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The Long-Term Effects of Financial Aid and Career Education: Evidence from a Randomized Experiment

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The Long-Term Effects of Financial Aid and Career Education: Evidence from a Randomized Experiment

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Abstract

I study the effects of the Future to Discover Project, a randomized experiment in which Canadian high school students were either invited to participate in career planning workshops or were made eligible for an $8,000 college grant. By matching the experimental data to post-secondary institution records and income tax files, I am able to examine the effects of the interventions on college enrollment, graduation, and earnings in adulthood. I show that the career education intervention greatly improved students' outcomes in the long run by improving academic matching. In contrast, the college grant had no long-term monetary benefits despite increasing college enrollment, which is consistent with classical models of human capital investment in the absence of credit constraints. My findings suggest that informational frictions and behavioral obstacles—rather than financial constraints—represent the primary barrier to four-year college enrollment faced by low-income students. And that they explain a large part of the gap in four-year college enrollment between high- and low-income students. JEL Codes: I22, I23, I24, D8, D31

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1 Introduction

Parental income is, across many countries, a strong predictor of post-secondary education enrollment.[1] In part, this stems from differences in academic preparation between students from high- and low-income families. But large differences remain even after controlling for academic achievement, raising concerns that students from low-income families might make sub-optimal educational choices due to financial, informational, or behavioral barriers (Lochner and Monge-Naranjo (2012); French and Oreopoulos (2017)).

In response to these concerns, governments and other institutions invest large sums in interventions promoting college access. These interventions can be broadly classified into the two following categories: outreach and career counseling interventions aimed at improving students' decision-making regarding post-secondary education; and financial aid interventions designed to help students cover the costs of post-secondary education (Page and Scott-Clayton (2016); Herbaut and Geven (2020)).

Two key questions emerge from the literature: 1) are these interventions effective in improving students' outcomes in the long run? and 2) what type of intervention is the most successful in doing so? While prior research has shown the effectiveness of career counseling programs as well as financial aid interventions in increasing the college enrollment rate of low-income students, little is known about their long-term effects. Yet, that is not clear that an increase in enrollment will translate into an increase in graduation and earnings. Recent studies have demonstrated that educational interventions tend to "fade out" over time (Bailey et al. (2020)). In the case of interventions promoting college access, the "fade out" can occur because such interventions might induce students with low expected returns to education to enroll in college.[2]

In this paper, I answer these questions by studying the short- and long-run impacts of the Future to Discover Project, a randomized control trial conducted between 2004 and 2008 by the Social Research and Demonstration Corporation (SRDC). The project selected 4,390 students from 30 high schools in New Brunswick (Canada) and randomly assigned them to either a career education intervention, a financial aid intervention, a mixed intervention, or a control group.

1. See, for example, Bailey and Dynarski (2011) and Chetty et al. (2014) for the US, Frenette (2017) for Canada, and Blossfeld and Shavit (1993) for twelve other countries. See Kinsler and Pavan (2011) and Hoxby and Avery (2013) for the gap in enrollment in selective colleges.

2. For example, classical models of human capital investment predict that, by lowering the cost of college, financial aid provision would increase enrollment for students at the margin of enrolling, leading to weak effects on long-term outcomes (Becker (1964)). Moreover, outreach programs can bias students' beliefs about their private returns to college enrollment leading to negative impacts of such interventions on long-term outcomes.

Students assigned to the career education intervention were invited to participate in twenty career planning workshops, conducted from Grade 10 through Grade 12. These workshops were designed to help students explore different post-secondary options, formulate their own post-secondary education plans in accordance with their interests and skills, and develop strategies to achieve their goals. An important element of the intervention is that it provided guidance on post-secondary education decision-making and application process, a dimension that has been found effective in raising college enrollment rates (Carrell and Sacerdote (2017)).

The financial aid was only randomized among students from low-income families. Students assigned to the financial aid intervention were eligible for a two-year $4,000 per year grant conditional on post-secondary education enrollment. The grant was substantial as it covered most of the tuition costs of undergraduate studies at that time in New Brunswick. Moreover, compared to existing financial aid programs, the intervention offered an early guarantee of aid with a simple application process—two features that have been shown to enhance application rates (Bettinger et al. (2012); Dynarski et al. (2021)).

To study the long-term effects of the interventions, I match the experimental data to confidential administrative data of post-secondary institution records and income tax files. The linked data allow me to investigate the causal impacts of the interventions on students' college enrollment, graduation, and earnings, from the end of high school through age 28.[3] In addition, using the factorial design of the experiment—the fact that two interventions were tested alone and combined—I can compare the relative effectiveness and synergy of career education and financial aid in improving low-income students' outcomes. To the best of my knowledge the Future to Discover Project is the only experiment that allows to do so.

In the second part of the paper, I examine the role that the three interventions had in aligning high- and low-income students' college enrollment and graduation rates. In particular, I estimate the effects of the interventions on the gaps in enrollment and graduation between students with similar academic achievement prior to treatment. Because most studies collect data on the specific group of students they are interested in, there is to date, little evaluation of the effects of such interventions on inequality.

I find that the career education intervention increased the share of low-income students who enrolled in four-year college by 8.3 percentage points. Going further, I find that it raised students' earnings in adulthood. In particular, I estimate that by age 28 low-income

3. By matching the experimental data to administrative data I build on previous work conducted by the SRDC (see, for example, Ford et al. (2012) and Hui and Ford (2018)). Specifically, the data used by the SRDC did not allow to accurately identify the impact of the interventions on college dropout and completion, and on earnings beyond age 24.

students assigned to the career education intervention earned 10% more on average in labor income. It suggests that the intervention effectively improved students' decision-making regarding post-secondary education through the reduction in information frictions and behavioral barriers (e.g., lack of attention and over-reliance on default options) targeted by the program.[4]

In contrast, I do not find evidence that the college grant increased low-income students' earnings, although it substantially increased their community college enrollment and graduation rates. One possible explanation for this finding, consistent with classical models of human capital investment in the absence of credit constraints, is that the aid increased enrollment and graduation for students whose expected benefits from enrolling are slightly smaller than the expected benefits of not doing so, leading to weak effects on long-term outcomes (e.g., Becker (1964)).

Together these findings suggest that informational and behavioral obstacles, rather than financial constraints, represent the primary barrier to four-year college enrollment faced by low-income students.

I also explore the effects of the career education intervention on high-income students. I find that the intervention also had positive effects on their earnings in adulthood. Suggestive evidence indicates that part of this increase in earnings is driven by the intervention inducing students with a high risk of dropping out from college not to enroll. In fact, the intervention decreased the share of high-income students who enrolled in four-year college by 3.8 percentage points, but this effect is mostly driven by lower-achieving students and I do not observe a similar decline in four-year college graduation.

It suggests that high-income students also suffer from information frictions and behavioral barriers. But while these obstacles lead some low-income students to academically under-match, they lead some high-income students to academically over-match

By improving academic matching, the career education intervention completely aligned high- and low-income students' four-year college enrollment behavior. In the control group, low-income students were 13 percentage points less likely to enroll in a four-year college than similarly-achieving high-income students. In the career education group, the gap is only 1 percentage point wide. It suggests that academic mismatch arising from informational and behavioral barriers explain a large part of the gap in four-year college enrollment between the two types of students.

My paper makes several contributions to the literature. First, I contribute to the scarce literature on the long-term effects of interventions promoting college access. While

4. See French and Oreopoulos (2017) for a review of the possible informational and behavioral barriers students face transitioning to college.

previous research has shown the effectiveness of career counseling programs in increasing the college enrollment rate of low-income students (e.g., Bettinger et al. (2012); Carrell and Sacerdote (2017); Castleman and Goodman (2018); Cunha, Miller, and Weisburst (2018); Oreopoulos and Ford (2019)), little is known about their long-term effects.[5] I show that career counseling programs are not only effective in increasing low-income students' college enrollment rates but are also powerful in improving students' outcomes in the long run.

The literature on the effects of student grant aid is more extensive. Numerous studies have shown the effectiveness of these grants in increasing both college enrollment and completion (e.g., Fack and Grenet (2015); Castleman and Long (2016), Goldrick-Rab et al. (2016)), and a handful of recent evaluations have shown small but positive effects of grant aid on earnings (Bettinger et al. (2019), Denning, Marx, and Turner (2019); Scott-Clayton and Zafar (2019))[6]. However, the estimates of the treatment effects on earnings are often imprecise and specific to the United States. My paper shows that providing students with additional financial support, in a country where a number of grants and loans are already available to the students, has no long-term monetary benefits.

Second, I add to the understanding of the factors contributing to the gap in educational attainment by parental income. To date, there is little consensus about the role played by credit constraints (e.g., Keane and Wolpin (2001); Belley and Lochner (2007); Lochner and Monge-Naranjo (2012)). Moreover, although recent studies have demonstrated the existence of informational and behavioral barriers for low-income students (e.g., Bettinger et al. (2012); Hoxby and Avery (2013); Dynarski et al. (2021)), little is known on the extent to which they contribute to the gap. This paper provides new evidence that informational and behavioral barriers explain most of the gap in four-year college enrollment between equally-achieving high- and low-income students.

More generally, my paper relates to the literature on the fading-out of educational interventions. As Bailey et al. (2020) explains, well-timed interventions introducing the "right" institutional changes are more likely to lead to persistent effects than interventions targeting skills directly. Consistent with this finding, I find that the career education intervention, which tackles informational and behavioral barriers, had large persistent effects on graduation and earnings.

5. Two studies show promising results on degree completion. Bettinger et al. (2012) show that providing students with personal assistance for the FASFA application increased their likelihood to complete two years of college by 8 percentage points. In addition, Castleman and Goodman (2018) show that an intensive post-secondary education counseling program substantially increased persistence throughout the third year of college although this effect was not statistically significant.

6. See Eng and Matsudaira (2021) for an exception.

2 The Future to Discover Project

In this section, I draw on Currie et al. (2007) to describe the Future to Discover experiment. Throughout the paper, sample sizes are rounded to the nearest 10 for data confidentiality concerns.

2.1 Context and Background

High school in New Brunswick, like in the US, runs from Grades 9 to 12, after which students can decide whether to enroll in post-secondary education or not. Students are typically 14 years old at the beginning of high school and graduate at age 18. Three main options are available to students who want to enroll in post-secondary education in Canada: four-year colleges or universities (hereafter, four-year colleges) offering programs that lead to a bachelor's degree; community colleges, also referred to as colleges of applied arts and technology or institutes of technology or science, which typically grant diplomas for technical studies of two years; and private career colleges that offer career-oriented programs of one year or less.

In Canada, the share of adults with a four-year college degree is nearly equal to 33 percent, which is comparable to most developed countries (Statistics Canada (2020)). However, unlike other countries, Canada is characterized by a very high enrollment rate in community and private career colleges: 26 percent of Canadian adults have a short-cycle tertiary diploma compared to 7 percent of adults in other OECD countries (Statistics Canada (2020)). The high enrollment rate in post-secondary education masks large disparities. A young Canadian adult from a family in the bottom income quintile is 30 percent less likely to attend a post-secondary institution than someone from a family in the top income quintile (Belley, Frenette, and Lochner (2014); Frenette (2017)).

2.2 Experimental Design

The Future to Discover project was designed and implemented by the SRDC with the support of Statistics Canada.[7] With the objective of finding out what works best to increase college enrollment, three interventions targeted to high school students were designed and tested in the Canadian province of New Brunswick, namely, a career education intervention, a financial aid intervention, and a mixed intervention.

7. The SRDC is a non-profit research organization based in Ottawa, Canada. The experiment received financial support from the Canada Millennium Foundation.

Figure 1 provides an overview of the experimental design. The Future to Discover project was implemented in thirty New Brunswick high schools. The schools were selected to participate in the experiment on the basis of a priority index computed from the size of the school, the number of low-income families in the school, and the number of other schools in the district.

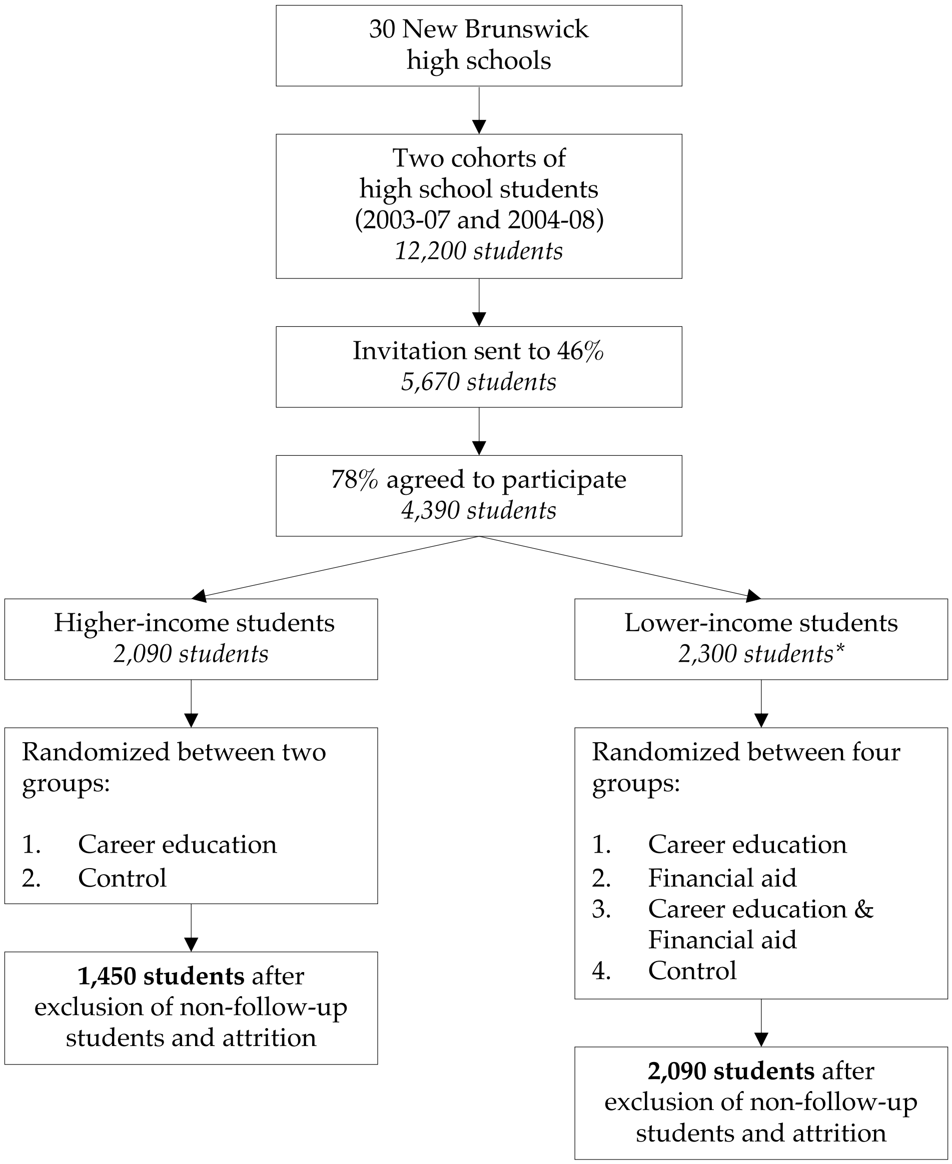


Figure 1: Experimental Design

Notes: The figure provides an overview of the experimental design with the number of students at each step of the randomization process. The numbers are derived from Currie et al. (2007).

Participants in the experiment were selected from the 2003–07 and 2004–08 high school cohorts during the spring of their ninth grade. A random sample of students—roughly 45%

or 5,670 students—was initially chosen among the freshmen cohorts to receive invitations to participate in the experiment. Upon invitation, students along with their parents, were required to give their written consent and answer the baseline survey in order to take part in the experiment. These requirements were fulfilled by about 78 percent of the students invited to participate.

During the baseline interview, the answering parent was asked to provide the annual household income as stated in his previous year's income tax returns. If the amount earned was above the provincial median, the student was classified as a high-income student and as a low-income student otherwise.[8] Low-income students were randomly assigned to the three treatment arms (career education, financial aid, mixed intervention) and the control group. High-income students were not eligible for financial aid and were accordingly only randomized between the career education and control groups. The randomization was conducted at the student level within each school.[9]

Tables A3 and A4 show baseline descriptive statistics (mean and standard deviation) for low- and high-income students in the control group, and report the differences between the control group and the treatment groups. The table shows a balance on almost all baseline characteristics. I find four significant differences out of 56 tests, a number that could have been obtained by chance alone. In addition, I test for whether the baseline characteristics jointly predict treatment status. I find no evidence that the baseline characteristics jointly predict treatment status for both high- and low-income students (p-value from F-test is 0.55 for low-income students and 0.95 for high-income students).

2.3 Career Education Program

Students assigned to the career education program were invited to participate in twenty career planning workshops, conducted from Grade 10 through Grade 12. The workshops were split into the following four series:

1. *Career Focusing*—The first workshop series was conducted in Grade 10. It included six workshops that were designed to guide students into the exploration of career op-

8. The threshold varied with family size. Six thresholds were defined, ranging from $40,000 for a single-parent family with one child to $60,000 for a family with two parents and three children or more.

9. Due to budgetary concerns the assignment ratios were adjusted for the second cohort of students, and a small random sample of students was excluded from the data collection. While the differential treatment assignment ratios across cohorts could lead to a complex empirical analysis design, the exclusion of students was conducted so as to equalize the assignment ratios across the two cohorts, allowing for a straightforward pooling of the students in the analysis. Although some administrative data are available for the non-follow-up students, I follow previous studies (Ford et al. (2012), Ford and Kwakye (2016), and Hui and Ford (2018)) and exclude them from my analysis. Table A1 presents the distribution of the students across parental income and the four randomization groups.

tions. Besides being taught how to research information on post-secondary education and labor market trends, students were encouraged to explore their post-secondary options through different activities and exercises.

2. *Lasting Gifts*—The second workshop series, which took place in Grade 11, was tailored toward the parents. The four workshops of the series aimed to encourage and assist the parents in getting involved in their children's career planning. Together with their children, parents were exposed to various career-planning approaches and were instructed to test these approaches through interactive activities and reflective exercises.

3. *Future in Focus*—The third workshop series was designed to help Grade 12 students build resilience to overcome unexpected life challenges. The workshops focused on the specific skills and attitudes needed to work through obstacles and on the importance of developing a support network.

