

Transformation of college to university and impacts on labor market outcomes

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Abstract

This paper studies the impacts of different types of post-secondary education on education and labor market outcomes. I first use variations of distances to institutions and exogenous variations of colleges that upgraded into universities to investigate the value added to university education. Then I separately estimate the impacts of the transformed universities and traditional colleges and universities. I compared results from OLS and IV regressions. To address the treatment heterogeneity, I adapt the locally linear specification from Mountjoy (2022). Results suggest that the difference between university and college graduates is marginal. However, university entry improves labor market outcomes, such as employment and earnings compared with cohorts without post-secondary education. Graduates from transformed universities obtain a higher probability of being employed and higher earnings compared with people without post-secondary education. Nonetheless, transformed university graduates may have worse performance in the labor market, compared with graduates from colleges or traditional universities. Furthermore, graduates from transformed universities are more willing to register for training when they are unemployed compared with the other three groups.

The Information Technology revolution has had a significant impact on wage determination and employment trends since the 1980s. In addition, a transformation occurred in the Canadian education system during the 1990s, wherein several colleges were converted into universities. As of now, Canada is home to approximately 100 universities, encompassing

both public and private institutions. Between 2000 and 2019, around 23 colleges in Canada underwent this transformation, accounting for 23% of the current universities in the country.

This shift from colleges to universities offers several notable advantages. Firstly, the conversion equips young individuals with the necessary skills to thrive in a labor market that increasingly demands analytical work due to technological advancements. Attending these new universities allows students to prepare for the evolving job market at an earlier stage compared to solely relying on on-the-job training. Secondly, the transition simplifies access to university-level education by reducing geographical and financial barriers. Students can now pursue a 4-year degree immediately, eliminating the need to transfer from community colleges to universities and thus saving time. Lastly, the transformation utilizes existing facilities for the establishment of new universities, resulting in cost savings for the government as opposed to constructing entirely new institutions.

However, some workers may prefer to work by hand and have comparative advantages in technical jobs. Diverting these students to universities instead of attending colleges may lead to a less ideal career path for them. Besides, the transformation from colleges to universities may lead to higher operating costs because universities may cover more expensive programs and involve a more systematic management structure. Thirdly, upgrading colleges to universities may not necessarily expand the overall capacity of higher education provision. Instead of increasing the educational opportunities, this transformation primarily involves changing the institutional status and degree titles. As a result, it might be more of a relabeling exercise for students rather than a substantial improvement in their capabilities. Consequently, the overall impact of the transition from colleges to universities can range from positive to neutral or even negative, leaving us with an intriguing open question.

The main research question of this project concerns the labor market effects of the transformation of colleges into universities. In addition, I examine how this transformation affects participation in continuous training through employment insurance programs. I begin by analyzing homogeneous treatment effects. Using the exogenous variation generated by the transformation of colleges into universities, I estimate the returns to university entry. I compare the results from OLS and IV regressions, under the identification assumption

that the distance between households and different types of post-secondary institutions is exogenous.

Next, recognizing that treatment effects may be heterogeneous and that IV estimates may not aggregate treatment effects with the correct weights, I adopt a locally linear specification following Mountjoy (2022) to estimate the marginal treatment effects. In the estimation, I use distance bins rather than a linear distance function. The results indicate that university entry leads to higher employment rates and wages compared to individuals without post-secondary education. However, the differences between college and university graduates remain ambiguous.

In the subsequent section, I separately analyze the effects of attending transformed universities. I find that graduates from these institutions experience higher employment and income levels compared to cohorts without post-secondary education. Nevertheless, they may fare worse than graduates from traditional colleges or universities. Interestingly, graduates from transformed universities are more likely to register for training programs when unemployed, suggesting that extended exposure to post-secondary education may foster a habit of continuous learning.

This paper contributes to the existing body of literature on higher education expansion and its impact on labor outcomes. Frenette (2009) examines the benefits of constructing new universities in Canada and finds that these developments led to an increase in university participation rates while decreasing college enrollment rates. Furthermore, he observes that employment rates and the probability of men moving out also increased following the establishment of new universities. In contrast, Blundell et al. (2022) investigate higher education expansion in the UK and surprisingly find that the college wage premium remained unchanged. They argue that this phenomenon cannot be explained by exogenous or endogenous technological change models. To address this, they propose a model that incorporates the choice between centralized and decentralized organizational forms for firms to explain the economic patterns observed in the UK higher education expansion. Similar to Blundell et al. (2022), I find no wage increase in graduates of transformed universities compared to college graduates.

Some papers focus on expansion and construction of colleges. Carneiro et al. (2018) focus on the construction of new colleges in Norway. They discover that the skilled wage increased due to a greater demand for skilled workers outweighing the increase in supply. These findings align with endogenous technical change models. Mountjoy (2022) explores the impact of access to two-year colleges on upward mobility. His research reveals value-added for individuals entering two-year colleges who would otherwise not attend college. However, there are negative effects on students who are diverted from immediate four-year entry. The author develops a new instrumental variables approach using locally linear specification to identify causal effects along multiple treatment margins. Compared to the existing literature, this paper addresses a gap by specifically examining the transformation of colleges to universities and quantifying the associated costs and benefits.

The expansion of higher education occurred across multiple countries. Dai et al. study returns to higher education in China using a fuzzy discontinuity in the months of births and find that the higher education expansion increases monthly wages by 21%. Walker and Zhu (2018) find that much of the variation in relative wages across courses is due to the quality of students selected in UK. Schultheiss et al. (2023) find that education expansion increases upskilling in job contents. Surprisingly, Berlingieri et al. (2022) find that college opening has no effects on wages in Germany. Ichino et al. (2022) find that higher education expansion in UK led to the selection into college of progressively less intelligent students from advantaged backgrounds and to a declining college wage premium across cohorts. Focusing on the Canadian context, my paper contributes to the literature by analyzing the relationship between higher education expansion and vocational education, and its potential long-term effects on university graduates.

The remainder of this paper is organized as follows. Section 1 provides the related institutional background. Section 2 describes the database I am using and provides summary statistics. In Section 3, I first discuss research designs of empirical analysis, and then I present results of university entry. I separately evaluate the impacts of transformed universities in Section 4. Finally, Section 5 concludes with a discussion.

1 Institutional background

Starting from the 1980s, higher education expanded in many countries. Several methods exist to expand higher education, including constructing new universities and colleges, expanding current universities, and upgrading colleges to universities. In Canada, colleges have been upgrading to universities since the 1990s. College universities are institutions between colleges and universities in Canada. In some provinces, college universities are similar to colleges, while they are similar to universities in other provinces. Since the definition of college university is ambiguous, I define granting full university status to colleges as colleges transition to universities. Polytechnic universities are counted as colleges. Following this definition, 22 colleges transformed into universities between 2000 and 2019, accounting for 22% of the current universities in the country. Table 3 displays the distribution of colleges' transition to universities across Canada. Not surprisingly, Alberta, British Columbia, and Ontario have the largest shares of colleges' transformation into universities. There was no transformation of colleges to universities in Quebec between 2000 and 2019. Around two million students enroll in post-secondary institutions in Canada every year. Among them, approximately 9% of students enroll in upgraded universities. The aforementioned statistics suggest that the scale of colleges' transformation into universities is large in Canada. The wave of transformation from colleges to universities is still ongoing in regions with fewer universities in Canada, such as Yukon, Northwest Territories, and Alberta. I define the time of transformation from colleges to universities to be the time when the institution got approval from the government to upgrade to a university or after the government passed a related Act. In the figure that describes variations of the transitions, number of students in transitioned universities increases over time in most provinces. In the table that describes characteristics of types of institutions, students were in general younger in transformed institutions before they upgraded to universities. After the institutions transformed to universities, the average age of students increased. But it is still younger than students in existing universities and colleges. The proportion of international students in upgraded universities increases after the transition. Existing universities have highest percentage of international students among the three types of institutions. The proportion of students in transformed universities who are in

STEM programs increases after the transition. Existing universities have highest percentage of STEM programs among the three types of institutions. On the other hand, proportion of students who are in career programs decreases after the transition.

The transformation from colleges to universities does not solely happen in Canada. Indeed, it is an important method of higher education expansion in many countries. Following the 1992 Further and Higher Education Act in the United Kingdom, around 33 polytechnics, 5 central institutions, and 40 colleges were transformed into “new universities”. The 78 new universities make up approximately 48.75% of the current universities in the United Kingdom. After the wave of transformation became quieter in developed countries in recent decades, the transition from colleges to universities is gaining momentum in developing countries. For instance, 22 colleges were approved to be upgraded to full university status in China in recent years, and more applications are pending reviews. Indeed, transforming colleges into universities is pivotal to expanding higher education in many countries.

Several reasons are associated with why colleges transform to universities in Canada. First and foremost, the higher education upgrade is to adapt to development of economy. The newly transformed universities mainly support local community and serve geographic area or regions. Local communities want to provide more higher education resources to retain residents, since they realize that some residents move to other regions to pursue higher education and never come back. Building local universities also makes higher education more affordable because students can pursue higher education closer to home. Secondly, since some of the upgraded universities are located in indigenous communities, transformation from colleges to universities will improve education in indigenous communities and reduce education inequality. One example is Yukon college, which transformed to Yukon University in recent years, and became the first university in the northern territories. Thirdly, for university colleges, transformation to full university status reflects the true nature of the school and enhance confidence of students. Examples include three university colleges in British Columbia which transformed to universities in year 2008. Fourthly, transformation happens when there is few local universities in the region. Colleges that transformed into universities are “stronger” colleges which were more similar to universities. These colleges

lobby to be upgraded and one of the potential purpose was to increase revenue by attracting international students. They can also obtain more funding from government. However, if the local economy requires more trade and technique jobs, government may upgrade colleges to polytechnic universities, instead of granting full university status. Examples are Red Deer Polytechnic and Northwestern Polytechnic in Alberta. Some colleges strategically target markets of pre-university programs and skill-training programs. Thus they do not have plans to upgrade to universities. (Example includes Langara College in British Columbia.)

2 Data

I use data from the Education and Labour Market Longitudinal Platform (ELMLP) to conduct empirical analysis. ELMLP is a comprehensive education data platform offered by Statistics Canada. ELMLP consists of several subdatasets. Post-secondary Student Information System (PSIS) is a national survey that provides detailed information on graduates and enrolments of Canadian public post-secondary institutions. I use this dataset to obtain information on the post-secondary education of students, including programs enrolled, duration of degree, majors, degrees, etc. The second component I use is the T1 Family File (T1FF), which is from individual and family income tax files. I use T1FF to link students to their family incomes and obtain their employment status, employment incomes, and total incomes. Besides, I use the information from Census tracts (CT) to find students' home address before they enter post-secondary institutions if their permanent address is missing in PSIS. I use information on their home address to construct distance variables from their homes to post-secondary institutions. The third important component I use in my analysis is the Employment Insurance Status Vector (EISV). I construct unemployment duration and participation rate of EI training from the employment insurance data. Lastly, I use the Longitudinal Immigration Database (IMDB) to obtain the immigration status of individuals.

