

Estimating the Value of Higher Education Financial Aid: Evidence from a Field Experiment*

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Abstract

Using data from a Canadian field experiment designed to elicit risk and time preferences and quantify financial barriers to higher education, we estimate the distribution of the value of financial aid for prospective students, and relate it to parental socio-economic background, individual skills, risk and time preferences. Our results point to credit constraints affecting a sizable share of prospective students. We find that most of the individuals are willing to pay a sizable interest premium above the prevailing market rate for the option to take-up a loan, with a median interest rate wedge equal to 6.6 percentage points for a \$1,000 loan. The willingness-to-pay for financial aid is also highly heterogeneous across students, with preferences, in particular discount factors, playing a key role in accounting for this variation.

Keywords: Higher Education Financing, Time and Risk Preferences, Field experiment.

JEL codes: I22, I23, J24

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1 Introduction

Despite inconclusive evidence on the relationship between credit constraints and the decision to attend higher education, many education policies are based on the premise that borrowing constraints preclude students from a modest background to access higher education.¹ Quantifying the importance of credit constraints in this context is a particularly challenging task, primarily because in most datasets one cannot directly identify the set of students who are constrained. In this paper, we propose a novel empirical strategy based on the elicitation, using experimental data, of the distribution of the willingness-to-pay for higher education financial aid packages.

Specifically, we specify and estimate an educational financing decisions model using data from a field experiment that was conducted in several Canadian high schools between 2008 and 2009.² The experiment consists of a sequence of choices between a cash payment and various types of financial aid: single loan, single grant and hybrid package composed of a loan and a grant.³ Loans conditions were similar to the Federal Canadian Student Loan Program. Financial aid packages varied from \$500 - \$4,000 and represented a high fraction of yearly tuition at any of the Canadian universities.⁴ Therefore, these financial packages remove, or reduce any potential liquidity constraints by providing education financing ahead of high-school graduation. As a consequence, potential students facing liquidity constraints are likely to attach a significant value to the opportunity of receiving a loan at the market rate, while those who do not perceive financial constraints will regard those opportunities as redundant.

We formulate the decision to accept a financial aid package as an intertemporal problem. The structure of our model is simple and may be described as follows. Young

¹See our next section for a review of literature on this topic.

²Montmarquette and Johnson (2015) who designed the experiment used in the present paper, estimated a reduced-form model of the decision to take-up loans. They focus primarily on the notion of loan aversion and conclude against the existence of sizable loan aversion in this context.

³This experiment uses tools from standard lab experiments and applies them to a sample of individuals drawn from the population of interest. As such, it qualifies as an “artefactual field experiment” as defined in Harrison and List (2004).

⁴Amounts are in Canadian dollars. 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. Similarly, the average US in-state tuition fees charged by public 4-year institutions for 2007-2008 was US \$6,200 according to the Bureau of Labor Statistics (Spotlight on Statistics: Back to College, 2010).

individuals, endowed with Constant Relative Risk Aversion (CRRA) preferences, must weigh the increase in utility generated by the acceptance of a cash payment against the expected future gain generated by a specific financial aid package. Although we do not observe the post high-school graduation decisions of agents, we can use information on their revealed preferences to infer the utility gains of accepting different financial aid packages. We derive the willingness-to-pay for financial aid opportunities, and use those estimates to uncover the distribution of the individual-specific additional rates of interest that each individual would be willing to pay to secure financial aid.

To the extent that education financing decisions are made prior to actual college enrollment, the decision to accept a financial aid package depends not only on the perceived magnitude of borrowing constraints, but also on the subjective probability of enrolling in higher education, as well as beliefs over other future outcomes such as probability of dropping-out from college. Understanding financial aid acceptance therefore requires taking into account both heterogeneity in risk aversion and discount factors, as well as financial resources provided by the family. Since the experiment was also designed to infer fundamental preference parameters for risk and time, it provides a unique opportunity to address this important question and allows us to separate the effects of preferences from other components such as skills, and parental background on the probability to accept financial aid. In the paper we investigate the role played by risk aversion and discount factors, which are allowed to be individual-specific and are flexibly estimated using our experimental data, by including them as determinants of higher education financing decisions.

The majority of our sample attaches a significant value to the option of accessing higher education loans, and would be willing to trade sizable increases in current consumption in return for the option to take-up a \$1,000 loan at the market interest rate in the near future. Notably, our estimates indicate that the median high school student would be willing to pay an interest rate premium of 6.6 percentage points on top of the prevailing market rate to secure a \$1,000 loan, consistent with the existence of substantial frictions in the market for college loans. The willingness-to-pay for financial aid is also found to be highly heterogeneous across students, while remaining non-negligible for the vast majority of the population. Overall, these results point to the existence of credit constraints which affect a large share of high school students in

Canada.

In terms of public policy, our estimates can be more generally interpreted as uncovering the willingness-to-pay for a counterfactual expansion in higher education financial aid offers. Since the set of financial aid offers include grants, our estimates also speak to the value of a significant reduction in university tuition fees. Students attach high values to grants. For instance, our estimation results imply that the median agent would be willing to trade a \$400 increase in current consumption against a \$1,000 reduction in tuition in the future.

Turning to time and risk preferences, our results indicate that students in our sample have a median discount factor of 0.83 and a median degree of relative risk aversion equal to 0.64. Individual-specific discount factors as well as risk aversion parameters, which are very dispersed across students, play an important role in explaining the willingness-to-pay for higher education financial aid. A variance decomposition analysis shows that these individual preference parameters are more important than all other determinants. For instance, they are about 6 times more important than parental education, parental income and numeracy test score in explaining the willingness-to-pay for a \$1,000 loan. Taken together, these findings highlight the importance of collecting data on individual time and risk preferences to improve our understanding of educational financing decisions and, more generally, of higher education demand.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the related literature and detail our contributions. The design of the field experiment and a summary of the data are discussed in Section 3. Sections 4 and 5 describe the model and the econometric specification. Section 6 discusses the identification and the estimation procedure. The estimation results are presented in Section 7. Finally, Section 8 concludes.

2 Background literature and contributions

The existence and the intensity of credit constraints are among the most important issues guiding public policies aimed at stimulating human capital formation such as loans, grants and work study programs (see [Lochner and Monge-Naranjo, 2012, 2016](#), and [Heckman and Mosso, 2014](#) for recent surveys). In the education context, credit

constraints denominate any barrier hindering potential students to finance tuition fees or consumption. At the empirical level, testing for the presence of credit constraints is challenging since borrowing restrictions are not observed in standard data sets. As a consequence, most of the papers have used indirect approaches.

One can distinguish four main strands in this literature. A first set of papers argue that one reason why the estimated returns to schooling using standard instrumental variable techniques may be larger than the OLS estimates is that the subpopulation of compliers tend to be more credit constrained, and thus face larger returns to schooling at the equilibrium (see, e.g., [Lang, 1993](#), and [Card, 1995](#)). A second strand of papers test for the importance of credit constraints by estimating short-term effects of parental income on the probability of enrolling in higher education, controlling for long-run factors such as ability (see, e.g., [Cameron and Heckman, 1998](#), [Carneiro and Heckman, 2002](#), and [Belley and Lochner, 2007](#)). The third one estimates or calibrates structural models in which credit constraints are explicitly represented, as in [Keane and Wolpin \(2001\)](#), [Cameron and Taber \(2004\)](#), [Lochner and Monge-Naranjo \(2011\)](#) and [Johnson \(2013\)](#). Finally, [Cameron and Taber \(2004\)](#) and [Brown, Scholz, and Seshadri \(2012\)](#) analyze various other testable implications of the existence of credit constraints. With the notable exceptions of [Belley and Lochner \(2007\)](#), [Lochner and Monge-Naranjo \(2011\)](#) and [Brown et al. \(2012\)](#), most of these studies conclude against the existence of a significant role played by credit constraints. ⁵

Recently, alternative approaches based on direct measures of credit constraints have been proposed. Although access to these measures provides a clear advantage to researchers, they are typically obtained at the expense of external validity. In addition, while quantifying the overall importance of education financing barriers in the economy requires evaluating their impact prior to actual college enrollments, direct measures are generally obtained from a sub-population of individuals who have already enrolled in higher education. A key reference in this literature is [Stinebrickner and Stinebrickner \(2008\)](#), who designed a survey of college students enrolled at Berea College (Kentucky)

⁵The intuition of [Belley and Lochner \(2007\)](#) is that changes across the 1979 and 1997 cohorts of the NLSY in the effect of income quantiles on college enrollment provides evidence in favor of credit constraints. Their argument is primarily based on the observation that college attendance rate among the low ability individuals has increased more over time for students coming from high income families.

in order to identify those who are credit constrained and to analyze differences in college drop-out decisions. The authors conclude that the majority of college attrition is explained by factors other than access to credit.⁶

In this paper, we follow another route and use rich data from a college education financing field experiment conducted among Canadian high school students to address this question. Importantly, this experiment provides us with direct measures of the opportunity cost of refusing various types of higher education financial aid packages. This unique feature of the data allows us to estimate the distribution of the monetary values associated with the option to take-up a college loan at the prevailing market interest rate. In the absence of credit constraints, one would expect these values to be small or negligible. On the other hand, large values associated with the option to take-up college loans are indicative of credit constraints.

