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Separating the Structural and Composition Impacts of Financial Aid on the Choice of Major*

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Abstract

Using the unique design of a field experiment among Canadian high school students combined with early life-cycle data collected 10 years later, we estimate the impacts of financial aid distributed as grants on the distribution of university majors. We find that financial aid raises net university enrollment and graduation rates but attracts marginal entrants with lower STEM enrollment probabilities than the population enrolling under the status quo (the composition effect). Among the latter population, financial aid also reduces STEM enrollment and graduation probabilities (the structural effect). Our results thereby reveal potential unintended consequences of financial aid on students' educational outcomes.

JEL Classification: I2, J1, J3

Keywords: *Financial Aid, College Enrollment, College Majors, STEM, Liquidity Constraints.*

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1 Introduction

Providing higher education services at the lowest cost possible is an objective shared by a large number of policy makers concerned with the reduction of education inequality. This objective is usually achieved by subsidizing higher education institutions and/or by the creation of individual financial aid programs. At the same time, it is increasingly common for the same policy makers to proclaim the need to increase university enrollments in scientific subjects (STEM). In this paper we answer the following question: is reducing the cost of higher education coherent with an increase in STEM enrollments?

Using data from a field experiment that took place in Canadian high schools in 2008-2009 merged with a baseline survey and follow-up data collected in 2019-2020, we estimate the causal effect of randomly drawn financial aid offers on the distribution of university majors, graduation, and post-graduation outcomes. We model the full sequence of relevant decisions exerted between the experiment and observed earnings around age 30. The different stages include i) choices between immediate cash and financial aid for post-secondary education, ii) decision about university enrollment, iii) initial field choice, iv) financial aid take-up decision, v) extensive margin labor supply, vi) completion of the initial degree and vii) wages at age 30. The paper focuses on the effect of aid taking the form of a one-time grant leading to a reduction in the cost of higher education regardless of the type of institution attended (two-year college or university) and independently from the field of study chosen.

The model separates the composition effect induced by financial aid offers generated by the experiment, from the structural (or behavioral) effect of aid on the field enrollment decisions after conditioning on skills (observed and unobserved) in the general population. We measure the former by the differences in skills and STEM enrollment probabilities between those who would have changed their enrollment and/or field choices because of potential aid and those who would attend university under the status quo. We measure the latter using the parameters of a random coefficient multinomial Logit model with observed and unobserved heterogeneity. The model includes three main types of determinants of individual decisions, i) individual cognitive and non-cognitive factors measured in high school, ii) variables measuring financial resources such as family income and self-reported financial hardship at baseline, and iii) additional opportunities driven by exogenous financial aid offers (our focus).

Our approach is semi-structural. It borrows partly from the policy evaluation literature in that it focuses on estimating the effect of a given public policy intervention and ignores deep structural parameters. However, it is also influenced by the structural literature since we model jointly all relevant stages necessary to measure the impact of financial aid and estimate a full distribution of the effects on specific outcomes of interest as opposed to an average effect. To achieve this, we treat the data as a panel of multiple discrete choices affected by unobserved heterogeneity. We motivate our approach by the potential existence of some common unobserved factor affecting all decisions and which prevails after conditioning on a wide set of individual skill measurements.[1]

One of the most original aspects of the experiment is that individuals had to exert a large number of high-stake binary choices between immediate cash payments and financial aid packages to be paid conditional on recontacting the managing firm with proof of higher education enrollment. One of the choices was drawn randomly at the end of the experiment, thereby providing exogenous variations in potential financial aid (after conditioning on choosing financial aid during the experiment). Prior to the experiment, high school students had to take the numeracy segment of the OECD International Adult Literacy Survey (IALS) and had to answer several questions documenting their ability level in mathematics and in verbal-reading activities. The IALS numeracy test measures the same skills as PISA but is administered to the general population between 16 and 65 in countries participating in the program. The survey also contained non-cognitive skill measurements targeting motivation in school and the individual level of mastery (the Pearlin score). Our model may be used to answer several policy-relevant questions. The main objectives of our paper, which are motivated by the claim shared by many policy institutions about the need to increase the number of students graduating in the sciences and which all constitute original contributions to the recent literature on the causal impact of higher education financial aid, are the following. (OECD (2014)).

The first general objective is to assess if lowering the cost of higher education by providing grants would change the distribution of college majors. More specifically, we are interested in the probability of enrolling in STEM subjects after conditioning on individual observed and unobserved heterogeneity. We refer to this as the structural (or behavioral) effect of financial aid generosity. A second objective is to separate the composition effect of financial aid generosity from its structural (behavioral) effect and evaluate their relative importance. A third objective is to separate the effect of financial aid on the initial field of study from its effect on graduation while taking into account field selectivity. This is important as there exist large differences in ex-ante graduation probabilities between fields (Altonji et al. (2016), Arcidiacono et al. (2024)), and those differences may be sufficient to generate seemingly positive effects of financial aid on university graduation rates if individuals are displaced from low graduation to high graduation rate majors and if the econometrician does not account for the endogeneity of field choices. These questions allow us to build bridges between our results and more commonly used approaches that focus on the effect of financial aid on enrollment and/or graduation but ignore field choices.

Our main results may be summarized in six main takeaways. First, we find that the enrollment decisions and field choices of around 35% of the population would be unaffected by financial aid whereas for the remaining 65%, individual decisions taken under increased aid generosity may or may not be altered depending on the amount.

Second, our findings suggest that university enrollment decisions are less elastic to aid amounts than the choice of a field of study. For instance, when modeling the field choice of the initial degree and its completion separately, enrollment university probabilities increase by 0.02 for each 1000$ of aid while the STEM enrollment probability (as a first degree) decreases by 0.08

[1] This argument is central to the approach developed in Carneiro et al. (2003).

for each additional 1000$ in favor of Social Sciences, Humanities, and Education (0.06) and Business (0.02). This confirms the existence of a structural effect and that the observed relationship between financial aid and field choices is not solely due to a composition effect.
Third, after conditioning on the field of study, realized financial aid reduces slightly the probability of completing the initial degree but this negative effect is compensated by a positive effect induced by the counterfactual deflection of STEM students toward fields with higher graduation rates, even after controlling for abilities. As a result, the overall proportion of university graduates increases by 0.01 to 0.02 for each additional 1000$ of financial aid. This finding illustrates one possible channel by which financial aid may increase graduation rates, a finding sometimes reported in the policy evaluation literature (Dynarski et al. (2023)). It also discloses an interesting paradox about financial aid; namely that while aid may raise university enrollments and even university graduation, it may simultaneously reduce post-education wages by changing the distribution of college majors.
Our fourth and fifth findings relate to our analysis of the composition effect. Among those induced to enter university because of financial aid, there are eight times more non-STEM than STEM students and those entering STEM would have lower math and IALS scores than STEM attendants under the status quo. At the same time, those attending university under the status quo but who would have enrolled in two-year colleges with additional aid would be five times more likely to be non-STEM students under the status quo. By contrast, we find that STEM students deflected toward two-year colleges would still have high STEM graduation probabilities.
Finally, our sixth result is that those who would enroll in university both under the status quo and with additional aid but would be displaced from STEM to non-STEM are the subgroup whose graduation probabilities would be increased the most because of additional aid. This is explained by their displacement to non-STEM fields with higher graduation rates. Interestingly, those individuals would have not only high Math and IALS scores but also higher STEM graduation probabilities than average. This last result illustrates clearly one "unintended consequence" of financial aid generosity.

To summarize, there is a strong composition effect induced by financial aid as indicated by the substantial difference between the STEM enrollment proportions of marginal university entrants (about 11%) and those enrolling in university under the status quo (above 40%). However, the entrants account for a small proportion of the population, and the overall decrease in STEM enrollments is far from being explained only by a pure composition effect. There is a possible analogy between the unintended consequences of financial aid generosity revealed by our analysis and the well-known disincentive effects of many transfer programs or social insurance systems (e.g., welfare benefits, unemployment insurance). Our results suggest that education policy designers, who often state the need to maximize STEM enrollments in light of recent technological innovation, may face a trade-off between favoring low tuition policies and stimulating STEM enrollments.

The remaining sections of the paper are constructed as follows. In Section 2, we discuss background literature. The next section is devoted to a detailed presentation of the experiment and the re-interview survey that took place ten years later. In Section 4, we present the model and discuss estimation issues. The structural effects of financial aid and its characteristics on enrollment are presented in Section 5 while the composition effects are discussed in Section 6. We discuss the results of an alternative specification and some limitations of our analysis in Section 7. Finally, we discuss some policy implications in the conclusion in Section 8.

2 Background Literature

Our paper contributes to three main domains of micro-econometric research concerned with education and human capital. First, we contribute to the literature on the evaluation of education financial aid programs. The literature is so vast that it is very challenging to synthesize, the difficulty being that each aid program analyzed may not only differ in the type of aid being offered (loans, grants, or a combination of both) and the institutional context but also in the admission conditions (e.g., some are need-based, others are merit-based), therefore making broad conclusions somewhat meaningless. For a detailed review, we refer the reader to the recent paper by Dynarski et al. (2023). In general, the literature focuses on two main outcomes: university enrollment and/or graduation. Some recent examples include Angrist et al. (2022), who study the effects of grants provided by the Buffett Foundation in Nebraska; Black et al. (2023) who use variations in federal loan limits to estimate the effects of access to student loans on educational attainments, earnings, debt, and repayment; Card and Solis (2022) who analyze the effects of loan programs on persistence and degree completion through a regression discontinuity approach based on eligibility thresholds in Chile; or Gurantz (2022) who focuses on nontraditional students. Our contribution to this literature is to analyze not only enrollment and completion outcomes but also dig deeper into the choice of major to better understand the underlying mechanisms.

Relatedly, we also attempt to contribute to the literature on the determinants and implications of the choice of college majors, which, like the financial aid literature, has expanded significantly in recent years. As of now, the literature on college majors, summarized in Patnaik et al. (2021) retains at least three major findings; the important variation in earnings across majors (almost as important as the college-high school premium), the importance of eliciting earnings subjective beliefs, and the key role played by individual-specific taste for majors in students' decisions. For the most part, many recent papers on field choices draw inference from sub-populations of individuals already enrolled in university, obviating the possibility of evaluating the ex-ante impact of financial aid. This is the case, for instance, of Bleemer and Mehta (2022); Arcidiacono et al. (2014); Wiswall and Zafar (2015); or Zafar (2012).