To compute the distance from home addresses to institutions, I require latitude and longitude coordinates for these locations. I employ the Postal Code Conversion File Plus to obtain the coordinates of these locations.

2.1 Descriptive statistics

Table 4 describes summary statistics of the sample. The datasets cover the years 2000 to 2019. The frequency of the main datasets is annual. I restricted the age to be between 23 to 42 because I focus on labor market outcomes and the median age of graduation is 23. In 2019, the median age of graduates in 2000 was 42. I drop immigrants who enter Canada after the age of 16. I drop observations from Quebec, Northwest Territories, Yukon, and Nunavut to simplify the analysis.

There are slightly more males than females in the sample. Observations are young in this sample with a mean of 27. The young age in the sample affects some labor outcomes in the next section. The variable “parental incomes” represents the total annual incomes of parents one year before students’ first entry into post-secondary education. In this sample, the total incomes are total incomes before tax and capital gains. I do not observe capital gains in the data. “D cma” represents the direct-line distance from home to the center of the home CMA one year before the student enters post-secondary. For cohorts without post-secondary education, that is the distance when they were 17 years old. Similarly, “D college”, “D transition” and “D_university” denote the shortest distance to colleges, transformed universities, and existing universities respectively. Ten percent of the sample are immigrants. On average, people have 7.5 years of work experience in the sample. 32 percent of the sample chose not to enter post-secondary education immediately after they graduated from high school. They may enter post-secondary education later in the sample. In my setup, I allow people who first choose no post-secondary education to return to school again because the endogenous variables, such as “ $\mathbf{1}\{\text{college}\}_i$ ” and “ $\mathbf{1}\{\text{university}\}_i$ ”, are their first choice. 29 percent of the sample chose college entry as their first enrollment in post-secondary. 33 percent chose to enter universities directly. And 6 percent of them chose a transformed university.

By age 24, the average duration of post-secondary education is 1.69 years. By age 30, the average duration in post-secondary education increases to 2.1 years. By age 24, 10 percent of the sample obtained a STEM degree. By age 30, 34 percent of the sample obtained a university degree. A university degree means a degree that is a bachelor’s degree or above. The average annual wage at age 24 is 30k Canadian dollars. Wage includes employment

earnings, other employment earnings, and self-employment earnings. The variable “incomes” denotes total incomes before tax and capital gains. “Incomes” contain other incomes and tax refunds, while variable “wage” does not. However, there is a large overlap between the two variables. 91 percent of the sample are employed at age 24. If the person has a positive wage, then the person is defined as employed. The person is unemployed if his wage is 0 and he is not a full-time student. I use “number of weeks for which benefits were received” in EI dataset to define “unemployment duration”. The unemployment duration is 26.7 weeks on average. People can get benefits for up to a maximum of 45 weeks in Canada. Among people who are unemployed and claim employment insurance benefits, 16 percent of them register for EI training programs. On average, they register for 0.23 courses. The average length of training is 2.5 weeks. Their employment earning is CAD 2600 per year on average when they claim EI.

3 Returns to post-secondary education

Before we study the impacts of transformed university, we investigate a general research question: how do higher post-secondary degrees affect labor market outcomes? The transformed universities provide exogenous variations for us to study the returns to university degrees compared with college degrees.

3.1 Homogeneous treatment effect

In the first subsection, I will first impose the homogeneous treatment assumption and study the impacts of different types of post-secondary education. Since we want to study how different types of post-secondary education affect education and labor market outcomes, let’s begin with OLS regressions. In the next OLS regression, I want to study how first enrollment in post-secondary education affects education and labor market outcomes. I define individual’s first choice of post-secondary education between ages 17 as 21 as the “first enrollment in post-secondary education”. I relax the age limit to 21 to allow more flexibility,

such as gap years and military service.

$$y_{it} = \alpha_0 + \alpha_1 \mathbf{1}\{\text{college}\}_i + \alpha_2 \mathbf{1}\{\text{university}\}_i + \alpha_3 X_{it} + \zeta_{0,CMA^*} + \varepsilon_{it} \quad (1)$$

Since my datasets mainly cover the years 2000 to 2019, and the people most affected by the reform were students in post-secondary institutions, I restrict individuals in my sample to be between the ages of 23 and 42. In 2019, the median age of graduates in 2000 was 42. At age 23, many young people graduate and enter their first job, so I restrict the age to be older than 22 to study labor market outcomes. I drop immigrants who enter Canada after the age of 16, because their motivation may differ from local students and the difference will affect education impacts. I remove observations from Quebec, Northwest Territories, Yukon and Nunavut in my main specification because their education systems are different from other provinces in Canada. I will bring back the observations from Quebec in the robustness check.

In the regression above, i represents an individual, while t represents time. The outcome variables, denoted as y_{it} , encompass various aspects, including the stem degree obtained by age 24 and 30, and university degree obtained by age 24 and 30. If the individual obtains a university degree by the age of 24, then $\mathbf{1}\{\text{obtain a university degree by age 24}\} = 1$. If the individual does not obtain a university degree by age 24, then the dependent variable $\mathbf{1}\{\text{obtain a university degree by age 24}\} = 0$. Additionally, labor market outcomes under scrutiny encompass wages, incomes, employment, EI training participation rate, length of training, and number of courses of EI training enrolled. Wage and income related variables are normalized to 2019 real price. The endogenous variables in the analysis include $\mathbf{1}\{\text{no post-secondary education}\}_i$, $\mathbf{1}\{\text{college}\}_i$ and $\mathbf{1}\{\text{university}\}_i$. The latter two variables take on a value of one depending on an individual's first educational choices between ages 17 and 21 in my sample, such as enrolling in a college, or enrolling in a university, respectively. I do not restrict the age of first enrollment to 18 and 19 because I want to encompass different situations, such as early age enrollment and gap years. If students attended the universities that were transformed from colleges, they enter the category $\mathbf{1}\{\text{university}\}_i$, if the college finished transformation to a university. If the college hasn't been transformed into a university, then the student's first choice is college education. In main specification, the definition

of individuals as having no post-secondary education is based on criteria that include never entering colleges or universities, never claiming the Full-Time Post-Secondary Education Deduction or specifying the number of months of Full-Time Post-Secondary School Enrollment in their tax files between ages 17 and 21, and not being immigrants. Moreover, if an individual arrived in Canada before the age of 17 and did not pursue post-secondary education, these observations are also included in the $\mathbf{1}\{\text{no post-secondary education}\}_i$ category. Defining people who have no post-secondary education and never claim benefits for post-secondary education will avoid issues caused by missing data. To avoid multicollinearity, the variable $\mathbf{1}\{\text{no post-secondary education}\}_i$ is omitted from the analysis. The control variables, denoted as X_{it} , encompass factors such as gender, age, and parental income. Parental incomes are defined at one year before first enrollment in commencing post-secondary education or when individuals are 17 years old. Controlling for parental incomes one year before the first enrollment in post-secondary education will allow me to remove bias caused by family wealth. For instance, people from wealthier family may be easier to find a job and their wages may be higher than those without a wealthy family background. Controlling for parental incomes is to study the effects of post-secondary education on labor market outcomes, conditional on a similar family wealth. Additionally, ζ_{CMA^*} captures the fixed effect associated with the CMA where individuals resided one year prior to their first enrollment in post-secondary education or when individuals were 17 years old.

OLS regressions can be problematic because of endogeneity. A natural extension to address endogeneity issues is instrumental variables estimation. I investigate the impact of expanding university program offerings while concurrently reducing college program availability, drawing inspiration from Mountjoy (2022). In the initial scenario, I assume a homogeneous treatment effect and proceed to estimate the following model.

$$\begin{aligned}
y_{it} &= \alpha_0 + \alpha_1 \mathbf{1}\{\text{college}\}_i + \alpha_2 \mathbf{1}\{\text{university}\}_i + \alpha_3 X_{it} + \zeta_{0,CMA^*} + \varepsilon_{it} \\
\mathbf{1}\{\text{college}\}_i &= \beta_{10} + \beta_{11} d_{1,it^*} + \beta_{12} d_{2,it^*} + \beta_{13} X_{it} + \zeta_{1,CMA^*} + v_{it} \\
\mathbf{1}\{\text{university}\}_i &= \beta_{20} + \beta_{21} d_{1,it^*} + \beta_{22} d_{2,it^*} + \beta_{23} X_{it} + \zeta_{2,CMA^*} + u_{it}
\end{aligned} \tag{2}$$

Similar to the OLS regression, the outcome variables y_{it} include stem degree obtained by

age 24 and 30, and university degree obtained by age 24 and 30. Labor market outcomes encompass wages, incomes, employment, EI training participation rate, length of training, and number of courses of EI training enrolled. The endogenous variables ($\mathbf{1}\{\text{no post-secondary education}\}_i$, $\mathbf{1}\{\text{college}\}_i$ and $\mathbf{1}\{\text{university}\}_i$) and control variables X_{it} (gender, age and parental incomes) are the same as the OLS analysis. the variable $\mathbf{1}\{\text{no post-secondary education}\}_i$ is omitted from the analysis to avoid multicollinearity. d_{1,it^*} and d_{2,it^*} are instrumental variables. d_{1,it^*} is the shortest distance between a college and the student's permanent address. d_{2,it^*} is the shortest distance between a university and the student's permanent address one year before the first enrollment in post-secondary education or when their address at age 17. t^* is one year before first enrollment in post-secondary institutions or when individuals were 17 years old.

The identification assumption is that distance between individuals and schools is not correlated with the error term, after controlling for individual characteristics, such as family wealth, and hometown fixed effect ζ_{CMA^*} . This assumption is reasonable if characteristics, such as gender and family wealth, and hometown fixed effects are sufficient to address the selection issue of distance. In addition, we need to assume that treatment effects are homogeneous to ensure that instrumental variable estimation and linear combination can identify the average impacts. I do not include work location and industry fixed effects to allow high-education groups to gather in some specific regions and industries. We can interpret coefficients as Table 1. α_1 and α_2 are effects of education in college, and education in an existing university compared with no post-secondary education respectively. $\alpha_2 - \alpha_1$ denotes the effects of switching from colleges to universities.

Table 1: Interpretation of coefficients

Coefficients	Interpretation
α_1	$y_{\text{college}} - y_{\text{no post-secondary}}$
α_2	$y_{\text{university}} - y_{\text{no post-secondary}}$
$\alpha_2 - \alpha_1$	$y_{\text{university}} - y_{\text{college}}$

Notes: The second column shows the corresponding interpretation of the coefficients.