4. *Post-secondary Ambassadors*—Six meetings with post-secondary education students from various institutions were organized over Grades 10 to 12. The invited students were asked to share their experiences and advice, providing high school students with peer mentors and role models.

The workshops were held on each school property right after school hours, with the exception of the second workshop series, which took place in the evening to facilitate the participation of the parents. From the randomization, 30 to 35 students were typically invited to the workshops in each school, allowing the meetings to be held in a classroom and facilitating interactions. The workshops were optional. Students were actively reminded about the date and location of the workshops through text messages, mails, and announcements in each school. They were also encouraged to attend through prizes and snacks.

In addition, students were given access to post-secondary and career information via a website and a magazine.[10] The two media shared the same content—a description of post-secondary options, a guide to the financial aid system, labor market trends, and links to other career education resources. The same content was offered across the two media in order to reach more students and parents with different habits and access to the internet.

The career education program can theoretically have several effects on students' college enrollment and earnings. On the one hand, the program can improve students'

10. Six issues of the magazine were sent to the students over Grades 10 to 12. To limit spillover, the website was restricted to treated students only via a unique access key. Students received their login information with the magazine's first issue and could access the website anytime from then on.

decision-making regarding post-secondary education by tackling several informational and behavioral barriers students might face. First, by pushing students to look for information on the costs and benefits of each post-secondary option, the program is expected to reduce misinformation. Second, by helping students think about their options and understand the long-lasting effects of their choices, it might minimize students' lack of attention, present bias, and over-reliance on default options—three behavioral barriers that have be found to be important in students' educational decisions (French and Oreopoulos (2017)). An improvement in decision-making can result, in turn, in an increase or to a decrease in college enrollment depending on the direction of the initial mistakes made by the students. It should however lead to an improvement in students' outcomes in the long run.

On the other hand, the program can bias students' beliefs about their private returns to college enrollment, leading to an increase in enrollment but negative effects on students long-run outcomes. That will be the case if, for instance, it pushes students to enroll in four-year college programs regardless of their academic ability.

2.4 Financial Aid

Students assigned to the financial aid intervention were eligible for a college grant worth up to $8,000. They could claim $2,000 each academic term they enrolled in post-secondary education, for a period of four terms or two years.[11] They were informed about the grant at the time of recruitment in Grade 9 and reminded about it at the end of Grade 12 and one year after high school.

The financial aid was substantial compared to tuition fees at the time of the experiment. Between 2007 and 2011, when most students from the sample enrolled in post-secondary education, tuition fees in New Brunswick for one year of undergraduate schooling were roughly equal to $5,500 in four-year colleges and $2,300 in community colleges.[12]

The financial intervention can affect students' outcomes in two ways. On the one hand, by reducing the amount students need to borrow to finance their education, the intervention might reduce financial barriers such as credit constraints and debt aversion. In that case, we would expect an increase in enrollment and an improvement in students' long-run outcomes. On the other hand, classical models of human capital investment

11. To receive the grant, students had to register in a post-secondary program recognized by the Canada Student Loans Program. It includes most four-year and vocational programs as long as they lead to a certificate, diploma, or degree. Students were eligible to receive the payments for three years after high school graduation.

12. Tuition fees from the four main four-year colleges were retrieved from Statistics Canada: *Table 37-10-0045-01 Canadian and international tuition fees by level of study*.

predict that the aid, by lowering the cost of college, would increase enrollment for students whose expected benefits from enrolling are slightly smaller than the expected benefits of not enrolling, resulting in limited benefits in the long run.

3 Empirical Framework

3.1 Data

I use data from three main sources.

1. *Experimental Data*—First, I obtained data from the SRDC on (i) students' characteristics collected through the baseline survey conducted in Grade 9 (demographics, family composition, socioeconomic status and aspirations); (ii) students' participation in the workshops and their claims to the financial aid; and (iii) student test scores and high school graduation.

2. *Canadian Post-Secondary Information System*—Second, I matched the experimental data obtained from the SRDC to the Canadian Post-Secondary Information System, which provides information on enrollment and graduation for the universe of students who attended a public post-secondary institution in Canada from the 2000–01 academic year to the 2017–18 academic year, allowing me to observe post-secondary education trajectories in public institutions until age 28 for both cohorts.[13]

3. *Statistics Canada Tax Filer Database*—The experimental data were also matched to earnings data from the Statistics Canada confidential tax filer database. The database provides information on earnings (labor income, total earnings) for all individuals who filed a tax return during a reference year. Because Canada requires anyone who owes taxes or qualifies for refunds or credits to file a tax return, the majority of adults, including post-secondary students, generally file a tax return every year, irrespective of their working status.

These data suffer from two limitations that I address in different ways. First, I cannot estimate the impact of the interventions on enrollment and graduation from private

13. The system aims to cover the universe of public post-secondary institutions. However, only 95 percent of these institutions are indeed covered (even fewer before 2009, when only 80 percent were covered by the system). In New Brunswick specifically, the platform does not cover the New Brunswick Community College—one of the two largest community colleges in New Brunswick—before 2010. This is challenging as I expect most of the impact of the program to happen from 2007 to 2009. To recover data from this institution, I supplement the platform until 2010 with data on enrollment and graduation gathered by the SRDC from the New Brunswick Department of Post-secondary Education, Training, and Labour.

institutions. This is likely a small limitation for the identification of enrollment and graduation from four-year and community colleges as they are nearly all public-funded. Only a few private, most of which are faith-based, four-year colleges exist, and they attract a tiny fraction of students (Jones and Li (2015)). However, a number of small private career colleges, which offer short and career-oriented programs of one year or less, are not captured by the administrative data. To identify the impact of the interventions on enrollment in these types of institutions, I rely on the survey conducted two and a half years after high school graduation. The survey is, however, conducted too soon to provide a reliable view of graduation.

Second, I do not observe earnings data beyond age 24 for the students who never enrolled in a public post-secondary institution or registered as an apprentice (34 percent of the sample). This stems from the fact that the link with earnings data was done in two waves. First, earnings until age 24 were initially acquired by the SRDC for all students in the sample. Second, earnings until age 28 were retrieved for students who enrolled in a public post-secondary institution or registered as an apprentice via the Canadian Education and Labour Market Longitudinal Platform. I address this limitation by imputing the missing data. Section 3.3 provides more details on the methodology used.

Appendix Section B summarizes the timeline of data coverage and details the construction of the outcomes of interest.

3.2 Analytic Samples

I exclude 49 students from the sample for whom less than two years of earnings data is available, suggesting that they might have moved out of the country or that their Social Insurance Number used to match the administrative data could not be relied upon. These students account for 1.4 percent of the initial sample. I find no evidence that the attrition rate differs by treatment group, as shown in Table A2. In Table A5 and A6, I also ensure that baseline characteristics remain balanced across treatment groups after excluding these students. In total, my sample is composed of 2,090 low-income students and 1,450 high-income students.

I further restrict my sample when looking at specific secondary outcomes for which data is not available for all students. It is the case for high school graduation and average test scores in Grade 12 that was not provided for all students, most likely because some students dropped out or transferred to another school.[14] This is also true for enrollment in

14. Test scores in Grade 12 are available for 80 percent of the low-income students and 91 percent of the high-income students. Graduation data are available for 87 percent of the low-income students and 94 percent of the high-income students.

private institutions for which I only have data for students who answered the survey.[15] I test and discuss potential threats to causal identification arising from selective missingness when presenting the results on these outcomes. Moreover, to enable the comparison of the treatment effects measured on the restricted samples with the ones measured from the full sample, I adjust the treatment effects on these outcomes using inverse probability weighting (IPW) (Seaman and White (2013)). This method puts more weight on observations that have, according to observed baseline characteristics, a high probability to be missing for the outcome of interest but are not. In practice, I construct the weights from Probit regressions of the missingness indicators on treatment dummies, baseline characteristics, and cohort and school dummies.

3.3 Imputation of Earnings Data

I seek to study the impact of the interventions on earnings at different ages, starting from age 19, when most students have left high school, until the age of 28, the most recent year for which I have data on earnings.

Earnings data may be missing for two reasons (Table A7). First, as explained in the data section, earnings data were not collected beyond age 24 for students who did not enroll in a public post-secondary institution. This is the case for roughly 1,210 students, or 34 percent of the entire sample. Second, over the period for which earnings data were collected, earnings records are missing for students who did not file a tax return during the reference year or filed the return too late. It is the case for 6 percent of the records.

To estimate the effects of the interventions on earnings, I need to account for these missing values. I address the issue by imputing the missing records rather than by restricting the sample to complete cases, which would lead to a loss of power and biases. I deal with the two types of missing values in different ways. First, I impute the missing records found over the period data were collected using linear interpolations from the available records of each individual.[16] Second, I forecast the earnings from age 25 to age 28 for each student whose data were only collected until age 24. For this purpose, I estimate a model which takes into account the students' past earnings records, their current level of education and years of experience and whether they are currently enrolled in post-secondary education.

I formally describe the linear interpolation method and the forecasting procedure in Appendix Section C.

15. 87 percent of the low-income students and 95 percent of the high-income students answered the survey.
16. The data restriction mentioned above ensure that I observe at least two years of earnings data points for each individual, making sure the interpolation is feasible for each individual.

3.4 Empirical Strategy

I first focus on the effect of the three interventions on low-income students. To recover the treatment effects, I estimate the following equation by Ordinary Least Squares (OLS),[17]

$$Y_i = \beta_0 + \beta_1 C_i + \beta_2 F_i + \beta_3 M_i + \boldsymbol{\beta_4 X_i} + \boldsymbol{\beta_5 S_i} + \epsilon_i \tag{1}$$

with Y_i is the outcome of interest for student i, C is a binary indicator equal to one if student i was assigned to the career education only group, F is a binary indicator equal to one if student i was assigned to the financial aid only group, and M is a binary indicator equal to one if student i was assigned to the mixed intervention group. $\boldsymbol{X_i}$ is a vector of baseline characteristics for student i and $\boldsymbol{S_i}$ is a vector of school-cohort dummies corresponding to the level of stratification.[18]

I follow the common practice of adjusting the results with the inclusion of baseline characteristics. I explore the sensitivity of the results to the exclusion of covariates in Tables A8, A9, and A10. The results do not significantly change when controls are removed, except for the treatment effects of the career education program on low-income students that are larger. I also report in the same table the results from the regressions where relevant controls are selected using the post-double-selection lasso method developed by Belloni, Chernozhukov, and Hansen (2013).[19] The treatment effects are virtually identical when controls are selected following the post-double-selection lasso method to when they are not.

The β_1 and β_3 coefficients capture the effects of eligibility for the career education program alone and combined with a financial nudge, respectively. Participation in the program was not compulsory—students were neither compelled to attend the workshop or to read the magazine/visit the website. However, note that nearly all students assigned to treatment were exposed to the program if we consider all forms of exposure. Among those assigned to treatment, 85 percent attended at least one workshop, 73 percent declared having read parts of the magazine, and 22 percent visited the website. In what follows, I use the terms "eligibility for the career education program" and "career education intervention"

17. I estimate the same linear model for both continuous and binary outcomes. Although a linear probability model can yield fitted values being outside the unit interval, it produces unbiased estimates of the average effects (Wooldridge (2010)).

18. The baseline characteristics included in the regression are all variables in Table A3, namely, gender, language spoken at home, whether one parent was born outside Canada, household composition, level of education of parents, whether student wants a four-year college degree and test score dummies.

19. The selection procedure chooses variables from the set of characteristics listed in Table A3 and their interactions that are significant predictors of either the outcome of interest Y_i or any of the treatment variables of interest, C_i, F_i, and M_i (Belloni, Chernozhukov, and Hansen (2013)).

interchangeably.

Since the intervention is randomized at the individual level in each school, I cannot rule out spillover effects. Spillover might have occurred in two ways. First, students from the career education group might have shared information they learned during the workshops or from the website and the magazine. They might have even lent the magazine or shared their login information with other students. Second, by changing the students' enrollment behavior, the program might have influenced students in the control group through peer effects. Assuming that the spillover effects, if any, would play in the same direction as of the direct effects, the impacts I estimate are lower bounds for the true impacts.

I report in all tables Huber–White robust standard errors and standard sampling-based significance levels. In addition, I report in Tables A11 and A12, randomization-based Fisher-exact p-values for the main outcomes of interest. These p-values do not rely on asymptotic properties but on the random assignment itself (Heß (2017), Young (2019)). I find that the exact p-values are virtually identical to the sampling-based p-values which is explained by the fact that the samples used are not small. I also address in the same table potential concerns arising from multiple hypothesis testing by computing sharpened q-values which control for the False Discovery Rate (Benjamini, Krieger, and Yekutieli (2006), Anderson (2008)). Most of the effects (72 percent) found to be significant using sampling-based significance levels survive multiple hypothesis testing correction. I indicate below when they do not.

I am also interested in understanding the treatment effects of eligibility for the career education program on high-income students as well as in the difference in effects between high- and low-income students. I thus estimate the following equation by OLS, on the restricted sample of students assigned to the control or career education groups,

$$Y_i = \gamma_0 + \gamma_1 HI_i + \gamma_2 C_i + \gamma_3 C_i \times HI_i + \boldsymbol{\gamma_4 X_i} + \boldsymbol{\gamma_5 S_i} + v_i, \tag{2}$$

where HI_i is a binary indicator equal to one if student i is a high-income student and 0 otherwise. γ_2 measures the treatment effect on low-income students, the sum of γ_2 and γ_3 the treatment effect on high-income students and γ_3 the treatment effect on the gap in outcome between the two types of students.

Additional specifications are used and described in the results section.

4 Results

4.1 Effects of the Career Education and Financial Aid Interventions on Low-Income Students' Outcomes

I first focus on the effects of eligibility for the career education program and eligibility for the college grant on low-income students' outcomes.

High school Graduation and Academic Performance

By changing students' post-secondary education aspirations, the interventions might have influenced students' effort and graduation plans. Therefore, I begin by exploring the effects of the interventions on high school graduation and academic performance in Table A13. The two interventions had no meaningful effects on students' academic performance as measured by average test scores in Grade 12, or on the fraction of students who graduated from high school. As a result, any effects observed in the next section on college enrollment are more likely to result from a change in aspiration than from a change in performance.

College Enrollment and Completion

I then explore, in Table 1, how low-income students' college enrollment and graduation rates were affected by the two interventions. My first three outcomes of interest are whether a student has ever enrolled in, graduated from, and dropped out of public college within 10 years of high school graduation. As mentioned before, public colleges include nearly all four-year and community colleges but exclude private career colleges that offer programs of one year and less. Column (1) reports the outcomes' means in the control group. I report the treatment effects of eligibility for the career education program in column (2) and eligibility for the financial aid in column (3). I also test whether the treatment effects of the two interventions are significantly different from each other and report the associated p-value in column (4).

In the control group, 52 percent of the low-income students ever enrolled in a public college—of these students, 69 percent graduated. I do not observe a significant change following the career education intervention in the fraction of students who enrolled, graduated, or dropped out of college. In contrast, the college grant significantly increased the fraction of students who enrolled and graduated from college: students assigned to the financial aid group were 8.0 percentage points more likely to enroll and 7.5 percentage points more likely to graduate than control group students and the two effects are

Table 1: Treatment Effects on Low-Income Students' College Enrollment and Graduation

Dependent variable	Control mean (1)	Career education (2)	Financial aid (3)	*P*-value difference (4)
Ever enrolled in any public college	0.52	0.034	0.080***	0.10
		(0.028)	(0.026)	
Ever graduated from a public college	0.36	-0.007	0.075***	0.00
		(0.028)	(0.026)	
Dropped out of college	0.15	0.032	-0.003	0.15
		(0.024)	(0.021)	
Group size	590	420	530	

Notes: The table reports the treatment effects of eligibility for the career education program and for the financial aid on college enrollment and graduation. Each row represents a separate OLS estimation of equation 1. Enrollment and graduation are measured within 10 years of high school graduation. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. For each outcome, I test whether the treatment effects of the two interventions are significantly different from each other and report the associated *p*-value in column (4). Group sizes are rounded to the nearest 10 for data confidentiality concerns.

significant at the 1 percent confidence level.[20]

In addition, relying on the follow-up survey conducted at age 20, I find that two interventions had essentially no impact on enrollment in private career colleges (Table A14).

Types of Colleges

I next investigate, in Table 2, the impact of the interventions on a set of indicators for the types of colleges students enrolled in and graduated from. The format of the table is identical to Table 1.

The insignificant effect of the career education intervention on college enrollment masks strong significant effects on the types of colleges students enrolled in. The fraction of students who ever enrolled in a four-year college rose by 8.3 percentage points following the intervention, which corresponds to a 36 percent increase from the control mean and is significant at the 1 percent level. Note that this increase is not balanced by an equivalent decrease in community college enrollment that would have otherwise been expected from

20. The increase in college enrollment occurred between ages 18 and 20 when students were still eligible for the financial aid (Figure A2–Panel A3).

Table 2: Treatment Effects on the Type of College Low-Income Students Enrolled in and Graduated from

Dependent variable	Control mean (1)	Career education (2)	Financial aid (3)	*P*-value difference (4)
Panel A—Enrollment				
First enrolled in a four-year college	0.21	0.057**	0.030	0.26
		(0.023)	(0.021)	
First enrolled in a community college	0.31	-0.017	0.048*	0.03
		(0.028)	(0.027)	
Switched to a community college	0.06	0.009	0.015	0.72
		(0.016)	(0.014)	
Switched to a four-year college	0.02	0.028**	0.002	0.02
		(0.011)	(0.008)	
Ever enrolled in a four-year college	0.23	0.083***	0.032	0.04
		(0.024)	(0.021)	
Ever enrolled in a community college	0.36	-0.012	0.065**	0.01
		(0.030)	(0.028)	
Panel B—Graduation				
Four-year college degree	0.14	0.037*	-0.003	0.07
		(0.021)	(0.018)	
Community college diploma	0.24	-0.033	0.076***	0.00
		(0.027)	(0.026)	
Panel C—Dropout				
Dropped out of a four-year college	0.08	0.041**	0.026	0.46
		(0.020)	(0.017)	
Dropped out of a community college	0.08	0.019	-0.017	0.09
		(0.021)	(0.018)	
Group size	590	420	530	

Notes: The table reports the treatment effects of eligibility for the career education program and for the financial aid on the type of college students enrolled in and graduated from. Each row represents a separate OLS estimation of equation 1. Enrollment and graduation are measured within 10 years of high school graduation. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. For each outcome, I test whether the treatment effects of the two interventions are significantly different from each other and report the associated *p*-value in column (4). Group sizes are rounded to the nearest 10 for data confidentiality concerns.

the null effect on any college enrollment.[21]

21. In line with these results, I find that eligibility for the career education program increased the fraction

The increase in four-year college enrollment translated into a significant increase in both four-year college graduation (+3.7 percentage points) and dropout (+4.1 percentage points).[22] Assuming that the *inframarginal* students—those who would still have enrolled in the absence of the intervention—were not affected by the intervention,[23] the results imply that 45 percent of the students induced to enroll in four-year college by the intervention graduated, and that 55 percent did not. This 45 percent success rate is not statistically different from the 61 percent success rate of the inframarginal students, suggesting that the students who were induced to enroll in four-year colleges by the intervention performed similarly to their peers.

