.521)
College	0.183	0.199	0.148	0.110	-0.213
	(0.049)	(0.056)	(0.063)	(0.084)	(0.836)
University	0.562	0.559	0.523	0.450	0.710
	(0.051)	(0.049)	(0.050)	(0.063)	(0.345)

Notes: Authors' estimation. Standard errors in parenthesis. Reference group: High-school graduates. Data as defined in Table 1 Kernel matching with optimal bandwidth.

Table A7: Propensity Score Matching, Men

	Trades		College		University	
Education equation	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Mother educ. trades, college	-0.0815	0.2684	0.2132	0.2705	-0.0882	0.2141
Mother educ. high-school	-0.1689	0.2531	0.0861	0.2609	-0.2295	0.2035
Mother educ. below high-school	-0.3816	0.2465	-0.0940	0.2561	-0.4385	0.2017
Father educ. trades, college	0.5419	0.2546	0.4362	0.2316	-0.5382	0.1797
Father educ. high-school	0.0560	0.2557	0.2170	0.2305	-0.6082	0.1709
Father educ. below high-school	0.2505	0.2321	0.1138	0.2104	-1.0233	0.1554
Age 20-24 years old	5.1894	0.3463	5.7415	0.3151		
Age 25-29 years old	5.6902	0.3290	6.1212	0.3047	6.1757	0.2152
Age 30-34 years old	5.9323	0.3208	6.1272	0.3025	6.3564	0.2096
Age 35-39 years old	5.9498	0.3213	5.8618	0.3055	6.2320	0.2153
Age 40-44 years old	5.9643	0.3273	6.1684	0.3077	6.6621	0.2150
Age 45-49 years old	5.9828	0.3380	6.1218	0.3198	6.5795	0.2263
Age 50-54 years old	5.4531	0.4024	6.0467	0.3534	6.7624	0.2540
Age 55-59 years old	5.5738	0.3613	5.7422	0.3454	6.3992	0.2466
High-school province NFL	0.9762	0.2020	-0.2046	0.2226	-0.2513	0.2225
High-school province PEI	0.5131	0.3865	-0.1082	0.3641	0.4632	0.3018
High-school province NS	0.6904	0.2087	0.0121	0.1957	-0.2824	0.2001
High-school province NB	0.3675	0.2343	0.2725	0.1836	-0.2139	0.2148
High-school province QUE	0.5531	0.1560	-0.0116	0.1299	-0.0041	0.1249
High-school province MAN	0.1676	0.2201	-0.6536	0.2113	-0.0309	0.1665
High-school province SAS	0.5749	0.1993	-0.4712	0.2159	0.0157	0.1762
High-school province ATA	0.6265	0.1907	-0.0406	0.1698	-0.0763	0.1698
High-school province BC	0.6293	0.1744	-0.2709	0.1683	-0.3342	0.1612
Birth rank first-born	-0.0457	0.1117	-0.0659	0.1056	0.0440	0.0980
Siblings 1 sister	0.1691	0.1331	0.0677	0.1291	-0.1407	0.1167
Siblings 2 sisters	-0.1112	0.1549	0.1294	0.1405	-0.3188	0.1310
Siblings 3 sisters	-0.1084	0.1472	-0.2041	0.1437	-0.4928	0.1334
Siblings 1 brother	-0.0733	0.1339	-0.2556	0.1229	-0.2446	0.1179
Siblings 2 brothers	-0.0609	0.1535	-0.1645	0.1434	-0.1768	0.1349
Siblings 3 brothers	-0.0201	0.1540	-0.2018	0.1482	-0.2682	0.1446
Constant	-6.7492	0.4648	-6.3864	0.4320	-5.0681	0.2909
N.Obs. & support	Off	On	Off	On	Off	On
Untreated (High-school)	0	645	0	645	0	626
Treated (Other education)	0	256	0	284	7	399
Total	0	901	0	929	7	1025

Note: The reference group is High School graduates for each estimation.