Our study also contributes to the experimental literature dealing with the estimation of risk and time preferences, including [Coller and Williams \(1999\)](#), [Holt and Laury \(2002\)](#) and [Andersen, Harrison, Lau, and Rutstrom \(2008\)](#) (see [Frederick, Loewenstein, and O'Donoghue, 2002](#), for a survey). To our knowledge, our paper is the first to nonparametrically estimate the joint distribution of risk aversion parameters and discount factors. This is possible thanks to the large number of choices that are recorded for each individual, which allows us to treat both risk aversion parameters and discount factors as individual fixed-effects. It is worth noting that, in this respect, our approach stands in sharp contrast to most of the dynamic discrete choice literature, where one generally imposes the restriction that all agents share the same discount factor and the same degree of risk aversion.⁷ The results obtained in this paper provide clear evidence that discount factors and risk aversion parameters are in fact highly heterogeneous across individuals.

⁶Recent work by [Delavande and Zafar \(2014\)](#) investigates the role played by credit constraints in the context of university choice in Pakistan. The authors address the identification issue by directly eliciting from the individuals the university they would have chosen in the (counterfactual) absence of financial constraints, and find that those constraints play an important role.

⁷Notable exceptions include [Arcidiacono, Sieg, and Sloan \(2007\)](#) and [Brodsky, Gary-Bobo, and Prieto \(2014\)](#), who allow for heterogeneous discount factors and relative risk aversion, respectively.

3 Data

The data used in the paper comes from “The Millenium Foundation Field Experiment on Education Financing”. The field experiment was conducted from October 2008 to March 2009. The sample, which consists of 1,248 Canadian full time senior high school students (or students enrolled in CEGEP, the equivalent of senior year of high school in Quebec), was drawn from both urban and rural sites across Canada. The students were between 16 and 18 years old at the time of the experiment. The experiment was funded by the Canada Millennium Foundation, a public enterprise created by the Canadian federal government, and was carried jointly by The Social Research and Demonstration Corporation (SRDC, Ottawa, Canada) and the Centre Interuniversitaire de Recherche en Analyse des Organisations (CIRANO, Montreal, Canada).⁸

The experiment was conducted using pen and paper choice booklets as well as simple random sampling devices like bingo balls and dice. Project cost considerations suggested that participants be drawn from locations with convenient travel connections from the SRDC Ottawa and CIRANO Montreal offices. Manitoba, Saskatchewan, Ontario and Quebec were the selected provinces. The implementation team was able to carry out work in urban and rural schools in each of the four provinces.⁹

The experiment consists of three parts. First, students must answer a set of questions aimed at measuring their rate of time preference. In those questions, individuals are offered a choice between two payments of different values to be made at different points in time. In our analysis we use the 24 questions that provide a cash payment within a day or a week. A second set of questions relate to the measurement

⁸See Appendix A for a more extensive description of the data.

⁹Experiment staff was granted access to the high schools and cooperated with student services staff to recruit and schedule senior students. Sessions took place during school hours (over two days). Participation to a Web survey and parental consent were required to participate in the experimental session. The experimental sessions were held in controlled environments including classrooms, libraries, career counseling rooms, activity rooms and auditoriums. All rooms were held on the campus where the student attended classes. The planned optimal number of participants per session was between 20 and 25 allowing the entire urban subject pool to be contained in 50 sessions. A total of 75 sessions were conducted with 50 as the maximum number of participants in any session. For showing up on time, each participant received a \$20 fee. Supplementary information regarding aspects of the experiment that we do not model may be found in [Montmarquette and Johnson \(2015\)](#).

of risk attitudes. Specifically, students are presented with a sequence of 55 binary choices between two lotteries in which risk is objectively stated. Finally, the third group of questions is a sequence of choices between a cash payment to be paid within one week from the day the experiment was carried, and the option to take-up a specific financial aid package covering future educational expenses. Should the student decide to exercise this option, the financial aid package is to be paid conditional on enrolling in a full-time program at any higher education institution in the country (within two years).¹⁰ Importantly, choices were incentivized as students were paid for one randomly drawn decision at the end of the session.

Overall, three types of financial aid packages were offered, namely grants, loans and hybrid loans which combines a loan and grant. In the paper we use a total of 17 financial aid decisions, with 5 choices with a single loan offer, 7 choices with a single grant offer, and 5 hybrid loan offers. These decisions are summarized in Table A3 in Appendix A.

Cash alternatives varied from \$25 to \$700, while grants and loans varied from \$400 to \$4,000. The variations in cash amounts and in the nature and the size of financial aid packages play a crucial role in our analysis. At the outset, it should be clear that these amounts are quite significant in the Canadian context. For instance, over the period considered, a grant of \$2,000 in 2008 would have covered 65% of yearly fee at University of Western Ontario and Queen’s University, and almost 100% at McGill University and Université de Montréal.

3.1 Describing the take-up rates

To describe the sensitivity of individual take-up to financial aid structure and cash payments, we plot below the take-up rates associated with various combinations of grants and loans, against specific cash payments. In Figure 1, the take-up rates are those obtained when the alternative cash payment was \$25 and \$700, respectively.¹¹ As expected, the take-up rates are inversely related to the amount of cash payment. For instance, 90% of individuals opted for a \$1,000 grant when offered a \$25 cash

¹⁰Over this period in Canada, the transition rate from high school to higher education was around 85% (see [Belley, Frenette, and Lochner, 2014](#)).

¹¹L stands for loan and G for grant.

payment, while only 40% opted for a \$1,000 grant when offered a cash payment of \$700. Those differences in take-up rates are very similar for the three financial aid packages considered in this figure (\$1,000 grant, hybrid \$1,000 loan combined with \$1,000 grant, and \$1,000 loan). Figure 2 reports the take-up rates for various sizes and types of financial aid packages and for a \$300 cash payment. This figure shows that, for all three types of packages, take-up rates increase with the size of the financial aid. However, the increase in take-up rates is relatively modest after \$1,000. Figure 2 shows that the marginal increase in take-up rates for additional financing is relatively small, with take-up rates respectively equal to 76% for a \$2,000 grant and 84% for a \$4,000 grant, against 68% for a \$1,000 grant and 39% for a \$500 grant. An explanation for those take-up rates being significantly below 1 even for a \$4,000 grant is that not all individuals in our sample intend to enroll in higher education, and as a consequence, some individuals will always value more current consumption over higher education financing opportunities. Besides, even some of the students expecting to enroll in higher education may choose a significantly smaller amount of cash payment over the option to take-up a grant as the latter can be used to pay for educational expenses only. A similar pattern can be observed for single loan offers, as the take-up rate for \$1,000 loan is 11%, to be compared to 17% and 24% for \$2,000 and \$4,000 loans, respectively.

Figures 1 and 2 also show that take-up rates for a grant of value x are very similar, and in fact always slightly higher, than for a hybrid financial package offering an additional loan of value x . This pattern likely reflects the fact that taking-up a hybrid financial aid package in practice entails taking-up both the loan and the grant associated with it, and thus paying the interests on the loan component. Depending on the expected future consumption profile as well as the existence and intensity of credit constraints, individuals may rationally attach a higher value to a grant offer than to an hybrid package adding a loan to the grant.