In contrast, the effect of the college grant on college enrollment is mostly driven by a 6.5 percentage points increase in community college enrollment. Going further, I observe a strong significant increase in community college graduation (+7.6 percentage points). The fact that the increase in community college graduation is of the same magnitude as the increase in community college enrollment could imply two things. Either all students induced to enroll in a community college successfully graduated from it, which suggests that they are doing (much) better than the *inframarginal* students (Table A16). Or some students who would have dropped out from community college in the absence of the intervention were induced to graduate.

As a result of all of the effects combined, the average number of years students spent in college was 0.24 higher in the career education group (p-value=0.08), and 0.15 higher in the financial aid group (p-value=0.19), than in the control group (Table A18).

I also explore the effects heterogeneity across skills in Table A15. While I observe that the effect of the career education intervention on four-year college enrollment was significantly higher for higher-achieving students, I do not find any major differences in the impact of the financial aid intervention across skills. This suggests that the two types of interventions reached different types of students, which is confirmed by the analysis of the mixed intervention in Section 4.2.

To sum up, the two interventions had contrasting effects on the types of colleges students enrolled in and graduated from.[24] On the one hand, the career education intervention increased four-year college graduation by 3.7 percentage points while decreasing community college graduation and increasing dropout. On the other hand, the financial aid intervention increased community college graduation by 7.6 percentage points while

of students who enrolled in four-year college at ages 18 and 19, as well as at later ages (Figure A1–Panel A1).

22. Note that these effects do not survive multiple hypothesis correction.

23. This is speculative as I cannot exclude that the program also influenced the *inframarginal* students through a change in major choice, effort, and access to financial aid.

24. The treatment effects are different between the two interventions for most outcomes of Table 2.

having no adverse effect on dropout.

From these results alone, it is unclear what will be the effects of the two interventions on students' long-term outcomes. These effects will ultimately depend on the returns to four-year and community college graduation for the marginal students, and on the magnitude of the adverse effects of college dropout.

Earnings

I finally present the results of the impact of the two interventions on labor income, unconditional on working, in Figure 2. The estimated effects capture the combination of the effects on the probability of working as well as on the wage earned when working. The Figure presents the estimated effects against age. Each point is estimated from equation 1, and the shaded area indicates the associated 90 percent confidence interval. The impact of the career education intervention and of the financial aid are presented in Panel (a) and (b), respectively. I also report in Table A19 the corresponding coefficients and standard errors. The same table presents the effects on total earnings, which include on top of labor income, self-employment earnings, unemployment insurance benefits, and other social benefits. All earnings are expressed in 2020 Canadian dollars.

The career education intervention marginally decreased low-income students' unconditional labor income between the ages of 19 and 21, which is in line with the increase in college attendance induced by the intervention. Conversely, I observe, starting from age 22, a growing positive effect of the intervention on average annual labor income. By the age of age 28, low-income students assigned to the career education group earned on average $3,300 more annually in labor income than control group students, corresponding to a 10 percent increase from the control mean of $31,700, and is statistically significant at the 10 percent confidence level (p-value=0.15 after correcting for multiple hypothesis testing). The effects on total earnings are largely identical (Table A19). Moreover, the increase in earnings does not stem from an increase in the likelihood of working but rather by an increase in wages as can be seen from Table A20.

Assuming the rise in income is solely driven by the 0.24-year increase in the length of post-secondary education observed in Table A18, it can be inferred that the students who were induced to get more schooling after the intervention had very high returns to it. More specifically, students earned on average $14,000 more annually by age 28 for each additional year of schooling students they were induced to get, which is significantly higher than the returns to schooling observed in the control group.[25] However, this is

25. In the control group, one year of post-secondary education is associated with a $3,000 increase in annual labor income by age 28.

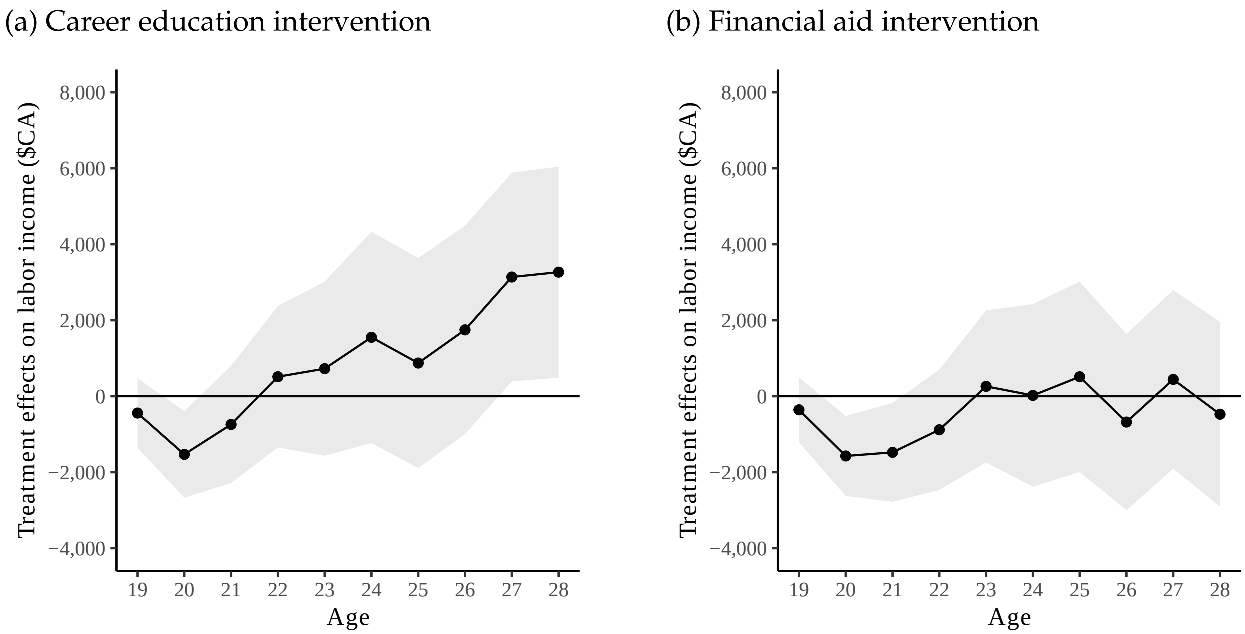


Figure 2: Impact on Labor Income Over Time

Notes: The figure plots the effects of eligibility for the career education program and for the financial aid on labor income against age. Point estimates together with the associated 90 percent confidence intervals are reported. Each point is estimated from a separate OLS estimation of equation 1. Huber–White robust standard errors are used to compute the confidence intervals. Earnings are expressed in 2020 Canadian dollars.

only suggestive as I cannot empirically rule out that other channels drove the increase in earnings, such as changes in major or occupational choices.

These findings imply that the intervention did lower the barriers students encountered in maximizing earnings. Since the intervention only changed students' decision-making process but not the environment they actually faced, it highlights the existence of informational and behavioral barriers for some students.

The decrease in labor income between the ages of 19 and 21 induced by the career education intervention is also observed with the financial aid treatment since they both had similar effects on college enrollment. Surprisingly, the financial aid intervention had no noticeable effect on labor income and total earnings beyond age 22, although it substantially increased graduation from community colleges. The lack of effect suggests that students were induced to enroll in and graduate from programs with on average limited monetary returns.

One possible explanation for this finding is that the aid increased enrollment and graduation for students whose expected benefits from enrolling/graduating are slightly smaller than the expected benefits of not doing so, leading to weak effects on long-term outcomes. This is consistent with classical models of human capital investment (e.g., Becker (1964)). One alternative explanation is that the intervention effectively improved students' long-term outcomes albeit along non-pecuniary dimensions that are not captured by monetary outcomes. In fact, college attendance is often associated with non-pecuniary benefits such as social interactions, improved health, less risky behaviors, and better occupational matching, which are not captured in my analysis (see, for instance, Oreopoulos and Salvanes (2011).).

The identification of the treatment effects on earnings hinges on the validity of the imputation performed. I address these concerns in Table A21 by showing how the results vary with alternative models of forecasting for the missing data. The treatment effects remain largely unchanged with different models. More specifically, none of the significant coefficients become insignificant and vice-versa. Moreover, I also check in Table A22 that the prediction errors are not correlated with students' treatment status by using the earnings observed at age 24.

4.2 Effects of the Mixed Intervention on Low-Income Students' Outcomes

I next explore the effects of the mixed intervention in Table 3 in order to understand the synergy between the two interventions. Column (1) reports the treatment effects of the intervention. For each outcome, I test whether the treatment effect of the mixed intervention is significantly different from the effect of the career education intervention and of the financial aid intervention and report the associated p-value in columns (2) and (3), respectively.

I find that the mixed intervention combined the effects of the career education and financial aid programs but had no additional effect, which suggests (i) a lack of synergy between the two types of interventions and (ii) that they reached different types of students.

Specifically, the mixed intervention increased the college enrollment rate similarly to the financial aid intervention, and increased the four-year college enrollment rate similarly to the career education intervention.[26] The fraction of students who enrolled in a community college was unaffected by the intervention. This is probably explained by the fact that the intervention induced some students who would not have enrolled in any college to enroll in a community college (financial dimension), and some students who would have enrolled in a community college to enroll in a four-year college (career education

26. As with the career education intervention, the treatment effect of the mixed intervention on four-year college enrollment was significantly higher for higher-achieving students (Table A15).

Table 3: Treatment Effects of the Mixed Intervention

Dependent variable	Treatment effects (1)	*P*-value diff. with career educ. (2)	*P*-value diff. with financial aid (3)
Panel A—Enrollment			
Ever enrolled in any public college	0.059**	0.36	0.42
	(0.028)		
Ever enrolled in a four-year college	0.087***	0.87	0.01
	(0.024)		
Ever enrolled in a community college	0.013	0.42	0.07
	(0.030)		
Panel B—Graduation			
Ever graduated from a public college	0.055**	0.04	0.47
	(0.028)		
Four-year college degree	0.026	0.61	0.13
	(0.021)		
Community college diploma	0.029	0.01	0.07
	(0.025)		
Dropped out of college	-0.003	0.15	0.99
	(0.024)		
Panel C—Earnings			
Labor income at age 28	1,588	0.35	0.19
	(1,688)		
Control group size	590		
Mixed intervention group size	540		

Notes: The table reports the treatment effects of eligibility for the career education program combined with eligibility for the financial aid on the main outcomes of interest. Each row represents a separate OLS estimation of equation 1. Enrollment and graduation are measured within 10 years of high school graduation. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. For each outcome, I test whether the treatment effect of the mixed intervention is significantly different from the effect of the career education intervention and of the financial aid intervention and report the associated p-value in column (2) and (3), respectively. Group size is rounded to the nearest 10 for data confidentiality concerns.

dimension).[27]

27. This is the case if we assume: (1) that students who would have enrolled in college in the absence of the intervention were not induced not to enroll following the interventions; (2) students who would have enrolled in a four-year college in the absence of the intervention were not induced to enroll in a community

Consistent with these effects on enrollment, students assigned to the mixed intervention group were more likely to graduate from any college and from four-year college than control group counterparts (+5.5 and +2.6 percentage points, respectively). The intervention also increased, as the career education intervention, four-year college dropout (Table A17). However, this increase is compensated by a rise in community college graduation. All in all, there was no change in the fraction of students who dropped out of college.[28]

Considering these findings, the effects of mixed intervention on earnings would be expected to be similar to those of the career education intervention. Indeed, the only difference observed between the effects of the career education intervention and of the mixed intervention is that unlike the former, the latter prompted some students to enroll in community college. However, the community college programs in which students were induced to enroll did not seem to yield any monetary returns. Consistent with the prediction, I observe a rise in annual labor income following the mixed intervention which is not statistically different from the effects of the career education intervention—although it is smaller and not significantly different from zero.[29]

4.3 Effects of the Career Education Intervention on High-Income Students' Outcomes

The design of the experiment allows me to assess the effects of eligibility for the career education program on high-income students. Table 4 presents the results on college enrollment and graduation. Column (1) reports the effects for low-income students, column (2) the effects for high-income students, and column (3) the impact differential between the two types of students, as estimated from equation 2.[30]

While I showed earlier that eligibility for the career education program substantially increased low-income students' enrollment in four-year colleges, a contrasting effect emerges for high-income students. High-income students assigned to the career education

college following the interventions; and (3) students who were induced to enroll in a four-year college by the career education intervention were also induced to enroll in a four-year college by the mixed intervention.

28. This is coming from two channels. First, as with the financial aid-only intervention, the dropout rate of students who enrolled in a community college decreased following the intervention from 30 to 23 percent (Table A16). Second, students assigned to the mixed intervention were more likely to switch and graduate from a community college after dropping out of a four-year college, compared to students in the career education group (Table A17).

29. Figure A3 shows the evolution of the treatment effects on labor income from ages 19 to 28. Table A19 reports the coefficients and standard errors plotted in the Figure and the results on total earnings. Table A21 presents the results for alternative models of forecasting.

30. The treatment effects reported for low-income students can slightly differ from the ones reported earlier in Tables 1 and 2 which is explained by a difference in the sample on which the coefficients from the control variables are estimated. See empirical strategy section.

Table 4: Comparison of the Treatments Effects on Low- and High-Income Students' College Enrollment and Graduation

Dependent variable	Low-income students (1)	High-income students (2)	Difference high vs. low (3)
Panel A—Enrollment			
Ever enrolled in any public college	0.040	-0.028	-0.068**
	(0.028)	(0.020)	(0.034)
	0.52	*0.78*	*0.26*
Ever enrolled in a four-year college	0.084***	-0.038*	-0.122***
	(0.024)	(0.021)	(0.032)
	0.23	*0.54*	*0.31*
Ever enrolled in a community college	-0.009	0.010	0.020
	(0.030)	(0.026)	(0.040)
	0.36	*0.41*	*0.05*
Panel B—Graduation			
Ever graduated from a public college	0.000	-0.013	-0.013
	(0.028)	(0.023)	(0.036)
	0.36	*0.62*	*0.26*
Ever graduated from a four-year college	0.038*	-0.016	-0.054*
	(0.021)	(0.021)	(0.030)
	0.14	*0.38*	*0.24*
Dropped out of a four-year college	0.041**	-0.025	-0.066**
	(0.019)	(0.018)	(0.026)
	0.08	*0.15*	*0.07*
Control group size	590	850	
Career education group size	420	600	

Notes: The table reports the treatment effects of eligibility for the career education program on low- and high-income students' outcomes. Each row represents a separate OLS estimation of equation 2. Enrollment and graduation are measured within 10 years of high school graduation. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Control means are reported in italic below the standard errors. For each outcome, I report the effect on low-income students (column (1)), the effect on high-income students (column (2)) and the difference in effect between the two types of students (column (3)). Group sizes are rounded to the nearest 10 for data confidentiality concerns.

group were 3.8 percentage points less likely to enroll in a four-year college than control group students. It is however empirically unclear whether this decrease is balanced by an increase in the fraction of students who enrolled in a community college or in the fraction of students who did not enroll at all, since none of these effects are significant. I also observe a reduction in the fraction of students who dropped out of four-year college following the intervention, although the effect is not statistically significant (p-value=0.16). It suggests that students who were induced not to enroll in a four-year college by the intervention would not have graduated in the absence of the intervention. Note that the effects on high-income students do not survive multiple hypothesis testing and should accordingly be taken with caution.

In next explore in Figure 3 the effects of the career education intervention on unconditional labor income from ages 19 to 28. Each point is estimated from equation 2, and the shaded area indicates the associated 90 percent confidence interval. The effects of the career education intervention on low-income students are presented in Panel (a) and the effects on high-income students in Panel (b). I also report in Table A23 the corresponding coefficients and standard errors together with the effects on total earnings.

(a) Treatment effects on low-income students

(b) Treatment effects on high-income students

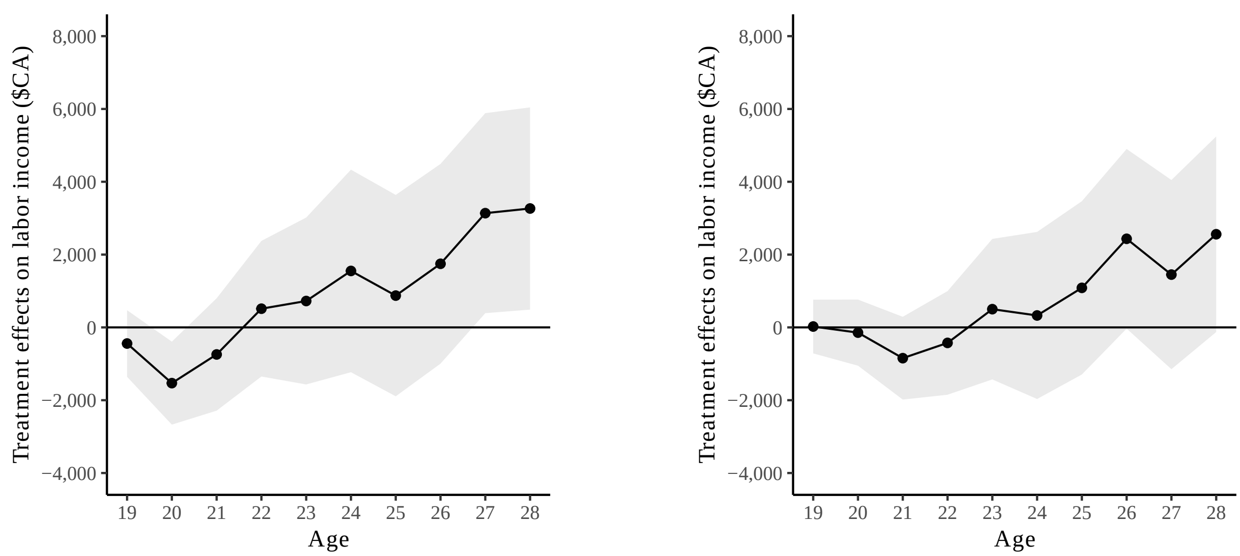


Figure 3: Impact on Labor Income Over Time

Notes: The figure plots the effects of eligibility for the career education program on labor income against age, for both low- and high-income students. Point estimates together with the associated 90 percent confidence intervals are reported. Each point is estimated from a OLS regression of the outcome on the treatment dummy, the treatment dummy interacted with the parental income dummy, the parental income dummy and controls for student baseline characteristics listed in Table A3. Huber–White robust standard errors are used to compute the confidence intervals. Earnings are expressed in 2020 Canadian dollars.