Three approaches are explored for modeling the distance: a linear function, a step

function, and bins of distances. The step function is defined as the following

$$\text{distance} = \begin{cases} = d & \text{if } d < 100 \\ = 100 & \text{if } 100 \leq d < 200 \\ = 200 & \text{if } 200 \leq d < 300 \\ = 300 & \text{if } 300 \leq d < 400 \\ = 400 & \text{if } 400 \leq d \end{cases}$$

The step function enhances the instrumental variables' strength in the analysis because the relationship between distance and education choice may be nonlinear and the step function reduce shape restrictions. However, the estimation with step function sometimes cannot obtain a reasonable magnitude of coefficients. One plausible explanation is that the large range of distances complicates the estimation. This is the reason why I choose bins of distances as the instrumental variables. I first divide the shortest distance to a college into seven bins. I denote bin n as $b_{cn,it^*} = 1 \{ \delta_1 < d_1 < \delta_2 \}_{n,it^*}$. δ_1 and δ_2 are some thresholds. For example, if the shortest distance to a college is within 10 kilometers, then $b_{c1,it^*} = 1$. Otherwise, it is zero. Similarly, I divide the shortest distance to a university into eight bins. I denote bin n as $b_{un,it^*} = 1 \{ \delta_1 < d_2 < \delta_2 \}_{n,it^*}$. The following table displays the thresholds.

bin	thresholds
b_1	$0 \leq d < 10$ (km)
b_2	$10 \leq d < 20$ (km)
b_3	$20 \leq d < 40$ (km)
b_4	$40 \leq d < 70$ (km)
b_5	$70 \leq d < 100$ (km)
b_6	$100 \leq d < 150$ (km)
b_7	$150 \leq d < 250$ (km)
b_8	$250 \leq d < 350$ (km)
b_9	$350 \leq d$ (km)

Bins of university and college are divided with the same thresholds. Since I omit the empty bins, then the numbers of bins to university and college are different. After I replace

instrumental variables with bins, regressions become

$$\begin{aligned}
y_{it} &= \alpha_0 + \alpha_1 \mathbf{1}\{\text{college}\}_i + \alpha_2 \mathbf{1}\{\text{university}\}_i + \alpha_3 X_{it} + \zeta_{0,CMA^*} + \varepsilon_{it} \\
\mathbf{1}\{\text{college}\}_i &= \beta_{10} + \sum_{n=1}^7 \beta_{11n} b_{cn,it^*} + \sum_{n=1}^8 \beta_{12n} b_{un,it^*} + \beta_{13} X_{it} + \zeta_{1,CMA^*} + v_{it} \\
\mathbf{1}\{\text{university}\}_i &= \beta_{20} + \sum_{n=1}^7 \beta_{21n} b_{cn,it^*} + \sum_{n=1}^8 \beta_{22n} b_{un,it^*} + \beta_{23} X_{it} + \zeta_{2,CMA^*} + u_{it}
\end{aligned} \tag{3}$$

3.2 Treatment effect heterogeneity

Similar to Mountjoy (2022), overidentification tests reject constant treatment effects across individuals. The rejection of overidentification test suggests we cannot find a single instrument that is exogenous from the error term: the instrument may be different across the evaluation point because of the treatment heterogeneity. Therefore, I use a locally linear specification to address the issue of treatment heterogeneity. The locally linear specification can separately identify the two margins of treatment effects: on one hand, more universities built will attract marginal students who would choose no post-secondary education; on the other hand, more universities nearby may diverge students who would benefit more from college degrees. Following Mountjoy (2022), I separately decompose the two effects.

$$MTE_4 = \omega MTE_{0 \rightarrow 4} + (1 - \omega) MTE_{2 \rightarrow 4} \tag{4}$$

Let's use 0, 2, and 4 to denote no post-secondary education, college entry, and university entry respectively. In the equation above, MTE_4 denotes the net effect of university entry. ω is the proportion of students who move from no post-secondary education to university, among the total number of movers to universities, if distances to university become closer. $MTE_{0 \rightarrow 4}$ represents the treatment effects of the “marginal students” who are indifferent between university education and no post-secondary education. $1 - \omega$ is the proportion of students who move from college to university, among the total number of movers to universities, if distances to university become shorter. $MTE_{2 \rightarrow 4}$ are treatment effects of

marginal students who are indifferent between college and university entry. Since we are evaluating the net effect of university entry, we consider the impact when students move from other choices to university entry. When we want to evaluate the impact of college entry, then we will evaluate $MTE_{4 \rightarrow 2}$, which denotes the marginal treatment effect when the student moves from university entry to college entry.

Since $MTE_{2 \rightarrow 4}$ means the marginal treatment effect if students move from college to university entry, we can write $MTE_{2 \rightarrow 4}$ as

$$MTE_{2 \rightarrow 4} = E[Y_4 - Y_2 | 2 \rightarrow 4 \text{ compliers}] \quad (5)$$

One of the reasons why marginal students move from colleges to universities is the changes in distances to universities and colleges. D_2 and D_4 represent first enrollment in college and university respectively. Thus

$$E[Y_4 | 2 \rightarrow 4 \text{ compliers when } (z_2, z_4, x) \rightarrow (z'_2, z_4, x)] = \frac{E[YD_4 | z'_2, z_4, x] - E[YD_4 | z_2, z_4, x]}{E[D_4 | z'_2, z_4, x] - E[D_4 | z_2, z_4, x]} \quad (6)$$

Z_2 and Z_4 are the shortest distance to college and university respectively. z_2 and z_4 are specific values of the distances. Let's write X as other covariates and the value of X as x . The numerator of equation 6 represents when Z_2 changes, conditional on Z_4 and X , the change in the mean of YD_4 . The interaction term YD_4 is the outcome of individuals who choose university entry. The denominator is the induced change in university entry. Therefore, $E[Y_4 | 2 \rightarrow 4 \text{ compliers when } (z_2, z_4, x) \rightarrow (z'_2, z_4, x)]$ represents mean of the outcome among $2 \rightarrow 4$ compliers. To study the effects on YD_4 and D_4 , we change Z_2 instead of Z_4 because when Z_2 changes, it will only affect outcomes related to university and college entry among the $2 \rightarrow 4$ compliers. When Z_2 changes, the choice of no post-secondary education may change. However, this will only affect YD_0 and YD_2 , instead of YD_4 . Suppose we change Z_4 , then the change of YD_4 and D_4 may come from a change in no post-secondary group, which is beyond the $2 \rightarrow 4$ compliers. Thus that is the reason why we move Z_2 instead of Z_4 .

When the change in the value of Z_2 is very small, we evaluate the marginal outcomes.

We have

$$\begin{aligned}
& E[Y_4 | \text{marginal } 2 - 4 \text{ compliers when } (z_2, z_4, x) \rightarrow (z'_2, z_4, x)] \\
&= \lim_{z'_2 \rightarrow z_2} \frac{E[YD_4 | z'_2, z_4, x] - E[YD_4 | z_2, z_4, x]}{E[D_4 | z'_2, z_4, x] - E[D_4 | z_2, z_4, x]} = \lim_{z'_2 \rightarrow z_2} \frac{\frac{E[YD_4 | z'_2, z_4, x] - E[YD_4 | z_2, z_4, x]}{z'_2 - z_2}}{\frac{E[D_4 | z'_2, z_4, x] - E[D_4 | z_2, z_4, x]}{z'_2 - z_2}} \quad (7) \\
&= \frac{\frac{\partial E[YD_4 | z_2, z_4, x]}{\partial Z_2}}{\frac{\partial E[D_4 | z_2, z_4, x]}{\partial Z_2}}
\end{aligned}$$

Equation 7 means the marginal outcome of going to a university for a student who is indifferent between college and university entry is equal to the ratio of two partial derivatives.

Similarly, the marginal outcome of entering a college is

$$E[Y_2 | \text{marginal } 2 - 4 \text{ compliers when } (z_2, z_4, x) \rightarrow (z_2, z'_4, x)] = \frac{\frac{\partial E[YD_2 | z_2, z_4, x]}{\partial Z_4}}{\frac{\partial E[D_2 | z_2, z_4, x]}{\partial Z_4}} \quad (8)$$

Then the marginal treatment effect of going from a college to a university is

$$MTE_{2 \rightarrow 4} = E[Y_4 - Y_2 | \text{marginal } 2 - 4 \text{ compliers at } (z_2, z_4, x)] = \frac{\frac{\partial E[YD_4 | z_2, z_4, x]}{\partial Z_2}}{\frac{\partial E[D_4 | z_2, z_4, x]}{\partial Z_2}} - \frac{\frac{\partial E[YD_2 | z_2, z_4, x]}{\partial Z_4}}{\frac{\partial E[D_2 | z_2, z_4, x]}{\partial Z_4}} \quad (9)$$

We need the variations of Z_2 and Z_4 to pin down the marginal outcomes for $E[Y_4 | \text{marginal } 2 - 4 \text{ compliers}]$ and $E[Y_2 | \text{marginal } 2 - 4 \text{ compliers}]$ respectively. Then the next question is how can we identify $MTE_{0 \rightarrow 4}$ if there is no distance to an institution which is called “no post-secondary education”? Let’s first study the components of $MTE_{0 \rightarrow 4}$.

$$\begin{aligned}
MTE_{0 \rightarrow 4} &= E[Y_4 - Y_0 | \text{marginal } 0 - 4 \text{ compliers at } (z_2, z_4, x)] \\
&= E[Y_4 | \text{marginal } 0 - 4 \text{ compliers at } (z_2, z_4, x)] - \frac{\frac{\partial E[YD_0 | z_2, z_4, x]}{\partial Z_4}}{\frac{\partial E[D_0 | z_2, z_4, x]}{\partial Z_4}} \quad (10)
\end{aligned}$$

The second equality in equation 10 because we can use the variation of Z_4 to identify $E[Y_0 | \text{marginal } 0 - 4 \text{ compliers at } (z_2, z_4, x)]$, the marginal outcomes of no post-secondary

education among students who are moving between no post-secondary education and university entry. We do not have a distance to “no post-secondary”. Thus we have to calculate $E[Y_4|\text{marginal } 0 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)]$ in an indirect way. If we reduce the distance to university Z_4 , more students will be attracted to university entry because it is closer to home. Students who move to university entry may come from two different groups: the first group is the marginal students with no post-secondary education and university graduates, and the second group is those who are indifferent between college and university. Then the effect on the interaction term YD_4 also depends on the effects of the two groups.

$$\begin{aligned}
& E[YD_4|z_2, z'_4, x] - E[YD_4|z_2, z_4, x] \\
&= E[Y_4|\text{marginal } 0 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)] \mathbb{P}(\text{marginal } 0 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)) \\
&\quad + E[Y_4|\text{marginal } 2 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)] \mathbb{P}(\text{marginal } 2 \rightarrow 4 \text{ compliers at } (z_2, z_4, x))
\end{aligned} \tag{11}$$

When divided by change in Z_4 and z'_4 gets closer to z_4 , equation 11 becomes

$$\begin{aligned}
& \frac{\partial E[YD_4|z_2, z_4, x]}{\partial Z_4} \\
&= E[Y_4|\text{marginal } 0 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)] \left(-\frac{\partial E[D_0|z_2, z_4, x]}{\partial Z_4} \right) \\
&\quad + E[Y_4|\text{marginal } 2 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)] \left(-\frac{\partial E[D_2|z_2, z_4, x]}{\partial Z_4} \right) \\
&= E[Y_4|\text{marginal } 0 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)] \left(-\frac{\partial E[D_0|z_2, z_4, x]}{\partial Z_4} \right) \\
&\quad + \frac{\frac{\partial E[YD_4|z_2, z_4, x]}{\partial Z_2}}{\frac{\partial E[D_4|z_2, z_4, x]}{\partial Z_2}} \left(-\frac{\partial E[D_2|z_2, z_4, x]}{\partial Z_4} \right)
\end{aligned} \tag{12}$$

