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University Quality and Labor Market Outcomes of Canadian Youth

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Abstract

This paper estimates the wage returns to the Canadian university reputation and quality by using the Maclean's magazine Best Overall Reputation ranking and a quality ranking based on an index constructed by the Principal Component Analysis of a set of university characteristics. The main data source is Youth in Transition Survey and the outcome of interest is the hourly wage rate of Canadian youth between 2003-2005. Using matching methods we draw some main results from this analysis. First, we find that returns to having a Bachelor's degree from a higher versus lower ranking university is 10.3% for women and 13.4% for men. The returns are higher when comparing the wages in the top and bottom tails of the reputation ranking distribution. Second, there are returns to university quality but the results are mixed. Third, the ranking premiums are higher for men than women. The results are robust through different specifications, sample exclusions and estimators.

JEL Classification: C21, I21, J16, J30
Keywords: Returns to Education, University Quality, Reputation, Wage Rates

1 Introduction

A student's investment in higher education is costly in terms of direct financial resources (tuition and fees) and opportunity costs of forgone earnings. However, the long-term economic benefits of tertiary education are well documented. Based on a cost-benefit analysis, students decide whether to enter university and further, which university to attend. This paper explores the role that university choice has in the level of hourly wages during the initial transition from schooling to labour market following graduation. It provides insights on whether the yearly published university rankings matter

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by quantifying the wage response to graduation from a university with a higher ranking. This is an important piece of information that high school graduates (and their parents) could use to make the right choice of university that matches best with their future career plans.

There is a vast literature on university that use data from the US and the European countries. The institutional structure of these countries are different from the Canadian education system. European countries have a mainly public and tuition-free university system. In the USA the universities are mainly private and tuition fees vary a lot. Meanwhile, Canadian universities are subsidized by the government and the tuition fees do not vary much. Given these differences, most of the results that US and European studies find may not be generalized to the Canadian case. University quality is a topic not well analyzed for Canada. This is in part due to the lack of Canadian data sets which identify the major(s) as well as the institution(s).

To our best knowledge, there is only one study conducted on Canadian data, Betts et al. (2007), which analyses the relationship of different university characteristics with earnings in the late 1980's and early 1990's. We build on the analysis and methodology of Betts et al. (2007) in several ways. Our paper provides the first Canadian study that investigates and estimates the university ranking premium on starting wages. The matching methods that we employ coupled with the rich dataset tackle carefully the identification issues that arise in this setting. In our approach we allow for nonlinearities in returns to university ranking. We use data from the older cohort of Youth in Transition Survey (YITS-B); it contains information on the participants for the years 1998 to 2008. An individual's university is directly observed in this micro data. The survey also tracks the job history of the participants.

We use two different university rankings. The first is the overall reputation ranking which is published by the Maclean's magazine and based on a survey the magazine conducts. Besides, we construct a new ranking for Canadian universities that we call university quality ranking. This is another novelty of this study. A natural question arises at this point, that is how to measure university quality? Some papers use university characteristics like professor to student ratio, professor salaries, number of students, retention rate etc.(Betts et al., 2007). Noticing a high correlation among the several university characteristics, other papers (Black and Smith, 2004, 2006) use factor analysis to combine them in one comprehensive index. Likewise, we use the principal component analysis to combine a set of different university traits, which signal different attributes of the universities, into a single index as a measure of quality. Based on this quality index we create the quality rankings.

Our findings indicate that, controlling for a set of individual and family characteristics, university rankings matter in determining the starting hourly wage rate of Canadian Bachelor degree graduates. We find that university reputation premium to having graduated from a top ranking university is 10% for women and 13.4% for men. When comparing the wages of the top 25% of the sample in the reputation ranking distribution to the bottom 25%, the returns are higher for both genders (15.2% for women and 29.9% for men). The ranking premium is higher for men than women and the results are robust through different specifications, samples and estimators. The results regarding the return to university quality are mixed. There is a 20.9% return for women when comparing two groups with a stark difference in university quality. For men we can only identify an estimate for the case when a high ranking university is defined as one with an above-median ranking. In that case, the return to university quality is 11.5% for men.

The paper is organized as follows. Having introduced the topic in this section, we review the existing literature in Section 2 and discuss the data and methodology in Sections 3 and 4, respectively. We analyze the empirical results in Section 5 and conclude in Section 6.

2 Literature Review

There is a vast literature that analyses the returns to education. Most of it is based on the Mincer (Mincer, 1958) earnings regression. It specifies the logarithmic wages as a function of years of schooling and years of experience as displayed in equation (1) below.

$$log\,\omega_i = \alpha_0 + \alpha_1 S_i + \beta_1 E_i + \beta_2 E_i^2 + u_i \tag{1}$$

where S_i is the years of schooling, E_i is the years of experience and E_i^2 is the experience variable squared. The coefficient α_1 is interpreted as the return to schooling. Card (1999) reviews the contributions to this research area. He concentrates mainly on the papers that challenge two main implicit assumptions of the Mincer model: exogeneity of the years of schooling variable and the functional form. Firstly, the education variable in the above set up may capture other confounding effects of unobservable characteristics like the ability of the individual. Ability conveys important information about the behaviour process of the students. When not because is an unobservable, it hides in the error term, $u_i = \gamma A_i + \varepsilon_i$, where A_i is ability and ε_i is an independent error term. If there is not any way to control for A_i then $Cov(S_i, u_i) \neq 0$. Violation of this orthogonality assumption yields inconsistent estimates and unreliable hypothesis testing. This is because of two reasons: higher ability individuals go to better schools and also some of the observed wage premium these individuals get could be attributed to university quality when it is actually innate ability. Researchers have applied different methods to solve this problem. Some assume "selection on observables" and in that case the above equation takes the following form

$$log\,\omega_i = \alpha_0 + \alpha_1 S_i + \gamma A_i^* + X\beta + \varepsilon_i$$

where A_i^* is a proxy measure of the latent ability (e.g.: high school grades, standardized test scores) and X includes other control variables (respondent's own background characteristics, experience and experience squared, family, friends and high school characteristics). In the information space of X and A_i^* the assumption $Cov(S_i, \varepsilon_i) = 0$ holds and S_i is no longer endogenous in the empirical model. Several other papers, due to data unavailability, deal with selectivity on unobservable variables by instrumental variable techniques[1] to isolate the returns to education on logarithmic wage from other confounding effects. Secondly, the assumption of the linear functional form of the Mincer equation is likely not to hold. The effect of education for the years 8, 12, 16 (coinciding to the completion of elementary school, high school and college or university) on the wage rate might be nonlinear - this is commonly known as the "sheepskin effect". Some non-linearities in those specific years of schooling might exist due to the fact that having completed a certain level of education and having obtained the diploma/certificate/degree documenting it, matters differently in the determination of a higher wage by the employee. What about the prestige of the institution that grants the degree? Will that induce an additional increase in the wage rate of the employer beyond the education level attained? This is where the topic discussed in this paper fits in the returns to education literature. Hence the above equation becomes:

$$log\,\omega_i = \alpha_0 + \alpha_1 S_i + \alpha_2 Q_i^* + \gamma A_i^* + X\beta + \varepsilon_i \tag{2}$$

where Q_i^* indicates the latent university quality variable. Our purpose is to examine the returns to

[1] A number of papers assume "selection on unobservables" and use proximity to college as an instrumental variable (IV) for years of education completed. Other instrumenting variables for S_i that are usually used are the education of the parents and the education of the partner/spouse. But those may be weak instruments for the university quality. Long (2008), instead, uses the average quality of the nearby colleges within a certain radius of the student as the instrument for the quality of the college that the student attends.