Table A8: Propensity Score Matching, Women

	Trades		College		University	
Education equation	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Mother educ. trades, college	-0.3111	0.3625	0.0406	0.3088	0.0338	0.2679
Mother educ. high-school	-0.4323	0.3510	-0.2520	0.3010	-0.2433	0.2601
Mother educ. below high-school	-0.3492	0.3431	-0.2545	0.2970	-0.6175	0.2576
Father educ. trades, college	0.2375	0.3055	-0.0859	0.2221	-0.4813	0.1977
Father educ. high-school	0.3126	0.3008	-0.0955	0.2168	-0.5734	0.1964
Father educ. below high-school	0.1239	0.2753	-0.4490	0.1953	-1.0548	0.1717
Age 20-24 years old	5.6650	0.3847	6.4894	0.3331	6.3195	0.2393
Age 25-29 years old	5.9981	0.3811	6.8897	0.3245	6.9689	0.2238
Age 30-34 years old	5.8886	0.3776	6.8196	0.3204	6.8141	0.2188
Age 35-39 years old	6.0250	0.3779	6.6518	0.3200	6.8225	0.2174
Age 40-44 years old	5.7783	0.3832	6.6448	0.3241	6.7361	0.2251
Age 45-49 years old	5.9185	0.3949	6.8194	0.3315	6.6665	0.2465
Age 50-54 years old	6.0135	0.4229	6.9108	0.3543	7.1308	0.2672
Age 55-59 years old	5.4580	0.4536	6.5521	0.3607	6.4513	0.4505
High-school province NFL	1.1164	0.2417	0.3023	0.2091	0.3507	0.2369
High-school province PEI	0.1217	0.3258	-0.3429	0.2588	-0.2954	0.3105
High-school province NS	0.5204	0.2282	-0.5162	0.2086	0.2624	0.1845
High-school province NB	0.2787	0.2555	0.2824	0.1680	0.2307	0.1990
High-school province QUE	0.3382	0.1759	0.0114	0.1236	0.0167	0.1377
High-school province MAN	0.2881	0.2299	-0.2257	0.1788	-0.0492	0.1889
High-school province SAS	0.4848	0.1922	-0.7703	0.1818	-0.4322	0.1843
High-school province ATA	0.2521	0.2110	-0.4819	0.1699	-0.1944	0.1727
High-school province BC	0.1262	0.1993	-0.7613	0.1666	-0.5394	0.1728
Birth rank first-born	0.0876	0.1217	-0.0297	0.1021	0.0598	0.1057
Siblings 1 sister	-0.2379	0.1462	-0.0752	0.1223	-0.1017	0.1312
Siblings 2 sisters	-0.4247	0.1656	-0.2101	0.1353	-0.1914	0.1426
Siblings 3 sisters	-0.3280	0.1666	-0.1016	0.1374	-0.1995	0.1497
Siblings 1 brother	-0.0436	0.1441	-0.0194	0.1182	-0.0506	0.1211
Siblings 2 brothers	-0.0066	0.1626	-0.0215	0.1329	-0.0289	0.1383
Siblings 3 brothers	0.1323	0.1580	0.1194	0.1354	0.0191	0.1426
Constant	-6.4293	0.5557	-6.0915	0.4689	-5.6440	0.3497
N.Obs. & support	Off	On	Off	On	Off	On
Untreated (High-school)	0	587	0	587	0	553
Treated (Other education)	1	198	11	413	14	364
Total	1	785	11	1000	14	917

Note: The reference group is High School graduates for each estimation.

Table A9: Polynomial Balancing Score Test, Men

	Trades		College		University	
	F-test	P-value	F-test	P-value	F-test	P-value
Mother education trades, college	1.37	0.23	1.36	0.24	0.14	0.98
Mother education high-school	0.90	0.48	0.68	0.64	0.27	0.93
Mother education below high-school	0.85	0.52	0.65	0.66	0.44	0.82
Father education trades, college	0.35	0.88	0.75	0.59	1.87	0.10
Father education high-school	0.09	0.99	0.45	0.81	1.25	0.28
Father education below high-school	0.30	0.92	0.98	0.43	1.32	0.25
Age 18-19 years old	0.87	0.50	0.67	0.64	.	.
Age 20-24 years old	0.17	0.97	0.23	0.95	0.15	0.98
Age 25-29 years old	0.24	0.94	0.30	0.91	0.21	0.96
Age 30-34 years old	0.48	0.79	1.02	0.40	0.42	0.84
Age 35-39 years old	0.27	0.93	0.68	0.64	0.98	0.43
Age 40-44 years old	0.63	0.68	2.83	0.02	0.85	0.51
Age 45-49 years old	0.02	1.00	0.93	0.46	1.42	0.22
Age 50-54 years old	1.43	0.21	0.72	0.61	0.48	0.79
Age 55-59 years old	0.73	0.60	0.43	0.83	0.63	0.68
Age 60-64 years old	0.12	0.99	0.86	0.51	0.38	0.87
High-school province NFL	0.21	0.96	0.93	0.46	0.13	0.99
High-school province PEI	0.34	0.89	2.51	0.03	0.18	0.97
High-school province NS	0.89	0.49	1.25	0.28	0.26	0.93
High-school province NB	0.48	0.79	0.61	0.69	0.57	0.72
High-school province ON	0.35	0.88	0.66	0.65	1.72	0.13
High-school province QUE	0.97	0.44	0.66	0.66	0.47	0.80
High-school province MAN	0.32	0.90	0.24	0.95	0.70	0.63
High-school province SAS	0.23	0.95	0.27	0.93	0.13	0.99
High-school province ATA	1.00	0.42	0.42	0.84	0.85	0.51
High-school province BC	0.52	0.76	1.38	0.23	0.70	0.62
Siblings 1 sister	0.29	0.92	1.98	0.08	0.46	0.80
Siblings 2 sisters	1.02	0.40	2.44	0.03	1.04	0.39
Siblings 3 sisters	0.25	0.94	0.49	0.78	1.30	0.26
Siblings 1 brother	1.57	0.16	0.77	0.57	1.14	0.34
Siblings 2 brothers	0.47	0.80	0.93	0.46	1.88	0.09
Siblings 3 brothers	0.39	0.85	0.24	0.94	1.32	0.25
First born	0.51	0.77	0.76	0.58	1.17	0.32