Figure 1: Take-up rates

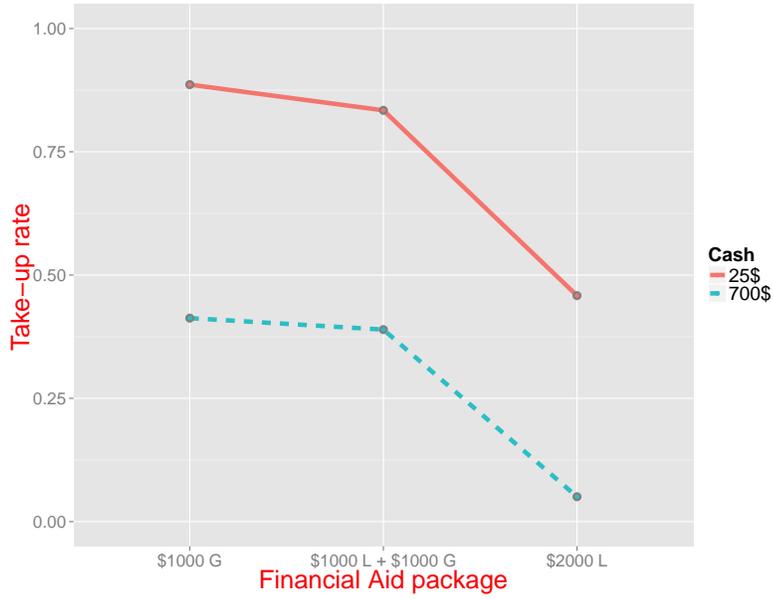
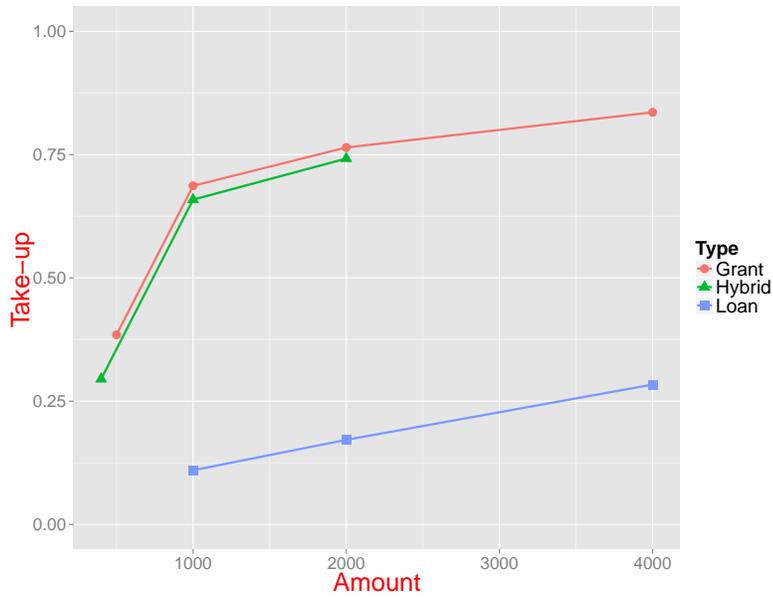


Figure 2: Take-up rates against \$300



4 The model

We assume that preferences over consumption are represented by a CRRA utility function. Namely, for each student i , the utility of consumption c is given by:

$$u(c, \theta_i) = \begin{cases} \frac{c^{1-\theta_i}}{1-\theta_i} & \text{if } \theta_i \neq 1 \\ \log(c), & \text{if } \theta_i = 1 \end{cases} \quad (1)$$

where θ_i denotes the individual-specific risk aversion parameter.

The large number of questions available from the experiment (96 in total) allows us to treat relative risk aversion rate as well as the annual discount factors as individual-specific parameters. Because individuals differ not only in their preferences, but also in their financial resources, we further allow for individual specific consumption endowments. In the rest of the section we follow the structure of the experiment and discuss the choice equations separately for each group of questions.

4.1 Time preference

A first set of questions (indexed by $q = 1, \dots, 24$) is devoted to measuring the subjective discount rate and consists of a sequence of choices between two alternatives: an early cash payment denoted by a_{0q} to be paid t_{0q} months from now, and another cash payment denoted by a_{1q} , and to be paid t_{1q} months from now. We denote by Y_{iq} a dummy variable which is equal to 1 if individual i chooses the early cash payment. Questions differ with respect to the amount of the cash payment, and the periods at which the earlier or later cash payments would be paid.

We express individual i 's probability to choose consumption at period t_{0q} versus period t_{1q} using a simple two-period consumption model:

$$\Pr(Y_{iq} = 1) = \Pr \left\{ \beta_i(t_{0q})[u(c_i + a_{0q}, \theta_i) - u(c_i, \theta_i)] \right. \\ \left. + \beta_i(t_{1q})[u(c_i, \theta_i) - u(c_i + a_{1q}, \theta_i)] + \varepsilon_{iq} > 0 \right\} \quad (2)$$

where ε_{iq} is an idiosyncratic preference shock and c_i the individual background consumption. The distributional assumptions and specification of the background consumption are discussed in Section 5. Finally, the individual discount rate applied for a payment to be received t_q months from now is assumed to be given by:

$$\beta_i(t_q) = \frac{1}{1 + \frac{t_q}{12} \cdot r_i}$$

where r_i denotes the individual annual subjective interest rate.

4.2 Risk aversion

A second set of questions relate to the measurement of the degree of relative risk aversion. In each of these questions, individuals are offered to choose between two alternatives, namely a lottery offering a_{0q}^1 with probability p_q and a_{0q}^2 with probability $1-p_q$, and another lottery offering a_{1q}^1 with probability p_q and a_{1q}^2 with probability $1-p_q$. Questions differ according to the state contingent cash payments ($a_{0q}^1, a_{0q}^2, a_{1q}^1, a_{1q}^2$) and probabilities ($p_q, 1-p_q$).¹² The generic choice probability for the first alternative is given by:

$$\Pr(Y_{iq} = 1) = \Pr \left\{ p_q \cdot \left(u(c_i + a_{0q}^1, \theta_i) - u(c_i + a_{1q}^1, \theta_i) \right) \right. \quad (3) \\ \left. + (1 - p_q) \cdot \left(u(c_i + a_{0q}^2, \theta_i) - u(c_i + a_{1q}^2, \theta_i) \right) + \varepsilon_{iq} > 0 \right\}$$

where ε_{iq} is an idiosyncratic preference shock, and $q = 25, \dots, 79$.

4.3 Choices between consumption and education financing

The third group of questions is a sequence of choices between a cash payment to be paid within one week, and a specific financial aid package covering educational

¹² As is standard in the experimental literature, we assume that individuals consume the windfall gain immediately upon reception.

expenses.

In order to interpret individual choices between cash payments and educational financial aid, we specify a stylized two-period model. Period 0 refers to the time when high school students are asked to choose between consumption and an education financing package, while period 1 refers to the residual life-cycle starting from high school graduation. For each choice, individuals must decide between a cash payment and a financial aid package which is to be paid conditional on higher education enrollment in period 1.

This structure of the model is as follows. Let a_{0q} and a_{1q} be the cash payment and financial aid transfer in question q . The potential financial aid offer (a_{1q}) offered in period 0 and to be paid at the beginning of period 1 is characterized by a two-element vector, denoted by $(g_q, \ell_q)'$ where g_q is the amount of the grant and ℓ_q the amount of the loan.¹³ The choice variable Y_{iq} is equal to 1 when an individual chooses financial aid a_{1q} , and 0 if she accepts consumption a_{0q} . As a consequence, the initial period consumption c_{0iq} is given by

$$c_{0iq} = c_i + a_{0q} \cdot (1 - Y_{iq})$$

The period 0 utility, denoted by $W(\cdot)$, of accepting or rejecting the financial aid is then given by:

$$W(Y_{iq} = 1) = u(c_i, \theta_i) + \varepsilon_{1iq} \tag{4}$$

$$W(Y_{iq} = 0) = u(c_i + a_{0q}, \theta_i) + \varepsilon_{0iq} \tag{5}$$

where ε_{0iq} and ε_{1iq} represent choice specific preference shocks.

Because we do not have data on actual choices exercised in subsequent periods, we focus on the estimation of the difference between future component of the utilities of accepting and rejecting financial aid. The intertemporal utilities of accepting and rejecting financial aid are given by $u(c_i, \theta_i) + \varepsilon_{1iq} + \beta_i EV_{iq}(Y_{iq} = 1)$ and $u(c_i + a_{0q}, \theta_i) + \varepsilon_{0iq} + \beta_i EV_{iq}(Y_{iq} = 0)$, respectively, where the future components $EV_{iq}(Y_{iq} = 1)$ and $EV_{iq}(Y_{iq} = 0)$ are the expected lifetime utilities associated with each choice.