the quality of the university degree attained, thus estimating parameter α_2. The research dedicated to analyzing the returns to university quality is extensive using US data, less so for European data and fairly new on Canadian data. Among the many relevant papers are Eliasson (2006); Chevalier and Conlon (2003); James et al. (1989); Brewer et al. (1998); Horstschraer (2011); Suhonen (2011); Heckman et al. (2003). The prominent papers in the US literature are Black and Smith (2004, 2006); Black et al. (2005); Long (2008, 2010); Monks (2000); Dale and Krueger (2002). Black and Smith (2004, 2006) use NLSY the 1979 cohort and see the effect of the 4-year college quality on the hourly 1989 and 1998 wage rate. These two papers raise the issue of measurement error of the proxies used for the latent quality variable. They try to fix this issue by building a quality index using factor analysis and principal component analysis. Another way of dealing with measurement error is through instrumental variables. Black and Smith (2006) derive a GMM estimator which they prefer best as opposed to factor analysis because it makes direct use of the covariance matrix between the proxy variables. They find an average impact of 0.039 on the logarithmic hourly wage rate caused by one unit increase in the quality index. Black and Smith (2004) in a matching framework, where the quality variable is a binomial indicator of attending a high quality[2] four-year college, find an impact of 12-14% increase in the log hourly wage rate. Long (2008) criticizes this method reasoning that the amount of the observations not used (pertaining to the inter-quartile range) is big which reduces the sample size a lot and thus the efficiency in estimation. The other critique is related to the fact that the "*estimates refer to discrete moves from one group of universities to the other and do not allow the estimation of the effect of moving up the quality distribution within a group of colleges*" (Long, 2008, pg.594). Long (2010) looks into the trend of how the effect of years of education and four-year college quality changes over a period of 30 years (1970-2000) by using three different datasets that cover each of the three decades. He decomposes the analyses by gender and race and finds that the changes in the years of education and quality effects on a set of outcome variables are heterogenous among subgroups but mainly increasing through years for some of them. Black et al. (2005) also conduct a through-time analysis of the university quality on wage rates and find that it is quite stable during the time span 1987-1998 with men benefiting more than women (except in 1989). They also consider a few other labour market outcomes apart from the logarithmic hourly wage rate such as educational attainment, graduate school attendance, labour force participation, hours of work during

[2] A four-year college here is defined as being "high quality" if it falls in the fourth quartile of the distribution of the quality index built by principal component analysis as opposed to falling in the first quartile.

the last year, marital status, number of children and spouse earnings.

Long (2010) includes the years of schooling and four-year college-quality variables separately in specifications. Meanwhile, Black and Smith (2004, 2006) and Black et al. (2005) argue that if years of schooling is not included it might bias the results. They show this by presenting both the results with and without the years of schooling. In this version of the paper we do not include the years of schooling in our specification.

Holmlund (2009) summarizes the studies which use European data. In this paper the author contributes to the literature through an analysis using a very big Swedish dataset on individuals and university characteristics and by employing quartile regressions. She finds that the returns to university quality are higher for the individuals who belong in the top quartiles of the income distribution.

To our knowledge, the only paper that attempts to estimate alumni's wage returns to university traits in Canada is Betts et al. (2007). They use data from the National Graduates Survey and pool together three cross sections for the years 1982, 1986 and 1990. This dataset lacks a measure for the latent ability of the participants. In the absence of this important variable that could help in addressing the selection issue, the authors use a fixed effect model which *''to the extent that the most able students in a province always attended universities A and B over the eight-year period under study,[...] sweep[s] average ability of the university's student body out of the wage equations"* (Betts et al., 2007, pg.10). The results are interpreted as *"something approaching a causal effect of [university] resources on student outcomes"* (Betts et al., 2007, pg.10). The outcomes of interest are labour force participation and annual earnings five years after graduation.

Differently from Betts et al. (2007), our analysis is based on one cross section of data. There are a few strengths in the dataset that we use. The availability of a measure for ability as well as a wealth of information on individual and family characteristics, allow us to assume that selection into universities of different quality is based on some observable variables, conditioning on which, sorting into universities is random. In this way, we are able to identify a causal effect of the university quality and reputation on hourly wage rates earned in the first job post-graduation. Apart for being a very recent dataset, YITS-B allows the identification of the universities and field of study attended and/or graduated, the occupation and the industry an individual has worked in. In this way, we could match the university one has attended to external (not within YITS-B) data on this university's characteristics from the Maclean's magazine.

3 Data

The main data set that we use is the Youth in Transition Survey Cohort B (YITS-B). Students of age 18 to 20 in December 1999 were surveyed every two years until April 2008, and each survey asks questions related to the past two years from the date of the interview. Detailed information on the sample size, time of the interview, reference time and age of the participants can be found in Table 1. In the first wave of data the students were 18-20 years old and this time corresponds to the age range in which most of them to have graduated from high school and enrolled in a PSE institution. By the third wave the age range is 22-24. By this age, we expect the students to have graduated from at least a PSE program and be in the job market.

Our sample focuses on the participants of YITS-B who have a Bachelor's degree or equivalent[3] as of December 2003. This subsample contains 2,520 observations, 59% (or 1,485) of which are women and 41% (or 1,035) are men. Because the individuals must have an overall post-secondary status "graduate, non-continuer" as of December 2007, the subsample shrinks further to 2,026 (60% or 1220 women and 40% or 806 men). Of the observations deleted, 494 were those people that graduated from BA program but are continuing another BA program or a post graduate program. Since they are still students, they are not counted in the labour force. Hence, 20.4% of all participants in cycle 3 of the survey have completed and attained one BA degree from a Canadian university. Within this sample we are only interested in those students that have started a full-time or a part-time paid job as an employee (self-employed individuals are dropped from the sample). This restriction and the unavailability of rankings for some universities reduces the sample even further to 672 women and 422 men. YITS-B is suitable for the purpose of this paper because it contains a wealth of information on the respondent, family, high school and friends, and especially detailed information about the PSE programs attended identifying the type of the degree, the type of the institution granting the degree, the code classification of this institution as well as the field of study. Table 2 contains detailed description of the individual characteristic varialbles used in our specification. We merge YITS-B with the university characteristics from external sources. The data on university[4] quality indicators are

[3]This number does not include the individuals who attained university diploma or certificate below Bachelor's (undergraduate level). Because their wage structure is different from a regular BA degree, they are excluded from the sample. Also the sample excludes those individuals that have attained a proffesional degree, an Master's or a PHD degree. The reason is that most likely their wages will be higher when compared to any BA graduate thanks to their post-graduate degree. Including these might confound the university quality effect with that of a higher degree. We choose to drop these observations firstly and then include them back in the sample as a robustness check exercise.

[4]The universities included in the sample are 45 and include: Universities of Toronto, McGill, British Columbia, Alberta,

obtained from the publicly available data in the university ranking issues of the Maclean's magazine published on November 2002, and Canadian Association of University Teachers (CAUT) Almanac published in 2002.

4 Methodology

4.1 Estimation Strategy and Identification

We use two university rankings. The first is the Maclean's magazine best overall reputation ranking which is constructed from the survey results that Maclean's magazine conducts. The survey asks high school counsellors, university officials, CEOs and corporate recruiters across Canada to rank all universities on three attributes: best quality, most innovative and leaders of tomorrow. Then, Maclean's calculates a best overall reputation ranking as an average of the rankings for the three attributes. The second is what we call the university quality ranking since it is based on the financial, physical and human capital inputs. We construct the university quality ranking by combining different university characteristics in one using the Principal Component Analysis. The detailed definitions of the university characteristics we use are provided in Table 3.

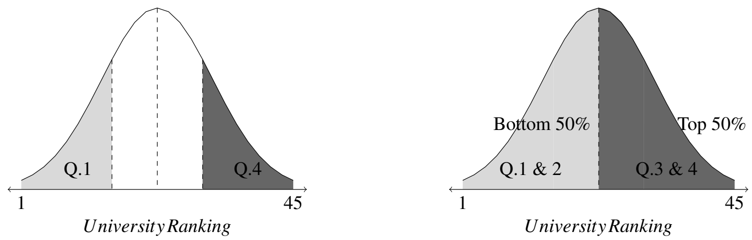
Principal Component Analysis (PCA) yields linear orthogonal combinations of the individual characteristics by assigning weights to each. These weights are determined by the solution of an optimization problem which seeks to maximize the extent that the index accounts for the covariance between the university characteristics. PCA may create as many orthogonal combinations, known as components, as there are inputs, in this case the university characteristics. Starting with the first component, the extent of covariance accountability that the component captures decreases in the second one and so on. Within a component the variable contributing most to the covariance is weighted highest. We use the first principal component (FPC) of the orthogonal transformation as our quality index. This is an efficient and optimal way of combining many university characteristics into one without worrying about the multicollinearity when these, otherwise, enter together in a regression equation.