Eligibility for the career education program did not have any noticeable impact on labor income between the ages of 19 and 24. Nevertheless, starting from age 25, I observe a growing positive difference in labor income between treated and control students although none of these differences are statistically significant. The effects are, however, substantial and at the margin of significance—high-income students assigned to the career education group earned, on average, $2,558 more annually in labor income by age 28 than control group students (*p*-value=0.12). As with low-income students, the increase in earnings does not come from an increase in the likelihood of working but rather by an increase in wages (Table A20). The treatment effects are found to be similar on total earnings.

The increase in earnings is consistent with the decline in four-year college dropout. It can also be driven by a change in students' major choices or the quality of the colleges they enrolled in. I however do not find evidence that the intervention changed these dimensions of enrollment even though I cannot rule out some small effects (Table A24).[31]

Together, these findings are consistent with a model where students lack information and rely on default options (French and Oreopoulos (2017)). For instance, some low-income students might not enroll in four-year colleges because of a lack of attention and information on opportunities. Inversely, some high-income students with low skills and taste for schooling might enroll in four-year colleges because that is the norm among their peers.

4.4 Impact on the Gaps in College Enrollment and Graduation Between High- and Low-income Students

By expanding low-income students' enrollment and graduation rates, the three interventions had sizable effects on the gaps in college enrollment and graduation between high- and low-income students—effects that are reinforced by the lower enrollment rates of high-income students assigned to the career education group. In this section, I evaluate the magnitude of the reduction in these gaps. I focus on the four-year college enrollment and graduation gaps since my previous findings have proven little monetary benefits of community college enrollment/graduation for the marginal students.

In particular, I am interested in the gaps in enrollment and graduation between students with similar academic achievement prior to treatment. To this end, I estimate the relationship between enrollment/graduation and student test scores in Grade 9, for each income group and treatment arm.[32] Results are illustrated in Figure 4 and Table A25

31. I do observe, conditional on enrollment, a small increase in the fraction of college students who enrolled in a STEM program. However, I do not observe a change in the overall fraction of students who enrolled in a four-year college program. It might be the case that students who were induced not to enroll in a four-year college following the intervention would not have enrolled in a STEM program in the absence of the intervention.

32. I standardize students test scores in each school and estimate the relationship using a polynomial

reports the average size of the gap across test scores and schools.[33]

Eligibility for the career education program for both high- and low-income students decreased the four-year college enrollment gap between equally-achieving students almost entirely. As a matter of fact, the four-year college gap among equally-achieving students decreased by 92 percent on average. In a similar manner the four-year college graduation gap decreased, on average, by 74 percent. The effect on graduation is smaller than that on enrollment as the dropout rate of college students was slightly higher in the career education group when compared to the control group.

I cannot attribute all of the decrease in the four-year college enrollment gap to a reduction in behavioral and informational barriers since the intervention might also have biased students' beliefs concerning their private returns to college enrollment. However, assuming that all students who were induced to graduate from a four-year college by the intervention did derive benefits from it, my findings indicate that behavioral and informational barriers drive at least 74 percent of the observed differences in four-year college graduation between high- and low-income students.

I further test this hypothesis by investigating how systematic the reduction in gaps is across schools (Figures A5 and Table A26). The idea is as follows. Suppose the career education program did bias students' beliefs concerning their private returns to college enrollment. In that case, we should not see a strong relationship between the size of the gap between high- and low-income students and the magnitude of the effects of the intervention. However, assuming that the size of the gaps in four-year college enrollment and graduation in each school reveals the extent of the barriers faced by the students, if the intervention effectively removed these barriers, we must observe a positive relationship between initial gap size and the treatment effects. I find that the schools where initial differences between high- and low-income students were the largest are those where the absolute reductions in the gaps were the most significant. Put differently, I observe a systematic and homogeneous decline in within-school inequality. The strong correlation between initial gap size and the magnitude of the treatment effects holds even after controlling for school characteristics. It suggests that the intervention effectively removed some of the barriers students faced, supporting the hypothesis that strong informational and behavioral barriers exist.

In addition, low-income students' eligibility for financial aid did not significantly affect the four-year college enrollment and graduation gaps, suggesting that financial barriers

of degree 2. I make sure that the Figures compare students attending the same schools by estimating the relationships in each school and by taking the average across schools. Refer to Appendix Section D for more details on the estimation procedure.

33. Figure A4 present the results for any college enrollment.

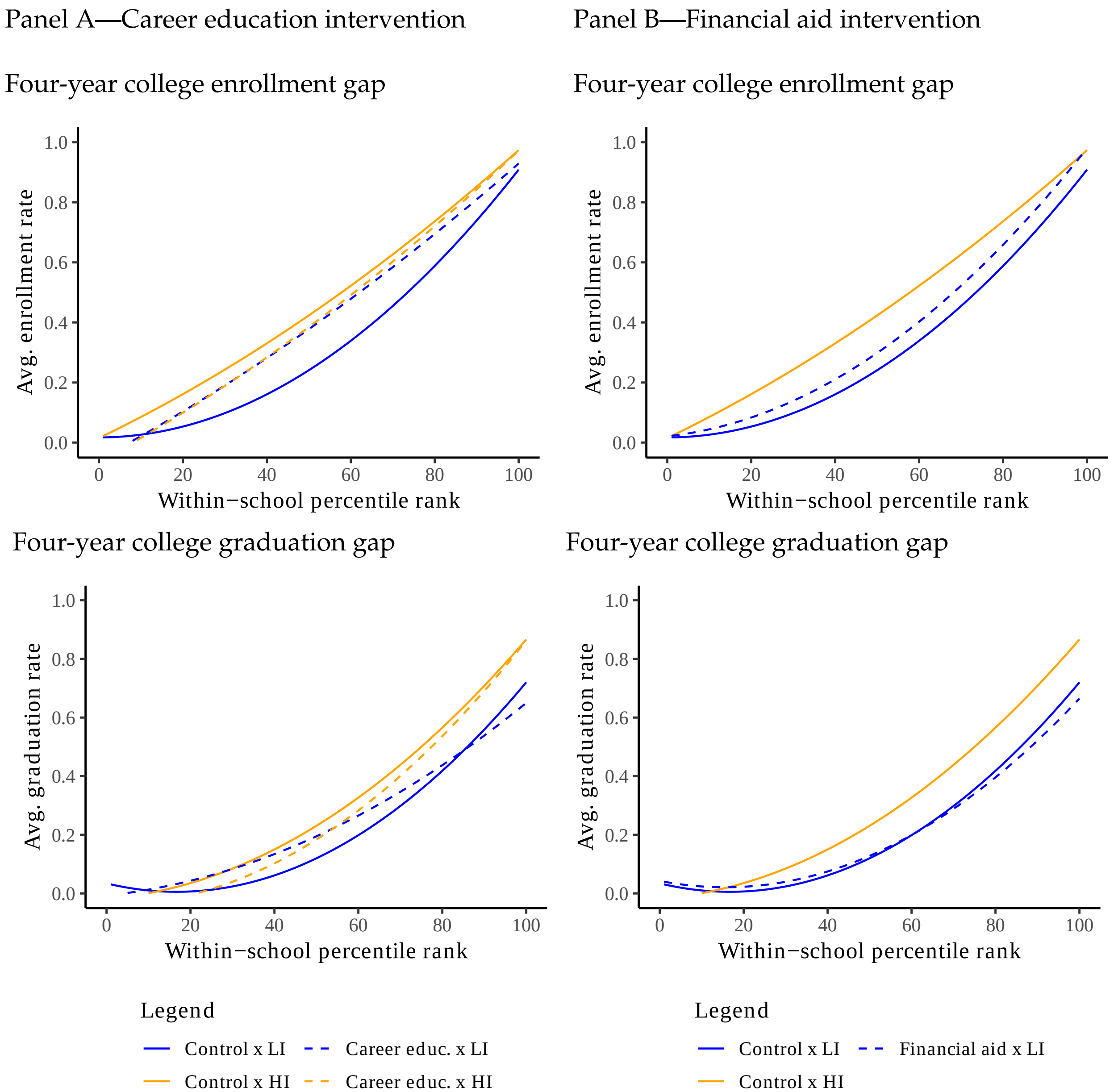


Figure 4: Enrollment Rates of High- and Low-Income Students
by Percentile Rank and Treatment Arms

Notes: The figure plots, across within-school test scores percentile rank, the four-year college enrollment and graduation rates of high- and low-income students. Panel A plots the rates for students in the career education group and Panel B the rates for students in the financial aid group. The enrollment rates in the control group are also shown for comparability purposes. Each rate is a simple average of the rates across the 30 schools, as estimated from equation A5.

do not play a major role in the four-year college enrollment and graduation gaps.

Overall, these findings indicate that career education is an important tool for aligning the four-year college enrollment and graduation rates of high- and low-income students with similar academic achievement. However, while the intervention effectively reduced inequality among equally-achieving pupils, differences in academic achievement account for a large part of the observed differences in enrollment and graduation between high- and low-income students (56–63 percent, Table A27). To fully decrease the gaps between the two types of students, one might also understand the factors driving the differences in academic achievement.

5 Conclusion

This paper investigates the effects of college grant aid, career education in high school, and the combination of the two on students' college enrollment, graduation, and earnings. I show that career education programs have the potential to improve students' long-term outcomes substantially. My results suggest that the reason why these types of programs are so effective stems from the existence of information and behavioral barriers that prevent students from making optimal decisions regarding post-secondary education. Removing these barriers will induce more low-income students and less high-income students to enroll in four-year colleges, resulting in a sharp reduction in the enrollment and graduation gaps between the two types of students.

One limitation of my study is the lack of power, which prevents any clear exploration of treatment effect heterogeneity. As the career education program resulted in increase in both graduation and dropout rates, I suspect heterogeneous benefits of the intervention on students. Further work should aim to understand who benefited from the intervention and who did not. This understanding would facilitate the design of career education programs that are better suited to helping all types of students.

Moreover, a key question remains unanswered: what features of the career education program were the more effective at increasing low- income students' enrollment? Previous studies suggest that the provision of information alone is not helpful is increasing students' enrollment rates (Bird et al. (2021); Kerr et al. (2015); Bonilla, Bottan, and Ham (2015); Hastings et al. (2016); Carrell and Sacerdote (2017)). By contrast, the intervention provided insights into the post-secondary education application process and decision-making, a dimension that has proven to be effective in increasing college enrollment rates (Avery (2013); Stephan and Rosenbaum (2013); Castleman, Page, and Schooley (2014); Carrell and Sacerdote (2017); Cunha, Miller, and Weisburst (2018); Oreopoulos and Ford (2019)). The fact that programs offering guidance are so efficacious in increasing the enrollment of students and (as I show) in enhancing their long-term outcomes is likely to be explained by their lack of attention when it comes to college possibilities (French and Oreopoulos (2017)).

In this paper, I also show that providing students with additional financial aid has no monetary benefits in the long run. This result was surprising given the fact that the intervention led to an increase in the fraction of students who enrolled and graduated from community colleges. It indicates that students were induced to enroll in programs with limited monetary returns. This lack of returns might be specific to the marginal students but might also arise from a general lack of benefits of some community college programs. My findings underscore the importance of understanding the returns to community college attendance.

The extent to which my findings extend to other contexts and countries remains to be seen. There are strong reasons to believe that my main finding, according to which career education programs are efficacious in enhancing students' long-term outcomes, can be extended to other contexts as well. In fact, many US-specific studies demonstrated that career counseling programs, as the program studied in this paper, are effective in increasing students' enrollment in four-year colleges. It is thus natural to think that they would also result in an increase in earnings.

However, my results on the effects of the financial aid intervention are possibly specific to the Canadian context. Two features of the Canadian context make it different from other countries. First, unlike other countries, Canada is characterized by a very high enrollment rate in community and private career colleges, which might make the results on community colleges specific to this country. Second, public colleges and universities are highly subsidized, and a number of grants and loans are already available in Canada, making financial constraints possibly less binding than in countries with weaker financial aid systems.

In the future, I plan to pursue my analysis of the Future to Discover experiment in three ways. First, I will continue to track students to confirm my findings on the long-term effects of the three interventions and assess their overall effects on lifetime earnings. Second, I will build a structural model of college enrollment under imperfect information and Bayesian learning to exactly quantify the extent to which students are affected by informational and behavioral barriers and provide counterfactual estimates of the gain in earnings that removing these barriers would create. Third, I will exploit exogenous variations in the timing of career counseling workshops created by weather conditions in order to identify how the timing of information affects the decisions made by students.

References

Anderson, Michael L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 103 (484): 1481–1495.

Avery, Christopher. 2013. "Evaluation of the College Possible Program: Results from a Randomized Controlled Trial."

Bailey, Drew H., Greg J. Duncan, Flávio Cunha, Barbara R. Foorman, and David S. Yeager. 2020. "Persistence and Fade-Out of Educational-Intervention Effects: Mechanisms and Potential Solutions." *Psychological Science in the Public Interest* 21 (2): 55–97.

Bailey, Martha, and Susan Dynarski. 2011. "Gains and Gaps: Changing Inequality in U.S. College Entry and Completion."

Becker, Gary S. 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.*

Belley, Philippe, Marc Frenette, and Lance J. Lochner. 2014. "Post-secondary attendance by parental income in the U.S. and Canada: Do financial aid policies explain the differences?" *Canadian Journal of Economics/Revue canadienne d'économique* 47 (2): 664–696.

Belley, Philippe, and Lance J. Lochner. 2007. "The Changing Role of Family Income and Ability in Determining Educational Achievement." *Journal of Human Capital* 1 (1): 37–89.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2013. "Inference on treatment effects after selection among high-dimensional controls." *Review of Economic Studies* 81 (2): 608–650.

Benjamini, Yoav, Abba M Krieger, and Daniel Yekutieli. 2006. "Adaptive linear step-up procedures that control the false discovery rate." *Biometrika* 93 (3): 491–507.

Bettinger, Eric P., Oded Gurantz, Laura Kawano, Bruce Sacerdote, and Michael Stevens. 2019. "The long-run impacts of financial aid: Evidence from California's Cal Grant." *American Economic Journal: Economic Policy* 11 (1): 64–94.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. "The role of application assistance and information in college decisions: Results from the H&R Bock FASFA experiment." *Quarterly Journal of Economics* 127 (3): 1205–1242.

Bird, Kelli A., Benjamin L. Castleman, Jeffrey T. Denning, Joshua Goodman, Cait Lamberton, and Kelly Ochs Rosinger. 2021. "Nudging at scale: Experimental evidence from FAFSA completion campaigns." *Journal of Economic Behavior and Organization* 183:105–128.

Blossfeld, Hans-Peter, and Yossi Shavit. 1993. *Persisting Barriers: Changes in Educational Opportunities in Thirteen Countries,* 408.

Bonilla, Leonardo, Nicolas L Bottan, and Andrés Ham. 2015. "Information Policies and Higher Education Choices: Experimental Evidence from Colombia."

Carrell, Scott, and Bruce Sacerdote. 2017. "Why do college-going interventions work?" *American Economic Journal: Applied Economics* 9 (3): 124–151.

Castleman, Benjamin L., and Joshua Goodman. 2018. "Intensive College Counseling and the Enrollment and Persistence of Low-Income Students." *Education Finance and Policy* 13 (1): 19–41.

Castleman, Benjamin L., and Bridget Terry Long. 2016. "Looking beyond enrollment: The causal effect of need-based grants on college access, persistence, and graduation." *Journal of Labor Economics* 34 (4): 1023–1073.

Castleman, Benjamin L., Lindsay C. Page, and Korynn Schooley. 2014. "The Forgotten Summer: Does the Offer of College Counseling After High School Mitigate Summer Melt Among College-Intending, Low-Income High School Graduates?" *Journal of Policy Analysis and Management* 33 (2): 320–344.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner. 2014. "Is the United States still a land of opportunity? Recent trends in intergenerational mobility." *American Economic Review* 104 (5): 141–147.

Cunha, Jesse M., Trey Miller, and Emily Weisburst. 2018. "Information and College Decisions: Evidence From the Texas GO Center Project." *Educational Evaluation and Policy Analysis* 40 (1): 151–170.

Currie, Sheila, Judith Hutchison, Reuben Ford, Isaac Kwakye, and Doug Tattrie. 2007. *Future to Discover: Early Implementation Report.* Technical report.

Denning, Jeffrey T., Benjamin M. Marx, and Lesley J. Turner. 2019. "ProPelled: The effects of grants on graduation, earnings, and welfare." *American Economic Journal: Applied Economics* 11 (3): 193–224.

Dynarski, Susan, C. Libassi, Katherine Michelmore, and Stephanie Owen. 2021. "Closing the Gap: The Effect of Reducing Complexity and Uncertainty in College Pricing on the Choices of Low-Income Students." *American Economic Review* 111 (6): 1721–56.

Eng, Amanda, and Jordan Matsudaira. 2021. "Pell grants and student success: Evidence from the universe of federal aid recipients." *Journal of Labor Economics* 39 (S2): S413–S454.

Fack, Gabrielle, and Julien Grenet. 2015. "Improving college access and success for low-income students: Evidence from a large need-based grant program." *American Economic Journal: Applied Economics* 7 (2): 1–34.

Ford, Reuben, Marc Frenette, Claudia Nicholson, Isaac Kwakye, Taylor S. Hui, Judith Hutchison, Sabina Dobrer, Heather S. Fowler, and Shopie Hébert. 2012. *Future to Discover: Post-secondary Impacts Report.* Technical report.

Ford, Reuben, and Isaac Kwakye. 2016. *Future to Discover: Sixth Year Post-secondary Impacts Report.* Technical report. Social Research and Demonstration Corporation.

French, Robert, and Philip Oreopoulos. 2017. "Behavioral barriers transitioning to college." *Labour Economics* 47:48–63.