Table A10: Polynomial Balancing Score Test, Women

	Trades		College		University	
	F-test	P-value	F-test	P-value	F-test	P-value
Mother education trades, college	0.54	0.75	1.23	0.29	0.45	0.82
Mother education high-school	0.27	0.93	0.09	0.99	0.28	0.92
Mother education below high-school	0.24	0.94	1.01	0.41	0.37	0.87
Father education trades, college	0.52	0.76	0.62	0.69	1.20	0.31
Father education high-school	1.36	0.24	1.97	0.08	0.94	0.46
Father education below high-school	0.86	0.51	2.01	0.07	0.23	0.95
Age 18-19 years old	1.13	0.34	1.04	0.39	.	.
Age 20-24 years old	1.00	0.42	0.64	0.67	0.91	0.47
Age 25-29 years old	1.89	0.09	0.25	0.94	0.16	0.98
Age 30-34 years old	0.29	0.92	0.65	0.66	3.36	0.01
Age 35-39 years old	0.65	0.66	1.75	0.12	0.64	0.67
Age 40-44 years old	0.29	0.92	1.02	0.40	0.77	0.57
Age 45-49 years old	0.06	1.00	0.21	0.96	1.59	0.16
Age 50-54 years old	2.31	0.04	0.41	0.84	0.15	0.98
Age 55-59 years old	0.90	0.48	0.30	0.91	1.47	0.20
Age 60-64 years old	0.10	0.99	0.84	0.52	1.09	0.36
High-school province NFL	4.61	0.00	2.67	0.02	0.92	0.47
High-school province PEI	0.14	0.98	1.15	0.33	0.33	0.90
High-school province NS	1.29	0.26	1.61	0.15	0.28	0.92
High-school province NB	1.08	0.37	0.61	0.70	0.58	0.71
High-school province ON	0.23	0.95	2.66	0.02	0.75	0.59
High-school province QUE	0.01	1.00	1.19	0.31	0.45	0.81
High-school province MAN	0.35	0.88	0.88	0.49	0.97	0.43
High-school province SAS	1.05	0.39	0.15	0.98	0.42	0.83
High-school province ATA	0.18	0.97	1.45	0.20	0.34	0.89
High-school province BC	0.85	0.51	0.12	0.99	1.48	0.20
Siblings 1 sister	0.30	0.91	0.27	0.93	0.41	0.85
Siblings 2 sisters	0.54	0.75	0.25	0.94	0.46	0.80
Siblings 3 sisters	1.62	0.15	0.54	0.74	1.41	0.22
Siblings 1 brother	0.83	0.53	0.99	0.42	0.25	0.94
Siblings 2 brothers	0.89	0.49	0.07	1.00	1.85	0.10
Siblings 3 brothers	0.72	0.61	1.15	0.33	0.32	0.90
First born	2.67	0.02	0.49	0.79	1.25	0.28