Since we assume that attendance at college and no post-secondary education decrease when the distance to university decreases, $\frac{\partial E[D_0|z_2, z_4, x]}{\partial Z_4}$ is negative. The negative sign in equation 12 is to ensure the weight is positive. From the last line of equation 12, we can obtain $E[Y_4|\text{marginal } 0 \rightarrow 4 \text{ compliers at } (z_2, z_4, x)]$. Combine equations 10 and 12, we have

$$\begin{aligned}
MTE_{0 \rightarrow 4} &= E[Y_4 - Y_0 | \text{marginal } 0 - 4 \text{ compliers at } (z_2, z_4, x)] \\
&= \frac{\frac{\partial E[YD_4 | z_2, z_4, x]}{\partial Z_4}}{-\frac{\partial E[D_0 | z_2, z_4, x]}{\partial Z_4}} - \frac{\frac{\partial E[YD_4 | z_2, z_4, x]}{\partial Z_2}}{\frac{\partial E[D_4 | z_2, z_4, x]}{\partial Z_2}} \frac{\frac{\partial E[D_2 | z_2, z_4, x]}{\partial Z_4}}{\frac{\partial E[D_0 | z_2, z_4, x]}{\partial Z_4}} - \frac{\frac{\partial E[YD_0 | z_2, z_4, x]}{\partial Z_4}}{\frac{\partial E[D_0 | z_2, z_4, x]}{\partial Z_4}} \quad (13)
\end{aligned}$$

If there is treatment heterogeneity, $E[Y_4 | 2 \rightarrow 4 \text{ compliers when } (z_2, z_4, x) \rightarrow (z'_2, z_4, x)]$ is different when Z_2 , Z_4 or X change. The linear instrumental variable regression may not accurately aggregate heterogeneous treatment groups. Therefore, an alternative approach is to estimate conditional expectations in equation 6 directly at each value of (z_2, z_4, x) . $MTE_{2 \rightarrow 4}$ and $MTE_{0 \rightarrow 4}$ are partial derivatives of conditional expectations. Thus, Mountjoy (2022) proposes a locally linear specification to estimate the conditional expectations of interest by assuming that we can approximate the conditional expectations at each (z_2, z_4) using a linear function. Since the MTE s are partial derivatives, the solutions to regressions will give us the partial derivatives. This means we can estimate the partial derivatives by simple regressions. For instance,

$$E[Y_2 | \text{marginal } 2 - 4 \text{ compliers when } (z_2, z_4, x) \rightarrow (z_2, z'_4, x)] = \frac{\frac{\partial E[YD_2 | z_2, z_4, x]}{\partial Z_4}}{\frac{\partial E[D_2 | z_2, z_4, x]}{\partial Z_4}} = \frac{\hat{\beta}_4^{YD_2}}{\hat{\beta}_4^{D_2}} \quad (14)$$

$\hat{\beta}_4^{YD_2}$ is the coefficient of the instrument Z_4 when we regress YD_2 on Z_4 , holding Z_2 and X to be constant. Similarly, $\hat{\beta}_4^{D_2}$ is the coefficient of the instrument Z_4 when we regress D_2 on Z_4 , holding Z_2 and X to be constant. D_2 is college enrollment. Mountjoy (2022) use a kernel weight to estimate $\hat{\beta}_4^{YD_2}$ and $\hat{\beta}_4^{D_2}$. The identification assumption is that controlling for characteristics, such as gender and family wealth, and hometown fixed effects will reduce the selection issue of the distance variable.

The linear distances do not work very well in Canada's setup, potentially because the magnitude of distance is larger in Canada compared with Texas, which is Mountjoy (2022)'s setup. Therefore, I use distance bins to be the instrument, instead of linear function of distances. Estimation using bins will give us the local estimation, so we do not need to use kernels if distance bins are the instruments. Suppose we are interested in the treatment

effects of a person who lives in a bin that covers the average distance to both university and college (both are bin 3 in my sample), then $\hat{\beta}_4^{YD_2}$ is the coefficient of the instrument bin b_{u3} (bin of distance to university) when we regress YD_2 on b_{u3} holding other b_{un} , b_{cn} (bins of distance to college) and X to be constant. Since there are more observations in each bin, the marginal treatment effect is similar to a local average treatment effect of students moving from the furthest bins to the bin that covers the average distances to the two types of institutions. I use bootstrap to obtain standard errors.

3.3 Results

In this section, before the discussion of the results, I will want to first elaborate definition of some variables in the tables. Variables are defined the same way across specifications.

Table 5 displays the results of the impacts of post-secondary education on education outcomes using OLS. In this table, the outcome variable “university degree at 24” is a dummy variable that is equal to one if the individual obtained a university degree by age 24. Otherwise, it is equal to zero. Similarly, “university degree at 30” denotes whether the individual obtained a university degree by age 30. “stem at 24” is an indicator function that is equal to one if the individual obtained a STEM degree by age 24. The “stem” variable is not restricted to people enrolled in post-secondary education. For people who choose to work after high school, if they do not obtain a STEM degree by age 24, then “stem at 24” is equal to 0. If they return to school and get STEM degrees by age 24, then “stem at 24” is equal to 1. The control variable “parental incomes” denotes the total annual incomes of parents one year before students’ first entry into post-secondary education. In this dataset, the total incomes are defined as total incomes before tax and capital gains. I do not observe capital gains in this dataset.

The OLS results suggest that if a student first enrolls in a university, the individual will have a 61.5 percentage points higher probability of obtaining a university degree by the age of 24, compared with those who choose no post-secondary and enter job markets after high school. The probability of obtaining a university degree is higher among students whose first enrollment is at a university, compared with those who first enter colleges. University

students are 21.6 percentage points more likely to obtain a STEM degree, compared with people who first choose no post-secondary education. University students are also more likely to obtain a STEM degree compared with college students. A female is more likely to obtain a university degree, and her degree is less likely to be a STEM degree compared with males. Students from wealthier families are more likely to get a university degree and a STEM degree. Immigrants also tend to hold university degrees and STEM degrees.

Table 6 describes the impacts of education on some non-monetary labor market outcomes. “Employment” is a dummy variable that equals one if the wage of the individual is not zero or missing in the same year. It is zero if the wage is zero and the individual is not a full-time student. Notice that the age range of my sample is between age 23 and 42. “Training”, “number of training courses” and “length of training” are variables from unemployment insurance. Variables that are related to unemployment insurance are restricted to unemployed people who have claimed employment insurance. “Training” is equal to one if the individual takes part in any EI training within the year. It is zero if the person claimed EI but did not enroll in any training courses. The variable “number of training courses” records the number of EI courses that the unemployed person has registered for in the year. “Length of training” denotes the average number of weeks of training in a year among unemployed workers. College graduates are more likely to be employed than university graduates in this sample, especially before age 24. But as they approach a more mature stage of their career, university graduates are more likely to be employed. The probability of registering for a training course for College students is 5 percentage points higher than the cohort with no post-secondary education. College graduates also register for more training courses and stay in training longer compared with the other two groups.

Next, let’s study the impact of education on income. Table 7 displays the OLS results. Wage contains people’s employment earnings. Total incomes include other incomes such as tax refunds, while wages only contain employment earnings. University graduates earn CAD 10,215 more than cohorts without post-secondary education. But incomes between college graduates and university graduates are relatively similar. Wages of females are CAD 10,690 less than males compared with males. Immigrants earn less in general.

The first approach I tried to address the endogeneity issue is instrumental variables estimation. As shown in regression 3, I use distance bins as instruments. Table 8 to Table 10 display results of IV regressions. In Table 8, different from results from OLS, people who directly enter universities after graduation from high school are 70.8 percentage points more likely to obtain a university degree by age 24 compared with those who first chose no post-secondary education. The difference between who first chose colleges and universities also widens. University graduates are 26.6 percentage points more likely to obtain a STEM degree by age 24 compared with those who chose no post-secondary as their first choice. Based on the Cragg-Donald Wald F statistics, we reject the null hypothesis that the instruments are weak. Table 9 shows results of labor market outcomes with IV regressions. The magnitude of coefficients is larger in the IV estimation than in the OLS. At age 24, university graduates are more likely to be employed than college graduates and people with no post-secondary education. University and college graduates are more likely to register for training when they are unemployed, compared with the no post-secondary group. Using IV regressions, as shown in Table 10, wages and incomes of college graduates are higher than university graduates. This may come from the not very accurate aggregation of IV regressions when there is treatment heterogeneity.

Table 11 displays results of marginal treatment effects estimated by locally linear specification. Similar to the IV regressions, I use distance bins as the instruments. Notice that the net effect of university entry can be decomposed with weights and marginal treatment effects using the following equation.

$$MTE_4 = \omega MTE_{0 \rightarrow 4} + (1 - \omega) MTE_{2 \rightarrow 4} \quad (15)$$

Table 11 shows $MTEs$ along different margins. I evaluate the marginal treatment effect of an “average” student who lived in a bin that covered the average distance to colleges and universities in the distribution. The coefficients we see in OLS and IV regressions are the net effects across heterogeneous groups after considering weights. And this is the reason why the magnitude of $MTEs$ in Table 11 is different from those we see before. From results

in Table 11, employment of students who switch from no post-secondary to either college entry or university entry increases. But the difference in employment between college entry and university entry is smaller. Students who change from no post-secondary education to university entry earn more than CAD 20,000 in general. Again, I want to emphasize that these results are marginal treatment effects, and we need to know the proportion of people who switch between education to calculate the net effect. That is the reason why the scale of the *MTEs* in Table 11 seems to be large. The difference in incomes and wages between college graduates and university graduates is smaller, consistent with results in OLS and IV regressions. Students whose first enrollment was university generally more likely to obtain a university degree. Variables related to employment insurance (training participation, length of training and number of courses) are only significant among people who switch from no post-secondary education to college. This result suggests more post-secondary education may help students to develop the habit of continuous learning. The coefficient of training participation rate are positive among marginal students who change from no post-secondary education to university entry, but the result is noisier due to the smaller sample size.

4 Estimating transformation impacts on education and labor market outcomes

In the previous section, I find that switching from no post-secondary to colleges or university will improve labor market outcomes, such as higher wages and probability to be employed. The transformed universities were originally colleges. Therefore, they may still be different from the old universities, even though they are formally transformed into universities. In this section, I will separately estimate the impacts of transformed universities from the old universities.