Frenette, Marc. 2017. *Postsecondary Enrolment by Parental Income : Recent National and Provincial Trends.* Technical report Economic insights, no. 70. Statistics Canada.

Goldrick-Rab, Sara, Robert Kelchen, Douglas N Harris, and James Benson. 2016. "Reducing income inequality in educational attainment: Experimental evidence on the impact of financial aid on college completion." *American Journal of Sociology* 121 (6): 1762–1817.

Hastings, Justine S., Christopher A. Neilson, Anely Ramirez, and Seth D. Zimmerman. 2016. "(Un)informed college and major choice: Evidence from linked survey and administrative data." *Economics of Education Review* 51:136–151.

Herbaut, Estelle, and Koen Geven. 2020. "What works to reduce inequalities in higher education? A systematic review of the (quasi-)experimental literature on outreach and financial aid." *Research in Social Stratification and Mobility* 65.

Heß, Simon. 2017. “Randomization inference with stata: A guide and software.” *Stata Journal* 17 (3): 630–651.

Hoxby, Caroline M., and Christopher Avery. 2013. “The Missing "One-Offs": The Hidden Supply of High-Achieving, Low Income Students.” *Brookings Papers on Economic Activity* 2013 (1): 1–65.

Hui, Taylor S., and Reuben Ford. 2018. *Education and Labour Market Impacts of the Future to Discover Project: Summary of Key Findings.* Technical report. Toronto: Higher Education Quality Council of Ontario.

Jones, Glen A., and Sharon X. Li. 2015. “The “Invisible” Sector: Private Higher Education in Canada.” In *Private Higher Education: A Global Perspective,* 1–33.

Keane, Michael P., and Kenneth I. Wolpin. 2001. “The Effect of Parental Transfers and Borrowing Constraints on Educational Attainment.” *International Economic Review* 42 (4): 1051–1103.

Kerr, Sari Pekkala, Tuomas Pekkarinen, Matti Sarvimäki, and Roope Uusitalo. 2015. “Post-Secondary Education and Information on Labor Market Prospects: A Randomized Field Experiment.”

Kinsler, Josh, and Ronni Pavan. 2011. “Family income and higher education choices: The importance of accounting for college quality.” *Journal of Human Capital* 5 (4): 453–477.

Lochner, Lance J., and Alexander Monge-Naranjo. 2012. “Credit Constraints in Education.” *Annual Review of Economics* 4 (1): 225–256.

Oreopoulos, Philip, and Reuben Ford. 2019. “Keeping College Options Open: A Field Experiment to Help all High School Seniors Through the College Application Process.” *Journal of Policy Analysis and Management* 38 (2): 426–454.

Oreopoulos, Philip, and Kjell G. Salvanes. 2011. “Priceless: The nonpecuniary benefits of schooling.” *Journal of Economic Perspectives* 25 (1): 159–184.

Page, Lindsay C., and Judith Scott-Clayton. 2016. “Improving college access in the United States: Barriers and policy responses.” *Economics of Education Review* 51:4–22.

Scott-Clayton, Judith, and Basit Zafar. 2019. “Financial aid, debt management, and socioeconomic outcomes: Post-college effects of merit-based aid.” *Journal of Public Economics* 170:68–82.

Seaman, Shaun R, and Ian R White. 2013. "Review of inverse probability weighting for dealing with missing data." *Statistical Methods in Medical Research* 22 (3): 278–295.

Statistics Canada. 2020. *Education Indicators in Canada: An International Perspective 2020.* Technical report.

Stephan, Jennifer L, and James E Rosenbaum. 2013. "Can High Schools Reduce College Enrollment Gaps With a New Counseling Model?" *Educational Evaluation and Policy Analysis* 35 (2): 200–219.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data.* MIT press.

Young, Alwyn. 2019. "Channeling Fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results." *Quarterly Journal of Economics* 134 (2): 557–598.

A Appendix—Additional Tables and Figures

Table A1: Assignment to Treatments, by Parental Income

	Low-income students	High-income students	All students
Control group	600 (28%)	850 (58%)	
Career education group	430 (20%)	610 (42%)	
Financial aid group	550 (26%)	.	
Mixed intervention group	550 (26%)	.	
Total	2,130	1,460	3,590

Notes: The table reports the number and fraction of students assigned to each of the treatment and control groups, by parental income. The fractions are reported in parentheses. Students excluded from the data collection are not shown in this table. Sample sizes are rounded to the nearest 10 for data confidentiality concerns.

Table A2: Test for Differential Attrition by Treatment Status

	Low-income students (1)	High-income students (2)
Attrition rate in control group	0.018	0.007
Difference between control group and		
Career education group	0.0062	-0.0028
	(0.0093)	(0.0040)
Financial aid group	0.0026	
	(0.0082)	
Mixed intervention group	-0.0062	
	(0.0073)	

Notes: Differences are obtained from an OLS regression of the attrition dummy on treatment dummies, strata dummies and controls. Each column represents a separate regression. Huber–White robust standard errors in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table A3: Baseline Characteristics and Differences Between Treatment and Control Groups. Low-income Students.

	Control mean	Career education group difference	Financial aid group difference	Mixed intervention group difference
Demographics:				
Woman	0.54	-0.009	0.003	-0.039
	(0.50)	(0.032)	(0.029)	(0.029)
English speaker	0.54	0.006	-0.006	-0.011
	(0.50)	(0.013)	(0.013)	(0.013)
One parent born outside Canada	0.38	-0.004	-0.007	0.031
	(0.49)	(0.031)	(0.029)	(0.029)
Household composition:				
Single parent	0.34	0.006	-0.006	0.016
	(0.48)	(0.030)	(0.028)	(0.028)
Parental working status:				
Parent(s) not working	0.20	0.001	-0.024	-0.016
	(0.40)	(0.025)	(0.023)	(0.023)
Highest level of education of parents:				
Four-year college degree	0.052	0.013	0.008	0.001
	(0.22)	(0.015)	(0.013)	(0.013)
Community college diploma	0.41	0.016	0.047	0.036
	(0.49)	(0.031)	(0.029)	(0.029)
High school diploma	0.32	-0.014	-0.017	-0.027
	(0.47)	(0.029)	(0.027)	(0.027)
Less than high school	0.22	-0.016	-0.039*	-0.010
	(0.42)	(0.025)	(0.023)	(0.024)
Aspiration in Grade 9:				
Wants a four-year college degree only	0.39	-0.002	-0.022	0.013
	(0.49)	(0.031)	(0.029)	(0.029)
Grade 9 average test score:				
Missing test scores	0.022	-0.001	0.001	0.001
	(0.15)	(0.003)	(0.003)	(0.004)
Bottom quintile	0.28	-0.077***	-0.032	-0.016
	(0.45)	(0.026)	(0.026)	(0.026)
Second quintile	0.24	-0.007	-0.031	-0.003
	(0.43)	(0.026)	(0.025)	(0.025)
Third quintile	0.19	0.004	0.032	-0.005
	(0.39)	(0.025)	(0.024)	(0.023)
Fourth quintile	0.15	0.027	0.035	0.028
	(0.36)	(0.023)	(0.022)	(0.022)
Top quintile	0.12	0.053**	-0.005	-0.005
	(0.32)	(0.022)	(0.019)	(0.019)
P-value F-test of joint significance			0.55	
Sample Size	600	1,030	1,150	1,150

Notes: Differences are based on OLS regressions of each characteristic on treatment and strata dummies. Joint test P-values are computed using a F-test of joint significance from a multinomial regression of treatment assignment on all listed characteristics and strata dummies. The sample is restricted to low-income students. Numbers in parentheses are (i) standard deviations in the control mean column and (ii) Huber–White robust standard errors in the difference with the control group columns. *** p<0.01 ** p<0.05 * p<0.1.

Table A4: Baseline Characteristics and Differences Between Treatment and Control Groups. High-income Students.

	Control mean	Career education group difference
Demographics:		
Woman	0.50	0.020
	(0.50)	(0.027)
English speaker	0.52	0.005
	(0.50)	(0.013)
One parent born outside Canada	0.13	0.001
	(0.34)	(0.018)
Household composition:		
Single parent	0.077	-0.012
	(0.27)	(0.014)
Parental working status:		
Parent(s) not working	0.022	-0.006
	(0.15)	(0.007)
Highest level of education of parents:		
Four-year college degree	0.30	-0.007
	(0.46)	(0.023)
Community college diploma	0.51	-0.017
	(0.50)	(0.026)
High school diploma	0.15	0.025
	(0.35)	(0.019)
Less than high school	0.037	-0.001
	(0.19)	(0.010)
Aspiration in Grade 9:		
Wants a four-year college degree only	0.49	-0.001
	(0.50)	(0.026)
Grade 9 average test score:		
Missing test scores in G9	0.020	-0.004*
	(0.14)	(0.002)
Bottom quintile	0.13	0.005
	(0.34)	(0.018)
Second quintile	0.17	-0.012
	(0.37)	(0.019)
Third quintile	0.19	0.005
	(0.39)	(0.021)
Fourth quintile	0.23	-0.017
	(0.42)	(0.022)
Top quintile	0.27	0.024
	(0.44)	(0.023)
P-value F-test of joint significance		0.95
Sample Size	850	1,460

Notes: Differences are based on OLS regressions of each characteristic on treatment and strata dummies. Joint test P-values are computed using a F-test of joint significance from a probit regression of treatment dummy on all listed characteristics and strata dummies. The sample is restricted to high-income students. Numbers in parentheses are (i) standard deviations in the control mean column and (ii) Huber–White robust standard errors in the difference with the control group columns. *** p<0.01 ** p<0.05 * p<0.1.

Table A5: Baseline Characteristics and Differences Between Treatment and Control Groups. Low-income Students. Post-Attrition.

	Control mean	Career education group difference	Financial aid group difference	Mixed intervention group difference
Demographics:				
Woman	0.54	-0.004	0.004	-0.035
	(0.50)	(0.032)	(0.030)	(0.030)
English speaker	0.53	0.007	-0.006	-0.010
	(0.50)	(0.013)	(0.013)	(0.013)
One parent born outside Canada	0.38	-0.003	-0.002	0.035
	(0.49)	(0.031)	(0.029)	(0.029)
Household composition:				
Single parent	0.34	0.008	0.000	0.019
	(0.47)	(0.030)	(0.028)	(0.028)
Parental working status:				
Parent(s) not working	0.21	-0.003	-0.027	-0.018
	(0.40)	(0.025)	(0.023)	(0.023)
Highest level of education of parents:				
Four-year college degree	0.053	0.012	0.004	0.001
	(0.22)	(0.015)	(0.013)	(0.013)
Community college diploma	0.41	0.018	0.047	0.029
	(0.49)	(0.031)	(0.029)	(0.029)
High school diploma	0.32	-0.015	-0.013	-0.023
	(0.47)	(0.030)	(0.027)	(0.027)
Less than high school	0.22	-0.015	-0.038	-0.007
	(0.42)	(0.026)	(0.023)	(0.024)
Aspiration in Grade 9:				
Wants a four-year college degree only	0.40	-0.011	-0.027	0.005
	(0.49)	(0.031)	(0.029)	(0.029)
Grade 9 average test score:				
Missing test scores in G9	0.022	-0.001	0.001	-0.001
	(0.15)	(0.003)	(0.004)	(0.003)
Bottom quintile	0.28	-0.080***	-0.032	-0.012
	(0.45)	(0.026)	(0.026)	(0.026)
Second quintile	0.24	-0.013	-0.032	-0.002
	(0.43)	(0.027)	(0.025)	(0.025)
Third quintile	0.19	0.007	0.030	-0.010
	(0.39)	(0.025)	(0.024)	(0.023)
Fourth quintile	0.15	0.028	0.035	0.030
	(0.36)	(0.024)	(0.023)	(0.022)
Top quintile	0.12	0.059***	-0.002	-0.004
	(0.32)	(0.022)	(0.019)	(0.019)
P-value *F*-test of joint significance			0.45	
Sample Size	590	1,010	1,120	1,130

Notes: Differences are based on OLS regressions of each characteristic on treatment and strata dummies. Joint test *P*-values are computed using a *F*-test of joint significance from a multinomial regression of treatment assignment on all listed characteristics and strata dummies. The sample is restricted to low-income students who are part of the final analytical sample. Numbers in parentheses are (i) standard deviations in the control mean column and (ii) Huber–White robust standard errors in the difference with the control group columns. *** p<0.01 ** p<0.05 * p<0.1.

Table A6: Baseline Characteristics and Differences Between Treatment and Control Groups. High-income Students. Post-Attrition.

	Control mean	Career education group difference
Demographics:		
Woman	0.50	0.019
	(0.50)	(0.027)
English speaker	0.52	0.005
	(0.50)	(0.013)
One parent born outside Canada	0.13	0.004
	(0.34)	(0.018)
Household composition:		
Single parent	0.073	-0.008
	(0.26)	(0.014)
Parental working status:		
Parent(s) not working	0.023	-0.006
	(0.15)	(0.007)
Highest level of education of parents:		
Four-year college degree	0.30	-0.005
	(0.46)	(0.024)
Community college diploma	0.52	-0.019
	(0.50)	(0.026)
High school diploma	0.15	0.025
	(0.35)	(0.019)
Less than high school	0.037	-0.002
	(0.19)	(0.010)
Aspiration in Grade 9:		
Wants a four-year college degree only	0.49	-0.002
	(0.50)	(0.027)
Grade 9 average test score:		
Missing test scores in G9	0.020	-0.004*
	(0.14)	(0.002)
Bottom quintile	0.13	0.002
	(0.34)	(0.018)
Second quintile	0.16	-0.012
	(0.37)	(0.019)
Third quintile	0.18	0.007
	(0.39)	(0.021)
Fourth quintile	0.23	-0.016
	(0.42)	(0.022)
Top quintile	0.27	0.022
	(0.44)	(0.023)
P-value F-test of joint significance		0.96
Sample Size	850	1,450

Notes: Differences are based on OLS regressions of each characteristic on treatment and strata dummies. Joint test P-values are computed using a F-test of joint significance from a probit regression of treatment dummy on all listed characteristics and strata dummies. The sample is restricted to high-income students who are part of the final analytical sample. Numbers in parentheses are (i) standard deviations in the control mean column and (ii) Huber–White robust standard errors in the difference with the control group columns. *** p<0.01 ** p<0.05 * p<0.1.

Table A7: Distribution of missing earnings records

	# of students (1)	# of data points (2)	# missing (3)	% missing (4)
Data collected until age 28	2,320	23,200	1,200	5.2 %
Data collected until age 24	1,210	12,100	5,400	44.6 %
Until age 24	1,210	7,260	560	7.7 %
Between ages 25 and 28	1,210	4,840	4,840	100 %
Total	3,540	35,400	6,600	18.6 %

Notes: The table reports the number of students for which earnings data were collected until age 28 and until age 24 in column (1), the corresponding number of earnings data points theoretically collected in column (2), and the number and fraction of missing records over the total number of data points in column (3) and (4).

Table A8: Sensitivity of the Results to the Inclusion and Exclusion of Controls. Career Education Intervention. Low-income Students.

Dependent variable	No control (1)	Controls (2)	LASSO (3)
Panel A—College Enrollment			
Ever enrolled in any public college	0.083***	0.034	0.031
	(0.031)	(0.028)	(0.028)
Ever enrolled in a four-year college	0.136***	0.083***	0.079***
	(0.029)	(0.024)	(0.024)
Ever enrolled in a community college	-0.002	-0.012	-0.012
	(0.030)	(0.030)	(0.030)
Panel B—College Graduation			
Ever graduated from any college	0.034	-0.007	-0.011
	(0.030)	(0.028)	(0.028)
Ever graduated from a four-year college	0.074***	0.037*	0.033
	(0.024)	(0.021)	(0.021)
Ever graduated from a community college	-0.024	-0.033	-0.034
	(0.027)	(0.027)	(0.026)
Panel C—College Dropout			
Dropped out of college	0.039	0.032	0.031
	(0.024)	(0.024)	(0.024)
Panel D—Earnings			
Annual labor income at age 28 (CA$)	5,555***	3,265*	3,786**
	(1,827)	(1,688)	(1,684)
Annual total earnings at age 28 (CA$)	5,668***	3,631**	4,032**
	(1,911)	(1,801)	(1,791)

Notes: The table reports the treatment effects of eligibility for the career education program on the main outcomes of interest, using different sets of controls. Column (1) reports the estimates from separate OLS regressions of the dependent variables on treatment and strata dummies only. Column (2) reports the estimates from separate OLS regressions of the dependent variables on treatment dummies, strata dummies, and controls for student baseline characteristics, as reported in the main tables. Column (3) reports the estimates from separate OLS regressions of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics selected using post-double-selection lasso. The sample is restricted to low-income students. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A9: Sensitivity of the Results to the Inclusion and Exclusion of Controls. Financial Aid Intervention. Low-income Students.

Dependent variable	No control (1)	Controls (2)	LASSO (3)
Panel A—College Enrollment			
Ever enrolled in any public college	0.103***	0.080***	0.080***
	(0.029)	(0.026)	(0.026)
Ever enrolled in a four-year college	0.053**	0.032	0.032
	(0.026)	(0.021)	(0.021)
Ever enrolled in a community college	0.072**	0.065**	0.066**
	(0.029)	(0.028)	(0.028)
Panel B—College Graduation			
Ever graduated from any college	0.093***	0.075***	0.074***
	(0.029)	(0.026)	(0.026)
Ever graduated from a four-year college	0.010	-0.003	-0.003
	(0.021)	(0.018)	(0.018)
Ever graduated from a community college	0.083***	0.076***	0.077***
	(0.027)	(0.026)	(0.026)
Panel C—College Dropout			
Dropped out of college	0.002	-0.003	-0.001
	(0.021)	-0.021	(0.021)
Panel D—Earnings			
Annual labor income at age 28 (CA$)	510	-473	-472
	(1,603)	(1,477)	(1,483)
Annual total earnings at age 28 (CA$)	1,441	530	545
	(1,564)	(1,483)	(1,485)

Notes: The table reports the treatment effects of eligibility for the financial aid on the main outcomes of interest, using different sets of controls. Column (1) reports the estimates from separate OLS regressions of the dependent variables on treatment and strata dummies only. Column (2) reports the estimates from separate OLS regressions of the dependent variables on treatment dummies, strata dummies, and controls for student baseline characteristics, as reported in the main tables. Column (3) reports the estimates from separate OLS regressions of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics selected using post-double-selection lasso. The sample is restricted to low-income students. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A10: Sensitivity of the Results to the Inclusion and Exclusion of Controls. Mixed Intervention. Low-income Students.