¹³For instance, an offer consisting of a grant has an entry equal to 0 for ℓ , while a loan has an entry equal to 0 for g . An hybrid offer that includes both a grant and a loan has a positive entry for both.

In practice, expected future value terms associated with each alternative $Y_{iq} \in \{0, 1\}$ depend on individual beliefs about a range of future outcomes, some of them being alternative specific. Notably, those beliefs include the subjective probabilities of enrolling in higher education conditional on receiving the financial aid offer a_{1q} , and conditional on not receiving the financial aid offer, for the alternatives $Y_{iq} = 1$ and $Y_{iq} = 0$ respectively. The expected future value terms in principle also depend on the perceived availability of higher education financing opportunities outside of the experiment, as well as possibly on beliefs over other future outcomes such as the probability of dropping-out from college. As those outcomes are not observed in the data, we treat those future components as unknown functions of parental socio-economic background and individual skills, as well as risk and time preferences. A key advantage of this approach relative to a more standard dynamic discrete choice model is that it avoids strong and untestable restrictions regarding the beliefs of the individuals and their evolution over the life cycle.¹⁴

Under these assumptions, agent i 's probability to accept the financial aid package proposed at question q is given by

$$\Pr(Y_{iq} = 1) = \Pr \left\{ u(c_i, \theta_i) - u(c_i + a_{0q}, \theta_i) + \beta_i \cdot \psi_{iq} + \varepsilon_{iq} > 0 \right\} \quad (6)$$

where $\psi_{iq} = EV_{iq}(Y_{iq} = 1) - EV_{iq}(Y_{iq} = 0)$ denotes the expected future utility gain associated to accepting financial aid, and $\varepsilon_{iq} = \varepsilon_{1iq} - \varepsilon_{0iq}$.

5 Specification

In the following, we assume that the idiosyncratic shocks are independent across individuals and questions, and identically distributed within each of the three groups of questions following a normal distribution with mean zero. We summarize in the rest of the section the specification of the background consumption and the expected

¹⁴An alternative approach would be to elicit beliefs about counterfactual future schooling choices and consumption paths. In the higher education context, notable references include Arcidiacono, Hotz, and Kang (2012), Stinebrickner and Stinebrickner (2014) and Wiswall and Zafar (2015a, 2015b) who use subjective expectations data to examine the determinants of college major choice.

future utility gain of accepting financial aid.

5.1 Background consumption

Until now, we have simplified the exposition by considering for each individual a unique background consumption variable c_i . However in order to capture contextual differences across groups of questions, we allow the background consumption levels, and therefore also the marginal utility of consumption to vary with the group of questions. Specifically, for each group of questions k (where $k \in \{1, 2, 3\}$ indexes the questions related to time preference, risk aversion and education financing, respectively), we denote the individual background consumption by c_i^k , which is assumed to depend on a vector of individual and family background characteristics denoted by Z_i :

$$c_i^k = \exp(\gamma_k Z_i) \tag{7}$$

The vector Z_i includes an intercept and a set of individual characteristics, namely gender, parental income (20-40K, 40-60K, 60-80K, 80-100K and more than 100K Canadian dollars per year), parental education (high school, vocational college and college) of the respondent of the parental survey, Canadian citizenship, place of residence (Quebec, Ontario, Saskatchewan, and a dummy for rural location) and family composition (existence of siblings younger or older than 18).¹⁵ This flexible specification allows each of these characteristics to have different weights within each group of questions.

5.2 Approximation of the future component

The expected future utility gain of accepting financial aid (ψ_{iq}) is a key component of the model. Standard structural dynamic estimation would require to posit a parametric form of the utility of potential future schooling choices as well as all the probability distributions that characterize the subjective beliefs of agents about future returns to education and experience. In this paper, we take another route and assume

¹⁵There are 269 individuals with missing income data, and 146 individuals with missing education data. We use a Gibbs sampling algorithm to impute those missing information using age, gender, location, income, education, citizenship variables in the full sample.

instead that the future component may be approximated by a parametric function that depends on the loan and grant amounts, time and risk preference parameters, skills (as measured by numeracy test scores), geographical location, parental income and education. We estimate this function using a flexible polynomial incorporating those variables in level and square as well as various interactions.¹⁶

6 Identification and estimation

In this section we first discuss the sources of identification of the key parameters of the model, before turning to the estimation procedure.

6.1 Identification

We start by informally discussing the sources of identification of the individual time preference and risk aversion parameters, before turning to the parameters of the expected future utility gain of accepting financial aid. We highlight below the main features of the experiment and of the model that are key to identification. While the experiment does provide us with separate sources of identification for those different sets of parameters, (point-)identification remains parametric in the sense that it relies on the distributional assumptions made on the idiosyncratic shocks.¹⁷

First, the risk aversion parameters are primarily identified from the sequence of choices described in Section 4.2 between two lotteries that differ in the cash payments and the probabilities associated with each payment. Importantly, variation across individuals in time preferences does not confound the identification of the risk aversion

¹⁶The exact specification is given in Appendix B. Interaction between risk aversion and discount factor, squared terms in those preference parameters, and dummies for the existence of siblings younger or older than 18 are excluded from this specification as they were not statistically significant when we allowed them to enter the future component. Our approach is in line with [Geweke and Keane \(2000\)](#), who advocate the estimation of the future component of the value function using a polynomial which records the movement of state variables implied by the law of motion. However, in contrast with [Geweke and Keane \(2000\)](#), we account for heterogeneity in individuals preferences and incorporate time and risk preference parameters in the polynomial.

¹⁷This should not come as a surprise since binary choice models are generally not point-identified without making distributional assumptions on the error term. Note that this is true even if the parameters of interest are not individual-specific (see, e.g., [Magnac and Maurin, 2008](#)).

parameters here since all of the state-contingent cash payments are immediate.

The main sources of identification of the individual discount rates are the choices between earlier and later cash payments that are described in Section 4.1. However, given that in our model individuals are endowed with non-linear CRRA preferences over consumption, part of this variation may of course also reflect heterogeneity across individuals in risk aversion. This highlights the importance of having access to choices that only depend on risk aversion, and not on discount factors.

Finally, having identified the time and risk preference parameters from the choices described above, the expected future utility gains of accepting financial aid (versus cash payment) are identified from the choices between immediate cash payment and education financial aid that are modeled in Section 4.3. Specifically, under our parametric assumptions, the expected future utility gains associated with the various types of financial aid are identified using the variation in take-up rates across discount rates. It is interesting to note that individual-specific discount rates effectively play the role of an exclusion restriction in this context, in that they only affect the choices through the future component of the utility. As such, aside from being of interest in its own right, the distribution of discount rates plays an important role in the identification of the willingness-to-pay for different financial aid packages.

6.2 Estimation

The model is estimated by maximum likelihood under the assumption that the error terms are independent across individuals and across questions, and identically distributed within each group of equations following a normal distribution with mean zero.¹⁸ Under these assumptions and keeping the conditioning on background

¹⁸Although the error terms are assumed to be independent across questions, individual choices are correlated across questions through the individual-specific risk and time preference parameters, and of course via their observed background characteristics too.

characteristics and numeracy score implicit, the log-likelihood is given by:¹⁹

$$\sum_{i=1}^{1,248} \sum_{q=1}^{96} Y_{iq} \log(\Pr(Y_{iq} = 1)) + (1 - Y_{iq}) \log(1 - \Pr(Y_{iq} = 1))$$

where for each group of questions the choice probabilities $\Pr(Y_{iq} = 1)$, which are given in Equations (2), (3) and (6) above, take a probit form.²⁰

7 Results

We present the estimation results as follows. The first part is devoted to the distributions of risk aversion and discount factors, and of the background consumption levels. The second part discusses the estimates of the expected future utility gain of accepting financial aid, for various types of financial packages. In the third part, we present the model fit. We introduce and discuss the willingness-to-pay for financial aid in Part 4, and then discuss the implications of these results in terms of credit constraints. Finally, we investigate the relative importance of family background characteristics, individual skills as well as time and risk preferences as determinants of the willingness-to-pay for financial aid.²¹

¹⁹In practice, the log-likelihood exhibits several local extrema. To overcome this difficulty, we use a multi-step procedure to derive starting values in the region of the global optimum. The first step consists of estimating risk aversion and background consumption parameters using the subset of questions designed to elicit risk preferences. Holding those parameters fixed, we then estimate individual discount rates using the time preferences questions. Finally, we estimate in a final step the future component of accepting the different types of financial aid using the school financing decisions. We use the outcomes of these three steps as starting values to estimate the full model via a single step maximum likelihood. Standard errors are estimated using bootstrap with 500 replications.