4.1 OLS and instrumental variable regressions

Same as in the previous section, let's first study the treatment effects with the homogeneous assumption. The OLS specification is similar to regression 1 in the previous section with a

separate estimation of transformed universities and other institutions.

$$y_{it} = \alpha_0 + \alpha_1 \mathbf{1}\{\text{transformed university}\}_i + \alpha_2 \mathbf{1}\{\text{college}\}_i + \alpha_3 \mathbf{1}\{\text{existing university}\}_i + \alpha_4 X_{it} + \zeta_{0,CMA^*} + \varepsilon_{it} \quad (16)$$

Same as the previous section, the outcome variables, denoted as y_{it} , encompass education and labor market outcomes. The endogenous variables in the analysis include $\mathbf{1}\{\text{no post-secondary education}\}_i$, $\mathbf{1}\{\text{transformed university}\}_i$, $\mathbf{1}\{\text{college}\}_i$ and $\mathbf{1}\{\text{existing university}\}_i$. The definitions of $\mathbf{1}\{\text{no post-secondary education}\}_i$, $\mathbf{1}\{\text{college}\}_i$ and $\mathbf{1}\{\text{existing university}\}_i$ are the same as the previous section. $\mathbf{1}\{\text{transformed university}\}_i$ is equal to one if a student attends the transformed institution after the transition. It is equal to zero in other scenarios. If the student attended a college that would be transformed in the future, then his first enrollment is college entry. To avoid multicollinearity, the variable $\mathbf{1}\{\text{no post-secondary education}\}_i$ is omitted from the analysis. The control variables, denoted as X_{it} , are also the same as in the previous section. ζ_{CMA^*} captures the fixed effect associated with the CMA where individuals resided one year before their first enrollment in post-secondary education or when individuals were 17 years old.

To address the endogeneity issue, a natural extension is instrumental variables estimation. I separately investigate the impact of transformed university programs following Mountjoy (2022).

$$\begin{aligned} y_{it} &= \alpha_0 + \alpha_1 \mathbf{1}\{\text{college}\}_i + \alpha_2 \mathbf{1}\{\text{existing university}\}_i + \\ &\quad \alpha_3 \mathbf{1}\{\text{transformed university}\}_i + \alpha_4 X_{it} + \zeta_{0,CMA^*} + \varepsilon_{it} \\ \mathbf{1}\{\text{college}\}_i &= \beta_{10} + \beta_{11} d_{1,it^*} + \beta_{12} d_{2,it^*} + \beta_{13} d_{3,it^*} + \zeta_{1,CMA^*} + v_{it} \\ \mathbf{1}\{\text{existing university}\}_i &= \beta_{20} + \beta_{21} d_{1,it^*} + \beta_{22} d_{2,it^*} + \beta_{23} d_{3,it^*} + \zeta_{2,CMA^*} + u_{it} \\ \mathbf{1}\{\text{transformed university}\}_i &= \beta_{30} + \beta_{31} d_{1,it^*} + \beta_{32} d_{2,it^*} + \beta_{33} d_{3,it^*} + \zeta_{3,CMA^*} + \epsilon_{it} \end{aligned} \quad (17)$$

Similar to the OLS regression, the outcome variables y_{it} include education and labor market outcomes (STEM degree, university degree, wages, incomes, employment, EI training participation rate, length of training, and number of courses of EI training). The endoge-

nous variables ($\mathbf{1}\{\text{no post-secondary education}\}_i$, $\mathbf{1}\{\text{transformed university}\}_i$, $\mathbf{1}\{\text{college}\}_i$ and $\mathbf{1}\{\text{existing university}\}_i$) and control variables X_{it} (gender, age and parental incomes) are the same as the OLS analysis. d_{1,it^*} , d_{2,it^*} and d_{3,it^*} are instrumental variables. d_{1,it^*} is the shortest distance between a college and the student's permanent address. d_{2,it^*} is the shortest distance between an existing university and the student's permanent address. d_{3,it^*} is the shortest distance between transformed universities and the student's permanent address. t^* is one year before first enrollment in post-secondary institutions or when individuals were 17 years old.

Similar to the previous section, the identification assumption is that distance between individuals and schools is not correlated with the error term, after controlling for individual characteristics and hometown fixed effect ζ_{CMA^*} . This assumption is reasonable if controlling for characteristics, such as gender and family wealth, and hometown fixed effects reduces the selection issue of distance. Besides, we need assumption of homogeneous treatment effect to ensure the linear weights from instrumental variable regressions are able to obtain the correct average impacts. We can interpret coefficients as Table 2. α_1 , α_2 , and α_3 are effects of education in college, education in an existing university, and education in a transformed university, compared with no post-secondary education respectively. $\alpha_3 - \alpha_1$ denotes the effects of switching from colleges to transformed universities, and $\alpha_3 - \alpha_2$ represents the effects of switching from existing universities to transformed universities.

Table 2: Interpretation of coefficients

Coefficients	Interpretation
α_1	$y_{\text{college}} - y_{\text{no post-secondary}}$
α_2	$y_{\text{existing university}} - y_{\text{no post-secondary}}$
α_3	$y_{\text{transition}} - y_{\text{no post-secondary}}$
$\alpha_3 - \alpha_1$	$y_{\text{transition}} - y_{\text{college}}$
$\alpha_3 - \alpha_2$	$y_{\text{transition}} - y_{\text{existing university}}$

Notes: The second column shows the corresponding interpretation of the coefficients.

Similar to the previous section, I tried three approaches to model the distance: a linear function, a step function, and bins of distances. Using bins of distances as the instrument will help us to obtain a reasonable magnitude of coefficients. Therefore, I choose bins of distances as the instrumental variables. I first divide the shortest distance to colleges into seven bins,

denoted as b_{cn,it^*} . And then I divide the shortest distance to existing universities into eight bins, b_{un,it^*} . Finally, I divide the shortest distance to transitions into nine bins, denoted as b_{tn,it^*} . The thresholds to cut bins are the same across the three types of institutions. But because students are closer to colleges and existing universities than to transitions, some of the remote bins of colleges and universities are empty and I have to drop them. That is the reason why the number of bins is different across institution types. When we use bins as the instruments, then the regression becomes the following equation.

$$\begin{aligned}
y_{it} = & \alpha_0 + \alpha_1 \mathbf{1}\{\text{college}\}_i + \alpha_2 \mathbf{1}\{\text{existing university}\}_i + \\
& \alpha_3 \mathbf{1}\{\text{transformed university}\}_i + \alpha_4 X_{it} + \zeta_{0,CMA^*} + \varepsilon_{it} \\
\mathbf{1}\{\text{college}\}_i = & \beta_{10} + \sum_{n=1}^7 \beta_{11n} b_{cn,it^*} + \sum_{n=1}^8 \beta_{12n} b_{un,it^*} + \sum_{n=1}^9 \beta_{13n} b_{tn,it^*} + \beta_{14} X_{it} \\
& + \zeta_{1,CMA^*} + v_{it} \\
\mathbf{1}\{\text{existing university}\}_i = & \beta_{20} + \sum_{n=1}^7 \beta_{21n} b_{cn,it^*} + \sum_{n=1}^8 \beta_{22n} b_{un,it^*} + \sum_{n=1}^9 \beta_{23n} b_{tn,it^*} + \beta_{24} X_{it} \\
& + \zeta_{2,CMA^*} + u_{it} \\
\mathbf{1}\{\text{transformed university}\}_i = & \beta_{30} + \sum_{n=1}^7 \beta_{31n} b_{cn,it^*} + \sum_{n=1}^8 \beta_{32n} b_{un,it^*} + \sum_{n=1}^9 \beta_{33n} b_{tn,it^*} + \beta_{34} X_{it} \\
& + \zeta_{3,CMA^*} + \epsilon_{it}
\end{aligned} \tag{18}$$

4.2 Heterogeneous treatment effects

As in the previous section, I follow Mountjoy (2022) and use a locally linear specification to study the heterogeneous treatment effects along different margins. I use t to represent outcomes related to transformed universities. The net treatment effects of education in transformed universities can be decomposed into three effects.

$$MTE_t = \omega_1 MTE_{0 \rightarrow t} + \omega_2 MTE_{2 \rightarrow t} + (1 - \omega_1 - \omega_2) MTE_{4 \rightarrow t} \tag{19}$$

Following the same logic as in Section 3, we can write the marginal treatment effects as partial derivatives of conditional expectations. Z_2 , Z_4 , and Z_t are distances to the nearest colleges, universities, and transformed universities respectively. D_2 , D_4 , and D_t represent first enrollment in college, university, and transformed universities respectively. We can use the variations of Z_2 and Z_t to identify the marginal treatment effect of a student moving from a college to a transformed university.

$$\begin{aligned} MTE_{2 \rightarrow t} &= E[Y_t - Y_2 | \text{marginal } 2 - t \text{ compliers at } (z_2, z_4, z_t, x)] \\ &= \frac{\frac{\partial E[YD_t | z_2, z_4, z_t, x]}{\partial Z_2}}{\frac{\partial E[D_t | z_2, z_4, z_t, x]}{\partial Z_2}} - \frac{\frac{\partial E[YD_2 | z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_2 | z_2, z_4, z_t, x]}{\partial Z_t}} \end{aligned} \quad (20)$$

Similarly, we identify the treatment effect of a marginal student who switches from an existing university to a transformed university with the exogenous variations of distance to old universities Z_4 , and distance to transitions Z_t .

$$\begin{aligned} MTE_{4 \rightarrow t} &= E[Y_t - Y_4 | \text{marginal } 4 - t \text{ compliers at } (z_2, z_4, z_t, x)] \\ &= \frac{\frac{\partial E[YD_t | z_2, z_4, z_t, x]}{\partial Z_4}}{\frac{\partial E[D_t | z_2, z_4, z_t, x]}{\partial Z_4}} - \frac{\frac{\partial E[YD_4 | z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_4 | z_2, z_4, z_t, x]}{\partial Z_t}} \end{aligned} \quad (21)$$

The marginal treatment effect of students who switch between no post-secondary education and transformed universities can be represented as

$$\begin{aligned} MTE_{0 \rightarrow t} &= E[Y_t - Y_0 | \text{marginal } 0 - t \text{ compliers at } (z_2, z_4, z_t, x)] \\ &= E[Y_t | \text{marginal } 0 - t \text{ compliers at } (z_2, z_4, z_t, x)] - \frac{\frac{\partial E[YD_0 | z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_0 | z_2, z_4, x]}{\partial Z_t}} \end{aligned} \quad (22)$$

When the distance to transformed universities decreases, the change in the interaction term YD_t depends on three groups: students who move from no post-secondary, from colleges and

from existing universities.

$$\begin{aligned}
& E[YD_t|z_2, z_4, z'_t, x] - E[YD_4|z_2, z_4, z_t, x] \\
&= E[Y_t|\text{marginal } 0 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \mathbb{P}(\text{marginal } 0 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)) \\
&\quad + E[Y_t|\text{marginal } 2 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \mathbb{P}(\text{marginal } 2 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)) \\
&\quad + E[Y_t|\text{marginal } 4 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \mathbb{P}(\text{marginal } 4 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x))
\end{aligned} \tag{23}$$