Dependent variable	No control (1)	Controls (2)	LASSO (3)
Panel A—College Enrollment			
Ever enrolled in any public college	0.071**	0.059**	0.059**
	(0.029)	(0.025)	(0.025)
Ever enrolled in a four-year college	0.096***	0.087***	0.085***
	(0.027)	(0.021)	(0.021)
Ever enrolled in a community college	0.017	0.013	0.010
	(0.028)	(0.028)	(0.028)
Panel B—College Graduation			
Ever graduated from any college	0.065**	0.055**	0.054**
	(0.029)	(0.026)	(0.026)
Ever graduated from a four-year college	0.034	0.026	0.025
	(0.022)	(0.018)	(0.018)
Ever graduated from a community college	0.031	0.028	0.026
	(0.026)	(0.026)	(0.026)
Panel C—College Dropout			
Dropped out of college	-0.002	-0.003	-0.003
	(0.021)	-0.021	(0.021)
Panel D—Earnings			
Annual labor income at age 28 (CA$)	2,260	1,588	1,522
	(1,596)	(1,506)	(1,494)
Annual total earnings at age 28 (CA$)	1,970	1,415	1,412
	(1,533)	(1,471)	(1,459)

Notes: The table reports the treatment effects of eligibility for both the career education and the financial aid interventions on the main outcomes of interest, using different sets of controls. Column (1) reports the estimates from separate OLS regressions of the dependent variables on treatment and strata dummies only. Column (2) reports the estimates from separate OLS regressions of the dependent variables on treatment dummies, strata dummies, and controls for student baseline characteristics, as reported in the main tables. Column (3) reports the estimates from separate OLS regressions of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics selected using post-double-selection lasso. The sample is restricted to low-income students. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A11: Fisher-Exact P-values and P-values Corrected for Multiple Hypothesis Testing. Low-Income Sample.

	Career education			Financial aid			Mixed intervention		
Dependent variable	Classic p-values (1)	Exact p-values (2)	FDR q-values (3)	Classic p-values (4)	Exact p-values (5)	FDR q-values (6)	Classic p-values (7)	Exact p-values (8)	FDR q-values (9)
Panel A—College Enrollment									
Ever enrolled in any public college	0.225	0.221	0.221	0.002	0.003	0.017	0.021	0.018	0.068
Ever enrolled in a four-year college	0.000	0.000	0.001	0.138	0.127	0.174	0.000	0.000	0.001
Ever enrolled in a community college	0.686	0.681	0.448	0.023	0.021	0.044	0.654	0.657	0.646
Panel B—College Graduation									
Ever graduated from any college	0.811	0.810	0.448	0.005	0.005	0.017	0.037	0.044	0.084
Ever graduated from a four-year college	0.082	0.065	0.171	0.880	0.884	0.686	0.154	0.160	0.275
Ever graduated from a community college	0.213	0.226	0.221	0.004	0.002	0.017	0.275	0.279	0.400
Panel C—College Dropout									
Dropped out of college	0.178	0.166	0.221	0.890	0.895	0.686	0.882	0.880	0.814
Dropped out of four-year college	0.037	0.031	0.153	0.128	0.123	0.174	0.005	0.005	0.026
Dropped out of community college	0.369	0.353	0.327	0.352	0.352	0.336	0.367	0.366	0.400
Panel D—Earnings									
Annual labor income at age 28 (CA$)	0.053	0.059	0.153	0.749	0.740	0.686	0.292	0.290	0.400
Annual total earnings at age 28 (CA$)	0.044	0.036	0.153	0.721	0.716	0.686	0.336	0.332	0.400

Notes: The table reports the p-values associated with the tests of significance of the main treatment effects of eligibility for the career education program, eligibility for the financial aid, and eligibility for both. Columns (1), (4), and (7) present the sampling based unadjusted p-values presented in the main text. Columns (2), (5), and (8) present the Fisher-exact p-values. And Columns (3), (6), and (9) present the sharpened q-values which control for the False Discovery Rate. Sample is restricted to low-income students.

Table A12: Fisher-Exact P-values and P-values Corrected for Multiple Hypothesis Testing. High-Income Sample.

	Career education		
	Classic p-values	Exact p-values	FDR q-values
Dependent variable	(1)	(2)	(3)
Panel A—College Enrollment			
Ever enrolled in any public college	0.161	0.153	0.549
Ever enrolled in a four-year college	0.065	0.069	0.549
Ever enrolled in a community college	0.684	0.686	0.810
Panel B—College Graduation			
Ever graduated from any college	0.571	0.557	0.750
Ever graduated from a four-year college	0.436	0.439	0.597
Ever graduated from a community college	0.774	0.772	0.810
Panel C—College Dropout			
Dropped out of college	0.896	0.901	0.810
Dropped out of four-year college	0.159	0.168	0.549
Dropped out of community college	0.244	0.246	0.549
Panel D—Earnings			
Annual labor income at age 28 (CA$)	0.116	0.107	0.549
Annual total earnings at age 28 (CA$)	0.096	0.090	0.549

Notes: The table reports the p-values associated with the tests of significance of the main treatment effects of eligibility for the career education program, eligibility for the financial aid, and eligibility for both. Columns (1), (4), and (7) present the sampling based unadjusted p-values presented in the main text. Columns (2), (5), and (8) present the Fisher-exact p-values. And Columns (3), (6), and (9) present the sharpened q-values which control for the False Discovery Rate. Sample is restricted to high-income students.

Table A13: Treatments Effects on Low-Income Students' High School Outcomes

	Std. average test score in Grade 12		Ever graduated from high school	
Treatment effect of	(1)	(2)	(3)	(4)
Career education	-0.032	-0.028	0.022	0.024
	(0.058)	(0.061)	(0.019)	(0.019)
P-value selective missingness	0.623		0.752	
Financial aid	-0.007	-0.014	0.000	0.000
	(0.052)	(0.054)	(0.019)	(0.019)
P-value selective missingness	0.454		0.223	
Inverse Probability Weights	N	Y	N	Y
Control mean	-0.20		0.85	
Sample size	1,720		1,860	

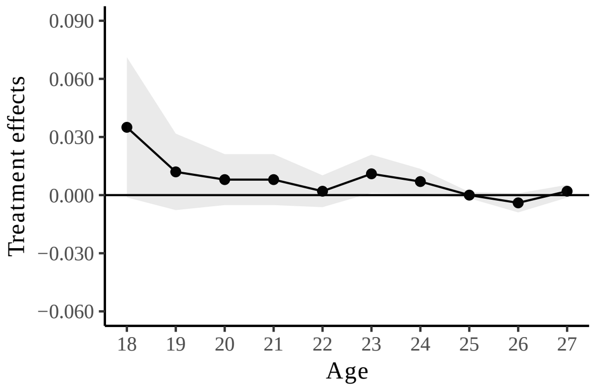
Notes: The table reports the treatment effects of eligibility for the career education program and eligibility for the financial aid on academic performance and high school graduation. Average test scores in Grade 12 is standardized with a mean of zero and a standard deviation of one across all students. Each column represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3 (see equation 1). I do not have information on test scores in Grade 12 and high school graduation for all students in the sample; test scores in Grade 12 and graduation data are missing for 20 percent and 13 percent of the low-income students, respectively. I test for selective attrition by regressing the indicator of missingness on the treatment dummies, strata dummies and controls, and report the p-value associated with the test of significance for each of the treatment coefficients. Columns (1) and (3) report the results of the unweighted regressions. To enable the comparison of the treatment effects measured on the restricted sample with the ones measured from the full sample, I also report the effects using IPW in columns (2) and (4). These weights are constructed from a probit regression of an indicator of missingness on treatment dummies, baseline characteristics, cohort and school dummies. The sample is restricted to low-income students. Sample sizes are rounded to the nearest 10 for data confidentiality concerns. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A14: Treatments Effects on Low-Income Students' Enrollment in Private Career Colleges

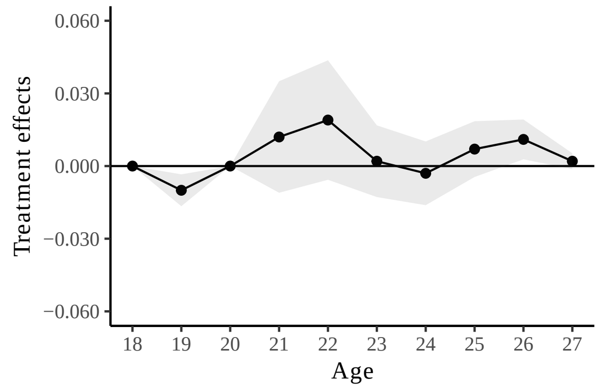
Treatment effect of	Enrolled in a private career college only (1)		(2)
Career education	0.006		0.008
	(0.024)		(0.024)
P-value selective missingness		0.508	
Financial aid	0.003		0.005
	(0.021)		(0.022)
P-value selective missingness		0.146	
Inverse Probability Weights	N		Y
Control mean		0.11	
Sample size		1,830	

Notes: The table reports the treatment effects of eligibility for the career education program and for the financial aid on private career college enrollment. The outcome takes the value of one if a student has ever enrolled in a private career college according to the survey conducted at age 20 but has never enrolled in a public college. Each column represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3 (see equation 1). 87 percent of low-income students answered the survey. I test for selective missingness by regressing the indicator of missingness on the treatment dummies, strata dummies and controls, and report the *p*-value associated with the test of significance for each of the treatment coefficients. Columns (1) and (3) report the results of the unweighted regressions and columns (2) and (4) of the regressions adjusted with inverse probability weights (IPW). These weights are constructed from a probit regression of an indicator of missingness on treatment dummies, baseline characteristics, cohort and school dummies. The sample is restricted to low-income students. Sample sizes are rounded to the nearest 10 for data confidentiality concerns. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

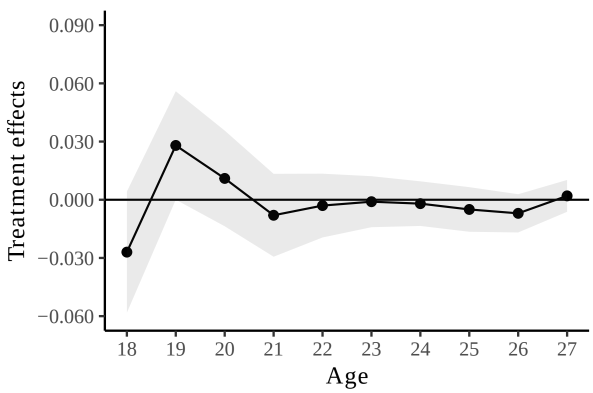
A1—Age at which students first enrolled in a four-year college



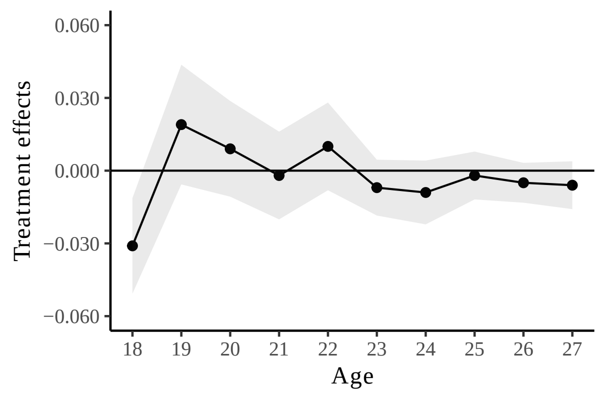
B1—Age at which students first graduated from a four-year college



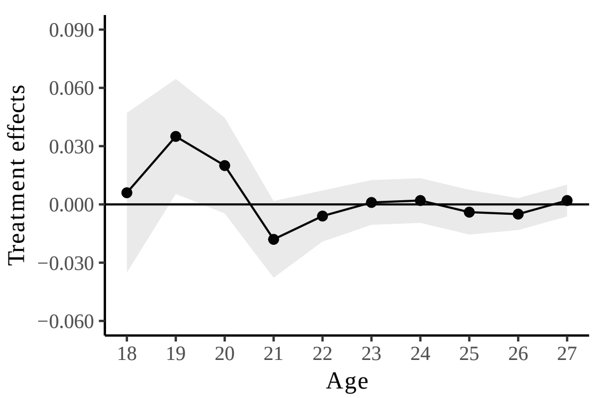
A2—Age at which students first enrolled in a community college



B2—Age at which students first graduated from a community college



A3—Age at which students first enrolled in any public college



B3—Age at which students first graduated from a public college

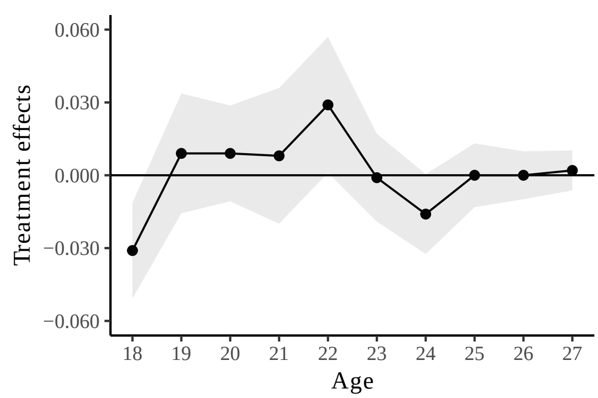


Figure A1: Dynamic Treatment Effects of Eligibility for the Career Education Program on College Enrollment and Graduation

Notes: The figure plots the effects of eligibility for the career education program on the fraction of students who first enrolled in college and who first graduated from college from ages 18 to 27. Point estimates together with the associated 90 percent confidence intervals are reported. Each point is estimated from a OLS regression of the outcome on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3. Huber–White robust standard errors are used to compute the confidence intervals.

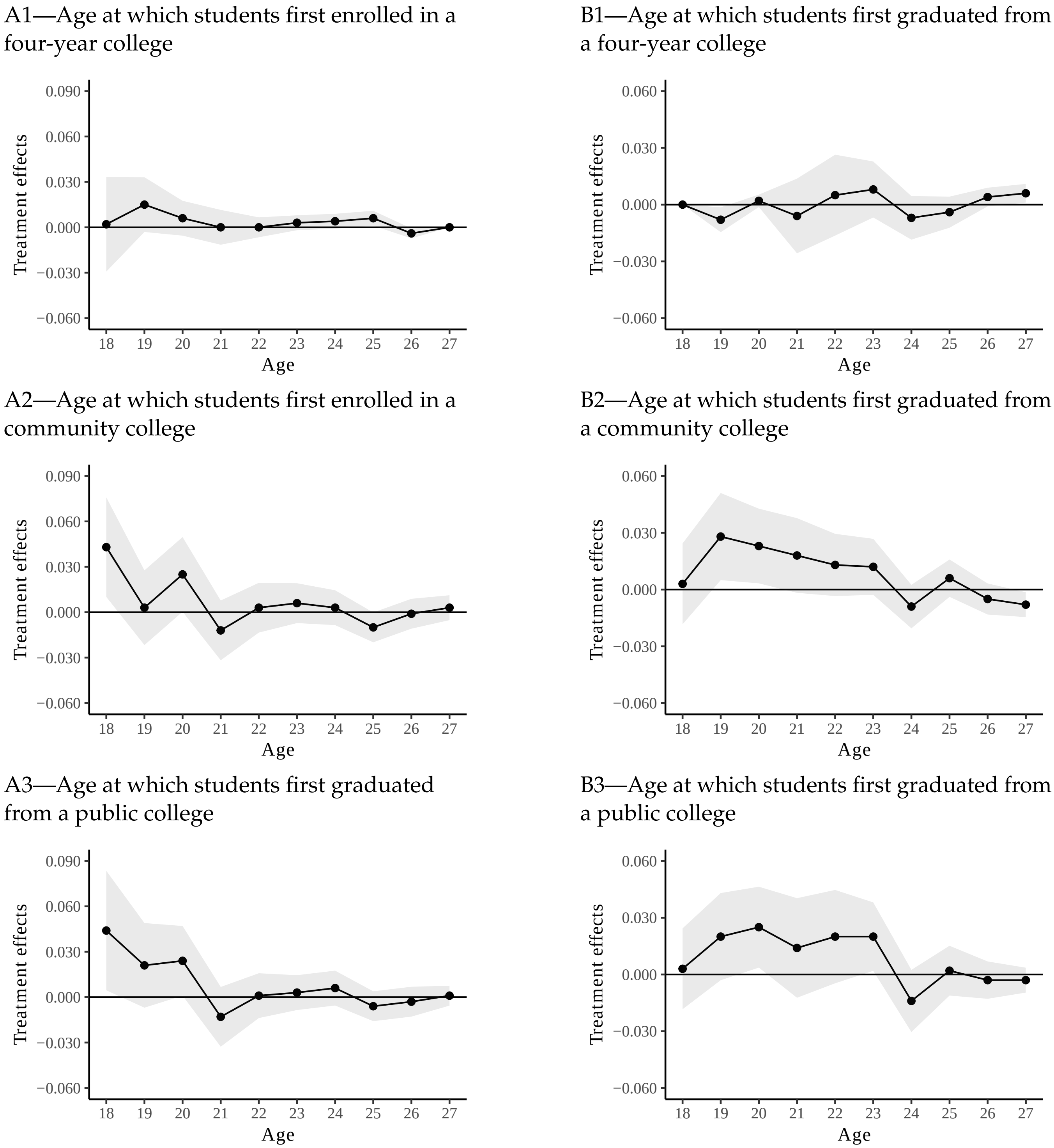


Figure A2: Dynamic Treatment Effects of Eligibility for the Financial Aid Intervention on College Enrollment and Graduation

Notes: The figure plots the effects of eligibility for the financial aid on the fraction of students who first enrolled in college and who first graduated from college from ages 18 to 27. Point estimates together with the associated 90 percent confidence intervals are reported. Each point is estimated from a OLS regression of the outcome on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3. Huber–White robust standard errors are used to compute the confidence intervals.