²⁰Our framework corresponds to a binary choice panel data model with fixed effects, where the longitudinal dimension is given by the various questions q . Our MLE estimator is therefore in principle subject to the incidental parameter problem (Neyman and Scott, 1948). However, in practice we expect the incidental parameter bias to be small here given the large number of questions that are used in the estimation (96 overall for each individual).

²¹Estimation results for the background consumption parameters associated with the financial aid questions are reported in Appendix C. Estimation results for the other background consumption as well as the future component parameters are available from the authors upon request.

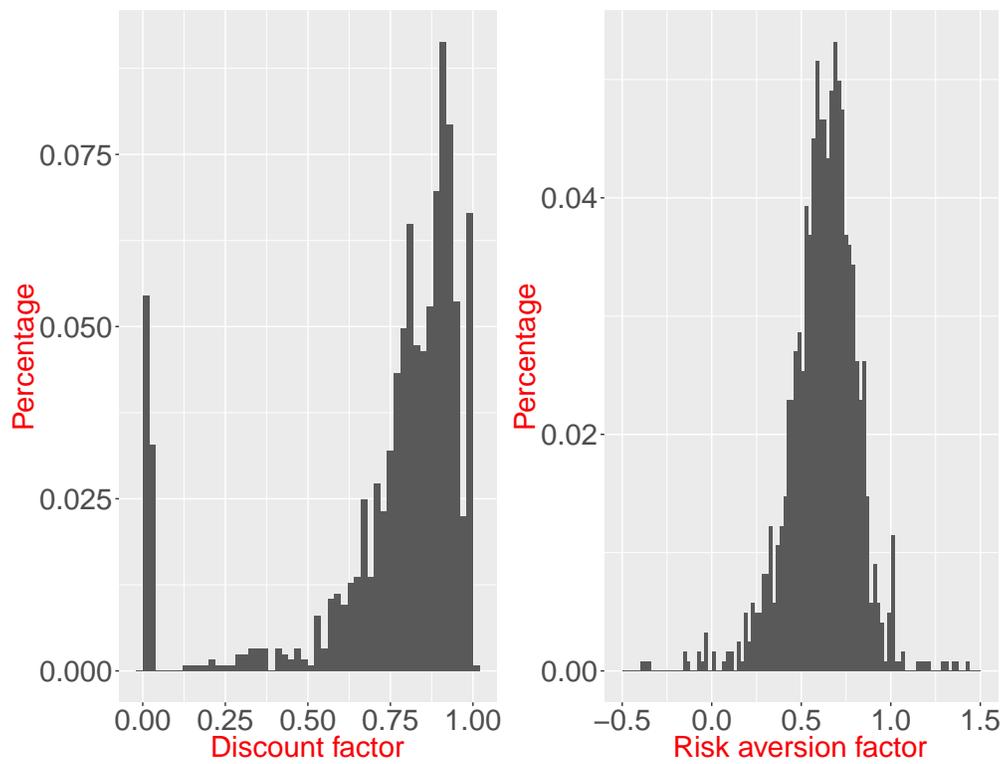
7.1 The distributions of risk aversion, discount factors and background consumption

The empirical distributions of the estimated degrees of relative risk aversion, $(\theta_i)_i$, and discount factors, $(\beta_i)_i$, are reported in Figure 3, while Table 1 describes the joint distribution of the estimated relative risk aversion parameters and discount factors. Starting with risk aversion, it is worth stressing that 97.2% of the estimated risk aversion parameters are significant at 5%, thus leading to the rejection of risk neutrality ($\theta = 0$) for the vast majority of the individuals in the sample. The distribution of risk aversion is skewed to the right and is characterized by a substantial degree of dispersion, as indicated by the inter-decile range (0.40 for the first decile and 0.85 for the last decile). Risk loving behavior ($\theta < 0$), however, is limited to 16 individuals out of 1,248. The median of the estimated risk aversion parameters (0.64) fits in the range of the relative risk aversion parameters that have been estimated in the literature on dynamic schooling choices. For instance, Keane and Wolpin (2001) estimate a smaller risk aversion coefficient (0.49), while Belzil and Hansen (2004) and Sauer (2004) find larger degrees of risk aversion (0.93 and 0.77, respectively). Particularly relevant for us is the paper by Brodaty et al. (2014), who, unlike the previous studies, estimate a dynamic model of schooling decisions that allows for heterogeneous degrees of relative risk aversion across individuals. In their paper, the estimated risk aversion coefficients range between 0.6 and 0.9. Our estimates exhibit a larger degree of heterogeneity across individuals, which may be partly due to the fact that we estimate the risk aversion parameters more flexibly than Brodaty et al. (2014) who assume the existence of a small number of heterogeneity types.

Turning to the time preferences, the discount factors are also found to be quite dispersed. The distribution is skewed to the left with its median (0.83) being larger than its mean (0.75). The empirical distribution of discount factors is essentially bimodal, with around 10% of our sample having an estimated discount rate lower than 0.33, while another 40% of the sample has discount rate higher than 0.87. This points to the co-existence of a myopic sub-population and a set of forward-looking individuals endowed with large discount factors of about 0.9.

The distribution of discount rates is difficult to compare to the rest of the lit-

Figure 3: Histogram of the risk aversion and discount factors



Notes: (i) The range of the risk factor has been restricted from -0.5 to 1.5 to improve display, excluding a total of 24 individuals. (ii) The binwidth has been set to 0.02.

Table 1: Discount factor and risk aversion

	Discount Factor	Risk Aversion
Min	0.00	-1.60
1st Dec.	0.33	0.40
1st Quart.	0.72	0.52
40th Pct.	0.80	0.60
Median	0.83	0.64
Mean	0.75	0.73
SD	0.27	1.00
60th Pct.	0.87	0.68
3rd Quart.	0.91	0.75
9th Dec.	0.96	0.85
Max	1.00	16.82
Correlation	-0.14	

Table 2: Background consumption

	Discount Questions	Risk Questions	Financial Questions
Mean	3.21	0.58	237.30
SD	36.37	1.02	274.75

erature for two main reasons. First and foremost, most of the relevant literature has focused on estimating a unique discount factor for a given population (see e.g. [Frederick et al., 2002](#)). Second, most estimates in the literature such as [Andersen et al. \(2008\)](#) have been obtained for different populations, typically university undergraduates or older. Nonetheless, it is interesting to note that our mean value matches that of [Andersen et al. \(2008\)](#) who report, using data from a field experiment conducted in Denmark, an estimate of 0.75 (under a risk neutrality assumption), while being lower than the value estimated under risk aversion (0.9).²²

Our data also allows us to examine the joint distribution of risk aversion and discount factors. Table 1 reports a negative correlation (-0.14, significant at 1%) between the discount rate and relative risk aversion. In the experimental economics literature, risk and time preferences are generally not elicited jointly and for this reason there exists to our knowledge very few estimates of the correlation between risk aversion and discount factors. A notable exception is [Andersen et al. \(2008\)](#), who discuss the bias affecting discount factor estimates when individuals are erroneously assumed to be risk neutral, and show that the joint elicitation of risk and time preferences result in lower discount rates estimates. [Andersen et al. \(2008\)](#) consider the joint distribution of risk aversion and discount rates using a parametric model in which both risk aversion and discount rates depend on observed heterogeneity and an orthogonal unobserved heterogeneity term. Consistent with our results, they report a weak positive correlation between risk aversion and impatience.

Finally, in our model, the level of background consumption allows us to capture differences in consumption levels due to heterogeneity in family background. As discussed earlier, background consumption is allowed to differ across groups of questions as well. Our estimates indicate that the consumption levels that are used to evaluate cash payments differ markedly across questions. For example, the mean reference consumption is around \$3 for discount rate questions, 50 cents for relative risk aversion choices, and \$237 for financial aid questions. The background consumption levels for the financial aid questions are also highly dispersed across individuals.

²²Some of the papers estimating dynamic models of schooling decisions also attempt to estimate the discount factor. Notably, [Keane and Wolpin \(1997\)](#) estimate a discount factor (0.85) that is very close to the median of our estimated distribution (0.83).