When divided by change in Z_t and when z'_t gets closer to z_t , equation 23 becomes

$$\begin{aligned}
& \frac{\partial E[YD_t|z_2, z_4, x]}{\partial Z_t} \\
&= E[Y_t|\text{marginal } 0 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \left(-\frac{\partial E[D_0|z_2, z_4, z_t, x]}{\partial Z_t} \right) \\
&\quad + E[Y_t|\text{marginal } 2 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \left(-\frac{\partial E[D_2|z_2, z_4, z_t, x]}{\partial Z_t} \right) \\
&\quad + E[Y_t|\text{marginal } 4 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \left(-\frac{\partial E[D_4|z_2, z_4, z_t, x]}{\partial Z_t} \right) \\
&= E[Y_t|\text{marginal } 0 \rightarrow t \text{ compliers at } (z_2, z_4, z_t, x)] \left(-\frac{\partial E[D_0|z_2, z_4, z_t, x]}{\partial Z_t} \right) \\
&\quad + \frac{\frac{\partial E[YD_t|z_2, z_4, z_t, x]}{\partial Z_2}}{\frac{\partial E[D_t|z_2, z_4, z_t, x]}{\partial Z_2}} \left(-\frac{\partial E[D_2|z_2, z_4, z_t, x]}{\partial Z_t} \right) + \frac{\frac{\partial E[YD_t|z_2, z_4, z_t, x]}{\partial Z_4}}{\frac{\partial E[D_t|z_2, z_4, z_t, x]}{\partial Z_4}} \left(-\frac{\partial E[D_4|z_2, z_4, z_t, x]}{\partial Z_t} \right)
\end{aligned} \tag{24}$$

Same as before, the negative sign in equation 24 is to ensure the weight is positive. Combining equations 22 and 24, we have

$$\begin{aligned}
MTE_{0 \rightarrow t} &= E[Y_t - Y_0|\text{marginal } 0 - 4 \text{ compliers at } (z_2, z_4, z_t, x)] \\
&= \frac{\frac{\partial E[YD_t|z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_0|z_2, z_4, z_t, x]}{\partial Z_t}} - \frac{\frac{\partial E[YD_t|z_2, z_4, z_t, x]}{\partial Z_2}}{\frac{\partial E[D_t|z_2, z_4, z_t, x]}{\partial Z_2}} \frac{\frac{\partial E[D_2|z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_0|z_2, z_4, z_t, x]}{\partial Z_t}} - \\
&\quad \frac{\frac{\partial E[YD_t|z_2, z_4, z_t, x]}{\partial Z_4}}{\frac{\partial E[D_t|z_2, z_4, z_t, x]}{\partial Z_4}} \frac{\frac{\partial E[D_4|z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_0|z_2, z_4, z_t, x]}{\partial Z_t}} - \frac{\frac{\partial E[YD_0|z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_0|z_2, z_4, z_t, x]}{\partial Z_t}}
\end{aligned} \tag{25}$$

Using the locally linear specification, we can estimate the partial derivatives of conditional

expectations using linear regressions. For instance,

$$E[Y_2 | \text{marginal } 2 - t \text{ compliers when } (z_2, z_4, z_t, x) \rightarrow (z_2, z_4, z'_t, x)] = \frac{\frac{\partial E[YD_2 | z_2, z_4, z_t, x]}{\partial Z_t}}{\frac{\partial E[D_2 | z_2, z_4, z_t, x]}{\partial Z_t}} = \frac{\hat{\beta}_t^{YD_2}}{\hat{\beta}_t^{D_2}} \quad (26)$$

$\hat{\beta}_t^{YD_2}$ is the coefficient of the instrument Z_t when we regress YD_2 on Z_t , holding Z_2 , Z_4 and X to be constant. The identification assumption is that selection issue of the distance variable will be reduced after I control for characteristics, such as gender and family wealth, and hometown fixed effects. Since I will use distance bins as the instruments, and suppose we are interested in the treatment effects of the average person who lives in a bin which covers the average distance to existing universities, transformed universities, and colleges (all are bin 4 in my sample), then $\hat{\beta}_t^{YD_2}$ is the coefficient of the instrument bin b_{t4} (bin of distance to transformed universities), when we regress YD_2 on b_{t4} holding other b_{tn} , b_{cn} (bins of distance to college), b_{un} (bins of distance to university) and X to be constant. Since there are more observations in each bin, the marginal treatment effect is similar to a local average treatment effect of students moving from the furthest bins to the bin that covers the average distances to the three types of institutions. I use bootstrap to obtain standard errors.

4.3 Results

I first study the correlation between post-secondary education and education outcomes, as well as labor market outcomes using OLS. In Table 12, students who first chose transformed universities are 37.5 percentage points more likely to obtain a university degree compared with those who first chose no post-secondary education and entered the job market. The existing universities provide more opportunities for their students to obtain a bachelor's or above degree, compared with the transformed universities. Besides, the probability of obtaining a STEM degree is lower in a transformed university compared with an existing university. These results imply that transformed universities may be different from traditional universities although they both have full university status. In terms of the labor market outcomes, Table 13 suggests students in transformed universities have a higher probability to be employed than university graduates at age 24, possibly students in transformed universities

graduate earlier. However, students who graduate from traditional universities may have a slightly higher employment rate at age 30. Table 14 shows that the wages and incomes of students from transformed universities may be lower than graduates from traditional universities and colleges. This is possible because colleges teach more technical skills which have higher demands. Students who enter transformed universities face competition from higher-ranking universities. Thus students entering transformed universities may earn less compared with students from colleges or traditional universities.

According to results from IV regressions in Table 15, students from transformed universities are less likely to get a university degree and a STEM degree compared with the OLS results in Table 12. From Table 16, at age 24, students from transformed universities are less likely to be employed compared with students from traditional universities and colleges. But the situation improves after they approach a more mature stage of their career. Students from transformed universities are more likely to register for training when they become unemployed. Similar to the OLS results, Table 17 shows that students who graduate from transformed universities may earn less wages than those from colleges and traditional universities.

The traditional IV regressions may not aggregate treatment effects correctly if there is heterogeneity. Table 18 displays the marginal treatment effects using locally linear specification and distance bins. Marginal students who move from colleges to transformed universities may be less likely to be employed in general. The difference in employment between traditional universities and transformed universities is ambiguous. Students from traditional universities may be better off after they accumulate some work experience. People who move from no post-secondary education to transformed universities are more likely to be employed at any stage of their career. Consistent with the OLS and IV regression results that I discussed above, columns 2 and 3 in Table 18 suggest students from transformed universities may earn less than students from colleges and existing universities. However the incomes of transformed university graduates are higher than people without post-secondary education in general. Students from transformed universities are less likely to obtain a university degree and a STEM degree compared with graduates from traditional universities. However,

students from transformed universities are more willing to register for training when they are unemployed in general.

5 Conclusion

In this paper, I study the impacts of post-secondary education on labor market outcomes. I compare results from OLS and IV regressions. Since there is treatment heterogeneity, I adjust the locally linear specification proposed by Mountjoy (2022). Instead of linear distance, I use distance bins as the instrumental variables.

I first use the exogenous variations of transformed universities to study the returns to university entry. I find that university entry increases the probability of being employed and the wages of the graduates, compared with people without post-secondary education. However, the difference between a university graduate and a college graduate is small. In the next step, I separate the transformed universities from existing universities and estimate the impacts of transformed universities. Similar to the results of universities versus colleges, I find enrollment in transformed universities increases the probability of being employed and wages compared with cohorts without post-secondary education. However, graduates from transformed universities may have worse labor market performance than college and traditional university graduates. Furthermore, graduates of transformed universities are more likely to register for training courses when they are unemployed, compared with cohorts without post-secondary education, college graduates, and traditional university graduates.

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Table 3: Colleges' transformation to universities across Canada between 2000 and 2019

	University	Students	Full-time	Example
Alberta	7	36,471	33,490	Mount Royal Junior College → Mount Royal University
British Columbia	6	67,934	53,045	Fraser Valley College → University of the Fraser Valley
Ontario	3	56,040	56,040	Algoma College → Algoma University
Manitoba	2	3,083	2,632	Collège de Saint-Boniface → Université de Saint-Boniface
Nova Scotia	2	6,771	6,771	College of Cape Breton → Cape Breton University
New Brunswick	1	500	300	Bethany Bible College → Kingswood University
Saskatchewan	1	2500	2500	Saskatchewan Indian Federated College → First Nations University of Canada
Total	22	173,299	154,778	

Notes: The third column summarizes total enrollment in universities that upgraded from colleges every year, and the fourth column shows number of full-time students every year.

Table 4: Descriptive statistics

Variables	Full sample
females	0.48
age	26.99
parental incomes	89200.00
D cma	9.86
immigrants	0.10
work experience	7.53
no post-secondary education	0.32
college entry	0.29
transformed university entry	0.06
university entry	0.33
D college	27.05
D transition	210.94
D university	47.29
years of post-secondary at age 24	1.69
years of post-secondary at age 30	2.10
stem by age 24	0.10
stem by age 30	0.12
university degree at age 24	0.28
university degree at age 30	0.34
wage at 24	30200.00
wage at 30	49200.00
wage	36600.00
incomes at 24	30000.00
incomes at 30	52100.00
incomes	38800.00
employment at 24	0.91
employment at 30	0.89
employment	0.90
unemployment duration	26.70
number of courses	0.23
training length	2.50
EI earning annual	2600.00
training annual	0.16

Notes: This table is not complete and I will vet out results of the last three columns in the next draft. The second column shows the means of the full sample. The third column describes the means of variables by looking at a sample that students' address to colleges was within tercile of the distribution.

Table 5: Effects on education (OLS)

	(1) university degree at age 24	(2) university degree at age 30	(3) stem at 24	(4) stem at 30
college	0.0726*** (250.91)	0.140*** (483.34)	0.0667*** (261.44)	0.0839*** (311.07)
university	0.615*** (2115.61)	0.707*** (2432.75)	0.216*** (839.87)	0.249*** (918.65)
female	0.0767*** (392.06)	0.0750*** (383.70)	-0.0692*** (-400.79)	-0.0883*** (-483.95)
age	0.00122*** (37.08)	0.00392*** (119.43)	-0.000930*** (-32.09)	-0.0000962*** (-3.14)
parental incomes	0.000000634*** (457.56)	0.000000579*** (418.90)	0.000000243*** (198.55)	0.000000231*** (179.12)
immigrants	0.0194*** (59.39)	0.0356*** (108.95)	0.0560*** (193.93)	0.0684*** (224.22)
Constant	-0.0931*** (-97.55)	-0.161*** (-169.06)	0.0361*** (42.85)	0.0227*** (25.56)
R ²	0.4304	0.4713	0.0951	0.1086

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college” and “university”.