Table A15: Treatment Effects by Average Test Scores in Grade 9

	Ever enrolled in		Ever graduated from	
Test scores percentile rank (within-school)	Any public college	Four-year college	Any public college	Four-year college
Panel A—Treatment effects of the career education intervention				
25th	0.04	0.07	0.00	0.05
50th	0.02	0.13	0.00	0.07
75th	0.02	0.12	-0.01	0.04
P-value interaction terms	0.86	0.06	0.98	0.33
Panel B—Treatment effects of the financial aid intervention				
25th	0.10	0.02	0.08	0.01
50th	0.10	0.05	0.11	0.00
75th	0.06	0.06	0.09	-0.02
P-value interaction terms	0.54	0.37	0.50	0.88
Panel C—Treatment effects of the mixed intervention				
25th	0.05	0.07	0.04	0.01
50th	0.09	0.12	0.01	0.03
75th	0.10	0.15	-0.02	0.05
P-value interaction terms	0.40	0.03	0.89	0.53

Notes: The table reports the heterogeneity of the treatment effects of the three interventions by average test scores in Grade 9 for the main outcomes of interest. The sample is restricted to low-income students. Average test scores in Grade 9 is standardized within each school. Treatment effects are computed at the 25th, 50th, and 75th within-school percentile of the average test scores distribution. Each column represents a separate OLS regression of the dependent variable on treatment dummies, treatment dummies interacted with average test scores and average test scores squared, strata dummies, and controls for student baseline characteristics listed in Table A3, average test scores and average test scores squared. Treatment effects are constructed from the coefficients on the treatment dummies and the interaction terms. Huber–White robust standard errors are estimated. I test whether the two interaction terms a jointly significant and report the associated p-value.

Table A16: Treatments Effects on Low-Income Students' College Completion Conditional on Enrollment

Dependent variable	Control mean (1)	Career education (2)	Financial aid (3)	Mixed intervention (4)
Panel A—Conditional on any college enrollment				
Ever graduated for college	0.71	-0.051	0.028	0.022
		(0.039)	(0.035)	(0.036)
Panel B—Conditional on four-year college enrollment				
Highest degree is a four-year college degree	0.61	-0.012	-0.088	-0.051
		(0.058)	(0.059)	(0.057)
Highest degree is a community college diploma	0.12	-0.009	0.050	0.043
		(0.039)	(0.041)	(0.039)
Dropped out	0.27	0.021	0.038	0.008
		(0.054)	(0.052)	(0.052)
Panel C—Conditional on community college enrollment				
Highest degree is a four-year college degree	0.10	0.053	-0.015	0.020
		(0.033)	(0.026)	(0.027)
Highest degree is a community college diploma	0.60	-0.112**	0.085*	0.046
		(0.055)	(0.046)	(0.048)
Dropped out	0.30	0.059	-0.070*	-0.066
		(0.050)	(0.041)	(0.044)
Sample size	590		2,090	

Notes: The table reports the treatment effects of eligibility for the career education program, for the financial aid and for both on college graduation conditional on enrollment. Each row represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3 (see equation 1). Graduation is measured by age 28. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. The sample is restricted to low-income students. Sample sizes are rounded to the nearest 10 for data confidentiality concerns.

Table A17: Treatments Effects on Low-Income Students' Post-Secondary Education Trajectories

Dependent variable	Control mean (1)	Career education (2)	Financial aid (3)	Mixed intervention (4)
Panel A—Students who first enrolled in a four-year college				
First enrolled in a four-year college	0.21	0.057**	0.030	0.075***
		(0.023)	(0.021)	(0.021)
Switched to a community college	0.06	0.009	0.015	0.029*
		(0.016)	(0.014)	(0.015)
Highest degree is a four-year college degree	0.11	0.018	-0.004	0.021
		(0.021)	(0.018)	(0.018)
Highest degree is a community college diploma	0.03	0.007	0.024**	0.021**
		(0.010)	(0.010)	(0.010)
Dropped out	0.06	0.027*	0.010	0.026*
		(0.016)	(0.014)	(0.014)
Panel B—Students who first enrolled in a community college				
First enrolled in a community college	0.31	-0.017	0.048*	-0.017
		(0.028)	(0.027)	(0.027)
Switched to a four-year college	0.02	0.028**	0.002	0.012
		(0.011)	(0.008)	(0.009)
Highest degree is a four-year college degree	0.02	0.019**	0.001	0.005
		(0.008)	(0.005)	(0.006)
Highest degree is a community college diploma	0.19	-0.051**	0.053**	0.008
		(0.024)	(0.024)	(0.024)
Dropped out	0.10	0.005	-0.015	-0.029*
		(0.019)	(0.017)	(0.016)
Sample size	590		2,090	

Notes: The table reports the treatment effects of eligibility for the career education program, for the financial aid and for both on college enrollment and completion by type of first enrollment. Each row represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3 (see equation 1). Enrollment is measured by age 27. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. The sample is restricted to low-income students. Sample sizes are rounded to the nearest 10 for data confidentiality concerns.

Table A18: Treatment Effects on Low-Income Students' Years of Post-Secondary Education

Dependent variable	Control mean (1)	Career education (2)	Financial aid (3)	Mixed intervention (4)
Total years spent in college	1.76	0.235*	0.150	0.273**
		(0.133)	(0.115)	(0.118)
Sample size	590		2,090	

Notes: The table reports the treatment effects of eligibility for the career education program, for the financial aid, and for both on the numbers of years of post-secondary schooling. Each row represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3 (see equation 1). Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A19: Treatments Effects on Low-Income Students' Earnings

Dependent variable	Control mean (1)	Career education (2)	Financial aid (3)	Mixed intervention (4)
Panel A— Labor income ($CA)				
Labor income at age 19	10,700	-443	-357	-1,119**
		(556)	(519)	(514)
			{0.880}	{0.231}
				{0.148}
Labor income at age 24	25,500	1,551	20	147
		(1,691)	(1,462)	(1,445)
			{0.371}	{0.404}
				{0.930}
Labor income at age 28	31,700	3,265*	-473	1,588
		(1,688)	(1,477)	(1,506)
			{0.035}	{0.346}
				{0.192}
Panel B—Total earnings ($CA)				
Total earnings at age 19	13,300	-523	-567	-1,070*
		(603)	(558)	(558)
			{0.942}	{0.369}
				{0.372}
Total earnings at age 24	31,300	1,980	62	190
		(1,629)	(1,412)	(1,384)
			{0.250}	{0.274}
				{0.927}
Total earnings at age 28	38,200	3,631**	530	1,415
		(1,801)	(1,483)	(1,471)
			{0.110}	{0.251}
				{0.584}
Sample size	590		2,090	

Notes: The table reports the treatment effects of eligibility for the career education program, for the financial aid and for both on labor income and total earnings by age. Each row represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3 (see equation 1). Earnings are expressed in 2020 Canadian dollars. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. For each outcome, I test whether the treatment effect of each of the two financial aid interventions is significantly different from the effect of the career education only intervention and report the associated p-value below the standard errors in square brackets. I also test whether the treatment effect of the mixed intervention is significantly different from the effect of the financial aid intervention and report the associated p-value below the standard errors in braces. The sample is restricted to low-income students. Sample sizes are rounded to the nearest 10 for data confidentiality concerns.

Table A20: Treatment Effects on Students' Probability of Working at Age 28

Treatment group	Low-income students (1)	High-income students (2)
Panel A—Dep. var.: Labor Income > 0		
Control Mean	0.95	0.94
Treatment Effects		
Career education intervention	0.001	0.000
	(0.014)	(0.013)
Financial aid intervention	-0.005	
	(0.014)	
Mixed intervention	0.002	
	(0.013)	
Panel B—Dep. var.: Labor Income $>$ \$16,000		
Control Mean	0.72	0.79
Treatment Effects		
Career education intervention	-0.013	0.028
	(0.027)	(0.021)
Financial aid intervention	-0.038	
	(0.026)	
Mixed intervention	-0.015	
	(0.026)	

Notes: The table reports the treatment effects of eligibility for the career education program, for the financial aid, and for both on the likelihood of reporting any labor income and annual labor income greater than $16,000 which roughly corresponds to a full time job at the minimum wage. Each column represents a separate OLS regression of the dependent variable on treatment dummies, strata dummies, and controls for student baseline characteristics (see equation 1). Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A21: Robustness of the Effects on Earnings to Alternative Forecasting Models.

	Career education			Financial aid			Mixed intervention		
Dependent variable	Main model (1)	Model with cov. (2)	Simple model (3)	Main model (4)	Model with cov. (5)	Simple model (6)	Main model (7)	Model with cov. (8)	Simple model (9)
Panel A— Low-income students									
Labor income	3,265*	3,176*	3,190*	-474	-533	-786	1,588	1,512	900
at age 28 ($CA)	(1,645)	(1,688)	(1,506)	(1,478)	(1,447)	(1,474)	(1,507)	(1,473)	(1,494)
Total earnings	3,631**	3,534**	3,556**	530	426	255	1,415	1,331	781
at age 28 ($CA)	(1,801)	(1,766)	(1,802)	(1,483)	(1,462)	(1,480)	(1,471)	(1,445)	(1,458)
Panel B— High-income students									
Labor income	2,558	2,616	2,665						
at age 28 ($CA)	(1,633)	(1,616)	(1,625)						
Total earnings	2,788*	2,827*	2,866*						
at age 28 ($CA)	(1,680)	(1,666)	(1,676)						

Notes: The table reports the treatment effects of eligibility for the career education program, for the financial aid and for both on labor income and total earnings by age, using alternative models of forecasting for the earnings data. The coefficients from Panel A are obtained by estimating equation 1 and the ones from Panel B are obtained by estimating equation 2. Earnings are expressed in 2020 Canadian dollars. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table A22: Prediction Error

Treatment group	Low-income students (1)	High-income students (2)
Panel A—Prediction Error > \$5,000		
Control group mean	0.251	0.273
Difference with control group		
Career education intervention	0.000	-0.007
	(0.028)	(0.024)
Financial aid intervention	0.027	
	(0.026)	
Mixed intervention	0.023	
	(0.026)	
Panel B—Prediction Error < -\$5,000		
Control group mean	0.259	0.332
Difference with control group		
Career education intervention	0.030	0.011
	(0.028)	(0.025)
Financial aid intervention	-0.008	
	(0.026)	
Mixed intervention	0.002	
	(0.026)	

Notes: The table reports the fraction of prediction errors greater than $5,000 and less than -$5,000 in the control group together with the differences in these fractions between the control group and each treatment group. The prediction errors are computed by taking the difference between the value at age 24 predicted by the forecasting model and the true observed value, for each student. Each column represents a separate OLS regression of the dependent variable on treatment dummies. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

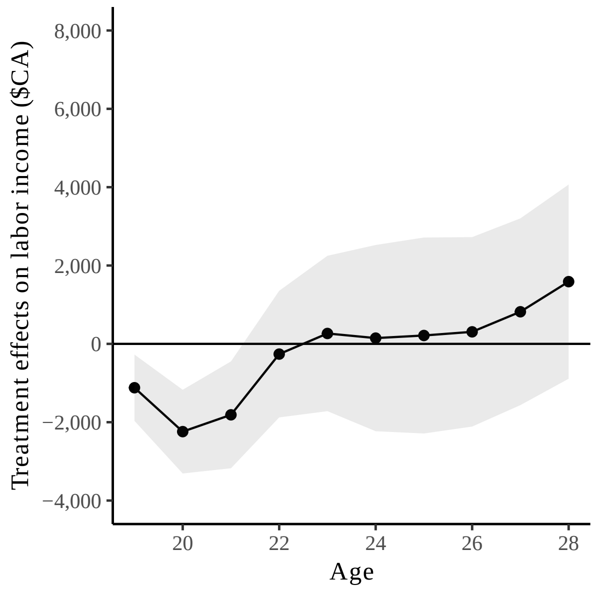


Figure A3: Impact of the Mixed Intervention on Labor Income Over Time

Notes: The figure plots the effects of the mixed intervention on labor income against age. Point estimates together with the associated 90 percent confidence intervals are reported. Each point is estimated from a OLS regression of the outcome on treatment dummies, strata dummies, and controls for student baseline characteristics listed in Table A3. Huber–White robust standard errors are used to compute the confidence intervals. Earnings are expressed in 2020 Canadian dollars.

Table A23: Comparison of the Treatments Effects on Low- and High-Income Students' Earnings

Dependent variable	Low-income students (1)	High-income students (2)	Difference high vs. low (3)
Panel A—Labor income ($CA)			
Labor income at age 19	-411	24	435
	(547)	(449)	(708)
	10,700	*11,000*	*300*
Labor income at age 24	1427	327	-1100
	(1,664)	(1,395)	(2,172)
	25,500	*31,800*	*6,300*
Labor income at age 28	3,050*	2,558	-491
	(1,655)	(1,633)	(,2325)
	31,700	*43,200*	*11,500*
Panel B—Total earnings ($CA)			
Total earnings at age 19	-455	14	469
	(591)	(558)	(813)
	13,300	*13,600*	*300*
Total earnings at age 24	1,906	8	-1,898
	(1,602)	(1,346)	(2,093)
	31,300	*36,500*	*5,200*
Total earnings at age 28	3,563**	2,788*	-774
	(1,746)	(1,680)	(2,423)
	38,200	*49,600*	*11,400*
Sample size		2,460	

Notes: The table reports the treatment effects of eligibility for the career education program on labor income and total earnings by age for both low- and high-income students. Each row represents a separate OLS regression of the dependent variable on the treatment dummy, the treatment dummy interacted with the parental income dummy, the parental income dummy and controls for student baseline characteristics listed in Table A3 (see equation 2). Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Control means are reported in italic below the standard errors. For each outcome, I report the effect on low-income students (column (1)), the effect on high-income students (column (2)) and the effect differential between the two types of students (column (3)). The sample is restricted to students who were assigned to the control or career education groups. Sample sizes are rounded to the nearest 10 for data confidentiality concerns.

Table A24: Treatments Effects on Low- and High-Income Students' College Enrollment in STEM Programs

	Low-income students (1)	High-income students (2)	Difference high vs. low (3)
Dependent variable: Ever enrolled in a four-year STEM program			
Unconditional on enrollment	0.010	0.012	0.002
	(0.016)	(0.018)	(0.024)
	0.06	*0.15*	*0.09*
Conditional on four-year college enrollment	-0.055	0.061*	0.116**
	(0.046)	(0.034)	(0.058)
	0.27	*0.28*	*0.01*

Notes: The table reports the treatment effects of eligibility for the career education program on low- and high-income students' probability to enroll in a STEM program. STEM stands for science, technology, engineering and mathematics.. Each row represents a separate OLS estimation of equation 2. Enrollment is measured within 10 years of high school graduation. Huber–White robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Control means are reported in italic below the standard errors. For each outcome, I report the effect on low-income students (column (1)), the effect on high-income students (column (2)) and the difference in effect between the two types of students (column (3)). Group sizes are rounded to the nearest 10 for data confidentiality concerns.

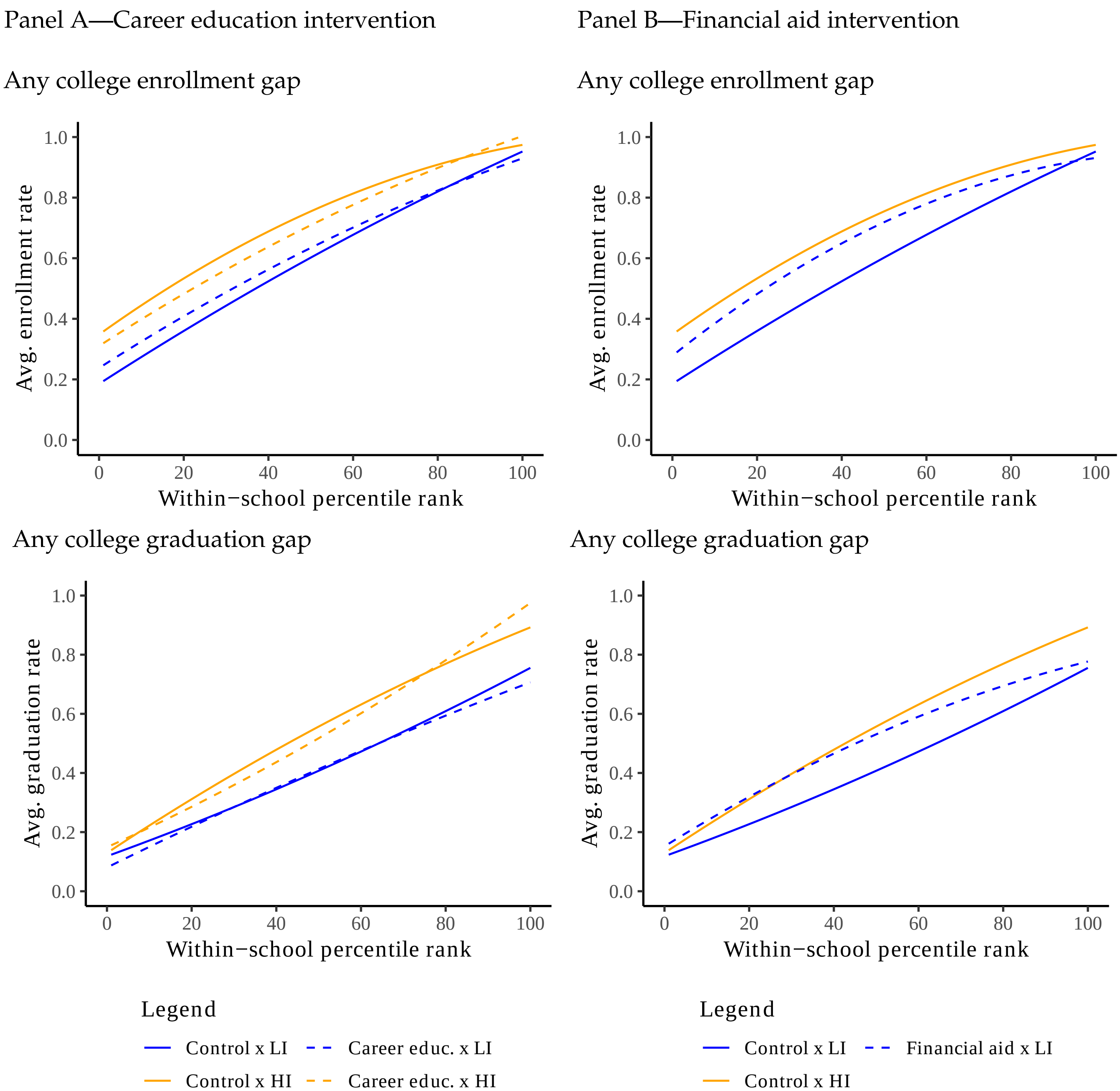


Figure A4: Enrollment Rates of High- and Low-Income Students by Percentile Rank and Treatment Arms

Notes: The figure plots, across within-school test scores percentile rank, the any college enrollment and graduation rates of high- and low-income students. Panel A plots the rates for students in the career education group and Panel B the rates for students in the financial aid group. The enrollment rates in the control group are also shown for comparability purposes. Each rate is a simple average of the rates across the 30 schools, as estimated from equation A5.