Having estimated the time and risk preferences for each individual in the sample, it is interesting to examine whether these parameters could be predicted by standard background characteristics. Table 3 below reports the results from a linear regression of the estimated individual-specific degrees of relative risk aversion and discount factors on a set of socio-economic background and demographic characteristics. The main takeaway from this table is that those characteristics only account for a very small fraction of the variation in risk aversion parameters and discount factors, the R^2 's for both regressions being low (0.016 and 0.085, respectively). Nonetheless, it is worth noting that females are significantly more risk averse and less forward looking than males. Immigrants also tend to be less forward looking, while children of college educated parents have a lower degree of risk aversion, although the coefficient is only significant at the 10% level. Finally, residents of Saskatchewan, which is the poorest region in the sample, have significantly lower discount rates.

At any rate, these results show that discount rates and risk aversion parameters are economic primitives which are mostly left unexplained by standard background and demographic characteristics. To the extent that, as discussed in Section 7.3.4, discount rates and risk aversion play a dominant role in explaining the willingness-to-pay for financial aid, this highlights the importance of eliciting these preference parameters.

Table 3: Understanding individual preferences

		Regression	
		β	θ
	Const	0.685*** (0.042)	0.857*** (0.162)
Parental	Drop-out	Ref.	Ref.
Education	High-school	0.018 (0.030)	-0.157 (0.116)
	Vocational College	0.009 (0.038)	-0.080 (0.149)
	College	0.034 (0.028)	-0.189* (0.110)
Parental	0-20K	Ref.	Ref.
Income	20-40K	0.023 (0.037)	0.202 (0.144)
	40-60K	0.034 (0.035)	0.074 (0.135)
	60-80K	-0.030 (0.036)	0.104 (0.142)
	80-100K	0.020 (0.037)	0.142 (0.144)
	+100K	0.030 (0.036)	0.157 (0.139)
	Rural	0.043** (0.021)	-0.101 (0.081)
	Female	-0.076*** (0.015)	0.118** (0.057)
	Immigrant	-0.141*** (0.031)	0.191 (0.121)
Province	Ontario	Ref.	Ref.
	Quebec	0.002 (0.019)	-0.047 (0.075)
	Manitoba	-0.005 (0.021)	-0.060 (0.082)
	Saskatchewan	-0.123*** (0.026)	0.107 (0.103)
R ²		0.085	0.016
Num. obs.		1,248	1,248

Notes: (i) Least squares weighted by the inverse of the standard errors of the estimated individual preference parameters, ii) standard errors reported in parenthesis, iii) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.2 The expected future gain of financial aid

In this subsection, we focus on the relevant decision variable between cash payment and financial aid. Specifically, Table 4 compares the distribution of the expected discounted future utility gain against the period 0 utility of accepting a cash payment, for various types of financial aid packages and cash payments. Period 0 utility gains of accepting a cash payment (denoted by $\Delta(\cdot)$) are evaluated as the difference in the initial period utility of consumption evaluated at the reference consumption level (c_i) plus a cash payment, and the initial period utility evaluated at the reference consumption level.

Table 4: Utilities of consumption and expected discounted future gain of financial aid

	$\Delta(c_{100})$	$\Delta(c_{300})$	$\Delta(c_{700})$	$\beta\psi(\ell_{1000})$	$\beta\psi(\ell_{2000})$	$\beta\psi(g_{1000})$	$\beta\psi(g_{2000})$
Min	0	0	0	0	0	0	0
1st Dec.	32	83	157	2.8	2.8	47	96
1st Quart.	48	122	223	15	19	148	237
40th Pct.	58	144	260	29	36	186	282
Median	66	156	280	40	50	206	305
Mean	74	167	303	62	68	210	301
SD	144	152	282	144	142	167	190
60th Pct.	73	173	305	55	64	227	330
3rd Quart.	84	198	345	77	86	263	370
9th Dec.	103	229	407	117	122	321	438
Max	4281	4282	7599	3048	3014	3214	3448

Notes: (i) $\Delta(c_x) = u(c_i + x) - u(c_i)$, (ii) $\beta\psi(\ell_{1000})$ (resp. $\beta\psi(\ell_{2000})$) denotes the expected discounted future utility gain associated with a \$1,000 (resp. \$2,000) loan, (iii) $\beta\psi(g_{1000})$ (resp. $\beta\psi(g_{2000})$) denotes the expected discounted future utility gain associated with a \$1,000 (resp. \$2,000) grant.

First, as expected, for a given amount of financial aid, the median value of a grant exceeds the value of a loan. The median future utility gain of a \$1,000 grant is more than 5 times as high as the expected utility gain of a \$1,000 loan, while the median gain associated with a \$2,000 grant is 6 times as large as the expected gain of a \$2,000 loan. More generally, the distribution of the discounted expected future utility gains for a grant first-order stochastically dominates that of the expected future gains for a loan. Second, the utility gain associated with a grant increases with its size, with the distribution of the utility gains of a \$2,000 grant dominating that of a \$1,000 grant. A similar pattern holds for loans. This result shows that, in most parts of

the distribution, the interest costs are not high enough to make a \$2,000 loan less attractive than a \$1,000 loan. Finally, the discounted expected future utility gains of the financial aid packages vary a lot across individuals, with the ratio of interdecile range over the median ranging from 1.1 (for a \$2,000 grant) to as much as 2.9 (for a \$1,000 loan).

We now examine the utility gains of accepting a cash payment. The distributions of the utility gains associated with a \$300 and \$700 cash payments dominate that of both types of loans. This is also true throughout most of the distribution of the utility gains associated with a smaller \$100 cash payment. On the other hand, the sign of the value of immediate cash versus grant varies across the distribution, with the median utility gain of accepting a \$700 cash payment ranging between the median gain of a \$1,000 grant and that of a \$2,000 grant.

Taken together, these results already provide suggestive evidence that the willingness-to-pay for financial aid packages is heterogeneous across high school students. However, our estimates allow us to go beyond the marginal distributions of utility gains associated with cash payments and financial aid, and directly compute individual-specific willingnesses-to-pay for the different types of financial aid packages that are proposed in the experiment. We report and discuss the estimated distributions of the willingness-to-pay for various types of financial aid packages in Section 7.3.

7.3 Borrowing constraints and the value of financial aid

7.3.1 Measurement

In this section, we combine the observed choices between cash transfers and financial aid packages with our model to evaluate the monetary values associated with the option to take-up the various types of financial aid. Before doing so, it is important to examine the ability of our model to fit the financial aid decisions from the experiment. Table A6 in Appendix D reports the empirical frequencies of financial aid acceptance and the predicted probabilities, for each of the 17 financial choices to exercise. Our model generally fits the data reasonably well, with a couple of exceptions. Most notably, we overestimate the take-up rates of \$1,000 grant and of the hybrid package (\$1,000 loan and \$1,000 grant) against \$700 cash payment, while we underestimate

the relatively high take-up rates for \$2,000 loans against \$25 cash payment.

In the following, we estimate individual-specific values of each type of grant, loan and hybrid loan that are proposed in the context of the experiment. Put into a public policy perspective, these estimates can be interpreted as uncovering the willingness-to-pay for a counterfactual expansion in higher education financial aid offers. We choose to pay specific attention to the willingness-to-pay for loans, which are a natural measure of the tightness of individual borrowing constraints. While constrained students may attach a significant value to the opportunity of taking-up a loan at the market rate, unconstrained students should only attach small or negligible values to those redundant opportunities.

Specifically, let c_{iq}^m be the incremental level of consumption that makes individuals indifferent between current consumption ($c_i + c_{iq}^m$) and the financial aid package at question q . For such a value, we have

$$u(c_i, \theta_i) + \beta_i \psi_{iq} = u(c_i + c_{iq}^m, \theta_i) \quad (8)$$

After a few steps of algebra, we obtain:

$$c_{iq}^m = \begin{cases} \exp\left(\frac{1}{1-\theta_i} \log\left((1-\theta_i)\beta_i \psi_{iq} + c_i^{1-\theta_i}\right)\right) - c_i & \text{if } \theta_i \neq 1 \\ \exp(\beta_i \psi_{iq} + \log(c_i)) - c_i & \text{if } \theta_i = 1 \end{cases} \quad (9)$$

c_{iq}^m is the maximum consumption increase that one would be willing to trade in order to secure the financial aid package. Throughout the rest of the paper, we use c_{iq}^m as the individual-specific measure of the willingness-to-pay for the financial aid package offered in question q .