Interestingly, there exists no estimate of the causal effect of the cost of higher education on the distribution of fields of study. The only studies that attempt to link financial aid to college majors have analyzed the impact of merit scholarship programs on STEM majors (Cornwell et al. (2006), Sjoquist and Winters (2015)) and tend to conclude in favor of detrimental effects of aid on STEM participation. Cornwell et al. (2006) report that the HOPE state-sponsored scholarship program, which took place in Georgia, reduced the take-up of math and science credits and raised the probability of choosing Education as a major. However, as recognized by the authors, it is hazardous to interpret this effect as causal given the selection process involved. However, since merit aid is by definition reserved for students with advantageous (observed and unobserved) characteristics, none of these studies can separate the composition from the behavioral effects. Using a RD design on administrative data for Canadian undergraduate students who received federal financial aid in terms of grants and loans, Liu (2024) finds little evidence that financial aid (grant or loan) significantly impacts students' initial choice of major, persistence, or degree completion. As mentioned in Patnaik et al. (2021), the relationship between financial aid generosity and college majors is practically unknown.

The potential impact of financial aid generosity on the field of study is far from being a trivial issue. Most theoretical models of education financing are presented as a high school-college marginal decision and study the optimal loan provision but ignore the role of labor supply (Lochner and Monge-Naranjo (2011)). When different majors have different effort requirements leading to different graduation probabilities, it is hard to dissociate the choice of a major from financing decisions. The connections are even more ambiguous once it is recognized that employment is a substitute for borrowing but that the amount of effort devoted to market work may impede academic effort and graduation differently across majors. For an agent seeking the optimal level of consumption smoothing between education and post-education periods, it may be impossible to separate the choice of a major from financing decisions. It follows that a general decrease in the cost of education may induce changes in field choice. As far as we know, there is no theoretical modeling of the joint decision of a college major and education financing that incorporates the arbitrage between work effort and borrowing and their impact on graduation.

These arguments help introduce another contribution of our research - the identification of some unintended consequences of raising financial aid generosity. Inasmuch as one is willing to accept the premise that different majors require different levels of effort (this is particularly well documented in Arcidiacono et al. (2012)), our approach allows us to capture (at least partially) the effect of aid generosity on effort exerted during education. At a purely intuitive level, it is easy to see how financial aid taking the form of a grant may impact differently on effort and on completion. To see this, compare two identical individuals enrolled in university and assume that one has a loan and that the other has a grant. The value of dropping-out being lower for someone with a loan (because of repayment), it follows that student loans may act as commitment device thereby reducing the non-graduation probability. Indeed, the disincentive effects of various transfer payments and/or social insurance programs on individual effort such as i) the reduction in search effort measured by the increase in unemployment duration when unemployment insurance becomes more generous (Nickell (1979)) or ii) the reduction in male labor supply induced by more generous welfare payments (Lemieux and Milligan (2008)) are now well documented. Our analysis of the displacement effects of financial aid across majors may indirectly speak to this literature as well.

3 Experimental and Survey Data

We make use of two complementary sources of data. The first one is the field experiment "Willingness to Borrow" that took place between the Fall of 2008 and the Spring of 2009 and that was combined with both student and parental surveys implemented one week before the experiment. The experiment was funded by the Canada Millennium Foundation (a public enterprise created by the Canadian federal government) and was carried out jointly by The Social Research and Demonstration Corporation (SRDC) and the Centre Interuniversitaire de Recherche en Analyse des Organisations (Montreal) between October 2008 and March 2009.[2]

The sample, consisting of 1,248 full-time Canadian students aged 16-18 years, was drawn from both urban and rural sites across 4 Canadian provinces (Ontario, Québec, Manitoba and Saskatchewan). As will become clear, the initial experiment generated an exogenous reduction in the cost of higher education through the provision of higher education grants. However, participating students were not aware that the experiment contained choices between cash and potential financial aid. They only knew that they could earn money if they participated.

The second source of data is taken from a follow-up survey that we conducted with SRDC between 2019 and 2021 and administered to the individuals who participated in the original experiments. The follow-up survey contains information about educational enrollment histories, including the field of study of the first degree completed, and early life-cycle professional outcomes of 512 of the initial participants. While SRDC was not able to re-contact the totality of participants, the large number of measurements taken at the baseline experiment (e.g., cognitive and non-cognitive skills, motivation, financial constraints, - see more details below), makes it possible to take into account selectivity in our estimation sample. However, as documented below, sample selectivity appears to be a relatively minor problem in our case.

3.1 The "Willingness to Borrow"Experiment

The experiment is described in detail in Johnson and Montmarquette (2015), Belzil et al. (2021), Belzil et al. (2021), and Jagelka (2024). To optimize space constraints, we only describe the main components of the survey and the financial aid experiment below. Many details regarding the experiment can also be found in the supplementary file.

3.1.1 Student and Parental Surveys

At least one week before the experimental session at school, students were given a unique identifying number to complete an online survey. The aim of the survey questions was to obtain a comprehensive profile of the participants and their family context. We provide a detailed description of each measurement used in the estimation of our model in the supplementary file.

[2]SRDC is well known for its management of the Self-Sufficiency project taking place in the 1990s in Canada.

To obtain easily interpretable results, we extract an average score out of the different types of measurements which we interpret as factors. Those may be split into three groups: cognitive skills, non-cognitive skills, and family resources.

1. The cognitive factors contain the following:

   - the International Adult Literacy Survey (IALS) numeracy test score which is an objective measure of the ability to use applied mathematics in concrete problems.
   - a subjective mathematics ability score computed from self-reported mathematical skills
   - a subjective verbal ability score computed from self-reported writing, reading, and oral communication skills

2. The non-cognitive factors incorporate the following:

   - the Pearlin Mastery score measuring individual perceived level of control over what happens to them
   - a factor measuring motivation while in high school identified from 7 items

3. The measures of household financial resources include the following variables:

   - the extent to which the student feels financially constrained, identified from 12 measures
   - household income as reported by parents

All these variables are summarized in Table A.1 in the appendix and are described in detail in the supplementary file.[3]

The correlation estimates between cognitive and non-cognitive components (Table 1) indicate that IALS numeracy scores, mathematics scores, and verbal ability scores are all positively correlated although one notes that the math score is much more strongly correlated with the IALS score (0.40) than with the reading score (0.20). Similarly, the IALS score is positively correlated with both the motivation factor (0.14) and the Pearlin factor (0.10) but those correlations are weaker than those measured for the subjective math score (0.24 for math-motivation and 0.16 for Math-Pearlin). A possible reason is that IALS scores, like all international standardized achievement tests, are less affected by incentive than math and reading scores which both reflect the impact of effort on grades obtained in class (Gneezy et al. (2019)). Another possible reason is that IALS scores (like PISA scores) may be measuring a more practical dimension of cognitive skills than does Math high school grades (Prada and Urzúa (2017)).

[3]Note that one student who reported being 30 years old in the baseline survey was excluded from the analysis, resulting in a sample of 1,247 students throughout instead of 1,248 in the initial sample.

Table 1: Correlations between Cognitive and Non-Cognitive Factors

	IALS	Math	Verbal	Motiv.	Pearlin
IALS	1.00	-	-	-	-
Math	0.40	1.00	-	-	-
Verbal	0.20	0.28	1.00	-	-
Motiv.	0.14	0.24	0.22	1.00	-
Pearlin	0.10	0.16	0.19	0.28	1.00

Note: All factors (IALS, Math, Verbal, Motivation, Pearlin) are standardized. Computed from the sample of 1247 individuals (Ontario, Manitoba, Québec and Saskatchewan) participating in the baseline experiment.

3.1.2 Choices between Financial Aid and Cash Payments

All subjects were presented with a set of decisions and paid for one, randomly selected decision, at the end of the session. The subjects were informed that they would be paid for one decision, but they did not know which one at the beginning of the session. The questions can be split into two main groups.

First, all individuals answered questions measuring their preferences for risk and time. The design of the questions is based on standard multiple-list approaches commonly used in experimental economics.[4] The second portion, which constitutes the main originality of the experiment, is devoted to individual decisions between cash payments and higher education financial aid.

The financial aid packages were offered conditional on entering post-secondary education and comprised various combinations of loans and grants. Before the start of the decision process, students were presented with the following definitions: *Grant:* "Educational grants will be disbursed if a participant enrolls in an institution for learning or training full-time within two years from the date of experiment participation. The grant will cover direct and indirect costs related to the learning activity. For tuition fees, payments will be made directly to the education institution. Receipts will be required for the reimbursement of other costs."

Loan: "Educational loans will be disbursed if a participant enrolls in an institution for learning or training full-time. These loans will be available up to two years from the date of the experiment. The loans are repayable upon the completion of the study or if the participant drops out of the program of study. The interest rate, which is the same as the one offered by the

[4] Belzil et al. (2021) use the experiment to estimate the value of higher education financial aid and to measure the relative importance of deep preference parameters (preferences for risk and time) in explaining the value of higher education. Jagelka (2024) uses individual decisions and the student survey to study the mapping between cognitive and non-cognitive traits on one hand, and individual preferences for risk and time on the other hand.

Canadian Federal Student Assistance program, is floating and is set at the prime rate (3.2% on average over the period of interest) plus 2.5%."

It is important to note that interest rates attached to loans are also practically identical to those provided by charter banks within private loans.

In total, there are four different types of offers.[5]

- Choices 1 to 5: choices between cash payments and classical loans. The loans vary between $1000 and $4000 while the cash payments vary between $25 and $700.
- Choices 6 to 15: choices between cash payments and hybrid offers containing both a loan and a grant. In all five cases, the amounts of loan and grant are equal within a given offer ($400, $1000, and $2000). Cash payments are similar to choices 1 to 5.
- Choices 11 to 15: identical to choices 6 to 10, except that the loan repayment is income contingent. Our decision to aggregate hybrid offers that include standard loans with hybrid offers incorporating income-contingent loans is data-driven. As documented in Belzil et al. (2021), participants attached practically no value to accessing income-contingent loans.
- Choices 16 to 22: choices between cash payments and grants equal to $500 (choice 20), $1000 (choices 16 to 19), $2000 (choice 21), and $4000 (choice 22).

These amounts should be put in perspective with relevant yearly tuition fees at Canadian universities. Over the period covered by our analysis, the average tuition was equal to $2,180 for Quebec, $5,667 for Ontario, $3,228 for Saskatchewan, and $5,064 for Manitoba over the period covered by the experiment.[6] Recall that actual payments range from 500$ to 4,000$ and that the average aid provided is about $2000, which corresponds to about a 50% decrease in a single year tuition, or 12% of the total tuition for a four-year program. Note that for Québec students, standard university programs last three years and also have much lower tuition. As an example, a 2000$ grant would almost completely cover the tuition for a single year or would correspond to a 33% decrease in the total college tuition.

As documented in the first three rows of Table A.2 in the appendix, loans have been chosen less frequently than grants or hybrids. In total, the average proportion of loans chosen (against cash) is equal to 22%, as opposed to 74% and 64% for grants and hybrid grants.