Queen's, McMaster, Dalhousie, Calgary, Western Ontario, Saskatchewan, Ottawa, Laval, Montreal, Sherbrooke, Manitoba, Simon Fraser, Victoria, Waterloo, Guelph, Memorial, New Brunswick, Carlton, Windsor, Regina, York, Concordia, Mount Allison, Acadia, Lethbridge, Wilfrid Laurier, Trent, St.Fransis Xavier, Bishop's, Prince Edward Island, Winnipeg, Saint Mary's, Lakehead, Brock, Laurentian, Brandon, Ryerson, Mount Saint Vincent, Moncton, Cape Breton and Nipissing. The data for university characteristics for UQAM, UOIT, St.Thomas, UNBC were not sufficient to build the quality index, thus the reason the observations belonging to these universities were dropped from the sample.

We calculate the FPC based on the correlation matrix and not the covariance matrix of the variables used. Unlike factor analysis, PCA is not scale invariant; the eigenvalues and eigenvectors of a covariance matrix differ from those of the associated correlation matrix. Usually, a PCA of a covariance matrix is meaningful only if the variables are expressed in the same units. In our case variables have different units, thus we use correlation matrix instead. Principal Component Analysis is built based on two main assumptions that all the variables have a multivariate normal distribution and that the covariance matrix of the observations has all distinct and strictly positive eigenvalues. We may test the first assumption by the multivariate normality test of Henze-Zirkler(1990). The university characteristics published in 2002 pass this test; we fail to reject the null hypothesis of multivariate normality (p-value=0.285).

The Maclean's magazine best overall reputation ranking is a categorical variable ranging in value from 1 to 45, a higher number corresponding to a better ranking. We construct the university quality ranking as a categorical variable also so that the results may be comparable among the two. The two rankings capture different attributes of universities. The reputation ranking may be partly based on the quality of education of each institution and reflects mainly the "label" effect of a university given that it is based on a survey about perceptions. The quality ranking, instead, is constructed by using all inputs and characteristics of universities including the reputation ranking which makes it more likely to capture the quality of education provided in these institutions.

We use different forms of the treatment variable (university ranking). First, in one of our OLS specifications we use the ranking variables as continuous variables ranging from one (lowest rank) to 45 (highest rank). In this specification, the coefficient indicates the average returns to an increase in the rank of reputation (quality) by one spot. Second, realizing that returns to ranking may be nonlinear, we defined the ranking variable as an indicator of value one if the university pertains to the fourth (or top) quartile of the university ranking distribution, and zero if it pertains to the first (or bottom) quartile. Referring to Figure 1, the quality variable is a value of one for all the individuals within the area "Q.4" (i.e. quartile 4), and zero for the individuals in the area "Q.1" as shown in panel (a). This definition of the treatment variable uses only the data in the tails of the distribution and thus 50% of the sample. In order to use all data available, we define a second treatment variable (panel (b) in Figure 1) which determines the treatment as graduating from a university in the top 50% of the ranking distribution versus the bottom 50%.



(a) (b)

Figure 1: Visual representation of the ranking indicator variables

As it is common in this literature, we start the analysis with the ordinary least squares (OLS) estimates. Next, we consider matching techniques to estimate returns to university quality: nearest neighbour matching and propensity score matching. There are several advantages in using matching methods relative to least squares (OLS) regression. First, least squares regression assumes the causal effect of the treatment is constant for each individual, while matching techniques estimate this effect for each individual i in the sample, and report and average of these effects. Second, unlike OLS, matching disposes of the assumption that the relationship between the treatment and the outcome of interest is linear. Third, the balancing property in OLS is assumed, whereas matching methods emphasize it and we can explicitly test for it (see Rosenbaum and Rubin, 1983). For a technical and detailed description on the matching techniques see Rosenbaum and Rubin (1985); Abadie and Imbens (2006); Cochran and Rubin (1973); Dehejia and Wahba (1999); Heckman et al. (1997, 1998b,a,c); Imbens (2000); Lec (2001); Rosenbaum and Rubin (1983, 1985); Rubin (1974, 1980).

Our identification strategy relies on the "selection on observable variables" assumption. In the data, we have a measure for the ability of the students, which is the high school grade point average. Students may select into universities of different reputation (quality) based on their ability. Table 4 shows the bivariate distribution of students conditional on university reputation and high school grades[5]. As expected top quartile universities attract mainly middle and high ability students; the middle ranking groups of universities educate mostly middle-ability students; whereas, lowest ranking group of universities attract middle and low ability students. Given that high ability is a potential source of selection, controlling for high school grades in our specifications helps identification.

[5]Note that the high school grades variable in our data is a categorical variable indicating a grade interval. Since the high school grades are self-reported, there is always the risk that they may be overstated. However, in YITS the students where asked to report a grade interval. This procedure diminishes significantly the risk of measurement error.

4.2 Matching Methods

Let the outcome be $log\,\omega_i$ representing the log hourly wage of each individual at the first job after they graduate from a Bachelor's degree. The potential outcome, which is a different notion than the observed outcome, for each treatment state is

$$log\,\omega_i = \begin{cases} log\,\omega_{1i} & \text{if } H_i = 1 \\ log\,\omega_{0i} & \text{if } H_i = 0 \end{cases}$$

where H_i is a treatment dummy variable that takes a value of one if the individual graduated from a high rank university and zero otherwise. Our coefficient of interest is the average treatment effect on the treated (ATT) defined as

$$ATT = E\left[log\,\omega_{1i} - log\,\omega_{0i} \mid H_i = 1\right]$$

An alternative way of formulating ATT is:

$$ATT = E\left[log\,\omega_{1i} \mid H_i = 1\right] - E\left[log\,\omega_{0i} \mid H_i = 1\right]$$

So, ATT is the average log hourly wage difference between those that graduated from a higher ranking university and the average log hourly wage that these same individuals would have had if they had graduated from a lower ranking university. The later is unobserved because we can not observe one same individual in both states, and thus we can not see both potential outcomes of an individual in the treatment and non-treatment case. So, $E\left[log\,\omega_{0i} \mid H_i = 1\right]$ can not be observed; it is commonly known as the counterfactual. We can only estimate the counterfactual by $E\left[log\,\omega_{0i} \mid H_i = 0\right]$ and thus estimate ATT as the difference between the average outcome of the treated (higher ranking university graduates) and of those who were not treated (lower ranking university graduates). However, this is only possible at a cost. As shown in (Angrist and Pischke, 2008, pg.11) the equation below clearly displays this cost, the selection bias.

$$\underbrace{E\left[log\,\omega_i \mid H_i=1\right]-E\left[log\,\omega_i \mid H_i=0\right]}_{\text{Observed Difference in Average Outcome}} = \underbrace{E\left[log\,\omega_{1i} \mid H_i=1\right]-E\left[log\,\omega_{0i} \mid H_i=1\right]}_{ATT} + \underbrace{E\left[log\,\omega_{0i} \mid H_i=1\right]-E\left[log\,\omega_{0i} \mid H_i=0\right]}_{\text{Selection Bias}}$$

Selection bias derives from the fact that students with certain attributes and background self-select into university education, and moreover self-select into the higher ranking universities.