Table 6: Effects on labor outcomes (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	employment	employment at 24	employment at 30	training	number of training courses	length of training
college	0.0829*** (337.99)	0.0833*** (327.93)	0.0824*** (248.77)	0.0535*** (66.95)	0.0708*** (56.86)	0.659*** (39.57)
university	0.0790*** (314.14)	0.0705*** (270.80)	0.0980*** (287.78)	0.0169*** (18.46)	0.0310*** (21.78)	0.388*** (20.38)
female	-0.0395*** (-252.20)	-0.0333*** (-208.76)	-0.0746*** (-330.67)	-0.152*** (-254.02)	-0.201*** (-215.16)	-1.807*** (-144.93)
age	0.00344*** (73.44)	0.00269*** (56.53)	0.00451*** (73.40)	0.00122*** (6.93)	0.00246*** (8.97)	0.0501*** (13.64)
parental incomes	0.000000252*** (227.33)	0.000000232*** (205.45)	0.000000297*** (177.44)	0.000000140*** (31.15)	0.000000172*** (24.51)	0.00000108*** (11.50)
immigrants	-0.0376*** (-143.76)	-0.0448*** (-166.87)	-0.0129*** (-31.77)	-0.0199*** (-16.16)	-0.0244*** (-12.74)	-0.114*** (-4.45)
work experience	-0.00461*** (-107.29)	-0.00267*** (-61.70)	-0.00548*** (-97.84)	-0.0177*** (-107.70)	-0.0254*** (-99.30)	-0.354*** (-103.72)
Constant	0.784*** (780.08)	0.797*** (777.22)	0.767*** (573.24)	0.304*** (83.00)	0.414*** (72.39)	4.421*** (57.82)
R ²	0.0375	0.0332	0.0634	0.0853	0.0659	0.0500

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college” and “university”.

Table 7: Effects on wages and incomes (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	wage	wage at 24	wage at 30	incomes	incomes at 24	incomes at 30
college	9553.4*** (414.05)	6807.2*** (229.29)	10750.2*** (207.07)	9366.6*** (449.36)	6005.1*** (220.58)	10779.3*** (215.41)
university	10215.9*** (431.72)	3418.4*** (112.24)	21052.0*** (394.56)	9367.4*** (438.20)	2397.2*** (85.83)	19995.2*** (388.79)
female	-10690.8*** (-725.57)	-9244.2*** (-495.31)	-23837.1*** (-674.17)	-8378.2*** (-629.41)	-7380.7*** (-431.22)	-19188.1*** (-563.01)
age	2787.0*** (631.73)	-551.9*** (-99.15)	595.7*** (61.86)	3133.5*** (786.20)	-883.0*** (-172.99)	269.5*** (29.04)
parental incomes	0.0410*** (392.32)	0.0341*** (257.84)	0.0719*** (273.95)	0.0410*** (434.63)	0.0385*** (317.37)	0.0695*** (274.92)
immigrants	-2642.3*** (-107.29)	-2904.2*** (-92.60)	-2044.6*** (-32.08)	-2730.2*** (-122.72)	-3079.9*** (-107.09)	-2260.9*** (-36.81)
work experience	-168.4*** (-41.66)	640.0*** (126.46)	-650.6*** (-74.12)	-1.270 (-0.35)	701.2*** (151.08)	-461.5*** (-54.55)
Constant	-42243.6*** (-446.38)	38745.7*** (322.98)	34590.4*** (164.95)	-50956.3*** (-596.02)	46773.4*** (425.17)	44321.9*** (219.27)
R ²	0.1444	0.0580	0.1209	0.1838	0.0547	0.1031

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college” and “university”.

Table 8: Effects on education (IV)

	(1)	(2)	(3)	(4)
	university degree at 24	university degree at 30	stem at 24	stem at 30
college	0.0160*** (4.02)	-0.00674* (-1.65)	0.0480*** (13.78)	0.0375*** (10.15)
university	0.708*** (200.12)	0.821*** (225.64)	0.266*** (85.72)	0.311*** (94.56)
female	0.0634*** (133.53)	0.0556*** (113.97)	-0.0767*** (-184.33)	-0.0983*** (-222.69)
age	0.00181*** (18.03)	0.00340*** (33.08)	-0.000486*** (-5.52)	0.0000971 (1.04)
parental incomes	0.000000454*** (83.06)	0.000000331*** (58.84)	0.000000154*** (32.06)	0.000000111*** (21.85)
immigrants	0.00251*** (4.29)	0.0107*** (17.71)	0.0473*** (92.20)	0.0567*** (104.08)
Constant	-0.120*** (-23.42)	-0.145*** (-27.60)	0.0521*** (11.64)	0.0604*** (12.71)
Cragg-Donald Wald F statistic	3380.8896	3380.8896	3375.0016	3384.7876
R ²	0.4167	0.4252	0.0874	0.0922

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college” and “university”.

Table 9: Effects on labor outcomes (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	employment	employment at 24	employment at 30	training	number of training courses	length of training
college	0.371*** (105.32)	0.387*** (106.61)	0.349*** (63.68)	0.178*** (19.08)	0.243*** (16.76)	1.565*** (8.12)
university	0.393*** (116.61)	0.371*** (109.18)	0.437*** (90.04)	0.209*** (14.25)	0.231*** (10.15)	1.348*** (4.46)
female	-0.0636*** (-168.29)	-0.0531*** (-142.99)	-0.105*** (-185.76)	-0.183*** (-68.99)	-0.231*** (-56.30)	-1.963*** (-35.86)
age	-0.00872*** (-65.75)	-0.00889*** (-66.29)	-0.0123*** (-51.52)	-0.00942*** (-11.70)	-0.00870*** (-6.98)	-0.00747 (-0.45)
parental incomes	-4.87e-08*** (-11.38)	-2.64e-08*** (-6.26)	-0.000000109*** (-16.81)	-6.46e-08*** (-3.65)	-3.21e-08 (-1.17)	0.000000176 (0.48)
immigrants	-0.0616*** (-128.43)	-0.0658*** (-136.56)	-0.0462*** (-66.40)	-0.0359*** (-19.28)	-0.0400*** (-13.89)	-0.187*** (-4.88)
work experience	0.0172*** (78.37)	0.0177*** (82.89)	0.0189*** (56.84)	-0.00328*** (-3.41)	-0.00930*** (-6.24)	-0.275*** (-13.89)
Constant	0.726*** (336.47)	0.722*** (324.25)	0.835*** (252.89)	0.371*** (27.04)	0.478*** (22.50)	5.179*** (18.32)
Cragg-Donald Wald F statistic	3368.9013	3142.1376	1378.4415	333.2609	333.2609	333.2609
R ²	-0.0818	-0.0884	-0.0777	0.0618	0.0535	0.0484

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college” and “university”.

Table 10: Effects on wages and incomes (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	wage	wage at 24	wage at 30	incomes	incomes at 24	incomes at 30
college	24021.1*** (73.66)	30122.6*** (69.98)	24090.4*** (29.69)	29796.6*** (96.29)	33399.5*** (82.44)	31090.4*** (38.97)
university	7652.2*** (24.47)	-2613.7*** (-6.50)	21885.4*** (30.41)	5621.9*** (18.95)	-1622.4*** (-4.29)	15010.1*** (21.21)
female	-9841.8*** (-280.89)	-7542.0*** (-171.47)	-23605.7*** (-281.72)	-7170.0*** (-215.67)	-5747.8*** (-138.80)	-18166.4*** (-220.53)
age	2814.5*** (228.93)	-449.7*** (-28.31)	476.1*** (13.41)	3170.9*** (271.80)	-865.3*** (-57.88)	363.0*** (10.40)
parental incomes	0.0509*** (128.26)	0.0542*** (108.23)	0.0729*** (75.66)	0.0557*** (148.04)	0.0582*** (123.56)	0.0799*** (84.33)
immigrants	-1491.7*** (-33.55)	-775.9*** (-13.59)	-1800.8*** (-17.46)	-1070.1*** (-25.36)	-961.5*** (-17.88)	-1154.1*** (-11.38)
work experience	3.126 (0.15)	774.5*** (30.62)	-367.6*** (-7.45)	236.5*** (12.24)	1008.0*** (42.33)	-391.0*** (-8.07)
Constant	-47415.5*** (-236.88)	28583.0*** (108.43)	35098.4*** (71.79)	-59282.3*** (-312.14)	35699.0*** (143.83)	38373.1*** (79.84)
Cragg-Donald Wald F statistic	3368.9013	3142.1376	1378.4415	3368.8792	3142.7209	1378.4415
R ²	0.0800	-0.0839	0.1069	0.0318	-0.1465	0.0531

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college” and “university”.

Table 11: Effects of education choices (MTE)

outcome	MTE _{0→4}	MTE _{2→4}	MTE _{0→2}
employment	0.64***	0.05**	0.48***
employment at 24	0.68***	0.13***	0.48***
employment at 30	0.79***	-0.22***	0.63***
incomes	23794.74***	220.47	26147.04***
incomes at 24	23687.50***	1847.17	25046.72***
incomes at 30	30713.44***	22936.47***	21804.31***
number of courses	0.71	0.99	0.31***
stem at 24	0.13***	-0.11***	0.09***
stem at 30	0.15***	-0.12***	0.09***
training	0.52	0.68	0.24***
annual length of training	-1.36	-3.75	2.47***
university degree at 24	0.33***	0.18***	0.10***
university degree at 30	0.38***	0.26***	0.12***
wage	24640.78***	4228.12	27102.77***
wage at 24	25610.65***	7239.44*	25337.28***
wage at 30	42464.85***	28428.32***	23746.83***

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

This table shows the marginal treatment effects of individuals who live in a bin that covers average distances to colleges and universities. Column 2 represents marginal treatment effects between cohorts without post-secondary education and university graduates. Column 3 represents marginal treatment effects of switching from colleges to universities. Column 4 shows marginal treatment effects between cohorts without post-secondary education and college graduates.

Table 12: Effects of transformed universities on education (OLS)

	(1)	(2)	(3)	(4)
	university degree at 24	university degree at 30	stem at 24	stem at 30
college	0.0705*** (248.07)	0.137*** (482.11)	0.0680*** (267.54)	0.0851*** (316.89)
transformed university	0.375*** (807.02)	0.486*** (1045.03)	0.0872*** (209.53)	0.115*** (262.71)
existing university	0.657*** (2248.22)	0.745*** (2547.39)	0.236*** (903.94)	0.271*** (980.16)
female	0.0742*** (386.05)	0.0724*** (376.71)	-0.0699*** (-406.77)	-0.0891*** (-490.37)
age	0.000343*** (10.62)	0.00312*** (96.66)	-0.00141*** (-48.91)	-0.000598*** (-19.60)
parental incomes	0.000000584*** (428.85)	0.000000532*** (390.76)	0.000000221*** (181.55)	0.000000209*** (162.09)
immigrants	0.0128*** (39.85)	0.0295*** (91.62)	0.0529*** (183.86)	0.0651*** (214.30)
Constant	-0.0657*** (-69.96)	-0.136*** (-144.90)	0.0507*** (60.40)	0.0380*** (42.81)
R ²	0.4507	0.4880	0.1041	0.1171

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college”, “transformed university” and “existing university”.