3.1.3 Actual Financial Aid Received

It is particularly important to understand that the actual financial aid received during the year following the experiment is different from the potential financial aid drawn randomly and should be regarded as endogenous for two main reasons.

[5] Section 2 of the supplementary material provides an example of those choices as they were presented to the students.

[6] In comparison, the average US in-state tuition fees charged by public four-year institutions for 2008-2009 were US $6,312 (US Department of Education, National Center for Education Statistics, 2008-2009 Integrated Postsecondary Education Data System).

First, and as documented in Table A.2, about 12% of the 1247 participants have been offered financial aid. However, those who selected financial aid offers over cash more often, were by definition also more likely to be offered financial aid as the randomization process set in after conditioning on individual choices.

Second, individuals who wanted to claim the amount of financial aid to which they were entitled were responsible for recontacting SRDC with proof of full-time enrollment in a higher-education institution. For this reason, the actual payment depended on individual behavior. For instance, individuals having drawn a loan or a small grant may have decided to avoid those administrative steps, and thereby to avoid taking up financial aid. This is no different than what prevails in most decisions concerning the take-up rate of any social program or even the decision to apply to federal financial aid programs such as FAFSA in the US.

The actual payment differed from the initial draw for another reason. Once the individuals re-contacted SRDC to claim their financial aid, SRDC decided to deviate from the protocol announced during the experiment and transform all loans into grants. This action, which was completely unanticipated by the students, was guided by the need to reduce subsequent management costs. It implied that all those who were entitled to a loan and recontacted SRDC received a surprise grant equal to the expected loan. Even individuals involved in the theoretical design of the experiment did not expect that SRDC would proceed that way.

Therefore, all actual financial aid amounts received were equivalent to a reduction in the cost of higher education, which we model to estimate how a change in the cost of education (partly driven by randomization) affects educational and other life-cycle outcomes.

As expected, the take-up rates vary according to whether or not a loan or a grant has been drawn. For instance, between 20% and 25% of those who drew a loan actually claimed it, whereas the grant and hybrid take-up rates were between 70% and 80%. In total, about 80% of all those who were entitled to financial aid actually claimed it. As explained earlier, all financial amounts received take the form of a one-time grant. The average amount paid was 1823$. Given that this amount represents substantially different shares of the cost of education in the different Canadian provinces involved in the experiment (see Section 3.1.2), we decided to exclude Québec students from our analysis.

3.2 The Follow-up Survey

The follow-up survey, which we designed jointly with SRDC, required to trace the largest number of participants from the Willingness to Borrow experiment. This turned out to be relatively challenging as initial participants were about 18 when they participated and therefore lived with their parents at that time. Nevertheless, SRDC was able to recontact 512 individuals (more than 40%) who agreed to respond to the follow-up survey. Among those, 336 individuals were coming either from Ontario, Manitoba, or Saskatchewan whereas 176 lived in Québec.

To investigate potential selectivity induced by the re-interview process, we ran an OLS regression of the probability of re-interview on the individual characteristics of Table A.1. The results, found in the second column of Table A.1, indicate that only two regressors (IALS scores and the female indicator) have a significant impact on re-interview.

The follow-up survey is a key element of our research plan. It provides us with information about individual education trajectories and even some early life-cycle economic outcomes measured around age 30. In particular, it is possible to know what field of study was chosen by those individuals who opted for higher education.

Differences between Treatment and Control

Table 2 below documents some key differences between treatment and control groups, defined as students who received financial aid versus students who did not. About 47% of the control group obtained a university degree (BA or more) while 64% of the treatment group did. Despite a much larger share of the treatment group choosing to go to university, a smaller share enrolled in STEM as their first post-secondary degree. Among those who enrolled in university, a larger share of the control group (13%) obtained a STEM degree compared to the treatment group (4%).

Table 2: Differences between Treatment and Control Groups

	Treatment (received aid)	Control (no aid)
Highest Grade Completed:		
- High School	10.0%	14.1%
- Post-Secondary (2Y)	26.4%	37.9%
- University	63.6%	47.4%
% of University Students:		
- Enrolled in STEM (1st degree)	25%	30%
- Graduated with a STEM degree	4%	13%
- Worked during Studies	78%	73%
Average Aid received	1823$	0$
# of students	50	462

We also note that receiving financial aid does not seem to reduce labor supply during studies as a larger fraction of the treatment group (78%) worked during their studies than in the control group (73%). Our challenge is to disentangle the portion of those differences driven by the endogeneity of the decision to take up aid (requiring proof of enrollment) from the pure causal effect of aid.

Field of Study

The re-interview contains specific information about the field of study chosen by every individual enrolling in a university. The information is based on the Statistics Canada Classification of Instructional Programs (CIP) version 1.0.[7] As our sample contains a limited number of individuals, it is necessary to aggregate many subjects into broader classes. However, given our specific interests in scientific subjects, we follow the literature and incorporate all scientific subjects into the standard STEM (Science, Technology, Engineering, and Mathematics) group. We group all subjects related to the social sciences, humanities, and education into another group, and refer to this group with the SS-H-E acronym. Grouping social sciences, humanities, and education together is motivated by two main facts. First, the distribution of IALS, Math, and Verbal scores are quite similar among those three groups but also, OLS regressions of earnings on individual skills and field choice indicators show that those are the subjects with the lowest returns to schooling. We leave Health and Business as single fields and end up with four different modalities, although our analysis focuses largely on the specificities of STEM degrees.

In Table 3 below, we report the average IALS, Math, Verbal, and Motivation standardized scores by field of graduation. As reported in studies performed in the US, there is clear evidence of strong selectivity across fields of study and in particular, with respect to STEM subjects. For instance, STEM students dominate all other majors in IALS, Math, Verbal, and Motivation scores. The difference is particularly strong in quantitative skills (Math and IALS) but they also dominate SS-H-E students in verbal scores (0.42 vs 0.24).

Table 3: Differences in Skills by Field of Graduation

Field of Study	IALS	Math	Verbal	Motivation
SS-H-E	0.23	0.01	0.24	0.29
Business	0.33	0.42	0.05	0.08
Health	0.22	0.18	0.17	0.07
STEM	0.63	0.95	0.42	0.54
2-year College (or less)	0.02	-0.06	-0.23	-0.08

Note: All measures have been standardized and computed from the re-interview sample (N=512). SS-H-E denotes Social Science, Humanities, and Education.

4 The Model

We model all key stages involved from the implementation of the "Willingness to Borrow" experiment in 2008-2009 until graduation and leverage the randomization procedure that took

[7] The original Statistics Canada Classification of instructional programs can be found at this address: https://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVD&TVD=299355

place at the end of the baseline experiment.[8]

Before starting, it is useful to remember that financial aid must be represented by three different variables, each of them capturing a specific stage of the following sequence: 1. the decisions between financial aid packages and immediate cash during the baseline experiment, which affect the probability of drawing a potential financial aid offer (denoted FAD); 2. the potential financial aid (denoted PFA) to be claimed and generated from the random draw among the set of decisions; 3. the actual financial aid offer (denoted AFA) following SRDC's decision to transform every offer into a grant once an individual contacted them to take-up aid.

We first present a model that separates the choice of the initial field of study when enrolling in university and its completion (graduation). Another version of the model where the field choice and graduation are subsumed into a multinomial variable indicating the field of graduation is a simplified version and will be described briefly at the end of this section.

4.1 Modeling the Initial Field at Enrollment

The model has seven different contributions to the likelihood, which each corresponds to a different stage of the decision process.

Stage 1: Financial Aid Decisions in the Experiment

During the experiment, individuals exerted 22 binary choices between financial aid packages and an immediate cash payment. There were 6 decisions involving loans, 7 decisions involving grants, and 10 decisions involving hybrid offers containing both a loan and a grant. The first stage data are the only ones that have been used in previous studies (Johnson and Montmarquette (2015), and Belzil et al. (2021)).

To simplify the model structure, we create three different variables recording the number of times an individual has chosen each type of offer and denote them by N_{loan}, N_{grant}, and N_{hybrid}. The vector containing those variables is denoted FAD. We estimate the determinants of each proportion using ordered logit models.

To minimize the number of equations, we present the generic notation for an offer of type o, where o may represent loans, grants, or hybrid offers. The number of offers of type o (with $j+1$ modalities) accepted by individual i is obtained from a valuation index, V_i^o defined as follows:

$$V_i^o = \beta_i^o + \beta_X^o \cdot X_i + \varepsilon_i^o \quad with\ o = loans, grants, hybrids$$

where ε_i^o is an i.i.d. Logistic random term (independent across individuals and types of offers), β_X^o measures the effect of all characteristics (cognitive skills, non-cognitive skills, and family background) included in the vector X and β_i^o is an individual-specific term correlated across

[8] This approach, consisting of combining structural methods with experimental or quasi-experimental methods, is advocated by Todd and Wolpin (2020).

different types of offers and also with other unobserved heterogeneity components of the model introduced below.

The probability of choosing modality j is given by

$$\begin{aligned}
\Pr(\#_{o,i} &= j) = \Pr(\gamma^o_{j-1} < \beta^o_{0,i} + \beta^o_X \cdot X_i + \varepsilon^o_i < \gamma^o_j) \\
&= \frac{\exp(\gamma^o_j - \beta^o_{0,i} - \beta^o_X \cdot X_i)}{1+\exp(\gamma^o_j - \beta^o_{0,i} - \beta^o_X \cdot X_i)} - \frac{\exp(\gamma^o_{j-1} - \beta^o_{0,i} - \beta^o_X \cdot X_i)}{1+\exp(\gamma_{j-1} - \beta^o_{0,i} - \beta^o_X \cdot X_i)}
\end{aligned}$$

where the $\gamma^{o\prime}s$ are threshold parameters to be estimated. For each type of offer, we normalize the first threshold parameter to 0.

Assuming conditional independence (the $\varepsilon^{o\prime}_i s$ are independent after conditioning on the individual-specific parameters), the contribution to the likelihood of individual financial aid decisions in the experiment, denoted $\Pr(FAD)$, is equal to the product of the $\Pr(\#_{o,i} = j)'s$.

Stages 2 and 3: The Decision to Enroll in University and the Choice of a Field of Study

In the months following the baseline experiment, individuals must decide on whether to enroll in post-secondary education (PSE) or not, and if enrolled in university, must choose a field of study. To avoid treating short studies as a university field, we model initial choices as the product of a binary decision between university enrollment vs short studies, and the field choice probability conditional on university enrollment.