Table A11: Sensitivity to Matching Bandwidths, Log Wages

	Kernel				Nearest Neighbours		
	Bandwidth				Neighbours		
	0.01	0.05	0.10	0.50	1	5	10
MEN							
Trades	0.106	0.115	0.118	0.154	0.113	0.101	0.108
	(0.039)	(0.036)	(0.031)	(0.033)	(0.062)	(0.045)	(0.042)
Community College	0.139	0.141	0.142	0.154	0.138	0.134	0.135
	(0.037)	(0.032)	(0.032)	(0.031)	(0.055)	(0.040)	(0.036)
University	0.359	0.350	0.357	0.390	0.337	0.349	0.358
	(0.042)	(0.043)	(0.036)	(0.033)	(0.057)	(0.050)	(0.044)
WOMEN							
Trades	0.004	0.023	0.026	0.025	-0.010	0.006	0.033
	(0.043)	(0.038)	(0.035)	(0.034)	(0.061)	(0.045)	(0.046)
Community College	0.204	0.196	0.194	0.202	0.247	0.202	0.204
	(0.034)	(0.034)	(0.033)	(0.030)	(0.047)	(0.039)	(0.035)
University	0.406	0.416	0.410	0.423	0.432	0.410	0.406
	(0.040)	(0.037)	(0.033)	(0.030)	(0.056)	(0.044)	(0.042)

Note: The reference group is High School graduates for each estimation. Standard errors in parenthesis. Epanechnikov kernel used in all kernel estimation.

Table A12: Heckman Correction Estimator, Men, Log Hourly Wages

	Trades		College		University	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDUCATION EQUATION (1^{st} Stage)						
Mother educ. trades, college	-0.0778	0.2682	0.2138	0.2703	-0.0904	0.2140
Mother educ. high-school	-0.1674	0.2530	0.0879	0.2607	-0.2310	0.2034
Mother educ. below high-school	-0.3802	0.2465	-0.0907	0.2559	-0.4399	0.2017
Father educ. trades, college	0.5420	0.2547	0.4337	0.2316	-0.5410	0.1796
Father educ. high-school	0.0572	0.2557	0.2151	0.2304	-0.6065	0.1708
Father educ. below high-school	0.2510	0.2323	0.1116	0.2104	-1.0246	0.1553
Age 20-24 years old	5.1919	0.3463	5.7388	0.4941		
Age 25-29 years old	5.6943	0.3288	6.1185	0.4900	6.1797	0.2150
Age 30-34 years old	5.9385	0.3205	6.1258	0.4887	6.3570	0.2092
Age 35-39 years old	5.9560	0.3209	5.8578	0.4927	6.2334	0.2150
Age 40-44 years old	5.9696	0.3271	6.1686	0.4947	6.6670	0.2149
Age 45-49 years old	5.9842	0.3381	6.1142	0.5000	6.5912	0.2258
Age 50-54 years old	5.4580	0.4022	6.0381	0.5239	6.7695	0.2539
Age 55-59 years old	5.5700	0.3614	5.7256	0.5170	6.4119	0.2461
High-school province NFL	0.9761	0.2019	-0.2024	0.2224	-0.2475	0.2222
High-school province PEI	0.5096	0.3854	-0.1195	0.3626	0.4722	0.3015