Self selection results in a correlation between the potential outcomes and the treatment reflected as a difference between $E\left[log\,\omega_{0i} \mid H_i=1\right]$ and $E\left[log\,\omega_{0i} \mid H_i=0\right]$. Notice that if

$$E\left[log\,\omega_{0i} \mid H_i=1\right]=E\left[log\,\omega_{0i} \mid H_i=0\right] \quad (3)$$

then selection bias would be zero and ATT can be easily estimated as the observed difference in log hourly wages,

$$\underbrace{E\left[log\,\omega_i \mid H_i=1\right]-E\left[log\,\omega_i \mid H_i=0\right]}_{\text{Observed Difference in Average Outcome}} = \underbrace{E\left[log\,\omega_{1i} \mid H_i=1\right]-E\left[log\,\omega_{0i} \mid H_i=1\right]}_{ATT}$$

A solution to the selection problem is the random assignment of students to universities of different quality. This would make the two groups (treated and untreated) comparable and make possible the calculation of the counterfactual as in equation (3). Random assignment can be guaranteed when the data are experimental and the researcher has direct control on assigning the treatment randomly. In the case of non-experimental data (e.g. survey data), researchers are able to assume that selection into universities is dependent only on some characteristics which can be observed or measured like family background, own attributes, past academic performance, etc. This is commonly known as the selection-on-observables or conditional independence assumption (CIA). In notation: $log\,\omega_h \perp H \mid X$ for all $H \in \{0,1\}$. What this says is that treatment is assigned "as if randomly" after we condition on sufficient variables based on which the individuals self-select or are selected by the universities. Thus, even though before conditioning on X, a matrix containing predetermined characteristics of individual i, we most likely have

$$E\left[log\,\omega_{0i} \mid H_i = 1\right] \neq E\left[log\,\omega_{0i} \mid H_i = 0\right]$$

Under CIA, after conditioning on X we have,

$$E\left[log\,\omega_{0i} \mid X_i, H_i = 1\right] = E\left[log\,\omega_{0i} \mid X_i, H_i = 0\right]$$

So, we can easily estimate the average treatment effect on the treated as

$$ATT = E\left[log\,\omega_{1i} \mid X_i, H_i = 1\right] - E\left[log\,\omega_{0i} \mid X_i, H_i = 0\right]$$

Nearest neighbour (NN) matching method calculates returns to education by finding for each treated individual at least one untreated individual that has the same values of X as the treated individual and calculate the difference in their hourly earnings. After doing this for each treated individual, ATT is just the mean of all these differences. One issue with NN matching is what the literature refers to as "curse of dimensionality". The more variables you include in X, the more you guarantee that CIA holds, however as the number of these variables increases the bigger the number of cells defined by the values of X get and each cell of the multivariate distribution of the treatment and X becomes less and less populated and some of these cells are even empty. When this happens, the calculation of the counterfactual is not possible.

Differently from NN matching, propensity score matching[6] (PSM) aiming to overcome the "curse of dimensionality" issue, calculates the counterfactual by matching the individuals on the probability of getting the treatment, known as the propensity score. In this way matching is done based on only one variable and it is less likely to have empty cells (shown by Rosenbaum and Rubin, 1983). For the PSM estimator, the CIA is represented as

$$log\,\omega_H \perp H \mid s(H,X) \text{ for all } H \in \{0,1\}$$

where $s(H,X)$ is the propensity score and is defined as the conditional probability of receiving treatment H having certain pre-treatment characteristics X.

[6]We use the *psmatch2* command in Stata of Leuven and Sianesi (2003).

5 Empirical Results

The average hourly earnings of men and women who graduated from a high ranking university (top quartile) is $3.00 higher than those who graduated from a lowest ranking university (bottom quartile). In Figure 2 we plot the empirical distributions of wages separately for the top and bottom ranking quartiles. In each of the panels, the wage density function is left skewed for the graduates of high ranking universities, and right skewed for those who graduated from lower ranking universities. This is true for reputation and quality rankings. For both genders there is a higher concentration of observations in higher wages for the graduates of selective universities. However, for those women that graduated from top ranking universities, their empirical distribution is bimodal with two clusters, one at the higher end and the other at the lower end of the wage distribution.

The descriptive statistics for the individual characteristic variables can be found in Table 5 in the Appendix. A lower fraction of women have parents with some post-secondary education than men. The number of dependent children reported is much higher for women than men, and they are more likely to have a non-single status. The descriptive statistics of university characteristics are shown in Table 6 in the Appendix. Maclean's magazine classifies the universities into three categories. The first category is the "Medical Doctoral" which includes those universities with a broad range of PhD programs and research as well as medical schools; the second category is the "Comprehensive" which includes those universities with a significant amount of research activity and a wide range of programs at the undergraduate and graduate levels including professional degrees; and the third category is the "Primarily Undergraduate" which includes those universities largely focused on undergraduate education with relatively few graduate programs. All university characteristics, are highest for the Medical/Doctoral universities and lowest for the Primarily Undergraduate universities, except for the Student Services, Alumni Support and Faculty to Student Ratio. By and large, Medical/Doctoral universities have the highest endowments and resources among the three categories.

5.1 Maclean's Magazine Reputation Ranking

The participants of the YITS-B survey graduated from high school in 1999 and most of them applied for a university program. Hence, university rankings published in 1999 were particularly important for them when making the choice as to which university to attend. On the other hand, most of this cohort graduated from university in 2002 and 2003. So, the potential employers would look at the 2002 rankings in order to create an idea of the quality of a degree and differentiate among many applicants for a job application. Because we aim at capturing the university ranking premium in the initial transition to labor market, we use the 2002 ranking data.

First we consider the Bachelor degree graduates that were employed full-time or part-time and test whether the university reputation ranking in Canada has an effect on wage rate. Table 7 contains the results that we retrieve by using the nearest neighbour matching estimator with bias correction (BCNNM) for two definitions of the treatment variable (i) graduating from a university in the top 25% versus bottom 25% of the reputation ranking distribution, and (ii) graduating from a university in the top 50% versus bottom 50% of the reputation ranking distribution. In all these specifications we condition on high school grades, Bachelor degree field of study and other individual characteristics.

The estimates show that female employees, who graduate from a university in the top quartile of the reputation ranking distribution earn a 15.2% increase in the hourly wage when compared to those females with the same measured ability and socio-economic characteristics that graduated from the bottom quartile university. Men earn almost twice as high premium (29.9%) as women. The reputation premium drops in magnitude when the full sample of Bachelor degree graduates is used, that is when we include the observations in the inter-quartile range of the ranking distribution. In this case we compare the hourly wage rates of half of the sample that graduated from better ranking universities than the other half. On average, reputation ranking premium for females is 10.3% and for males is 13.4%.

5.2 University Quality Ranking

In this subsection we repeat the above analysis with a different ranking variable. Firstly we build a quality index by using the first principal component of the principal component analysis of a set of university characteristics. The data were publicly published in 2002 by the Maclean's magazine and CAUT Almanac. Then, we construct a ranking variable based on this index. Our index is a proxy for university quality; it is a measure that relies on the amount of inputs of universities which translate into facilities and opportunities for their students. The inputs include several indicators of student body composition, faculty qualification and achieved grants, and lastly financial resource allocation. We believe that the returns to university quality ranking would capture the higher human capital that graduates from high-quality universities posses. This would distinguish them in the labor market by the knowledge and skills that they posses rather then by the reputation of their degree.

Table 8 in the Appendix displays the return to university quality that we estimate by using the nearest neighbour matching approach with bias correction. We can see that for women there are statistically significant returns to having a Bachelor's degree from a university that belongs to the top quartile of the university quality distribution. Women with higher quality education earn 20.9% more than those who received a lower quality education. Notice that in this case the difference in the treatment received from the treatment and control group is highest, thus the return is expected to be high. When the treatment variable aims to compare the top 50% with the bottom 50% of the quality distribution, the return for women is not statistically significant and small in magnitude. The reason is that the inclusion of the inter-quartile range of the university quality distribution dilutes the difference in wages.

There seems to be no returns to attending a top quartile quality university versus a bottom quartile quality university for men. The sample size is much smaller and the standard error of the estimate is high. In this regression the balancing property is not satisfied, that is there were not enough observations in the control and treatment cells determined by the control variables. However, when we compare the top half with the bottom half of the university quality distribution, the return of attending a high quality university is 11.5% for men.