Our choice is motivated by the relatively broad definitions of the fields of study that we use and which correspond practically to standard university faculty divisions.[9] We assume that both of these decisions depend on potential financial aid represented by the outcome of the random draw (since the enrollment decision is made before the transformation of loans into grants) and record hybrid offers using the grant component. Estimating a different parameter for the grant component of a hybrid offer is needed since the focus of our subsequent analysis is on the effect of an overall reduction in the cost of education induced by a grant and we cannot rule out that individual behavior may differ according to whether or not the grants is accompanied by a loan. As noted earlier, receiving potential offers requires having selected financial aid over cash during the experiment, so we allow individual decisions to depend also on the vector FAD.

We denote the university variable indicator by $Univ_i$ and thereby obtain the following choice probability:

$$\Pr(Univ_i = 1) = \frac{\exp(\beta^u_i + \beta^u_W \cdot W_i + \beta^u_{PFA,i} \cdot PFA_i)}{1+\exp(\beta^u_i + \beta^u_W \cdot W_i + \beta^u_{PFA,i} \cdot PFA_i)}$$

[9] Another reason to assume the existence of an initial field of study chosen before enrolling is that in all large Ontario and Manitoban universities, every application must target a specific faculty which usually has its own requirements.

where

$$W_i = \{X_i, FAD_i\}$$

and β_i^u and $\beta_{PFA,i}^u$ are individual-specific parameters, and β_W^u are vectors of parameters to be estimated. The inclusion of the financial aid decisions taken during the experiment (FAD) into W_i captures the possibility that ex-ante valuations of financial aid may be indicative of enrollment intentions even after conditioning on the random draw.

The probability of enrolling in field j (given one has decided to enroll in university) is a Mixed-Multinomial Logit defined as follows:

$$\Pr(Field_i = j) = \frac{\exp(\phi_i^j + \phi_W^j \cdot W_i + \phi_{PFA,i}^j \cdot PFA_i)}{\sum_{f=allfields}(\exp(\phi_i^f + \phi_W^f \cdot W_i + \phi_{PFA,i}^f \cdot PFA_i)}$$

where the $\phi_i^j{}'s$ are individual-specific intercept terms representing unobserved taste for specific majors (possibly correlated with initial conditions), the $\phi_{PFA}^j s$ measure the effect of potential financial aid on the initial field, and the $\phi_W^{j}{}'s$ are vectors of parameters to be estimated. When estimating the model, we use the field 'Social Sciences-Humanities and Education' as the outside option.

Stage 4: The Take-up Probability

The probability of claiming financial aid (essentially the probability of recontacting the firm managing the experiment) is a binary Logit. The take-up probability also depends on potential financial aid since the decision is based solely on the information available at the end of the experiment. This probability can tell us about the profile of students who could benefit the most from financial aid. For those who have been offered financial aid, the claim probability is defined as follows:

$$\Pr(Claim_i \mid offer) = \frac{\exp(\beta_i^c + \beta_X^c \cdot W_i + \beta_{PFA}^c \cdot PFA_i)}{1 + \exp(\beta_i^c + \beta_X^c \cdot W_i + \beta_{PFA}^c \cdot PFA_i)}$$

where the parameter β_i^c is an individual-specific intercept term representing the unobserved propensity to claim financial aid and β_W^c and β_{PFA}^c are parameters to be estimated. We therefore interpret the estimated probability as the reduced form of a more complex object. As far as we know, this probability has never been estimated before.

When modeling the decision to work during studies and degree completion, we must now incorporate the fact that all loans have been transformed into grants and assume that all subsequent outcomes depend on the actual financial aid variable (AFA). For those who have drawn a grant at the end of the experience, $AFA = RFA$, whereas for those who drew a loan, the nature of the offer was changed from a loan to a grant.

Stage 5: The Decision to Work

We assume that the decision to work depends on W_i, on realized financial aid (AFA) but also on a binary variable ($STEM_i$) recording whether or not someone has enrolled in a STEM subject.[10] We model the probability to work (the extensive margin) using a binary Logit which is defined as:

$$\Pr(Work_i) = \frac{\exp(\beta_i^w + \beta_W^w \cdot W_i + \beta_{AFA}^w \cdot AFA_i + \beta_{STEM}^w \cdot STEM_i)}{1 + \exp(\beta_i^w + \beta_W^w \cdot W_i + \beta_{AFA,i}^w \cdot AFA_i + \beta_{STEM}^w \cdot STEM_i)}$$

where the parameter β_{0i}^w is an individual-specific intercept term representing unobserved propensity to work and β_W^w, β_{STEM}^w and β_{AFA}^w are parameters to be estimated.

Stage 6: The Graduation Probability

In order to capture differences between those attending two-year colleges and those attending university, we estimate a graduation probability for each group (indexed by $k = 2Y, Univ$). Each graduation probability depends on actual financial aid, on the labor supply extensive margin. The probability of graduating from university also depends on the initial field of study through the endogenous STEM indicator, which is not the case for two-year college graduation since we do not model the field for short studies. As with other binary outcomes, we assume it to be Logistic and incorporate an individual-specific intercept, β_i^{gk}, representing unobserved ability (or motivation) to graduate. The other parameters are defined similarly as those previously introduced.

$$\begin{aligned} \Pr(Grad_i)^k &= \\ & \frac{\exp(\beta_i^{g,k} + \beta_{iW}^{g,k} \cdot W_i + \beta_{AFA}^{g,k} \cdot AFA + \beta_{STEM}^{g,k} \cdot STEM_i + \beta_w^{g,k} \cdot Work_i)}{1 + \exp(\beta_i^{g,k} + \beta_W^{g,k} \cdot W_i + \beta_{AFA}^{g,k} \cdot AFA + \beta_{STEM}^{g,k} \cdot STEM_i + \beta_w^{g,k} \cdot Work_i)} \\ \text{with } k &= 2Y, Univ \text{ and } \beta_{STEM}^{g,2Y} = 0 \end{aligned}$$

Stage 7: Earnings at 30

The last element of the model is the distribution of yearly earnings (in logs) measured around age 30, which we denote by $E_{i,30}$. We assume that log earnings follow a Normal distribution with regression function:

$$E_{i,30} = \beta_i^E + \beta_X^E \cdot X_i + \beta_{AFA,i}^E \cdot AFA_i + \epsilon_{i,30}^E$$

where β_i^E and $\beta_{AFA,i}^E$ are individual-specific parameters and where $\epsilon_{i,30}^E$ is Normal with mean 0 and standard deviation σ^E. The effect of financial aid generosity is captured by $\beta_{AFA,i}^E$ but its

[10] We use only a binary indicator for STEM since exploratory analysis showed very little differences between other majors.

sign is difficult to predict as it may be positive for those induced to enter university because of financial aid but may also be negative for those deflected to lower paid majors because of aid. We denote its density by $\phi(E_{i,30)}$.

Modeling Selectivity: Probability of being in the Follow-up Survey

Finally, to account for potential selectivity induced by the re-interview process (post-experiment outcomes are only observed for those who were re-contacted successfully), we formulate the probability of belonging to the follow-up survey as a function of all observed factors and actual financial aid received. The latter variable is introduced as we cannot rule out that the decision to respond to the interview more than 10 years later was affected by the decision to re-contact SRDC in the period following the experiment in order to claim financial aid.

Defining a binary indicator, RI, equal to 1 for those who have been re-interviewed and 0 if not, we obtain the following expression:

$$\Pr(RI_i = 1) = \frac{\exp\{\beta_i^r + \beta_{AFA}^r \cdot AFA + \beta_W^r \cdot W_i\}}{1 + \exp\{\beta_i + \beta_{AFA} \cdot AFA + \beta_W \cdot W_i\}}$$

where r_{0i} is an individual-specific term.[11]

Identification and Estimation

To achieve identification and facilitate estimation, we assume a form of conditional independence. More precisely, we assume that the seven stages are stochastically independent after conditioning on observed and unobserved heterogeneity. We view this assumption as relatively mild as the take-up rate decision intervenes more than six months after the participation in the experiment. A similar argument is applied to graduation outcomes (field of study) as the time elapsed between both decisions is even longer.

Because we have a relatively limited number of individuals (especially when fitting the model to three provinces only) and a large number of controls for cognitive and non-cognitive skills, we assume that unobserved heterogeneity is represented by four types.[12]

Each type m is defined as a vector with the following elements:

$$\{\beta_m^o, \beta_m^u, \beta_{PFA,m}^u, \phi_m^j, \phi_{PFA,m}^j, \beta_m^C, \beta_m^w, \beta_m^{g,k}, \beta_m^r, \beta_m^E, \beta_{AFA,m}^E\}\ m = 1, ..4$$

where $j = STEM, SSHE, BUSINESS., HEALTH$, $o = loans, grants, hybrids$ and $k = 2Y, univ$.

[11] All results presented below have been obtained after using all individuals in the first step likelihood and using the re-interview probability to control for selectivity. An alternative approach, which empirically leads to similar results, was to make use only of the re-interview sample for all stages.

[12] Analyses performed with more or fewer types (3 to 6) showed that marginal effects did not significantly change.

The type probabilities are equal to the following:

$$\Pr(type\ m) = \frac{\exp(t_m)}{\sum_{n=1}^{4} \exp(t_n)}$$

where the $t's$ are parameters to be estimated.

In order to nest more conventional approaches in which field choices are ignored when estimating the effect of financial aid, we impose the restriction that for a subset of the population, both enrollment and field decisions are unaffected by financial aid. We therefore impose that

$$\begin{aligned}
\beta^u_{PFA,1} &= \beta^u_{PFA,2} = 0 \\
\phi^j_{PFA,1} &= \phi^j_{PFA,2} = 0 \text{ for all fields } j \\
\phi^E_{AFA,1} &= \phi^E_{AFA,2} = 0
\end{aligned}$$

where the earnings equation restriction ($\phi^E_{AFA,1} = \phi^E_{AFA,2} = 0$) follows logically from the fact that in the absence of any effect of financial aid on enrollment and/or field, we should also observe no effect of aid on wages at 30.

All components of the model are estimated jointly. Parameter estimates are obtained by forming the following likelihood function (for a given individual i)

$$\begin{aligned}
L_i &= \sum_{m=1}^{4} \Pr type(m) \cdot \Pr(FAD \mid type\ m) \cdot \Pr(RI_i = 1, type\ m) \\
.\Pr(Uni_i &\mid type\ m) \cdot \Pr(Field_i = j \mid type\ m) \cdot \Pr(Claim_i \mid type\ m) \\
\cdot \Pr(Work_i &\mid type\ m) \cdot \Pr(Grad_i \mid type\ m) \cdot \Pr(\log earnings_i \mid type\ m)
\end{aligned}$$

The total likelihood is obtained by forming the product of all individual contributions. Estimates are obtained using Fortran routines. In total, the likelihood contains 4778 choices/outcomes probabilities and requires the estimation of 243 parameters.