High-school province NS	0.6925	0.2086	0.0083	0.1956	-0.2817	0.2000
High-school province NB	0.3687	0.2345	0.2770	0.1835	-0.2153	0.2146
High-school province QUE	0.5548	0.1560	-0.0114	0.1299	-0.0054	0.1248
High-school province MAN	0.1704	0.2199	-0.6505	0.2110	-0.0295	0.1665
High-school province SAS	0.5758	0.1993	-0.4726	0.2160	0.0150	0.1761
High-school province ATA	0.6293	0.1905	-0.0407	0.1697	-0.0766	0.1698
High-school province BC	0.6307	0.1743	-0.2706	0.1683	-0.3352	0.1612
Siblings 1 sister	0.1771	0.1316	0.0801	0.1276	-0.1474	0.1157
Siblings 2 sisters	-0.0980	0.1515	0.1515	0.1359	-0.3309	0.1282
Siblings 3 sisters	-0.0916	0.1413	-0.1795	0.1382	-0.5086	0.1286
Siblings 1 brother	-0.0661	0.1328	-0.2480	0.1223	-0.2529	0.1164
Siblings 2 brothers	-0.0498	0.1510	-0.1493	0.1413	-0.1880	0.1325
Siblings 3 brothers	-0.0046	0.1493	-0.1799	0.1439	-0.2828	0.1408
Constant	-6.7893	0.4536	-6.4299	0.5565	-5.0383	0.2800
Hazard=$\rho\sigma$	-0.1987	0.0794	-0.0231	0.0781	-0.0437	0.0440
WAGE EQUATION (2^{nd} Stage)						
Marital status married	0.1418	0.0424	0.1737	0.0411	0.1068	0.0405
Marital status div./wd./sep.	0.0970	0.0571	0.1572	0.0600	-0.0085	0.0570
Province NFL	-0.3360	0.0702	-0.3198	0.0680	-0.3386	0.0677
Province PEI	-0.2528	0.1099	-0.2517	0.1021	-0.3240	0.0889
Province NS	-0.2006	0.0659	-0.1392	0.0608	-0.1635	0.0607
Province NB	-0.1892	0.0715	-0.1890	0.0597	-0.1984	0.0690
Province QUE	-0.1043	0.0488	-0.0512	0.0424	-0.0555	0.0422
Province MAN	-0.1559	0.0625	-0.1518	0.0619	-0.1933	0.0557
Province SAS	-0.1514	0.0668	-0.1621	0.0667	-0.1473	0.0619
Province ATA	-0.0813	0.0551	-0.0823	0.0496	-0.0208	0.0495
Province BC	-0.0030	0.0525	-0.0086	0.0492	-0.0407	0.0465
Immigrant	-0.0444	0.0663	0.0000	0.0659	-0.0619	0.0570
Experience	0.0272	0.0048	0.0316	0.0044	0.0365	0.0044
Experience squared	-0.0005	0.0001	-0.0006	0.0001	-0.0007	0.0001
Children at home 1	-0.0289	0.0478	-0.0354	0.0477	0.0127	0.0487
Children at home 2	-0.0119	0.0438	-0.0287	0.0443	0.0059	0.0439
Children at home 3 or more	0.0016	0.0622	-0.0381	0.0619	0.0581	0.0591
Union/Collective agreement	0.2815	0.0284	0.2592	0.0283	0.2027	0.0278
Education dummy	0.4573	0.1296	0.2271	0.1270	0.5076	0.0646
Constant	2.1613	0.0495	2.1783	0.0581	2.1915	0.0477