5.3 Sensitivity Analysis

In the previous sections we only discussed the returns estimated by the Nearest Neighbour matching (NNM) method with bias correction. The reason we prefer this estimator is two fold. First, NNM methods make use of few but very close matches when compared to Propensity Score matching (PSM) which may provide a few more in number but lower quality matches. This property makes NNM a relatively more efficient estimator. Second, Abadie and Imbens (2002) show that in finite samples the matches may not be exact in their characteristics, and this creates a bias. Abadie and Imbens (2006) suggest a bias-correction adjustment based on a linear regression and show that it performs better than NNM without bias correction and ordinary least squares.

Tables 9 and 10 in the appendix replicate the our results using different estimators. The covariates in each specification include the measure for ability (Overall high school GPA), rural versus urban residence dummy while in high school, rural versus urban residence dummy while full-time employed, number of dependent children, citizen status dummy, marital status, province of residence dummies, parental education dummies and undergraduate degree field of study indicators. Each of the cells in these two tables contains the parameter estimate and the standard error (see details in the table footnote). Referring to column (2) in Table 9 , we may see that the results presented in the previous two sub-sections are independent of the methodology used. Even though the estimated magnitude varies a little, the statistical significance is almost the same always indicating significant returns to university reputation ranking. Note that NNM with bias-correction estimates are more efficient than the Propensity Score Matching estimates.

In Table 9 we also consider different sample exclusions (column (1) to (4)). One could argue that the best students with a deep interest in the subjects most likely will continue post-graduate education and attend a master's degree or choose to attain a professional degree. For this reason consider the differences in BCNNM estimates between columns (1) - (3) and (2) - (4). As we include the students that have finished a professional degree or a master's degree the reputation premium estimates decrease for women but increase for men. This decrease in magnitude for women may be attributed to the fact that high ability graduates from low-ranking universities will pursue a graduate degree that will complement their skills. In this way the difference between the Bachelor degree graduates with higher versus lower reputation diminishes. For men, the contrary seems to happen. In this case, high ability graduates from high-ranking universities will pursue a graduate degree increasing further the premium of university ranking. However, this speculation should not be interpreted as selection to graduate school. Table 11 shows that the probability of attending a graduate program, conditional on ability and a set of demographic characteristics, is not affected by the reputation (or quality) ranking of the university where undergraduate studies were completed. Thus, this results indicate that there is no selection to graduate school caused by the reputation or quality ranking of the university. One other source of selection might be self-employment. In YITS-B only 5% of the students choose to be self employed. This is a small number of observations that most likely will not effect the results in this paper.

Lastly, even though we trust that a measure for ability goes a long way in identifying a causal effect of university rankings on wages, we acknowledge that there may be other unobservable traits of individuals that could determines their decision-making. One such variable is motivation. In the

YITS-B questionnaire there is a question about the aspirations of students. More specifically, they are asked the highest level of education they "would like to get", differentiating from the question "as things stand now, what is the highest level of education you plan to get?". A further question asks them if motivation is standing in their way of attaining the level of education they would like to achieve. We use these two questions to create a variable that would capture the motivation and preferences of the students. The results have negligible changes in magnitude after controlling for this variable[7]. Since curse of dimentionality is important in matching methods, we choose to maintain a parsimonious specification and not include this variable in the analysis presented in the paper.

6 Conclusion

In this paper we estimate the wage returns of university reputation and quality rankings for Canadian youth. Two university rankings are used. One is the Maclean's magazine best overall reputation ranking. We also build a new university ranking based on a quality index that we construct as the principal component of the Principal Component Analysis of several university characteristics. University characteristics data are retrieved from the Maclean's magazine November 2002 issue and CAUT Almanac 2002 issue. The analysis is split by gender. Our main data source is Youth in Transition Survey and the outcome variable of interest is the starting hourly wage in the first job after graduating from university. Several main findings emerge from the analysis in this paper. Firstly, we observe that the lack of an ability measure, individual and parental characteristics in the specifications would produce misleading results. Our findings indicate that university quality matters a lot for both genders when we do not control for high school grade point average (GPA), which in turn convey important information about the behaviour process. This is because of two reasons: higher ability individuals go to better schools and some of the observed wage premium these individuals get could be attributed to university quality when it is actually innate ability. Hence, the availability of a measure for ability helps identify an unbiased estimate for the returns to education quality.

We employ matching methods and provide a sensitivity analysis through different estimators and sample exclusions. The findings indicate that university reputation premium to graduating from a top ranking university is 10% for women and 13.4% for men. When comparing the wages of the top 25%

[7]This set of estimates are available on request.

of the sample in the reputation ranking distribution to the bottom 25%, thus excluding the middle-ranking observations, the returns are higher for both genders: 15.2% for women and 29.9% for men. The ranking premiums are higher for men than women and the results are robust through different specifications, samples and estimators.

The analysis in the present paper may be extended further in several aspects. First, we plan to see whether the university ranking affects other outcomes like yearly earnings and other benefits in the job, satisfaction in the job, probability to drop out of university and probability to graduate. A last extension to consider is building a better university quality index that would take into account that universities may rank differently based on field of study. In this paper we can only look at the short term effects of university quality and reputation. It would be very interesting to study the long-term effects and, in particular, to test if reputation or quality of the university would take individuals to different wage profiles.

Appendix

Table 1: Timing of cycles for YITS - B and overall sample size

	Obs	Participants Age	Refence Time Period	Time of the Interview
Cycle 1	22,378	18-20	Jan1998-Dec1999	Jan2000-Apr2000
Cycle 2	18,779	20-22	Jan2000-Dec2001	Jan2002-Apr2002
Cycle 3	14,817	22-24	Jan2002-Dec2003	Jan2004-Apr2004
Cycle 4	12,435	24-26	Jan2004-Dec2005	Jan2006-Apr2006
Cycle 5	9,946	26-28	Jan2006-Dec2007	Jan2008-Apr2008

Table 2: Definitions of individual characteristics and other variables

Variable Name	Definition
Dependent Variable	
Log hourly wage	Logarithmic hourly wage paid when first hired (first job) after graduating university.
Personal Characteristics	
Overall high school GPA	The overall high school grade point average (GPA). This variable is reported in intervals of 10 percentage points. Hence, it is a chategorical variable.
Bachelor Degree Field of Study	A set of 11 dummy variables indicating the undergraduate field of study which include: (1) Education; (2) Visual and Performing Arts, and Communications Technologies; (3) Humanities; (4) Social and Behavioral Sciences, and Law; (5) Business, Management and Public Administration; (6) Physical and Life Sciences, and Technologies; (7) Mathematics, Computer and Information Sciences; (8) Architecture, Engineering and Related Technologies ; (9) Agriculture, Natural Resources and Conservation; (10) Health, Parks, Recreation and Fitness; (11)Personal, Protective and Transportation Services.
Rural Dummy	Indicator of rural or urban geography of the most recent residence of the survey participant. This is derived based on the Statistical Area Classification (SATYPE) 2001 Census geography.
Number of Children	Number of dependent children of the respondent.
Citizen Dummy	Indicator variable takes the value 1 if the respondent is a Canadian citizen and 0 otherwise.
Full-time Dummy	Indicator variable takes the value 1 if the respondent is working full-time in his first job after graduating from university and 0 otherwise.
Professional degree and Master's Dummy	Indicator variable takes the value 1 if the respondent has graduated from a professional degree or Master's before starting their first job after full-time schooling and 0 otherwise.
Marital Status	A dummy variable is generated for each "married and/or living with partner" and "separated, divorced or widowed". The omitted category is "single".
Residential Province Dummies	A dummy variable is generated as an indicator variable for each of the Canadian regions: Atlantic, BC, Manitoba and Saskatchewan, Alberta, Quebec and the other provinces. The omitted category is Ontario.
Parental Variables	
Father PSE	A dummy variable indicating that father has some post-secondary educaiton: "College", "University and Professional Degrees", "Graduate Degree". Omitted category is "high school or less than high school education".
Mother PSE	A dummy variable indicating that mother has some post-secondary educaiton: "College", "University and Professional Degrees", "Graduate Degree". Omitted category is "high school or less than high school education".
Quality Measures	
Categories	Medical Doctoral, Comprehensive and Primarily Undergraduate
Quality Ranking 2002	First Principal Component of the Principal Component Analysis (PCA) of the university characteristics shown in table 3
Reputation Ranking	This ranking combines all 48 universities from the three categories into one group. Maclean's editors solicited the opinion of 5,467 high-school guidance counsellors, university officials, CEOs and corporate recruiters across Canada. The reputation survey of Maclean's is both regional and national in character, dividing the country into the following areas: the Atlantic provinces, Quebec, Ontario, and the four Western provinces. All respondents completed a national survey; university officials and guidance counsellors also completed regional surveys. The respondents rank the universities as the Highest Quality, as the Most Innovative, and as Leaders of Tomorrow. The Maclean's magazine calculates a Best Overall Reputation Ranking by weighting equally the rankings for the three attributes.