7.3.2 Willingness-to-pay for financial aid

In Table 5 below, we summarize the distributions of the estimated willingness-to-pay for the three types of financial aid packages (loan, grants and hybrid loans) of sizes \$1,000 and \$2,000.²³ Our results indicate that the median high school student would

²³For the ease of exposition, we focus hereafter on financial aid packages of sizes \$1,000 and \$2,000. Estimation results for alternative amounts of financial aid are available from the authors upon request.

be willing to forego a \$58.6 increase in current consumption to secure a \$1,000 loan at the market interest rate in the near future. The willingness-to-pay for a \$1,000 loan is highly heterogeneous across students, with an interdecile range equal to \$180. While a quarter of the students are willing to sacrifice more than \$116 for the option to take-up a \$1,000 loan, students in the bottom quartile are only willing to sacrifice less than \$20. In the next subsection we will examine how much of this heterogeneity is attributable to risk and time preference parameters, skills, as well as family background, socio-economic and geographical characteristics.

Table 5: The distribution of willingness-to-pay

Quantiles	\$1,000			\$2,000		
	Loan	Grant	Hybrid	Loan	Grant	Hybrid
1st Dec.	4.26	50.81	55.43	5.95	128.4	118
1st Quart.	20.29	245.4	239.7	33.55	458.6	359.1
Median	58.58	396.1	372.2	82.26	678.4	504.7
3rd Quart.	116	556.1	509.1	141.7	923.1	664.2
9th Dec.	183.9	721.8	649.8	207.9	1199	828.1

Note: Amounts are in Canadian dollars.

Put into a public policy perspective, the value of a grant is equivalent to a tuition reduction, or a higher education subsidy. Not surprisingly, the value of a grant is typically much larger. The median student would be willing to trade in \$396 increase of their current consumption for the option to take-up a \$1,000 grant. Contrary to loans, only a small proportion of the population attaches low values to grant availability. For instance, less than 10% of the students would sacrifice less than \$50 for a \$1,000 grant, while around half of them would do so for a \$1,000 loan. More generally, for both amounts of financial aid (\$1,000 and \$2,000), the distribution of the willingness-to-pay for a grant stochastically dominates that of a loan.

Turning to the hybrid packages, adding a loan to a grant generally has a small negative impact on the value of the package. This pattern holds true in most parts of the distributions of the willingness-to-pay. In practice, taking-up a hybrid loan involves taking-up both the grant and the loan components of the package. As a result,

how much students are willing to trade for a hybrid package versus a single grant depends on the incremental value of a loan, as well as on the interest cost associated with it. Our results indicate that, in this context, the latter effect dominates. At any rate, this provides additional evidence that our model fits the descriptive patterns previously reported in Section 3 (Figure 2).

Finally, for loans, grants as well as hybrid loans, the value of the package generally increases with the size of the financial aid. Specifically, the distribution of the willingness-to-pay for a \$2,000 loan (grant) stochastically dominates that of a \$1,000 loan (grant), while a (\$2,000 loan, \$2,000 grant) hybrid loan also dominates that of a (\$1,000 loan, \$1,000 grant) hybrid loan. In particular, the results for loans provide suggestive evidence that, at least for a subset of the students in the sample, getting access to a \$1,000 loan is not enough to remove higher education credit constraints.

One can quantify the magnitude of, and heterogeneity in credit market imperfections by converting the willingness-to-pay for any given loan into the interest rate wedge that students would be willing to pay on top of the prevailing ($r_0 = 5.7\%$) market interest rate in order to secure the option to take-up that loan. Specifically, for a given loan of size l and willingness-to-pay c_m , we define the effective interest rate as the interest rate, denoted by $r_1(l, c_m)$, such that:

$$(1 + r_1(l, c_m))(l - c_m) = (1 + r_0)l \tag{10}$$

where $l - c_m$ is the principal of the loan net of the willingness-to-pay, and $(1 + r_0)l$ is the total repayment (principal plus interest fees). Note that $r_1(l, c_m)$ is larger than r_0 for any positive willingness-to-pay c_m . We report in Table 6 below the distribution of the interest rate wedges ($r_1(l, c_m) - r_0$) associated with a \$1,000 loan and a \$2,000 loan:

Table 6: The distribution of interest rate wedges (in percentage points)

Quantiles	\$1,000 loan	\$2,000 loan
1st Dec.	0.45	6.02
1st Quart.	2.19	7.50
Median	6.58	10.2
3rd Quart.	13.9	13.8
9th Dec.	23.8	18.0

Note: Interest rate wedges are computed with respect to the prevailing market interest rate of 5.7%.

These results indicate that most of the students in our sample are willing to pay a sizable interest rate premium above the prevailing market rate for the option to take-up a loan. The median interest rate premium students would be willing to pay is large and equal to 6.58 (10.2) percentage points for a \$1,000 (\$2,000) loan, respectively.²⁴ As expected given the results on the willingness-to-pay for loans documented earlier, the interest rate premia also exhibit much heterogeneity across students. For the case of \$1,000 loans, the interest wedge ranges from 0.45 to 23.8 percentage points for the first and the last decile, respectively. Overall, these results point to the existence of credit constraints, in the form of frictions in the market for college loans, which affect a substantial share of high school students in Canada. Our estimates further show that a non-negligible fraction of high school students attach pretty large values to the option to take-up a college loan.²⁵ From a policy standpoint, our findings indicate that expanding higher education financial aid may in fact be socially desirable in this context, in spite of the Canadian higher education system being already heavily subsidized.²⁶

²⁴Interest rate wedges are lower for a \$1,000 loan than for a \$2,000 loan from the third quartile. This pattern is consistent with the willingness-to-pay increasing less with the amount of the loan in the top part of the distribution.

²⁵To the extent that some individuals in the sample are likely to have low, or even zero subjective probabilities of enrolling in college, our results effectively provide a lower bound on the value attached to financial aid expansion among those students who anticipate enrolling in higher education. In practice 9.6% of the individuals in the sample have refused all financial offers that included a grant, presumably indicating a very small subjective probability of attending higher education for those students.

²⁶In Appendix E, we report the distribution of the willingness-to-pay separately for Ontario and

7.3.3 Statistical decomposition

We now examine the determinants of the value attached to financial aid. Before estimating marginal effects, we evaluate the relative importance of the main components of the willingness-to-pay for financial aid, namely (i) preference parameters (risk aversion and discount factors), (ii) skills (numeracy test score), (iii) family background characteristics (parental income and education) and (iv) other socio-economic and geographical variables such as gender, province, an indicator for living in a rural area, and family composition.

Understanding the determinants of the willingness-to-pay for financial aid is important from a policy standpoint. Notably, if skills or family background characteristics play an important role in this decomposition then these results may provide some guidance regarding the optimal targeting of higher education financial aid opportunities. On the other hand, if most of the variation in willingness-to-pay is attributable to risk and time preferences, then identifying who would benefit more from an expansion in higher education financial aid would prove much more challenging as these preferences are typically unknown to the policy maker.

Since our model is highly non-linear, there are multiple possible ways to decompose the willingness-to-pay. In the following we simply regress linearly the willingness-to-pay on various sets of characteristics. We then compute the adjusted coefficient of determination (Adjusted R^2) associated with each specification, and divide it by the Adjusted R^2 obtained when all four groups of determinants (i)-(iv) are included. The corresponding ratio can be interpreted as a measure of the relative importance of each group of variables.

As we did before, we focus our analysis on the willingness-to-pay for a \$1,000 loan and a \$1,000 grant. The decomposition results are reported in Table 7. We highlight two main takeaways. First, as indicated by the ratios of adjusted R^2 (0.52 for loans and 0.61 for grants), time and risk preference parameters are more important than all other determinants taken together. This is true for both loans and grants. A

Québec. Our estimates are consistent with the institutional differences across these two provinces. In particular, the distribution of the willingness-to-pay for a \$1,000 loan in Ontario dominates almost everywhere the distribution in Québec, consistent with higher levels of (net) tuition fees in Ontario than in Québec.

second noteworthy finding is the low incremental explanatory power of numeracy test scores and parental background variables.²⁷ For the case of a \$1,000 loan, the relative explanatory power increases by about 15% (from 0.52 to 0.60), while it increases by less than 7% only (from 0.61 to 0.65) for a \$1,000 grant. Overall, these results provide evidence that time and risk preference parameters play a dominant role in accounting for the variation across individuals in willingness-to-pay for financial aid. As such, our findings highlight the importance of collecting data on individual time and risk preferences to improve our understanding of educational financing decisions. Next, we report and discuss the marginal effects associated with those preference parameters, as well as with the numeracy scores and background characteristics.