With our approach, it is also possible to recover type probabilities given observed choices:

$$\Pr(type\ m \mid choices)_i = \frac{\Pr type(m) \cdot L_i(type\ m)}{L_i}$$

and use them to associate unobserved heterogeneity to observed regressors which are not used at the estimation level. As will become clear later, we will regress those probabilities on measures of risk and time preferences obtained during the experiment (Belzil et al. (2021)) and thereby infer that the types that are more likely to select a specific field can also be characterized in terms of their preferences for risk and time.

4.2 Modeling the Field of the Highest Grade Completed

When modeling the field of highest grade completed, the institutional difference between students from Québec and other provinces becomes irrelevant and therefore include the former into our analysis. This raises both the number of individuals and outcomes. We retain most of the elements (stages) developed earlier except that the field choice and the graduation steps are subsumed in a multinomial variable, denoted $FHGC$, which has the following modalities; $STEM, SSHE, BUS., HEALTH$ and $NODEGREE$. As we estimate the field associated with the highest degree among those who enrolled in university, the modality $NODEGREE$ designates those who never graduated with a university diploma.

The contribution to the likelihood for $FHGC$ is given by

$$\Pr(FHGC_i = j) = \frac{\exp(\phi_i^j + \phi_W^j \cdot W_i + \phi_{PFA,i}^j \cdot AFA_i)}{\sum_{f=allfields}(\exp(\phi_i^f + \phi_W^f \cdot W_i + \phi_{PFA,i}^f \cdot AFA_i)}$$

where the replacement of PFA by AFA is motivated by the fact that graduation is taking place after the transformation of potential loans into realized grants. We also remove the contribution of labor supply for logical reasons as the extensive margin information relates to the first degree and for a small number of individuals, the highest grade completed is not the one associated to the first degree attended.

The rest of the contributions are identical and we thereby obtain the following likelihood function:

$$\begin{aligned} L_i &= \sum_{m=1}^{4} \Pr type(m) \cdot \Pr(FAD \mid type\ m) \cdot \Pr(RI_i = 1). \Pr(Uni_i \mid type\ m) \\ \cdot \Pr(Claim_i &\mid type\ m) \cdot \Pr(FHGC_i = j) \cdot \Pr(\log earnings_i \mid type\ m) \end{aligned}$$

Note that as we estimate this version of the model including Québec students as well, the total number of choices/outcomes increases to 6280.

5 The Structural Effects of Financial Aid

In Section 5.1, we present a summary of the main results for each component of the model specification that separates the initial degree decision from its completion outcome. When doing so, we use the participants coming from Ontario, Manitoba, and Saskatchewan and remove Québec students because their path to university is different – they must attend a two-year CEGEP general program to enroll in a university program that lasts three years, as opposed to four in other provinces. Students from other provinces transit directly from high school to higher education (like in the US) and can either select shorter studies (two-year college) or enter university directly after high school graduation.

Since the implementation of the model requires the estimation of about 243 parameters, we include the entire set of estimates in the supplementary file and focus on the main marginal effects here.

In Section 5.2, we briefly present the main estimates obtained when adding Québec participants. Recall that to do so, we need to modify our model and focus on the field choice associated with the highest degree attained, thereby omitting the initial field equation. When doing so, we consider non-graduation as an additional option (the outside option).

In both cases, we focus on the structural effects of aid on various model components, especially on enrollment and field of study. The analysis of the differences in skills between those who would enter (or leave) university because of additional aid and those who would have exerted the same choices under the status quo and with additional aid (what we refer to as the "composition effect" of financial aid) will be performed in Section 6.

In Section 5.3, we review the effects of individual skill heterogeneity on university enrollments, STEM enrollment, and graduation. In Section 5.4, we illustrate the importance of unobserved heterogeneity by linking differences in field selection to information about deep preference parameters elicited during the baseline experiment.

5.1 University Enrollment and the Initial Field of Study

All marginal effects of financial aid are computed for a 1,000$ lump sum grant although actual financial aid packages in the experiment vary between 500$ and 4000$. Standard errors of the marginal effects have been obtained with parametric bootstrap methods using the standard errors of the model parameters and are evaluated at the sample averages of the regressors. Note that because marginal effects are potentially influenced by unobserved heterogeneity, we report type-specific marginal effects (computed at the type-specific unobserved heterogeneity value) as well as average effects computed over types.

Financial Aid vs Cash in the Experiment

The individual decisions made during the baseline experiment have already been analyzed structurally in Belzil et al. (2021) so we report the Ordered Logit estimates in the appendix rather than here. In short, the results indicate that the most important determinants of financial aid valuations are motivation in school, mathematics skills, and verbal skills. These are variables that are naturally associated with a higher probability of entering higher education. Among the financing variables, only the financial stress indicator increases financial aid valuation. Family income, on the other hand, is found to play no role (as noted in Belzil et al. (2021).[13]

University Enrollment and Initial Field of Study

[13] Belzil et al. (2021) analyze the mapping of individual risk and time preferences onto ex-ante valuation of financial aid disclosed in the experiment (what constitutes the first stage of our model) but did not have access to the data used in this study.

The type-specific marginal effects (along with their standard errors) of potential financial aid on the probability of enrollment and on the field enrollment probabilities are found in the upper part of Table 4. The average effects of aid on all components of the model are summarized in the left-hand portion of Table 5.

Table 4: Type Probabilities and Marginal Effects of Financial Aid on University Enrollment and Field

Model: Initial Field (# observations=4778)				
	Type 1	Type 2	Type 3	Type 4
Type Probabilities	0.167	0.191	0.331	0.311
Univ. enroll.	0.000	0.000	-0.128**	0.202**
	-	-	(0.009)	(0.016)
STEM	0.000	0.000	-0.0974**	-0.138**
			(0.010)	(0.011)
Business	0.000	0.000	-0.004*	0.057**
			(0.002)	(0.015)
SS-H-E	0.000	0.000	0.102**	0.081**
			(0.009)	(0.010)
Health	-	-	-	-
Model: Field of Highest Grade (# observations=6280)				
	Type 1	Type 2	Type 3	Type 4
Type probabilities	0.150	0.197	0.349	0.304
Univ enroll	0.000	0.000	-0.125**	0.198**
	-	-	(0.009)	(0.013)
STEM	0.000	0.000	-0.188**	-0.240**
			(0.019)	(0.030)
Business	0.000	0.000	0.158**	0.076**
			(0.020)	(0.017)
SSHE	0.000	0.000	-0.074**	0.164**
			(0.019)	(0.024)
Health			0.069**	-0.011
			(0.011)	(0.006)
Non-graduation	0.000	0.000	0.034**	0.012**
	-	-	(0.005)	(0.003)

Note: All marginal effects are computed at average regressors and averaged over unobserved types. For Types 1 and 2, parameters have been fixed to zero. Standard errors of the marginal effects have been obtained from parametric bootstrap methods using standard errors of the model parameters at sample averages of the regressors. Estimates with ** (*) are significant at the 1% (5%) level.

Table 5: Average Effects of Potential and Realized Aid on various Outcomes

<table>
<tr><th></th><th colspan="4">Model</th></tr>
<tr><th></th><th colspan="2">Initial Field</th><th colspan="2">Field Highest Grade</th></tr>
<tr><th>Financial Aid (1,000$ Grant)</th><th>Potential</th><th>Realized</th><th>Potential</th><th>Realized</th></tr>
<tr><td>University Enrollment</td><td>0.021**
(0.005)</td><td>-</td><td>0.016**
(0.004)</td><td>-</td></tr>
<tr><td>Fields:</td><td></td><td></td><td></td><td></td></tr>
<tr><td>- STEM</td><td>-0.075**
(0.006)</td><td>-</td><td>-</td><td>-0.139**
(0.015)</td></tr>
<tr><td>- Business</td><td>0.017**
(0.004)</td><td>-</td><td>-</td><td>0.078**
(0.011)</td></tr>
<tr><td>- SS-H-E</td><td>0.059**
(0.005)</td><td>-</td><td>-</td><td>0.024**
(0.008)</td></tr>
<tr><td>- Health</td><td>-</td><td>-</td><td>-</td><td>0.021**
(0.004)</td></tr>
<tr><td>Take-Up</td><td>0.126**
(0.006)</td><td></td><td>-</td><td>0.069**
(0.003)</td></tr>
<tr><td>Work (extensive)</td><td>-</td><td>0.013**
(0.008)</td><td>-</td><td>0.025**
(0.004)</td></tr>
<tr><td>Graduation (short-studies)</td><td></td><td>0.012**
(0.002)</td><td>-</td><td>-</td></tr>
<tr><td>Graduation University</td><td></td><td>-0.024**
(0.003)</td><td>-</td><td>-</td></tr>
<tr><td>Non-Graduation</td><td></td><td></td><td></td><td>0.016**
(0.003)</td></tr>
<tr><td>Log Earnings (at 30)</td><td>-</td><td>-0.084**
(0.030)</td><td>-</td><td>-0.047**
(0.020)</td></tr>
<tr><td># of observations</td><td colspan="2">4778</td><td colspan="2">6280</td></tr>
</table>

Note: All marginal effects are computed at averages regressors and averaged over unobserved types. Standard errors of the marginal effects have been obtained from parametric bootstrap methods using standard errors of the model parameters at sample averages of the regressors. Estimates with ** (*) are significant at the 1% (5%) level.

There are three main findings to take-out from Tables 4 and 5. First, enrollment and field decisions of more than one third of our population (about 36%) would be perfectly inelastic to financial aid amounts since the proportions of type 1 and type 2 are respectively equal to 0.167

and 0.191. For the remaining part of the population, enrollment and/or field would depend on the amount of financial aid. Standard policy evaluation approaches would therefore disclose estimates obtained from less than two thirds of our population.

A second finding is that despite an average positive effect of financial aid on university enrollment probabilities of the order of 0.02 for each addtional 1000$ (Table 5), the type-specific effects (in the top panel of Table 4) are not monotone across types as we obtain a positive effect (around 0.20) for one third of the population and a negative effect (around -0.13) for the remaining type. This means that financial aid induces some people to enter university and at the same time, induces others to choose two-year college instead. We return to the implications of this result when discussing composition effects in Section 6.

The most striking finding is however the negative impact of potential financial aid on the STEM enrollment probabilities. This is particularly clear when comparing average field specific enrollment probabilities shown in Table 5. The effect of aid is found to be -0.075 for STEM. This negative effect is compensated by positive increases for the Social Sciences-Humanities-Education subjects (+0.059) and Business (+0.017).