Table 3: Definitions of university characteristics

Variable Name	Definition
Proportion who graduate	Percentage of full-time second-year undergraduates who completed their degree within one year of the expected graduation date.
Classes Taught by Tenured Faculty	The percentage of first-year classes taught by tenured or tenure-track professors
Faculty with PhDs	Percentage of full-time faculty with a PhD degree
Average Entering Grade	The average final-year grades of freshman students entering from high school or Quebec's CEGEP system.
Student Awards	The five-year tally of the number of students, per 1,000, who have won national awards.
Faculty Awards	The five-year tally of the number of full-time professors, per 1,000, who have won national awards.
Faculty Social Sciences and Humanities Grants(SSHR)	The average size and number of peer-adjudicated research grants from both the Social Sciences and Humanities Research Council and the Canada Council. The size of grants is listed per eligible full-time faculty member; the number of grants is per 100 eligible full-time faculty members. The ranking reflects a weighted average of the two.
Medical Science Grants(MedSci)	The average size and number of peer-adjudicated research grants from both the Natural Sciences and Engineering Research Council and the Medical Research Council. The size of grants is listed per eligible full-time faculty member; the number of grants is per 100 eligible average of the two.
Operating Budget	These figures show the size of operating expenditures per weighted full-time-equivalent student
Student Services	Percentage of total operating expenditures devoted to student services
Scholarships & Bursaries	Percentage of total operating expenditures devoted to scholarships and bursaries
Library Holdings per Student	These figures show the number of volumes in all campus libraries, divided by the number of full-time-equivalent students.
Library Acquisitions	To gauge the currency of resources, Maclean's measures the proportion of the library budget allocated to updating the university's collection.
Library Expenses	A measure of financial commitment, this indicator shows the percentage of the university budget devoted to maintaining library services.
Alumni Support	The percentage of alumni who made gifts to the university over a five-year period.
Student Faculty Ratio	The ratio of the number of full-time tenured faculty members to the number of students enrolled in an university. These data are collected from the yearly publication of CAUT Almanac.
Number of Full-time Students	Number of full-time students in a university
Number of Part-time Students	Number of part-time students in a university
Tuition	Tuition fee for Bachelor of Arts programs.
Compulsory and Ancillary Fees	Other fees that are paid additional to tuition fees for Bachelor of Arts programs.

Table 4: Cross tabulation by high school GPA and university reputation

High School Grade(%)	Ranking quartiles				
	First Quartile	Second Quartile	Third Quartile	Fourth Quartile	Total
60-79	8.39	5.93	3.85	13.75	31.87
80-89	8.35	11.21	9.56	20.22	49.34
90-100	2.31	5.16	3.74	7.58	18.79
Total	19.01	22.31	17.14	41.45	100

Note: The numbers in each cell are the cell percentage determined by the university reputation ranking and ability. The total number of observations is 910.

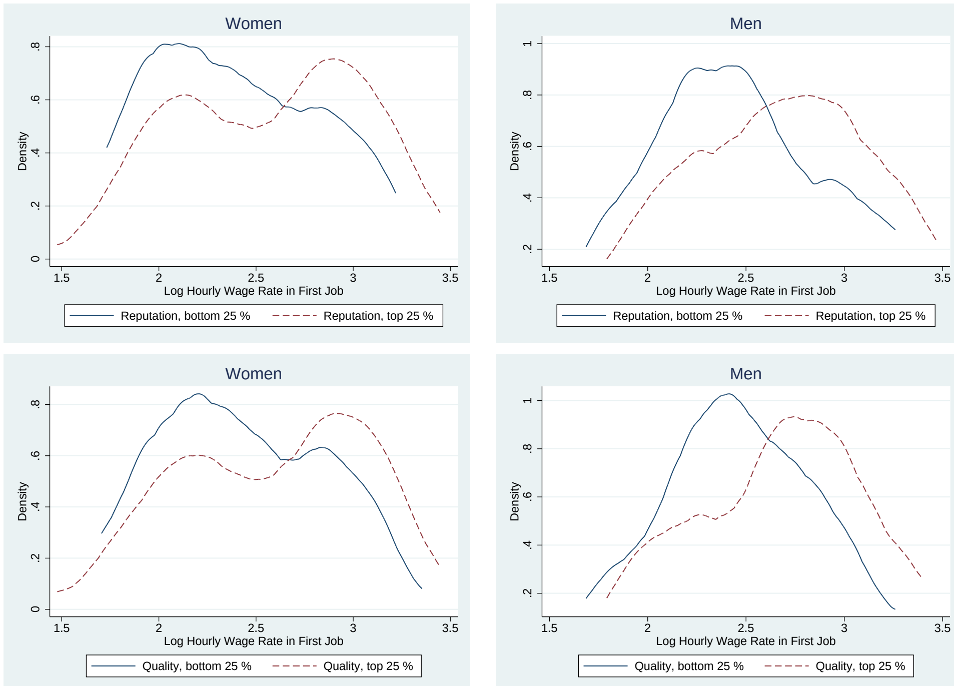


Figure 2: Empirical distribution of log hourly wages by gender, reputation and quality of university

Table 5: Descriptive statistics of individual characteristics

Variable	Mean	Standard Deviation	Obs. No.
Women			
Mother PSE	0.486	0.500	808
Father PSE	0.561	0.497	747
Rural Dummy	0.179	0.377	841
Number of dependent children	0.220	0.593	845
Citizen of Canada dummy	0.969	0.191	848
Married or Living with partner dummy	0.568	0.495	845
Separated/Divorced/Widow dummy	0.011	0.107	845
Men			
Mother PSE	0.573	0.495	565
Father PSE	0.627	0.484	536
Rural Dummy	0.121	0.326	572
Number of dependent children	0.133	0.428	590
Citizen of Canada dummy	0.938	0.241	592
Married or Living with partner dummy	0.486	0.500	590
Separated/Divorced/Widow dummy	0.007	0.107	590