Table 13: Effects of transformed universities on labor outcomes (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	employment	employment at 24	employment at 30	training	number of training course	training length
college	0.0826*** (336.69)	0.0830*** (326.45)	0.0822*** (247.62)	0.0537*** (67.13)	0.0710*** (56.99)	0.662*** (39.76)
transformed university	0.0910*** (233.19)	0.0875*** (218.99)	0.0974*** (153.23)	0.0278*** (17.73)	0.0440*** (18.01)	0.496*** (15.19)
existing university	0.0772*** (301.02)	0.0679*** (255.93)	0.0985*** (282.60)	0.0141*** (14.86)	0.0276*** (18.63)	0.358*** (18.11)
female	-0.0395*** (-251.98)	-0.0333*** (-208.33)	-0.0747*** (-330.90)	-0.152*** (-253.20)	-0.200*** (-214.51)	-1.803*** (-144.47)
age	0.00346*** (73.87)	0.00275*** (57.79)	0.00448*** (72.82)	0.00131*** (7.44)	0.00259*** (9.44)	0.0507*** (13.80)
parental incomes	0.000000254*** (228.54)	0.000000235*** (207.43)	0.000000297*** (176.87)	0.000000143*** (31.68)	0.000000175*** (24.91)	0.00000110*** (11.77)
immigrants	-0.0373*** (-142.63)	-0.0444*** (-165.32)	-0.0130*** (-31.90)	-0.0197*** (-15.97)	-0.0242*** (-12.59)	-0.111*** (-4.34)
work experience	-0.00458*** (-106.65)	-0.00267*** (-61.61)	-0.00544*** (-97.04)	-0.0177*** (-107.98)	-0.0254*** (-99.61)	-0.354*** (-103.76)
Constant	0.783*** (778.45)	0.795*** (774.76)	0.768*** (573.37)	0.302*** (82.28)	0.411*** (71.76)	4.402*** (57.51)
R ²	0.0376	0.0334	0.0634	0.0854	0.0660	0.0500

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college”, “transformed university” and “existing university”.

Table 14: Effects of transformed universities on wages and incomes (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	wage	wage at 24	wage at 30	incomes	incomes at 24	incomes at 30
college	9549.7*** (413.54)	6803.0*** (228.91)	10964.3*** (210.98)	9365.7*** (448.92)	5999.6*** (220.14)	10969.7*** (218.98)
transformed university	8208.4*** (223.62)	2899.9*** (62.04)	12292.6*** (123.51)	7848.0*** (236.64)	2291.0*** (53.44)	12076.6*** (125.88)
existing university	10611.6*** (439.45)	3556.4*** (114.54)	22215.3*** (407.15)	9668.8*** (443.20)	2454.7*** (86.21)	21069.2*** (400.58)
female	-10704.3*** (-726.41)	-9242.6*** (-495.07)	-23870.2*** (-675.42)	-8387.3*** (-629.99)	-7376.1*** (-430.81)	-19219.0*** (-564.14)
age	2774.1*** (628.53)	-556.5*** (-99.92)	564.4*** (58.62)	3123.5*** (783.31)	-884.6*** (-173.19)	237.8*** (25.62)
parental incomes	0.0406*** (388.00)	0.0340*** (256.59)	0.0707*** (269.32)	0.0407*** (430.91)	0.0384*** (316.69)	0.0685*** (270.50)
immigrants	-2701.4*** (-109.67)	-2926.1*** (-93.26)	-2164.6*** (-33.99)	-2775.4*** (-124.71)	-3089.9*** (-107.38)	-2371.1*** (-38.62)
work experience	-162.8*** (-40.27)	642.1*** (126.85)	-624.8*** (-71.20)	3.126 (0.86)	701.7*** (151.16)	-434.5*** (-51.36)
Constant	-41916.4*** (-442.61)	38859.2*** (323.62)	35244.4*** (168.09)	-50704.9*** (-592.62)	46812.7*** (425.12)	44975.6*** (222.53)
R ²	0.1448	0.0580	0.1221	0.1840	0.0546	0.1042

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college”, “transformed university” and “existing university”.

Table 15: Effects of transformed universities on education (IV)

	(1)	(2)	(3)	(4)
	university degree at 24	university degree at 30	stem at 24	stem at 30
transformed university	0.00590** (2.07)	-0.00945*** (-3.19)	0.0472*** (19.30)	0.0526*** (20.32)
college	0.0154*** (4.52)	-0.0106*** (-2.97)	0.0739*** (25.18)	0.0685*** (22.00)
existing university	0.747*** (251.58)	0.843*** (273.05)	0.268*** (104.89)	0.311*** (115.12)
female	0.0684*** (175.43)	0.0642*** (158.32)	-0.0731*** (-217.63)	-0.0937*** (-263.66)
age	-0.00172*** (-23.00)	-0.00103*** (-13.27)	-0.00129*** (-20.07)	-0.000873*** (-12.80)
parental incomes	0.000000449*** (98.04)	0.000000360*** (75.50)	0.000000178*** (45.16)	0.000000144*** (34.41)
immigrants	-0.00387*** (-7.06)	0.00646*** (11.35)	0.0481*** (102.22)	0.0580*** (116.29)
Constant	-0.0376*** (-9.30)	-0.0348*** (-8.28)	0.0573*** (16.51)	0.0671*** (18.24)
Cragg-Donald Wald F statistic	2579.0160	2579.0160	2582.1529	2582.5991
R ²	0.4044	0.3993	0.1013	0.1105

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college”, “transformed university” and “existing university”.

Table 16: Effects of transformed universities on labor outcomes (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	employment	employment at 24	employment at 30	training	number of training course	training length
transformed university	0.124*** (55.61)	0.0758*** (33.82)	0.125*** (20.13)	0.147*** (12.83)	0.231*** (12.96)	1.603*** (6.71)
college	0.237*** (85.81)	0.226*** (80.54)	0.0673*** (19.57)	0.0762*** (10.01)	0.0969*** (8.17)	-0.220 (-1.39)
existing university	0.177*** (71.73)	0.136*** (54.97)	0.160*** (54.37)	0.0631*** (5.65)	0.0631*** (3.62)	0.242 (1.04)
female	-0.0433*** (-150.33)	-0.0326*** (-113.00)	-0.0808*** (-196.79)	-0.162*** (-82.65)	-0.210*** (-68.65)	-1.859*** (-45.41)
age	-0.000760*** (-7.73)	-0.000144 (-1.46)	0.00192*** (14.76)	-0.00206*** (-3.64)	-0.000597 (-0.68)	0.0433*** (3.66)
parental incomes	0.000000190*** (57.05)	0.000000218*** (65.43)	0.000000209*** (47.25)	8.82e-08*** (6.69)	0.000000133*** (6.50)	0.00000113*** (4.10)
immigrants	-0.0409*** (-97.13)	-0.0446*** (-104.33)	-0.0204*** (-36.58)	-0.0245*** (-15.01)	-0.0279*** (-10.98)	-0.126*** (-3.69)
work experience	0.00324*** (22.70)	0.00279*** (20.39)	-0.00229*** (-15.21)	-0.0136*** (-24.45)	-0.0213*** (-24.58)	-0.374*** (-32.14)
Constant	0.734*** (373.09)	0.736*** (364.17)	0.811*** (284.92)	0.329*** (26.30)	0.457*** (23.51)	5.761*** (22.11)
Cragg-Donald Wald F statistic	2577.8941	2401.1202	1037.0103	243.9213	243.9213	243.9213
R ²	0.0065	-0.0010	0.0533	0.0824	0.0634	0.0467

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college”, “transformed university” and “existing university”.

Table 17: Effects of transformed universities on wages and incomes (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	wage	wage at 24	wage at 30	incomes	incomes at 24	incomes at 30
transformed university	2181.4*** (10.06)	-4652.4*** (-16.84)	76.35 (0.08)	15213.4*** (75.00)	8409.8*** (32.82)	5152.6*** (5.42)
college	17500.5*** (65.35)	15638.4*** (45.13)	6715.3*** (12.41)	25130.6*** (100.31)	21637.7*** (67.34)	17087.1*** (32.45)
existing university	-532.6** (-2.22)	-18393.2*** (-60.50)	10907.9*** (23.50)	1773.8*** (7.90)	-12387.5*** (-43.93)	9037.6*** (20.02)
female	-9155.5*** (-327.70)	-6495.2*** (-182.59)	-22686.9*** (-351.20)	-7042.9*** (-269.45)	-5242.8*** (-158.90)	-17774.3*** (-282.87)
age	3120.2*** (327.34)	140.6*** (11.53)	1100.1*** (53.70)	3313.2*** (371.54)	-462.5*** (-40.92)	720.2*** (36.14)
parental incomes	0.0591*** (182.90)	0.0680*** (165.47)	0.0847*** (121.44)	0.0583*** (192.66)	0.0662*** (173.63)	0.0854*** (125.93)
immigrants	-779.0*** (-19.07)	496.1*** (9.42)	-909.7*** (-10.36)	-794.7*** (-20.79)	-166.1*** (-3.40)	-773.9*** (-9.06)
work experience	-529.1*** (-38.26)	-186.5*** (-11.06)	-1363.0*** (-57.53)	31.74** (2.45)	388.5*** (24.85)	-999.6*** (-43.37)
Constant	-46394.0*** (-243.09)	31301.4*** (125.68)	36797.8*** (82.11)	-58148.4*** (-325.68)	38400.3*** (166.22)	41548.3*** (95.31)
Cragg-Donald Wald F statistic	2577.8941	2401.1202	1037.0103	2577.8577	2400.9518	1037.0103
R ²	0.0752	-0.0794	0.1145	0.0540	-0.1080	0.0810

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

The coefficients of interest are “college”, “transformed university” and “existing university”.

Table 18: Effects of transformed universities of education choices (MTE)

outcome	MTE _{2→t}	MTE _{4→t}	MTE _{0→t}	MTE _{2→4}
employment	-0.04***	-0.05***	0.11***	0.04***
employment at 24	-0.04***	0.06***	0.07***	-0.02
employment at 30	-0.01	-0.05***	0.06***	-0.01
incomes	-1.6e+04***	-5.5e+04***	5275.12***	12180.75***
incomes at 24	-4489.99***	8533.44***	10789.22***	-1.1e+04***
incomes at 30	-1.2e+04***	-8215.98***	-2275.20	3157.99
number of courses	0.19***	0.32***	0.23***	0.19***
stem at 24	-0.03***	-0.07***	0.01	0.32***
stem at 30	-0.05***	-0.15***	0.02***	0.32***
training	0.15***	0.25***	0.17***	0.22***
annual length of training	2.83***	4.99***	2.14***	0.30
university degree at 24	0.11***	-0.58***	0.08***	0.42***
university degree at 30	0.19***	-0.65***	0.16***	0.46***
wage	-9397.18***	-4.2e+04***	1733.90***	15665.67***
wage at 24	2544.71***	20937.10***	5038.08***	-8770.64***
wage at 30	-1.6e+04***	989.98	-1.3e+04***	7100.08***

Notes: t statistics in parentheses = “* p<0.1 ** p<0.05 *** p<0.01”

This table shows the marginal treatment effects of individuals who live in a bin that covers average distances to colleges, traditional universities, and transformed universities. Column 2 represents marginal treatment effects of switching from colleges to transformed universities. Column 3 represents marginal treatment effects of switching from traditional universities to transformed universities. Column 4 represents marginal treatment effects between cohorts without post-secondary education and transformed university graduates. Column 4 shows marginal treatment effects of switching from colleges to existing universities.