To the extent that a STEM degree requires more academic effort than other fields of study, we interpret this result as suggesting that a reduction in the cost of education tends to reduce academic effort even though it may raise net university enrollments.[14] This sort of unintended consequence of financial aid is masked in papers analyzing only enrollment and/or graduation outcomes regardless of the field of study.

The Decision to Take-up Financial Aid

According to the protocol ruling the actual payment of financial aid for those whose random draws generated an entitlement to financial aid, it was necessary to show a proof of enrollment in a full-time post-secondary education program. This feature of the protocol, in line with regulations existing in many actual financial aid programs (US, Canada, UK and others), implies that the decision to take-up financial aid may depend on potential financial aid and on individual characteristics. The estimates found in Table 5 disclose that for every additional 1,000$, the take-up probability increases by 0.126 when averaged across types, which is the direction we would expect for that estimate.

Does Financial Aid Reduce Labor Supply?

One of the most important features of post-secondary time allocation decisions is whether students work in parallel with their studies or not. As noted in Table 2, more than 70% of those enrolled in higher education report having worked during their studies (excluding summer time employment). Similar findings have also been documented in the US (Ashworth et al. (2021), Belzil et al. (2022), and Aucejo et al. (2024)).

[14]There is some empirical evidence in the literature on college majors (at least in the US) that STEM students devote more time to academic activities than do other students (Arcidiacono et al. (2024)).

Despite the importance of labor supply while in school, its causal impact on educational outcomes is still unclear. Employment while in school may be seen as an education financing decision (Keane and Wolpin (2001)) but may also be regarded as an investment decision, especially for those who decide to diversify their time allocation because they are uncertain about college completion or uncertain about post-graduation outcomes (Arcidiacono et al. (2024)). Depending on the underlying objective of the individual, an exogenous reduction in the cost of higher education driven by randomized financial aid may have a different effect on the propensity to work.

As reported in the second column of Table 5, and assuming that individual labor supply decisions during university are exerted after the take-up rate decision (and before the choice of field), the average marginal effect is positive and small (0.013) but statistically significant at conventional levels. This might be surprising as one might expect that a reduction in the cost of education may reduce the need to work during study and may free up time for study. This is not the case in our sample.

Financial Aid and the Graduation Probability

In our model, graduation depends on realized financial aid, on employment, and on the field (after conditioning on observed and unobserved heterogeneity). This implies the existence of both a direct effect (after conditioning on the field) of aid and an indirect effect of aid on the field. This sort of distinction would also be masked in empirical studies using standard policy evaluation methods.

As is clear from the results found in Table 5, the effect of aid differs considerably between short studies (two-year college) and university. It is found to be positive (0.012) on the probability of graduating from two-year colleges while its impact is negative (-0.024) on university graduation. As mentioned earlier, there exist many segments of the micro-econometric literature that document the disincentive effects of various transfer programs and/or social insurance policies on individual effort.[15] This negative effect might also be interpreted as a reduction in individual effort.

Using Brazilian data in which it is possible to differentiate between the effects of a grant and a loan on university graduation, Comunello (2024) reports a negative effect for grants but a positive effect for loans. She interprets this result as evidence in favor of a commitment device induced by loans.

However, comparing the effects of aid on graduation with those obtained for STEM enrollment probabilities already discussed, one notes that our estimates imply that field choices are much more elastic to financial aid than grade completion.

Additional Marginal Effects

[15] This is particularly true for Unemployment Insurance (Nickell (1979)), welfare payments (Lemieux and Milligan (2008)) and other policies of the same nature.

In Table A.3 in the appendix, we present some additional average marginal effects obtained when modeling the initial field. As we assume that labor supply decisions are made after enrollment decisions, the recursive nature of the model identifies the effect of enrolling in STEM on both labor supply and university graduation. We find that enrolling in STEM reduces the probability of working during university by -0.124.

Our results also stress the importance of controlling for field selectivity when evaluating the effect of aid on graduation since the effect of enrolling in STEM is even stronger on the probability of completing the first degree. The estimate, equal to -0.292, points to the specificity of STEM subjects. This means that after conditioning for both observed and unobserved heterogeneity, the initial field chosen by the individual (more precisely, whether or not it is a STEM subject) is a much more important determinant of graduation than financial aid.

This result points to the importance of distinguishing between the direct and the indirect effect as the latter is not separable from the former in standard policy evaluation approaches focusing either on enrollment or graduation.

*Early Life-C*ycle *Wages*

Finally, after conditioning on observed and unobserved heterogeneity, the effect of financial aid on log earnings at age 30 (Table 5) is found to be negative (equal to -0.084) but is also imprecisely estimated. This is possibly explained by the conflict between the positive effects of aid on university enrollment which pushed wages of those who would have otherwise graduated from two-year colleges, and the negative effects generated by the displacements of some individuals from university to two-year colleges as well as other students who would switch from STEM to non-STEM subjects such as Social Sciences and Humanities.[16]

5.2 Financial Aid and the Field of the Highest Grade Completed

The marginal effects of financial aid generosity obtained for the model specification dealing with the highest grade completed are found in the lower panel of Table 4 (type-specific estimates) and the right-hand side columns of Table 5. For all components of the model, we incorporate a binary indicator for Québec students to account for differences in enrollment, field choice, and take-up decisions.

The results are generally consistent with those obtained when modeling the initial field choice. Specifically, we find again that about 35% of the population would be unaffected by financial aid. Adding the Québec participants did not change much the marginal effects of aid on the university enrollment probabilities as the average effect is 0.016. However, adding Québec students has reinforced the negative effect of aid on STEM graduation as the average effect is now equal to -0.139 for each additional 1000$. This may not be surprising as the specification subsumes the effect of aid on enrollment and graduation into one object.

[16] As of now, the effect of financial aid on post-education wages has been neglected in the financial aid literature. Indeed, an important question would be if financial aid policies tend to reduce mismatch in the labor market or if they tend to increase overeducation.

The remaining estimates measuring the effects of aid on labor supply and on the take-up rate are similar and do not require much discussion. There are two main differences between the model that separates the initial field and the graduation outcome (discussed in Section 5.1) and the current one. First, adding Québec students allows us to consider four different subjects (Health could not be incorporated before). Second, as we are modeling the field of the highest grade completed conditional on enrolling in university, it is necessary to incorporate an additional option to the multinomial logit for those who never obtained a university degree. The positive estimate obtained for the non-graduation option, equal to 0.016, is therefore coherent with the negative effect of aid on the probability of terminating a university degree discussed before.[17]

5.3 The Role of Measured Skills

One specificity of our data is the availability of individual cognitive and non-cognitive skill measurements around age 18 which allows us to compare the importance of randomized financial aid amounts with individual-specific observed skills. In Table 6, we report a subset of the marginal effects of individual skill measures (IALS, Math, Verbal, and Motivation) on the main outcomes. For the model of the initial field, we report the effects on the university enrollment probability, the probability of enrolling in STEM, and on the university graduation probability. For the model that considers the field of the highest grade attained, we report the marginal effects on the university enrollment probability and the STEM graduation probability. All estimates are for a one-standard-deviation change in a particular skill.

The most striking finding in Table 6 is the small impact that the IALS score has on STEM enrollment (top panel) or STEM graduation (bottom panel). This is interesting in light of the importance that the media attach to comparisons of PISA scores obtained by different countries since IALS and PISA measure the same skills on different populations (Yamamoto (2002)). A one standard deviation in IALS score raises the probability of enrolling in STEM by 0.0216 only and reduces the STEM graduation probability by 0.0116. As a comparison, a one standard deviation change in Math score is five times more important than the IALS as it increases STEM enrollment proportion by 0.107.

Taken as such, our results imply that a high IALS score has little predictive power on the propensity to either enroll in STEM or graduate with a STEM degree.

A second finding to note is the importance of the Motivation factor. For both models, Motivation in school is the strongest predictor of university enrollment (0.104 for the initial enrollment model and 0.075 for the highest grade completed model) and the second strongest for both STEM enrollment (0.056) and STEM graduation (0.095).

[17]We also estimated a version where the effect of financial aid is allowed to differ for Québec students. The results indicate that the probability of graduating in STEM is lower among Québec students but that this is not explained by differences in the reaction to financial aid.

Table 6: The Role of Individual Skills on University and STEM Enrollment and Degree Completion

	Skills			
	IALS	Math	Verbal	Motivation
Initial Field Model:				
Univ. Enrollment	0.084**	0.056**	0.070**	0.104**
	(0.004)	(0.005)	(0.006)	(0.007)
STEM Enrollment	0.022**	0.107**	0.040**	0.056**
	(0.003)	(0.007)	(0.008)	(0.005)
Degree Completion	-0.045**	0.098**	0.021**	0.013**
	(0.004)	(0.009)	(0.003)	(0.004)
Highest Field Model:				
Univ. Enrollment	0.049**	0.047**	0.063**	0.075**
	(0.004)	(0.003)	(0.006)	(0.005)
STEM Graduation	-0.012**	0.132**	-0.006**	0.095**
	(0.004)	(0.010)	(0.002)	(0.009)

Note: Marginal effects with standard errors in parentheses. All marginal effects are computed for one standard deviation in each specific skill. Estimates with ** (*) are significant at the 1% (5%) level.

5.4 Interpreting Unobserved Heterogeneity

As documented in Table 7, unobserved heterogeneity is an important determinant of the field at enrollment (top panel). For instance, Type 1 has the one with the highest proportion of students enrolling in STEM, whereas Type 3 individuals tend to choose Social Sciences and related subjects (SS-H-E) more than do other types. We also note that Type 2 individuals are more likely to choose business than other types.

Table 7: Predicted Probabilities of Latent Types by Field

Model: Initial Field				
	Type 1	Type 2	Type 3	Type 4
STEM	0.44	0.15	0.22	0.45
Business	0.13	0.56	0.18	0.26
SS-H-E	0.43	0.29	0.60	0.29
Health	-	-	-	-
Model: Field Highest Grade				
	Type 1	Type 2	Type 3	Type 4
STEM	0.08	0.04	0.15	0.19
Business	0.09	0.48	0.22	0.21
SS-H-E	0.41	0.36	0.31	0.33
Health	0.32	0.07	0.22	0.21
No Degree	0.10	0.05	0.10	0.06

Note: The type-specific probabilities have been computed at the average values of individual characteristics.

Using Bayesian methods, it is possible to link individual type probabilities (conditional on observed choices) to observed regressors not used when estimating the model. We leverage the set of questions measuring preferences for risk and time in the original experiment (in 2008-2009) to investigate the role played by deep preference parameters.