Table 6: Descriptive statistics for university characteristics

Variable 2002	Category	Mean	Std. Dev.	Min	Max	Obs
Average Entering Grade	1	84.867	1.959	82.000	89.000	15
	2	81.000	3.376	75.000	86.000	11
	3	79.619	2.636	76.000	85.000	19
Faculty with PhDs	1	94.607	2.840	88.800	98.400	15
	2	90.836	5.682	76.700	97.200	11
	3	81.971	13.209	38.200	95.300	19
Classes Taught by Tenured Faculty	1	56.620	9.546	38.700	72.600	15
	2	56.427	13.345	38.200	81.000	11
	3	63.557	11.282	39.100	85.700	19
Proportion who Graduate	1	86.853	5.710	72.600	92.900	15
	2	78.882	5.356	69.900	88.100	11
	3	76.710	9.213	54.000	92.300	19
Tuition	1	3338.333	1145.014	1663.000	4860.000	15
	2	3503.273	859.207	1668.000	4265.000	11
	3	4023.286	1027.281	1668.000	6584.000	19
Compulsory and Anscillary Fees	1	499.000	256.840	222.000	1143.000	15
	2	471.364	200.355	203.000	807.000	11
	3	427.429	236.353	65.000	892.000	19
Student Awards	1	5.733	1.852	2.500	9.500	15
	2	3.982	1.658	1.400	6.500	11
	3	1.795	1.247	0.200	4.300	19
SSHR Size	1	8420.200	3583.352	2780.000	14353.000	15
	2	4622.273	1973.140	1947.000	8502.000	11
	3	2297.238	1331.677	235.000	4967.000	19
SSHR Number	1	26.437	11.776	10.480	47.730	15
	2	16.431	8.347	7.220	33.950	11
	3	9.696	5.138	1.500	21.850	19
MedSci Size	1	66920.470	22555.350	24486.000	106137.000	15
	2	43145.450	18467.220	22248.000	80531.000	11
	3	13147.190	8840.186	0.000	34930.000	19
MedSci Number	1	119.352	34.513	62.650	194.000	15
	2	109.886	34.551	53.170	165.450	11
	3	51.153	25.624	0.000	92.540	19
Scholarships and Bursaries	1	9.429	2.596	4.750	13.690	15
	2	6.756	2.279	3.990	10.790	11
	3	4.893	2.345	1.450	9.180	19
Student Services	1	4.713	0.952	3.440	6.890	15
	2	5.119	1.101	3.880	7.440	11
	3	6.350	1.876	4.190	10.530	19
Library Acquisitions	1	45.818	4.774	37.960	51.180	15
	2	39.887	6.258	29.270	50.450	11
	3	36.438	5.563	28.290	49.340	19
Library Expenses	1	6.467	1.257	4.670	9.370	15
	2	6.510	0.656	5.350	7.470	11
	3	5.518	0.981	3.820	7.460	19
Library Holdings per Students	1	228.600	63.201	145.000	349.000	15
	2	213.091	57.146	133.000	312.000	11
	3	224.667	74.374	74.000	364.000	19
Faculty Awards	1	5.960	2.782	2.500	10.700	15
	2	3.455	2.490	0.500	8.200	11
	3	1.843	2.251	0.000	8.800	19
Operating Budget	1	8398.400	983.984	6981.000	10736.000	15
	2	7857.273	666.390	6741.000	8767.000	11
	3	7380.286	1186.084	4827.000	9533.000	19
Full Time Students	1	21698.330	9016.881	9003.000	44126.000	15
	2	14131.640	6265.645	7149.000	30056.000	11
	3	4184.667	2416.590	1887.000	11163.000	19
Part Time Students	1	7186.200	4568.307	2211.000	16728.000	15
	2	5330.455	3503.734	1512.000	12546.000	11
	3	1942.000	2506.355	281.000	12047.000	19
Alumni Support	1	16.653	4.339	9.800	25.400	15
	2	13.200	4.144	4.600	20.400	11
	3	18.350	7.494	3.200	32.500	19
Faculty Student Ratio	1	0.1733	0.029	0.100	0.220	15
	2	0.225	0.034	0.160	0.280	11
	3	0.202	0.048	0.130	0.270	19

Table 7: Returns to university reputation ranking, BCNNM

Y=log(hourly wage)	Top vs. Bottom 25%	Top vs. Bottom 50%
Women	0.152**	0.103**
	(0.061)	(0.045)
	322	620
Men	0.299***	0.134***
	(0.084)	(0.051)
	214	400

Standard errors in parenthesis. ***Significance at 1%, **Significance at 5%, *Significance at 10%. The third number in each cell is sample size. The sample includes only the individuals that graduated from a Bachelor's degree and started a job full-time or part-time. BCNNM stands for Bias Correction Nearest Neighbor Matching.

Table 8: Return to university quality rankings, BCNNM

Y=log(hourly wage)	Top vs. Bottom 25%	Top vs. Bottom 50%
Women	0.209***	0.009
	(0.057)	(0.047)
	332	620
Men	-0.031	0.115**
	(0.081)	(0.053)
	193	400

Standard errors in parenthesis. ***Significance at 1%, **Significance at 5%, *Significance at 10%. The third number in each cell is sample size. The sample includes only the individuals that graduated from a Bachelor's degree and started a job full-time or part-time. BCNNM stands for Bias Correction Nearest Neighbor Matching.

Table 9: Starting wage returns to university reputation rankings

Y=log(w/h)	(1)		(2)		(3)		(4)	
	F	M	F	M	F	M	F	M
OLS								
Cont.Var	0.005*	0.006*	0.005***	0.006***	0.004**	0.007***	0.004***	0.007***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
4v1	0.195***	0.182**	0.171***	0.191***	0.153***	0.213***	0.131***	0.198***
	(0.062)	(0.073)	(0.053)	(0.063)	(0.057)	(0.066)	(0.048)	(0.057)
43v21	0.102**	0.141***	0.070*	0.138***	0.088**	0.163***	0.069*	0.150***
	(0.045)	(0.052)	(0.039)	(0.044)	(0.042)	(0.048)	(0.036)	(0.041)
NNM								
4v1	0.265***	0.234***	0.215***	0.227***	0.243***	0.231***	0.215***	0.198***
	(0.069)	(0.078)	(0.057)	(0.076)	(0.065)	(0.074)	(0.054)	(0.068)
43v21	0.140***	0.203***	0.109**	.183***	0.143***	0.199***	0.124***	0.169***
	(0.049)	(0.058)	(0.045)	(0.053)	(0.046)	(0.054)	(0.042)	(0.049)
BCNNM								
4v1	0.239***	0.074	0.152**	0.299***	0.196***	0.207**	0.138**	0.355***
	(0.071)	(0.087)	(0.061)	(0.084)	(0.068)	(0.087)	(0.056)	(0.068)
43v21	0.139***	0.127**	0.103**	0.134***	0.134***	0.130**	0.091**	0.150***
	(0.050)	(0.056)	(0.045)	(0.051)	(0.047)	(0.055)	(0.043)	(0.048)
PSM								
4v1	0.264***	0.225**	0.157**	0.254***	0.225***	0.21***	0.151***	0.263***
	(0.079)	(0.119)	(0.068)	(0.102)	(0.070)	(0.069)	(0.062)	(0.088)
43v21	0.138***	0.109*	0.090**	0.114**	0.123***	0.164***	0.089**	0.138***
	(0.057)	(0.073)	(0.048)	(0.06)	(0.053)	(0.052)	(0.043)	(0.054)
OBS								
4v1	250	187	322	214	283	202	425	273
Full	417	310	620	400	514	359	748	466

Note: Standard errors in parenthesis. ***Significance at 1%, **Significance at 5%, *Significance at 10%.
Estimators used are Ordinary Least Squares (OLS), Nearest Neighbour Matching (NNM), Nearest Neighbour Matching with Bias Correction (NNM BCE) and Propensity Score Matching (PSM).
Sub-sample (1) includes the Bachelor degree graduates with full-time employment post-graduation. Sub-sample (2) includes the Bachelor's degree graduates with a full or part-time employment post-graduation. In all the specifications we add a full-time employee indicator variable. Sub-sample (3) includes the Bachelor, professional or Master's degree graduates with full-time employment post-graduation. In all the specifications we add a professional and Master's degree indicator variable. Sub-sample (4) includes the Bachelor, professional or Master's degree graduates with full or part-time employment post-graduation. In all the specifications we add a full-time indicator variable and a professional degree and Master's indicator variable.