Note: The reference group is High School graduates for each estimation.

Table A13: Heckman Correction Estimator, Women, Log Hourly Wages

	Trades		College		University	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDUCATION EQUATION (1^{st} Stage)						
Mother education trades, college	-0.3029	0.3627	0.0399	0.3088	0.0377	0.2679
Mother educ. high-school	-0.4246	0.3512	-0.2535	0.3010	-0.2402	0.2601
Mother educ. below high-school	-0.3389	0.3432	-0.2563	0.2970	-0.6136	0.2576
Father educ. trades, college	0.2415	0.3060	-0.0854	0.2221	-0.4862	0.1974
Father educ. high-school	0.3067	0.3013	-0.0949	0.2168	-0.5759	0.1962
Father educ. below high-school	0.1208	0.2759	-0.4468	0.1951	-1.0622	0.1712
Age 20-24 years old	5.6220	0.3838	6.4766	0.3856	6.3593	0.4280
Age 25-29 years old	5.9589	0.3802	6.8768	0.3821	7.0085	0.4205
Age 30-34 years old	5.8466	0.3768	6.8072	0.3802	6.8529	0.4172
Age 35-39 years old	5.9853	0.3770	6.6381	0.3816	6.8652	0.4166
Age 40-44 years old	5.7427	0.3824	6.6281	0.3861	6.7814	0.4204
Age 45-49 years old	5.8830	0.3941	6.8018	0.3917	6.7130	0.4334
Age 50-54 years old	5.9818	0.4220	6.8939	0.4120	7.1800	0.4454
Age 55-59 years old	5.4293	0.4519	6.5373	0.4156	6.9649	0.4491
High-school province NFL	1.1159	0.2418	0.3014	0.2090	0.3567	0.2366
High-school province PEI	0.1188	0.3251	-0.3439	0.2589	-0.2926	0.3098
High-school province NS	0.5203	0.2278	-0.5147	0.2085	0.2610	0.1844
High-school province NB	0.2702	0.2551	0.2823	0.1680	0.2321	0.1989
High-school province QUE	0.3310	0.1755	0.0118	0.1236	0.0166	0.1376
High-school province MAN	0.2844	0.2301	-0.2286	0.1786	-0.0500	0.1890
High-school province SAS	0.4783	0.1918	-0.7687	0.1817	-0.4375	0.1840
High-school province ATA	0.2360	0.2098	-0.4796	0.1697	-0.1998	0.1724
High-school province BC	0.1194	0.1990	-0.7596	0.1665	-0.5426	0.1727
Siblings 1 sister	-0.2597	0.1430	-0.0706	0.1213	-0.1179	0.1280
Siblings 2 sisters	-0.4530	0.1609	-0.2022	0.1325	-0.2119	0.1379
Siblings 3 sisters	-0.3659	0.1581	-0.0916	0.1331	-0.2255	0.1424
Siblings 1 brother	-0.0552	0.1431	-0.0152	0.1173	-0.0561	0.1207
Siblings 2 brothers	-0.0289	0.1595	-0.0138	0.1302	-0.0426	0.1362
Siblings 3 brothers	0.1079	0.1542	0.1287	0.1317	0.0015	0.1391
Constant	-6.3290	0.5491	-6.0971	0.4742	-5.6397	0.5099
Hazard=$\rho\sigma$	-0.3039	0.0991	-0.2959	0.0666	-0.1229	0.0414
WAGE EQUATION (2ND STAGE)						
Marital status married	0.0589	0.0367	0.0561	0.0333	0.0937	0.0335
Marital status div./wd./sep.	0.0516	0.0479	0.1034	0.0422	0.0793	0.0448
Province NFL	-0.5739	0.0998	-0.3576	0.0727	-0.2536	0.0732
Province PEI	-0.2134	0.0913	-0.1370	0.0818	-0.1755	0.0842
Province NS	-0.3399	0.0710	-0.2052	0.0683	-0.2755	0.0524
Province NB	-0.2263	0.0734	-0.2836	0.0565	-0.2204	0.0590
Province QUE	-0.1435	0.0542	-0.0856	0.0432	-0.0616	0.0421
Province MAN	-0.1806	0.0690	-0.1335	0.0584	-0.1597	0.0565
Province SAS	-0.2890	0.0638	-0.1287	0.0662	-0.1949	0.0583
Province ATA	-0.0924	0.0554	-0.0663	0.0506	-0.0940	0.0457
Province BC	-0.0072	0.0535	0.1444	0.0540	-0.0019	0.0454
Immigrant	0.0683	0.0667	0.0009	0.0546	-0.0138	0.0557
Experience	0.0257	0.0047	0.0305	0.0042	0.0322	0.0041
Experience squared	-0.0004	0.0001	-0.0006	0.0001	-0.0006	0.0001
Children at home 1	-0.0121	0.0384	-0.0306	0.0354	-0.0170	0.0368
Children at home 2	-0.0121	0.0425	-0.0032	0.0374	0.0213	0.0399
Children at home 3 or more	0.0920	0.0627	0.0165	0.0606	0.1089	0.0602
Union/Collective agreement	0.2771	0.0304	0.2517	0.0267	0.2358	0.0277
Education dummy	0.5361	0.1657	0.6653	0.1062	0.6193	0.0631
Constant	2.0022	0.0546	1.8736	0.0618	1.9822	0.0483

Note: The reference group is High School graduates for each estimation.