Table A25: Impact on Inequality between High- and Low-Income Students

	Enrollment		Graduation	
	Any public college	Four-year college	Any public college	Four-year college
A—Control group				
Avg. gap among equally-achieving	0.13	0.13	0.12	0.09
B—Career education for both high- and low-income students				
Avg. gap among equally-achieving	0.07	0.01	0.13	0.02
Difference with gap in control group	-44%	-92%	1%	-74%
C—Financial aid targeted to low-income students				
Avg. gap among equally-achieving	0.04	0.08	0.03	0.09
Difference with gap in control group	-68%	-39%	-73%	3%

Notes: The table reports the treatment effects of eligibility for career education for both high- and low-income students and eligibility for the financial aid for low-income students on the gaps in enrollment and graduation between high- and low-income students. Each average gap among equally-achieving students is obtained by estimating the size of the gap in each school at different points of the within-school score distribution in Grade 9, and taking the average. See Appendix Section D for more details.

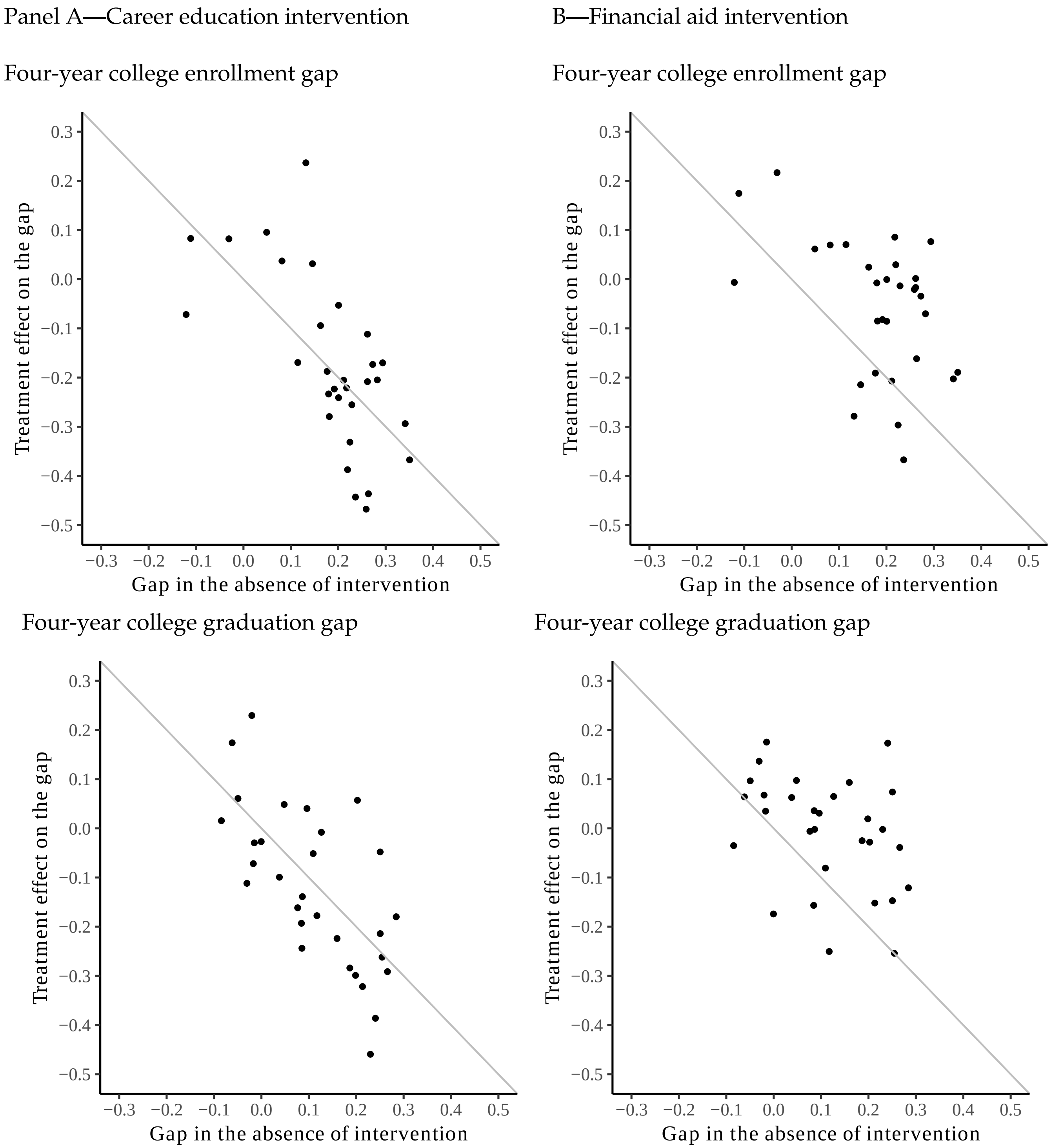


Figure A5: Treatment Effects on the Four-Year College Enrollment and Graduation Gaps Against Initial Gap Sizes

Notes: The figure plots, for each school, the magnitude of the reduction in the four-year college enrollment gap between high- and low-income students following each intervention, against the size of the gap in the control group. The gaps are measured at the median of the test score distribution in each school, as estimated from equation A5. The grey line indicates the values for which the gap is reduced by 100%.

Table A26: School-level Relationship Between the Treatment Effects on the Gap in Four-year College Enrollment and the Initial Gap Size

	School-level treatment effect on the four-year college enrollment gap			
	Career education intervention		Financial aid intervention	
Independent variables	(1)	(2)	(3)	(4)
School-level gap in control group	-0.995***	-0.943***	-0.555**	-0.584**
	(0.217)	(0.272)	(0.205)	(0.226)
Constant	0.006	-0.173	0.044	-0.038
	(0.047)	(0.218)	(0.044)	(0.182)
Additional school-level controls	N	Y	N	Y
Observations	30	30	30	30
R-squared	0.43	0.46	0.21	0.42
Adj. R-squared	0.41	0.33	0.18	0.27

Notes: The table reports the coefficients from school-level OLS regressions of the magnitude of the reduction in the four-year college enrollment gap following the different interventions on the size of gap in the control group. Columns (1) and (2) report the results for the treatment effects of the career education intervention and columns (3) and (4) for the financial aid intervention. The gaps are measured at the median of the test score distribution in each school, as estimated from equation A5. Additional school level controls, in columns (2) and (4), include school size, fraction of English speakers, fraction of immigrants, fraction of higher-income students, fraction of students with an unemployed parent, and average test score in Grade 9. Robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%

Table A27: Oaxaca-Blinder Decomposition of the Gaps in Enrollment and Graduation between High- and Low-Income Students. Control Group Students.

	Income group			Explained gap		Unexplained gap	
	High-income students	Low-income students	Gap	Size	% of total gap	Size	% of total gap
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ever enrolled in any college	0.782	0.520	0.262***	0.122***	47%	0.139***	53%
			(0.021)	(0.006)		(0.022)	
Ever enrolled in a four-year college	0.535	0.229	0.306***	0.171***	56%	0.135***	44%
			(0.020)	(0.006)		(0.020)	
Ever graduated from any college	0.617	0.357	0.260***	0.130***	50%	0.130***	50%
			(0.023)	(0.006)		(0.022)	
Ever graduated from a four-year college	0.375	0.140	0.235***	0.149***	63%	0.087***	37%
			(0.019)	(0.006)		(0.018)	
Sample Size	850	590	1,440				

Notes: The table reports the enrollment and graduation rates of high- and low-income students in the control group. Column (3) reports the differences between the two types of students. I decompose the gap between what can be explained by differences in academic preparation in Grade 9 between high- and low-income students and what cannot, following the Oaxaca-Blinder method. Academic preparation is measured as student average test score in Grade 9 and the quality of the school attended through school fixed effects. To decompose the gap I estimate a linear probability model of enrollment/graduation on average test score, average test score squared and school fixed effects, and use the weights from a pooled regression. Robust standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%.

B Appendix—More on the Data

B.1 Data Coverage

Figure A6: Timeline of Administrative Data Coverage

- Spring 2004 - Recruitment of the first freshmen cohort
- Spring 2005 - Recruitment of the second freshmen cohort
- Spring 2007 - End of high school for most cohort 1 students
- Spring 2008 - End of high school for most cohort 2 students
- December 2013 - End of tax data coverage for cohort 1 students not in the PSIS/RAIS
- December 2014 - End of tax data coverage for cohort 2 students not in the PSIS/RAIS
- December 2017 - End of tax data coverage for students in the PSIS/RAIS
- Spring 2018 - End of post-secondary education data coverage

Notes: The figure presents the timeline of administrative data coverage. Students in cohort 1, and cohort 2 were in Grade 9 during the 2003-04 and 2004-05 academic year, respectively. RAIS stands for Registered Apprenticeship Information System. PSIS stands for Post-Secondary Information System.

B.2 Outcomes of Interest

Standardized average test scores in Grade 12: The student average test scores in Grade 12 standardized with a mean of zero and a standard deviation of one across all students. Data collected by the SRDC from the New Brunswick Department of Education.

Ever graduated from high school Indicator variable which takes the value of one if the student has graduated from high school at any point in time. Data collected by the SRDC from the New Brunswick Department of Education.

Ever enrolled in any public college Indicator variable which takes the value of one if the student has ever enrolled in any public college within 10 years of the theoretical end of high school (i.e., until spring 2017 for the first cohort and until spring 2018 for the second cohort). Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development. Exclude enrollment in private four-year colleges and private career colleges.

Ever enrolled in a four-year college Indicator variable which takes the value of one if the student has ever enrolled in a public four-year college (or university) within 10 years of the theoretical end of high school (i.e., until spring 2017 for the first cohort and until spring 2018 for the second cohort). Author's calculation from the PSIS. Exclude enrollment in private four-year colleges.

Ever enrolled in a community college Indicator variable which takes the value of one if the student has ever enrolled in a community college within 10 years of the theoretical end of high school (i.e., until spring 2017 for the first cohort and until spring 2018 for the second cohort). Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development.

Enrolled in a private career college only Indicator variable which takes the value of one if the student has ever enrolled in a private career college but never in a public college within two and half years of the theoretical end of high school. Author's calculation from the survey conducted by the SRDC two and half years after the students' theoretical end of high school.

First enrolled in a four-year college Indicator variable which takes the value of one if a student's first enrollment in a public college is in a public four-year college (or university). Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development.

First enrolled in a community college Indicator variable which takes the value of one if a student's first enrollment in a public college is in a community college. Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development.

Enrolled in a four-year college after attending a community college Indicator variable which takes the value of one if a student first enrolled in a community college and later in a public four-year college. Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development.

Enrolled in a community college after attending a four-year college Indicator variable which takes the value of one if a student first enrolled in a public four-year college and later in a community college. Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development.

Ever graduated from a public college Indicator variable which takes the value of one if the student has ever graduated from a public college within 10 years of the theoretical end of high school (i.e., until spring 2017 for the first cohort and until spring 2018 for the second cohort). Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development. Exclude graduation from private four-year colleges and private career colleges.

Highest degree earned is a four-year college degree Indicator variable which takes the value of one if the student's highest degree earned is a four-year college degree (i.e., a bachelor's degree). Author's calculation from the PSIS. Exclude graduation from private four-year colleges.

Highest degree earned is a community college diploma Indicator variable which takes the value of one if the student's highest degree earned is a community college diploma or certificate. Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development. Exclude graduation from private four-year colleges and private career colleges.

Dropped out of college Indicator variable which takes the value of one if a student (i) has ever enrolled in a public college, (ii) has never graduated from any public college, and (iii) is not enrolled during the 2016–17 academic year for cohort one and during the 2017–18 academic year for cohort two. Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development. Exclude graduation from private four-year colleges and private career colleges.

Years spent in college It indicates the number of years a student was enrolled in a public college within 10 years of the theoretical end of high school. Author's calculation from the PSIS and the data collected by the SRDC from the New Brunswick Department of Training and Employment Development. Exclude years enrolled in a private institution.

Labor income It indicated the student employment income from T4 Slips. It includes all paid-employment income, i.e. wages, salaries, and commissions, before deductions and excludes self-employment income. Expressed in 2020 Canadian dollars. Data collected from the Statistics Canada taxfiler database.

Total earnings It indicated the student total income before tax from T1 tax form. It includes employment income, self-employment income, investment income, and government transfers (pension, unemployment insurance, child benefits, etc). Expressed in 2020 Canadian dollars. Data collected from the Statistics Canada taxfiler database.

C Appendix—Imputation Procedure for Earnings Data

I proceed in two steps. First, I impute the missing data to ensure that I observe a complete set of earnings over the period data were collected following a linear interpolation. Second, I forecast the earnings until 28 for students whose data are only available until age 24.

Linear Interpolation

Over the period data were collected, 6 percent of the data points are missing. For the missing records occurring between two known records (46 percent of the missing values), I impute y at age x by finding the closest points (x_0, y_0) and (x_1, y_1) on each side of x for which y is observed, and calculating:

$$y = \frac{y_1 - y_0}{x_1 - x_0}(x - x_0) + y_0. \tag{A1}$$

For the missing points found after two known records (34 percent of the missing values), I use the two closet points on the left side of x. For the missing records found before two known records I assign the value of zero to y (25 percent of the missing values).

Forecasting

I estimate the following equation by OLS on the full sample of students,

$$\begin{aligned} y_{i,t} =& \beta_0 + \beta_1 y_{i,t-1} + \beta_2 Exp_{i,t} + \beta_3 Enroll_{i,t} + \beta_4 Enroll_{i,t-1} \\ &+ \beta_5 GradFourYear_{i,t} + \beta_6 GradCoColl_{i,t} + \epsilon_{i,t} \end{aligned} \tag{A2}$$

where $y_{i,t}$ is student i annual earnings at year t, $y_{i,t-1}$ is student i annual earnings at year $t-1$, $Exp_{i,t}$ is student i years of experience accumulated at year t,[34] $GradFourYear_{i,t}$ and $GradCoColl_{i,t}$ are dummies capturing the highest degree earned by student i at year t, and $Enroll_{i,t}$ and $Enroll_{i,t-1}$ are dummies capturing whether student i was enrolled in post-secondary education during any semester of the year. $\epsilon_{i,t}$ is an error term. I also test the robustness of the results to alternative choices of covariates. The estimated forecasting models are presented in Table A28.

For each student whose data are only available until age 24, I then forecast, in cascade, earnings from ages 25 to 28 using the estimated coefficients from equation (A2) and the earnings observed at age 24.

34. I use as a proxy for experience the number of years a student has not been observed enrolled in a public post-secondary education from the end of high school until year t.

Table A28: Forecasting Models

	Y_t = Labor income at t			Y_t = Total earnings at t		
	Main model	With covariates	Simple model	Main model	With covariates	Simple model
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Y_{t-1}	0.897***	0.874***	0.927***	0.924***	0.908***	0.950***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Exp_t	-576***	-494***	-151***	-701***	-632***	-254***
	(47)	(47)	(37)	(44)	(44)	(35)
$Enroll_t$	-6,365***	-6,672***		-5,793***	-6,069***	
	(267)	(269)		(249)	(252)	
$Enroll_{t-1}$	52	-369		-612**	-922***	
	(258)	(259)		(241)	(242)	
$GradFourYear_t$	4,987***	4,579***		4,333***	3,923***	
	(230)	(257)		(215)	(241)	
$GradCoColl_t$	3,199***	3,085***		2,490***	2,372***	
	(206)	(209)		(193)	(196)	
Constant	7,728***	11,476***	5,792***	8,830***	12,005***	
	(244)	(818)	(158)	(229)	(766)	
Baseline Characteristics	N	Y	N	N	Y	N
Observations	30,460	30,460	30,460	30,460	30,460	30,460
R-squared	0.723	0.728	0.708	0.760	0.762	0.748

Notes: The table reports in columns (1) and (4) the coefficients obtained from the estimation of equation (A2) by OLS, in columns (2) and (5) the coefficients obtained from the estimation of equation of (A2) adding students baseline characteristics and school fixed effects as controls, and in columns (3) and (4) the coefficients obtained from the estimation of equation (A2) where the independent variables are restricted to Y_{t-1}, Exp_t and a constant. Columns (1), (2) and (3) present the models for labor income, and Columns (4), (5) and (6) for total earnings. Standard errors are reported in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%. Sample sizes are rounded to the nearest 10 for data confidentiality concerns.

D Appendix—Estimation of the Gaps between High- and Low-Income Students

I divide the sample into six groups of students according to the experimental and income groups they belong to. I estimate, in each group, the relationship between the outcome of interest Y and average test scores in Grade 9 and school-cohort effects. Formally, I estimate the following equation by OLS,

$$Y_{i,gt} = \sum_{k=1}^{30} \gamma_{k,gt} 1[S_i = k] + \beta_{1,gt} TS_i + \beta_{2,gt} TS_i^2 + \epsilon_i, \tag{A3}$$

where TS_i is student i standardized average test score in Grade 9 and S_i is a categorical variable indicating the school attended by student i in Grade 9.

From the regression, I can compute an approximation of the mean of outcome Y at different points of the test score distribution for each school. Precisely, the predicted outcome mean for a student of type g, with a standardized average test score in Grade 9 ts, attending school s, and belonging to experimental group t is,

$$E(Y_{gt} | TS_i = ts, S_i = k) = \gamma_{k,gt} + \beta_{1,gt} ts + \beta_{2,gt} ts^2. \tag{A4}$$

And the gap in outcome Y between equally-achieving high- and low-income students belonging to experimental group $t1$ and $t2$, respectively, is,

$$\begin{aligned} E(Y_{ht1} - Y_{lt2} | TS_i = ts, S_i = k) = & \gamma_{k,ht1} - \gamma_{k,ly2} \\ & + (\beta_{1,ht1} - \beta_{1,lt2}) ts + (\beta_{2,ht1} - \beta_{2,lt2}) ts^2 \end{aligned} \tag{A5}$$

The average gap across test scores and the thirty schools is then,

$$\frac{1}{30} \sum_{k=1}^{30} (\gamma_{k,ht_h} - \gamma_{k,lt_l}) + \int_{-\infty}^{+\infty} \left((\beta_{1,ht_h} - \beta_{1,lt_l}) ts + (\beta_{2,ht_h} - \beta_{2,lt_l}) ts^2 \right) f(ts), \tag{A6}$$

with $f(ts)$ the test score distribution.