Table 10: Starting wage returns to university quality rankings

Y=log(w/h)	(1)		(2)		(3)		(4)	
	F	M	F	M	F	M	F	M
OLS								
Cont.Var	0.004**	0.004	0.005***	0.004*	0.003*	0.005**	0.004***	0.005**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
4v1	0.147*	0.146*	0.125**	0.145**	0.125**	0 .175**	0.120**	0.161**
	(0.067)	(0.083)	(0.058)	(0.072)	(0.062	(0.075)	(0.054)	(0.065)
43v21	0.159***	0.134**	0.117***	0.141***	0.133***	0.145***	0.109***	0.142***
	(0.047)	(0.055)	(0.041)	(0.047)	(0.043	(0.051)	(0.037)	(0.043)
NNM								
4v1	0.123*	0.129	0.139**	0.109*	0.122**	0.144*	0.147***	0.119*
	(0.067)	(0.082)	(0.058)	(0.077)	(0.062)	(0.079)	(0.054)	(0.073)
43v21	0.141***	0.157***	0.108**	0.118**	0.137***	0.145***	0.112***	0.109**
	(0.050)	(0.059)	(0.045	(0.054)	(0.046)	(0.055)	(0.042)	(0.051)
NNM BCE								
4v1	0.179***	-0.117	0.209***	-0.031	0.08	0.033	0.107*	0.093
	(0.068)	(0.094)	(0.057)	(0.081)	(0.066)	(0.102)	(0.056)	(0.087)
43v21	0.097*	0.08	0.009	0.115**	0.129***	0.115**	0.035	0.133***
	(0.054)	(0.059)	(0.047)	(0.053)	(0.048)	(0.056)	(0.044)	(0.049)
PSM								
4v1	0.269***	0.179*	0.207**	0.041	0.09	0.054	0.133*	0.124
	(0.091)	(0.119)	(0.090)	(0.125)	(0.072)	(0.118)	(0.102)	(0.120)
43v21	0.181***	0.096*	0.111**	0.092*	0.195***	0.098*	0.109**	0.110***
	(0.059)	(0.069)	(0.053)	(0.063)	(0.071)	(0.061)	(0.560)	(0.054)
OBS								
4v1 Sample	227	145	332	193	281	173	407	228
Full Sample	456	327	620	400	514	359	748	466

Note: Standard errors in parenthesis. ***Significance at 1%, **Significance at 5%, *Significance at 10%.
Estimators used are Ordinary Least Squares (OLS), Nearest Neighbour Matching (NNM), Nearest Neighbour Matching with Bias Correction (NNM BCE) and Propensity Score Matching (PSM).
Sub-sample (1) includes the Bachelor degree graduates with full-time employment post-graduation. Sub-sample (2) includes the Bachelor's degree graduates with a full or part-time employment post-graduation. In all the specifications we add a full-time employee indicator variable. Sub-sample (3) includes the Bachelor, professional or Master's degree graduates with full-time employment post-graduation. In all the specifications we add a professional and Master's degree indicator variable. Sub-sample (4) includes the Bachelor, professional or Master's degree graduates with full or part-time employment post-graduation. In all the specifications we add a full-time indicator variable and a professional degree and Master's indicator variable.

Table 11: University rankings and probability to attend a professional or graduate degree

	Top vs. Bottom 25%		Top vs. Bottom 50%	
Treatment Variable:	Reputation Ranking	Quality Ranking	Reputation Ranking	Quality Ranking
Women	0.037	0.086	0.002	0.045
	(0.194)	(0.213)	(0.148)	(0.155)
Men	-0.268	0.258	-0.106	-0.055
	(0.255)	(0.279)	(0.193)	(0.201)

Note: Each cell represents a probit regression and reports only the marginal effect estimate of the treatment variable, conditional on ability measure and demographic characteristics liste in table 5. Standard errors in parenthesis. ***Significance at 1%, **Significance at 5%, *Significance at 10%.

References

Econometric Evaluation of Labour Market Policies, chapter Identification and Estimation of Causal Effects of Multiple Treatments under the Conditional Independence Assumption, pages 43–58. Heidelber ca/Springer, 2001.

Alberto Abadie and Guido W. Imbens. Simple and bias-corrected matching estimators. *Technical report, Department of Economics, University of California, Berkeley.*, 2002.

Alberto Abadie and Guido W. Imbens. Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267, 2006.

Joshua D. Angrist and Jorn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 2008.

Julian Betts, Christofer Ferrall, and Ross Finnie. The role of university characteristics in determining post-graduation outcomes: Panel evidence from three recent canadian cohorts. Technical report, Analytical Studies, Research Paper Series, Statistics Canada, Catalogue no. 11F0019MIE, no.292, 2007.

Dan Black, Kermit Daniel, and Jeffrey Smith. College quality and the wages in the united states. *German Economic Review*, 6(3):415–443, 2005.

Dan A. Black and Jeffrey A. Smith. How robust is the evidence on the effects of college quality? evidence from matching. *Journal of Econometrics*, 121:99–124, 2004.

Dan A. Black and Jeffrey A. Smith. Estimating the returns to college quality with multiple proxies for quality. *Journal of Labour Economics*, 24 (3):701–728, 2006.

Dominic J. Brewer, Eric R. Ride, and Ronald G. Ehrenberg. Does it pay to attend an elite private college? *Journal of Human Resources*, pages 106–123, 1998.

David Card. The causal effects of education on earnings. In O. Ashenfelter and David Card, editors, *Handbook of Labour Economics*, volume 3, chapter 30, pages 1801–1863. Elsevier Science B.V, 1999.

Arnaud Chevalier and Gavan Conlon. Does it pay to attend a prestigous university? *Center for Economics of Education, London School of Economics and Political Science, Houghton Street, London WC2A 2AE*, 2003.

W. Cochran and Donald B. Rubin. Controlling bias in observational studies. *Sankyha*, 35:417–446, 1973.

Stacy Dale and Alan B. Krueger. Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables. *The Quarterly Journal of Economics*, 79(2):1491–1527, 2002.

R. H. Dehejia and S. Wahba. Causal effects in non-experimental studies: Re-evaluating the evaluation of training programmes. *Journal of the American Statistical Association*, 94:1053–1062, 1999.

Kent Eliasson. The role of ability in estimating the returns to college choice: New swedish evidence. *Umea Economic Studies no. 691. Umea University.*, 2006.

James J. Heckman, H. Ichimura, and Petra E. Todd. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies*, 64:605–654, 1997.

James J. Heckman, H. Ichimura, J.A. Smith, and Petra E. Todd. Characterising selection bias using experimental data. *Econometrica*, 66(5), 1998a.

James J. Heckman, H. Ichimura, and Petra E. Todd. Matching as an econometric evaluation estimator. *Review of Economic Studies*, 65:261–294, 1998b.

James J. Heckman, R. J. LaLonde, and J. A. Smith. The economics and econometrics of active labour market programmes. In O. Ashenfelter and David Card, editors, *The Handbook of Labour Economics*, volume 3A. 1998c.

James J. Heckman, Lance J. Lochner, and Petra E. Todd. Fifty years of mincer earnings regressions. Technical report, National Bureau of Economic Research, Inc., 2003.

Linda Holmlund. The effect of college quality on earnings: Evidence from sweden. *Department of Economics, Umea University. Mimeo*, 2009.

Julia Horstschraer. Quality signals in action? the importance of rankings and excellence labels for university choice of high-ability students. ZEW, Manuscript, August 2011.

Guido W. Imbens. The role of propensity score in estimating dose-response functions. *Biometrika*, 87(3):706–710, 2000.

Estelle James, Nabeel Alsalam, Josef C. Conaty, and Duc-Le To. College quality and future earnings: Where should you send your child to college? *AEA Papers and Proceedings, Economics of Eduucation Industry*, 79(2):247–252, 1989.

Edwin Leuven and Barbara Sianesi. Psmatch2: Stata module to perform full mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. *"http://ideas.repec.org/c/boc/bocode/s432001.html".This version 4.0.4 10nov2010 E. Leuven, B. Sianesi.*, 2003.

Mark C. Long. College quality and early adult outcomes. *Economics of Education Review*, 27: 588–602, 2008.

Mark C. Long. Changes in the returns to education and college quality. *Economics of Education Review*, 29:338–347, 2010.

Jacob Mincer. Investment in human capital and personal income distribution. *Journal of Political Economy*, 66(4):281–302, 1958.

James Monks. Thereturns to individual and college characteristics, evidence from the national longitudinal survey of youth. *Economics of Education Review*, 19:279–289, 2000.

Paul R. Rosenbaum and Donald B. Rubin. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55, 1983.

Paul R. Rosenbaum and Donald B. Rubin. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38, 1985.

Donald B. Rubin. Estimating causal effects of treatments in randomised and non-randomised studies. *Journal of Educational Psychology*, 66:688–701, 1974.

Donald B. Rubin. Bias reduction using mahalanobis-metric matching. *Biometrics*, 36:293–298, 1980.

Tuomo Suhonen. *Does University Quality Affect Studend's Subsequant Earnings? Evidence from Finland Using Field-of-Study Specific Quality Measures*. PhD thesis, School of Business and Economics, University of Jyvvaskyla, Finland, January 2011.