Table A14: IV Estimator, Men, Log Hourly Wages

	Trades		College		University	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDUCATION EQUATION (1^{st} Stage)						
Same province as high-school	0.0169	0.0441	-0.0072	0.0440	-0.1537	0.0401
Siblings 1 sister	0.0427	0.0415	0.0219	0.0423	-0.0622	0.0396
Siblings 2 sisters	-0.0458	0.0460	0.0547	0.0452	-0.1103	0.0435
Siblings 3 sisters	-0.0150	0.0439	-0.0333	0.0445	-0.1669	0.0435
Siblings 1 brother	-0.0329	0.0408	-0.0701	0.0402	-0.0670	0.0387
Siblings 2 brothers	-0.0005	0.0468	-0.0185	0.0467	-0.0233	0.0451
Siblings 3 brothers	0.0159	0.0468	-0.0342	0.0472	-0.0847	0.0472
Marital status married	0.2080	0.0446	0.1955	0.0439	0.2034	0.0432
Marital status div./wd./sep.	0.2447	0.0604	0.0782	0.0650	0.1403	0.0611
Province NFL	0.2635	0.0658	-0.1174	0.0734	-0.0925	0.0726
Province PEI	0.1131	0.1111	-0.0606	0.1109	0.0852	0.0958
Province NS	0.2139	0.0644	-0.0162	0.0664	-0.0379	0.0656
Province NB	0.0624	0.0729	0.0664	0.0647	-0.1536	0.0735
Province QUE	0.1386	0.0488	0.0048	0.0463	0.0249	0.0453
Province MAN	-0.0095	0.0636	-0.2045	0.0632	-0.0980	0.0596
Province SAS	0.1660	0.0659	-0.1227	0.0695	-0.0635	0.0664
Province ATA	0.1891	0.0556	-0.0220	0.0545	-0.0608	0.0539
Province BC	0.2028	0.0517	-0.0901	0.0531	-0.0438	0.0506
Immigrant	0.0596	0.0704	0.0403	0.0713	0.1582	0.0614
Experience	-0.0041	0.0047	-0.0053	0.0048	-0.0006	0.0047
Experience squared	-0.0001	0.0001	-0.0001	0.0001	-0.0002	0.0001
Children at home 1	-0.0401	0.0508	-0.1120	0.0517	-0.1667	0.0522
Children at home 2	-0.0615	0.0465	-0.1446	0.0477	-0.1677	0.0470
Children at home 3 or more	-0.1060	0.0664	-0.1156	0.0671	-0.0932	0.0635
Union/Collective agreement	0.0956	0.0300	-0.0202	0.0307	0.0365	0.0299
Constant	0.0832	0.0737	0.4294	0.0730	0.6556	0.0684
R-squared		0.102		0.085		0.105
F-test joint signif. instruments		F(7,875)=0.88		F(7,903)=1.19		F(7,1025)=5.57
		Prob>F = 0.52		Prob>F=0.31		Prob>F = 0
Endogeneity test (residual coef.)		0.3730		-0.2176		0.0460
		Prob>z = 0.34		Prob>z = 0.51		Prob>z = 0.77
WAGE EQUATION (2^{nd} Stage)						
Education dummy	-0.2256	0.4136	0.4062	0.3332	0.4057	0.1510
Marital status married	0.2218	0.0970	0.1310	0.0793	0.1187	0.0525
Marital status div./wd./sep.	0.1906	0.1179	0.1394	0.0685	0.0000	0.0609
Province NFL	-0.1668	0.1281	-0.2960	0.0812	-0.3533	0.0703
Province PEI	-0.1847	0.1217	-0.2392	0.1078	-0.3220	0.0907
Province NS	-0.0700	0.1110	-0.1354	0.0632	-0.1687	0.0612
Province NB	-0.1567	0.0774	-0.2007	0.0649	-0.2143	0.0733
Province QUE	-0.0235	0.0762	-0.0532	0.0437	-0.0622	0.0423
Province MAN	-0.1542	0.0651	-0.1151	0.0893	-0.1998	0.0584
Province SAS	-0.0458	0.0979	-0.1410	0.0780	-0.1560	0.0633
Province ATA	0.0217	0.0949	-0.0793	0.0517	-0.0253	0.0501
Province BC	0.1126	0.1001	0.0072	0.0575	-0.0460	0.0467
Immigrant	-0.0196	0.0765	-0.0087	0.0695	-0.0567	0.0615
Experience	0.0301	0.0051	0.0331	0.0049	0.0371	0.0044
Experience squared	-0.0006	0.0001	-0.0005	0.0001	-0.0007	0.0001
Children at home 1	-0.0380	0.0546	-0.0103	0.0625	0.0047	0.0562
Children at home 2	-0.0226	0.0529	0.0030	0.0674	-0.0012	0.0519
Children at home 3 or more	-0.0243	0.0801	-0.0121	0.0761	0.0523	0.0618
Union/Collective agreement	0.3136	0.0492	0.2638	0.0302	0.2042	0.0288
Constant	2.2167	0.0630	2.1028	0.1409	2.2268	0.0765
R-squared		0.168		0.233		0.349

Note: The reference group is High School graduates for each estimation.