The binary decisions are representative of the multiple price list approach used in experimental economics and contain a large number of decisions between risky and safer lotteries as well as decisions between cash payments to be paid immediately or in the future.[18]

To proceed, we construct a measure of the propensity to be forward-looking by computing the proportion of times an individual has selected future payments and proceed similarly with risk lotteries by measuring the proportion of choices corresponding to the safer options. We then regress each conditional type probabilities separately on both preference indicators and an intercept term (Table A.4 in the appendix).

There are three main results to take away from the table. First, the strongest relationship is the link between time preferences and STEM enrollment or graduation. That is, the more students are forward-looking, the more likely they are to enroll in STEM. This suggests that a STEM degree is regarded as an investment. A second interesting finding is that the decision to

[18] Belzil et al. (2021) make use of these binary choices to estimate the ex-ante value of financial aid whereas Jagelka (2024) uses them to analyze the mapping from individual cognitive and non-cognitive traits onto economics primitives.

enroll in Social Sciences and related fields seems in no way related to forward looking behavior or risk aversion. This suggests that students may choose these subjects mostly because of their intrinsic preferences or, put differently, that the consumption value of these subjects is the dominant determinant. Finally, Business seems to be negatively related to forward-looking behavior but also negatively related to risk aversion.

6 The Composition Effects Induced by Financial Aid

To investigate composition effects, we use the model specification that separates field choice and graduation. We simulate a large number of individual decisions under the status quo (no aid) and replicate the same exercise with a 2,000$ grant since it approximately corresponds to the average actual financial aid paid in the data.[19]

When characterizing various subgroups, it is important to remember that the effect of aid on university enrollment is non-monotonic. There are individuals (Type 3) enrolling in university when receiving additional aid but enrolling in two-year college under the status quo and there are also individuals (Type 4) doing the opposite (enrolling in short studies with aid but enrolling in university under the status quo). To characterize the subgroups, it is informative to split them into two main groups according to their enrollment decisions under the status quo; those entering two-year college and those entering university.

In total, we can identify eight different subgroups. For each of them, we compute their average Math and IALS scores as those are strong predictors of the capacity to complete a STEM degree as well as their Verbal scores. To illustrate the impact of financial aid on graduation outcomes, we also report their average counterfactual differences in graduation rates predicted with a 2000$ grant and under the status quo. A positive (negative) entry in the column labeled Δ Grad means that increasing aid generosity would increase (decrease) the graduation probability in a given subgroup. The results are summarized in Table 8.

[19] Simulations have been obtained from an artificial sample of 50000 observations.

Table 8: Characteristics, Field Choice Probabilities, and Graduation Probabilities of various Subgroups

Scenario		Freq.	IALS	Math	Verbal	ΔGrad
Aid=0$	Aid=2K$					
2Y college	2Y college	44.0%	-0.323	-0.354	-0.242	0.004
2Y college	Non-STEM	7.6%	-0.568	-0.559	-0.468	-0.098
2Y college	STEM	0.9%	-0.559	-0.134	-0.243	-0.462
Total		52.5%				
Non-STEM	2Y college	6.5%	0.288	0.049	0.346	0.131
Non-STEM	Non-STEM	20.1%	0.250	-0.024	0.278	-0.021
STEM	2Y college	1.9%	0.579	0.862	0.497	0.403
STEM	Non-STEM	8%	0.391	0.406	0.400	0.269
STEM	STEM	10.9%	0.550	0.780	0.581	-0.017
Total		47.5%				

Characterizing Various Subgroups

First, there are three different subgroups that comprise the group of individuals attending two-year colleges under the status quo. Those three subgroups account for 52.5% of our population and are analyzed in the top portion of Table 8. The vast majority of those individuals, about 44% of our population, would also attend a two-year college with a grant of 2000$ but there is also a smaller proportion of individuals who would be induced to attend university if they received a 2,000$ grant.

Among this latter group, those who would enroll in non-STEM subjects are eight times more important than those entering STEM (7.6% vs 0.9%). Students displaced from two-year colleges to non-STEM university subjects would have IALS scores 0.568 standard deviations lower than the population average and Math scores 0.559 standard deviations below average. Their Verbal scores would also be much below average (-0.468).

Those induced to choose STEM subjects because of aid expansion would have similar IALS scores (0.559 standard deviations below average) but higher Math scores than those choosing non-STEM (0.134 standard deviations below population average) and higher Verbal scores. Overall, marginal university entrants therefore have lower quantitative skills than the population average.

The second set of subgroups is composed of all those attending university under the status quo and corresponds to 47.5% of our population. Their characteristics are found in the lower portion of Table 8. The majority of those, corresponding to 26.6% of our population, choose non-STEM fields whereas the remaining subgroups (20.8% of the population) choose STEM. It is interesting to note that those deflected from university to two-year colleges following an expansion in financial aid are three to four times more likely to enroll in non-STEM (6.5% vs 1.9%). The STEM students displaced to two-year colleges tend to have both high IALS and Math scores (0.579 and 0.862) as well as high Verbal scores. This suggests that those displaced from STEM to two-year colleges would still have a potentially higher probability of STEM graduation than those entering university in a STEM program because of financial aid. We will get back to this point below.

Finally, and as implied by the negative marginal effects of aid on STEM enrollment, we also identify a subgroup of individuals with relatively high Math and IALS scores (both around 0.4 standard deviations above average) that would be induced to enroll in non-STEM fields instead of STEM when receiving 2000$. This group represents about 8% of our total population, whereas about 11% of our population is composed of students who persist in STEM subjects regardless of financial aid. Not surprisingly, those who would persist are also those with the highest level of quantitative skills (Math and IALS) as well as the highest level of verbal skills (0.581).

Adding up ex-ante STEM students enrolling in two-year colleges because of aid with the subgroup of students choosing STEM under the status quo and moving to non-STEM subjects, we obtain that about half of all those choosing STEM under the status quo would no longer do it with a 2000$ expansion in financial aid. While these numbers depend on the amount of aid provided, they nevertheless illustrate potential unintended consequences of higher education financial aid.

Financial Aid and Graduation

We now compare the graduation outcomes of each of these subgroups (column "ΔGrad" in Table 8). First, and not surprisingly, because financial aid attracts individuals into university enrollment and because university graduation probabilities are lower than two-year college graduation, those entering university have lower graduation rates, especially if they enrolled in STEM (-0.462).

Second, among those enrolling in university under the status quo, the effect of aid on graduation depends on whether the status quo subject is STEM or non-STEM but also on whether the individual is displaced to a two-year college or a non-STEM subject. The largest positive graduation gradient is for those leaving STEM for a two-year college (0.403). Those displaced from STEM to non-STEM subjects also experience a large increase in graduation probabilities (0.269).

In order to relate our approach to the literature using standard policy evaluation techniques, it is informative to compute the total effect of aid on graduation rates. In our model, aid has a direct effect (after conditioning on field and individual heterogeneity) but also an indirect effect through its effect on enrollment and field. In the policy evaluation literature focusing on graduation outcomes, only a total effect can be evaluated. In Table 9, we report the total effects of aid on graduation implied by our model. We do it for both the model that separates initial field enrollment and graduation and the one that considers the field of the highest grade attained. In the former, we consider graduation from either two-year college or university and also from university only whereas in the latter, we can only measure its effect on university graduation.

Table 9: The Average Effects of Aid on Graduation

	Model	
	Initial Field	Field Highest Grade
Graduation (any level)	0.022	-
Graduation University	0.015	0.010

Note: The average effects of aid on graduation are computed assuming a grant of 2000$.

For the initial field model, we obtain a total increase of about 2 percentage points (0.022) for a 2,000$ grant. For university graduation, the effect is twice smaller, equal to 0.015. The higher impact obtained for graduation at any level is easily explained by the fact that not only does aid help two-year college graduation but it also pushes people away from university toward two-year colleges that have very high graduation rates.

With the model of highest grade completed, the effect on university graduation, equal to 0.010, is virtually the same as the one obtained with the initial field model.

These estimates, which are in line with many positive estimates of the effect of aid on university graduation reported in the policy evaluation literature (Dynarski et al. (2023)), hide the underlying mechanisms generating the positive effect of aid. The overall positive effect of aid on university graduation is explained by the displacement of potential STEM students either to university subjects that are characterized by higher graduation probabilities or to two-year college programs with even higher degree completion rates. These estimates disclose an interesting paradox about financial aid; namely, while aid may raise university enrollments and even university graduation, it may simultaneously reduce post-education wages by changing the distribution of college majors.

The Relative Importance of the Composition and the Structural Effects

Finally, to evaluate the relative importance of the composition effect and the structural effect, we make use of the STEM enrollment proportions predicted under the status quo and those predicted when receiving 2000$. For each simulated enrollment outcome, we compute the STEM graduation probability conditional on enrollment. Combining both enrollment and conditional graduation probabilities, we obtain a total (unconditional) STEM graduation predicted frequency. This enables us not only to evaluate the relative importance of the composition and structural effects measured from observed graduation frequencies, but also to obtain a separate quantification of the composition and structural effects both at the enrollment and graduation levels.

First, consistent with descriptive statistics (Table 10) and with parameter estimates presented earlier, the average proportion of individuals enrolling in STEM in the experiment population drops from 21% to 12%. When measured out of the sub-populations enrolling in university, the drop is more substantial as we find that 44% of the university enrollees choose STEM under the status quo whereas 25% choose it when receiving 2000$. However, this large drop of about 20 percentage points incorporates both a structural and a composition effect as the population of individuals enrolling when receiving a 2000$ grant is different from the one enrolling under the status quo. We indeed showed earlier that a reduction in the cost attracts a new sub-population with low STEM enrollment probability and induces some potential STEM students to enroll in two-year college instead. As seen in rows 4 and 5 of the table, the portion of university entrants choosing STEM with a 2,000 grant would only be equal to 11% and about 23% of the university leavers would have chosen STEM under the status quo.

Table 10: STEM Enrollments and Graduation Proportions

	STEM Enrollment		Conditional STEM Graduation		Predicted STEM Graduation	
	Aid=0$	Aid=2K$	Aid=0$	Aid=2K$	Aid=0$	Aid=2K$
Population	0.21	0.12	0.52	0.46	0.10	0.05
University Attendants	0.44	0.25	0.58	0.48	0.26	0.12
University Stayers	0.46	0.28	0.60	0.56	0.28	0.16
University Entrants	0.00	0.11	0.46	0.43	0.00	0.05
University Leavers	0.23	0.00	0.51	0.35	0.12	0.00
STEM under Status Quo	1.00	0.53	0.62	0.58	0.62	0.32

Note: The enrollment proportions are obtained from simulated outcomes (Table 8). The conditional STEM graduation probabilities are computed after conditioning on STEM enrollment. University Attendants include all those attending university either under the status quo or with aid=2K. University Stayers include all those attending university both under the status quo and with aid=2K. University Entrants include all those who attend university only when aid=2K. University Leavers include all those who attend university only under the status quo.