Table A15: IV Estimator, Women, Log Hourly Wages

	Trades		College		University	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDUCATION EQUATION (1^{st} Stage)						
Same province as high-school	-0.0312	0.0489	-0.0731	0.0463	-0.1863	0.0414
Siblings 1 sister	-0.0741	0.0440	-0.0079	0.0420	-0.0062	0.0406
Siblings 2 sisters	-0.1179	0.0482	-0.0249	0.0456	-0.0193	0.0447
Siblings 3 sisters	-0.0900	0.0476	-0.0030	0.0455	-0.0527	0.0458
Siblings 1 brother	-0.0058	0.0431	-0.0118	0.0405	0.0110	0.0388
Siblings 2 brothers	0.0150	0.0481	0.0181	0.0452	0.0441	0.0440
Siblings 3 brothers	0.0468	0.0466	0.0422	0.0452	-0.0139	0.0442
Marital status married	0.0269	0.0421	0.0587	0.0399	0.0151	0.0384
Marital status div./wd./sep.	0.0399	0.0548	0.0890	0.0508	0.0172	0.0514
Province NFL	0.3605	0.0821	0.1140	0.0759	0.0344	0.0821
Province PEI	0.0524	0.0932	-0.1253	0.0871	-0.2150	0.0935
Province NS	0.1252	0.0691	-0.2423	0.0723	0.0366	0.0594
Province NB	0.0040	0.0758	0.0882	0.0607	-0.0607	0.0669
Province QUE	0.0806	0.0544	-0.0281	0.0471	-0.0371	0.0477
Province MAN	-0.0036	0.0699	-0.1335	0.0630	-0.1297	0.0633
Province SAS	0.1186	0.0633	-0.2858	0.0665	-0.1908	0.0639
Province ATA	0.0454	0.0589	-0.1758	0.0549	-0.1459	0.0523
Province BC	0.0517	0.0557	-0.2579	0.0537	-0.1448	0.0505
Immigrant	-0.0215	0.0758	0.0580	0.0662	0.0787	0.0639
Experience	-0.0003	0.0049	-0.0156	0.0047	-0.0097	0.0046
Experience squared	-0.0001	0.0001	0.0002	0.0001	0.0000	0.0001
Children at home 1	0.0227	0.0443	-0.0195	0.0424	-0.0340	0.0423
Children at home 2	-0.0282	0.0482	0.0411	0.0443	-0.0421	0.0455
Children at home 3 or more	0.0428	0.0726	0.0214	0.0729	0.0348	0.0688
Union/Collective agreement	0.0969	0.0352	0.2318	0.0315	0.3105	0.0301
Constant	0.2487	0.0838	0.5923	0.0755	0.6423	0.0698
R-squared		0.063		0.150		0.198
F-test joint signif. instruments		F(7,760)=1.21		F(7,985)=0.72		F(7,939)=3.41
		Prob>F = 0.2971		Prob>F = 0.6514		Prob>F = 0.0013
Endogeneity test (residual coef.)		-0.0618		0.2362		-0.0626
		Prob>z = 0.84		Prob>z = 0.53		Prob>z = 0.73
WAGE EQUATION (2^{nd} Stage)						
Education dummy	0.1040	0.3063	-0.0184	0.3905	0.5147	0.1826
Marital status married	0.0584	0.0376	0.0799	0.0418	0.0935	0.0342
Marital status div./wd./sep.	0.0519	0.0498	0.1311	0.0572	0.0787	0.0460
Province NFL	-0.4078	0.1310	-0.2603	0.0816	-0.2427	0.0731
Province PEI	-0.1912	0.0833	-0.2102	0.0890	-0.1975	0.0921
Province NS	-0.2711	0.0713	-0.3344	0.1095	-0.2723	0.0529
Province NB	-0.2039	0.0670	-0.2260	0.0654	-0.2200	0.0599
Province QUE	-0.1017	0.0528	-0.0901	0.0418	-0.0693	0.0435
Province MAN	-0.1485	0.0622	-0.2085	0.0750	-0.1629	0.0612
Province SAS	-0.2340	0.0682	-0.3096	0.1217	-0.2178	0.0676
Province ATA	-0.0615	0.0525	-0.1753	0.0752	-0.1078	0.0486
Province BC	0.0117	0.0510	-0.0131	0.1075	-0.0221	0.0495
Immigrant	0.0774	0.0673	0.0189	0.0629	-0.0180	0.0588
Experience	0.0299	0.0044	0.0308	0.0072	0.0345	0.0045
Experience squared	-0.0005	0.0001	-0.0006	0.0001	-0.0007	0.0001
Children at home 1	-0.0101	0.0398	-0.0281	0.0381	-0.0112	0.0386
Children at home 2	-0.0035	0.0436	0.0067	0.0425	0.0238	0.0411
Children at home 3 or more	0.0963	0.0657	0.0240	0.0643	0.1165	0.0616
Union/Collective agreement	0.2708	0.0432	0.3094	0.0961	0.2158	0.0623
Constant	2.0442	0.0691	2.1782	0.2054	2.0175	0.0961
R-squared	0.266		0.251		0.400	

Note: The reference group is High School graduates for each estimation.