To remove the portion of the drop explained by a pure composition effect, we need to compute the difference in STEM enrollment proportions for a sub-population with constant composition. A natural candidate is the sub-population of university stayers; that is, the set of individuals predicted to enroll in university both under the status quo and with the grant. Among those, the model predicts that 28% of individuals would select STEM when receiving a 2000$ subsidy while

46% would select STEM under the status quo, corresponding to a drop of about 18 percentage points. Similarly, if one focuses only on the sub-population enrolling in STEM under the status quo, we find a strong negative effect of aid as only 53% of those enrolling under the status quo would still do it when receiving a 2000$ grant.

All in all, there is a strong composition effect induced by financial aid as indicated by the substantial difference between the STEM enrollment proportions of marginal university entrants (about 11%) and those enrolling in university under the status quo (above 40%). However, the entrants account for a small proportion of the population (as documented in Table 8) and the overall decrease in STEM enrollments is far from being explained only by a pure composition effect.

The conditional graduation probabilities are found in the 3rd and 4th columns of Table 10. When comparing university attendants with university stayers, we find reasonable evidence of a composition effect in the conditional graduation probabilities. Among university attendants, the difference in probabilities due to aid is equal to 0.10 (0.58-0.48) whereas among stayers, the difference is only 0.04 (0.60-0.56). The difference for those choosing STEM under the status quo is of the same magnitude although their graduation probabilities (0.62 and 0.58) are higher. As a consequence, our estimates imply that conditional STEM graduation is less sensitive to financial aid generosity than STEM enrollments. Overall, these relatively lower differences in conditional graduation probabilities indicate that the negative effect of aid on STEM graduation (exposed in the last two columns the table) is primarily explained by its effect on enrollment decisions rather than on degree completion.

7 Discussion

7.1 Alternative Specification

One key assumption we have maintained when estimating the model is the sequential nature of individual decisions and in particular, we assumed that the decision to work is made conditional on field choice (and enrollment). This assumption, which allows us to use a recursive model structure, is debatable as one may argue that both the decision to work and the field choice are exerted simultaneously. Similarly, our recursive structure assumes that graduation outcomes depend on the labor supply decision as well as on the initial field selected, but one may again argue that those outcomes are jointly determined.

In order to assess the sensitivity of our estimates of the effect of financial aid on the main outcomes of interest, we also estimated the reduced-form of the system. That is, we formed the joint likelihood of all decisions except the probability of working during higher education and eliminated all endogenous right-hand side variables (work and field) from the graduation equations. This was done for both models and in each case, the remaining elements of the model have not been changed.

The results are summarized in Table A.5 in the appendix. There are two different types of estimates to distinguish; those measuring the effects of aid on enrollment, field and wages, and those measuring the impact of aid on graduation. While the interpretation of the former is the same as the effects presented in Table 4, the marginal effect of aid on graduation outcomes must be interpreted differently as it incorporates not only a direct effect but also an indirect effect transmitted through field enrollments, since financial aid tends to push students to enroll in high-graduation-rate majors instead of STEM (the structural effect).

Comparing results of Table 5 with those of Table A.5, we can assert that the marginal effects of aid on enrollments, field choices and take-up behavior are robust and in particular, that they were not driven by the recursive structure that we assumed. As normally expected, the only parameter affected by not having a recursive structure is the effect of aid on university graduation in the initial field model. Precisely, the effect, equal to -0.024 after conditioning on field choice (5), remains negative but has been divided by two (-0.013, Table A.5). This difference indicates that the latter is an estimate of the total effect of aid which incorporates a potentially positive indirect effect due to field reallocation away from STEM subjects as well as university-two-year college enrollment decisions.

7.2 Limitations

While our study is based in parts on a randomization procedure of financial aid amounts (something practically never achieved in the literature), it has, like any study, some limitations.

First, our interpretation of the results is based on the assumption that a lump sum grant paid at the start of the studies acts as a reduction in the cost of higher education. In practice, tuitions are paid on a per-semester basis as a student progresses toward a degree so we cannot guarantee that participants' reaction to a reduction in university tuition would necessarily be identical to that observed for a one time grant of the same amount.

A second limitation has to do with the type of aid generated by the experiment. Our analysis focuses on a reduction in the cost of education generated by grants because all loans promised at the end of the baseline experiment were transformed into grants. It should therefore be reminded that none of our results may be used to predict how a change in loan availability would impact enrollment decisions and field choices. Indeed, one may assume that those contracting loans may have a different incentive to choose a high paying major and may therefore react differently to a change in loan generosity.[20]

8 Conclusion

In light of recent technological developments, it is common for institutions involved in public policies to proclaim the need to increase the number of students graduating in the sciences.

[20] See Lochner and Monge-Naranjo (2016) of a survey of the theoretical literature on student loans.

It is therefore relevant to ask if existing education policies such as financial aid programs or tuition policies have an impact on the field of study chosen by university graduates. Using the combination of a unique high-stake field experiment and survey data collected ten years later, we were able to estimate the causal effect of a reduction in the cost of education on the distribution of fields of study and graduation outcomes among the population of university enrollees.

Our estimates, which show that financial aid reduces STEM enrollment but increases graduation as it displaces individuals toward high-graduation rate fields, demonstrate that financial aid policies may have impact beyond their global effect on enrollment and/or graduation probabilities. Moreover, this negative impact on STEM enrollment is far from being only a composition effect. While marginal university participants have lower STEM enrollment and graduation probabilities, there is clear evidence that aid also affects the behavior of those who would enroll in STEM subjects under the status quo.

While the effect of aid on the distribution of college majors is practically never studied, our results may not be that surprising since a voluminous segment of micro-econometric research has already pointed out in different contexts that transfer payments or social insurance programs may lead to a reduction in individual effort (e.g., labor supply, search effort). Our findings are therefore compatible with the proposition that as governments pay an increasing share of individual higher education expenditures, a given portion of the student population respond by choosing fields of study that require less effort.

Taken as such, our findings illustrate the arbitrage faced by higher education policy makers. Inasmuch as increases in both enrollment and graduation induced by low tuition policies may be welcome, the negative effects of student aid on STEM graduation may constitute severe unintended consequences. This suggests that countries favoring both very low tuition policies and high STEM enrollments may need to develop parallel programs that provide stronger incentives to choose STEM fields.

Finally, our findings raise many questions that could be addressed in future work. In particular, as financial aid alters the composition of the university student population and also induces changes in the distribution of fields of study, it may have some impact on job match quality as well as on the incidence of over-education. These are issues that we plan to examine next.

Appendix Tables

Table A.1: Characteristics of Individuals in the Re-interview Sample and Determinants of the Probability of Re-interview

	Mean	Prob(re-interview)
IALS	0.21	0.072**
Math (subj)	0.12	0.020
Verbal	0.05	-0.016
Motivation	0.07	-0.011
Pearlin	0.03	-0.002
Rural	0.17	-0.060
Female	0.59	0.099**
Income (in thousand $)	74.27	0.001
Constrained	-0.03	-0.004
R squared	-	0.060
# students	1247	1247

Note: All factors (IALS, Math, Verbal, Motivation, Pearlin) as well as the financial stress indicator (Constrained) are standardized. Estimates with ** (*) are significant at the 1% (5%) level. The number of individuals re-interviewed (# of 0's in the left-hand side variable of the regression) is equal to 512.

Table A.2: Financial Aid vs. Cash Decisions in the Experiment and Actual Take-up Rates

	Proportion choosing aid	Proportion	N
Cash vs Loans	22%		1247
Cash vs Grants	74%		1247
Cash vs Hybrids	64%		1247
Offered Aid (Initial Sample)		12%	1247
Offered Aid (Re-interviewed)		12%	512
Take-up (Initial sample)		71%	1247
Take-up (Re-interview)		79%	512

Table A.3: Additional Marginal Effects in the Initial Field Model: The Effects of STEM Enrollment and Labor Supply

	Dependent Variables		
	Labor Supply	Graduation	
Determinants		2-year college	University
STEM enrollment	-0.124**	-	-0.292**
	(0.007)	-	(0.027)
Labor Supply	-	0.001	-0.087**
	-	(0.007)	(0.011)

Note: Marginal effects with standard errors in parentheses. Estimates with ** (*) are significant at the 1% (5%) level.

Table A.4: Relating Type Probabilities and Field Choices to Risk and Time Preferences

	Dependent Variables: Type probabilities given choices					
Model	Initial Field			Highest Grade Field		
	STEM (Type 4)	SS-H-E (Type 3)	Business (Type 2)	STEM (Type 4)	SS-H-E (Type 1)	Business (Type 2)
Intercept	0.190**	0.378**	0.236**	0.089*	0.071**	0.352**
	(0.055)	(0.049)	(0.005)	(0.045)	(0.017)	(0.042)
Forward Looking	0.529**	-0.010	-0.407**	0.548**	-0.046**	-0.491**
	(0.053)	(0.048)	(0.045)	(0.044)	(0.016)	(0.041)
Risk Averse	0.116**	0.078	-0.177**	-0.027	-0.011	0.100
	(0.008)	(0.074)	(0.069)	(0.067)	(0.025)	(0.063)
R squared	0.11	0.01	0.10	0.11	0.01	0.11

Note: For each field, we present the dominant type (see Table 7). N = 512 students in all regressions. Estimates with ** (*) are significant at the 1% (5%) level.

Table A.5: Alternative Specification - Reduced-Form Estimates

	Model			
	Initial Field		Field Highest Grade	
Financial Aid (1,000$ Grant)	Potential	Realized	Potential	Realized
University Enrollment	0.026**	-	0.019**	-
	(0.005)		(0.004)	
Fields:				
- STEM	-0.079**	-	-	-0.141**
	(0.005)			(0.015)
- Business	0.015**	-	-	0.086**
	(0.006)			(0.011)
- SS-H-E	0.064**	-	-	0.023**
	(0.005)			(0.008)
- Health	-	-	-	0.018**
				(0.004)
Take-Up	0.126**		0.069**	
	(0.006)		(0.003)	
Graduation (short-studies)		0.010**	-	-
		(0.002)		
Graduation University		-0.013**	-	-
		(0.004)		
Non-Graduation		-		0.015**
				(0.003)
Earnings (at age 30)	-	-0.082**	-	-0.049**
		(0.030)		(0.019)

Note: All marginal effects are computed at the average of regressors and averaged over unobserved types. Standard errors of the marginal effects have been obtained from parametric bootstrap methods using standard errors of the model parameters at sample averages of the regressors. SS-H-E denotes Social Science, Humanities and Education. Estimates with ** (*) are significant at the 1% (5%) level.

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