Table 7: Statistical decomposition

	$c^m(\ell_{1000})$				$c^m(g_{1000})$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Ratio Adjusted R^2	0.52	0.52	0.60	1	0.61	0.61	0.65	1
Risk and Discounting	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Skills		Yes	Yes	Yes		Yes	Yes	Yes
Parental education and income			Yes	Yes			Yes	Yes
Geography and Family structure				Yes				Yes

7.3.4 Explaining the willingness-to-pay

We now turn to the marginal effects of parental background variables and other observed attributes and preferences on the willingness-to-pay for financial aid. Table 8 below reports the average marginal effects for two types of financial aid packages,

²⁷Note that this holds true even though, as discussed earlier, background and demographic characteristics accounts for very little of the variation in time and risk preferences.

namely a \$1,000 loan and a \$1,000 grant.²⁸

We first examine the effects of parental income. There is a large empirical literature on the relationship between parental income and schooling attainment (Heckman and Mosso, 2014). Economists have long debated on the magnitude of the causal effects of parental income on educational outcomes, in particular college enrollment. Identifying those effects is a complicated task as family income is also likely correlated with individual abilities, as well as preferences for schooling. The experiment used in this paper allows us to go beyond evaluating the impact of parental income on schooling attainment as we can directly quantify how the willingness-to-pay for education financial aid, a measure that increases with the intensity of credit constraints, vary with family income. Doing so is also an important step towards evaluating the effectiveness of publicly provided financial aid policies that are meant to equalize opportunities across income groups. The results reported in Table 8 illustrate the differences in willingness-to-pay across income classes, using as a reference those who earn \$20,000 or less. The results indicate that the willingness-to-pay for a \$1,000 loan is non-linear and non-monotonic as the highest willingness-to-pay is found for the \$40,000-\$60,000 income group. However, the marginal effects across income groups are very small. For instance, on average, young individuals raised in families earning \$40,000-\$60,000 would only be willing to pay \$2.4 more for the option to take-up a \$1,000 loan, relative the lowest income reference group. This is consistent with the very low explanatory power associated with parental education and income that was documented in Table 7. A similar pattern holds for grants. The highest willingness-to-pay for a \$1,000 grant is found for students from the \$60,000-\$80,000 income group, who would pay only \$2.5 more than those from the reference group. Consistent with the low explanatory power of those characteristics, the marginal effects of parental education on the willingness-to-pay for a \$1,000 loan and a \$1,000 grant are also generally very small.

The co-existence of positive and sizable values attached to loans and grants, documented in Section 7.3.2 (Table 5), with the quasi-independence of the willingness-

²⁸The fact that the magnitudes of the marginal effects tend to be larger for a \$1,000 grant than for a \$1,000 loan partly reflects the difference in scale across both outcomes, with the standard deviation of the willingness-to-pay for a \$1,000 grant being equal to \$223, against \$77 for a \$1,000 loan.

Table 8: Explaining the willingness-to-pay (average marginal effects)

	$c_m(\ell_{1000})$	$c_m(g_{1000})$
θ	3.70*** (0.89)	6.03*** (0.13)
β	33.57*** (9.70)	49.60*** (10.30)
Numeracy	-0.07** (0.04)	0.75*** (0.14)
0-20K	Ref.	Ref.
20-40K	-1.10*** (0.23)	-0.38** (0.19)
40-60K	2.40*** (0.30)	-0.69*** (0.13)
60-80K	-0.42** (0.23)	2.50*** (0.41)
80-100K	-0.78*** (0.13)	0.09 (0.08)
+100K	0.13 (0.07)	-0.54*** (0.13)
Drop-out	Ref.	Ref.
High-school	-0.64 (0.14)	1.70 (0.28)
Vocational College	0.59 (0.59)	2.10 (0.65)
College	-0.26 (0.25)	0.70 (0.32)
Ontario	Ref.	Ref.
Quebec	-0.58 (0.12)	-0.20 (0.05)
Manitoba	1.10 (0.20)	1.70 (0.26)
Saskatchewan	2.10 (0.34)	-0.97 (0.17)

Notes: i) Standard errors reported in parenthesis, ii) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

to-pay with respect to parental income indicates two important features of the Canadian higher education financing system. First, the median Canadian high school student is not satiated with financial aid opportunities, and the marginal utility of financial aid is non-negligible. Second, it does appear that the higher education public policies in place in Canada are successful in equalizing the marginal utility of financial aid opportunities across various income groups, as differences in family income have pretty much no impact on the value that young individuals would attach to a counterfactual expansion in higher education financial aid opportunities.

Finally, as was already noted in the previous section, there is clear evidence that individual differences in the willingness-to-pay for financial aid are mostly explained by deep (time and risk) preference parameters. We now discuss their marginal effects. The effect of the discount factor is easily predictable as the structure of the experiment implies that the benefit of financial aid can only be experienced in the future while the cash payment is practically immediate. Indeed, as shown in Table 8, the marginal effect of the discount factor on the willingness-to-pay for grants and loans is positive and significant, both statistically and economically. All else equal, increasing the discount factor by one standard deviation leads to a \$34 (\$50) increase in the willingness-to-pay for a \$1,000 loan (\$1,000 grant). This marginal effect is in particular much larger than any of the effects associated with a \$20,000 income differential.

However, the marginal effect of risk aversion on the willingness-to-pay for grants or loans is more intricate because risk aversion affects not only the value of accepting a cash payment but also the value of financial aid, with the effect of risk aversion on the value of financial aid being ambiguous.²⁹ Indeed, while high-school students who are more risk averse are also those who would benefit more from the future consumption smoothing opportunity provided by financial aid, individuals who accept financial aid can only exercise the option to take-up a loan or a grant if they end up enrolling in higher education. Those who are more risk averse and who are also not certain of entering higher education, or are not sure when they are likely to do so, will be particularly sensitive to the latter feature. As a consequence, it is in theory not possible

²⁹Although with CRRA preferences the effect of risk aversion on the marginal utility of immediate consumption is in theory ambiguous too, and depends on the level of background consumption, it is always negative in our case since the background consumption happens to be larger than 1 for all the individuals in the sample.

to sign unambiguously the effect of risk aversion on the willingness-to-pay for financial aid. Because both individual-specific enrollment uncertainty and future parental transfers are unobserved in our context, our model is not capable of separating those two channels, and, while interesting, any discussion about their relative importance would lie beyond the scope of the paper. At this stage, we only note that the marginal effect of a one standard deviation increase in risk aversion on the willingness-to-pay for a \$1,000 grant and a \$1,000 loan are both positive (equal to around \$4 for loans and \$6 for grants), but are 8 to 10 times smaller than the marginal effects of discount factors.

8 Conclusion

In this paper, we estimate the distribution of the willingness-to-pay for higher education financial aid using data from a field experiment conducted in Canada where high school students had to choose between immediate cash payments and various types of higher education financing packages. Our model of financial aid acceptance decisions is based on an explicit trade-off between the increase in current utility following an immediate cash payment and the expected future gain associated with a specific financial aid package. As the experiment also allows us to estimate the distributions of individual risk aversion and discount factors, we are able to uncover how preference parameters for time and risk affect the willingness-to-pay for the various types of financial aids.

Our results show that the majority of students attach a sizable value to accessing student loans. Consistent with the existence of significant frictions in the market for college loans, we find that the median high school student in our sample would be willing to pay a large 6.6 percentage points interest rate premium on top of the prevailing market rate to secure a \$1,000 loan. The median interest rate premium is even higher for a \$2,000 loan, at about 10 percentage points. Taken together, these findings point to the existence of credit constraints affecting a sizable share of the population of high school students.

Importantly, our results also disclose a large degree of heterogeneity in both risk aversion and discount rates. The majority of the students exhibit a mild degree of

risk aversion, while the distribution of discount factors is bimodal with individuals with low discount factors coexisting with forward-looking individuals. These results are of interest in their own right, especially since the vast majority of the schooling choice literature abstracts from these sources of heterogeneity in individual choices. Interestingly, we find that the willingness-to-pay for financial aid is dominated by individual preferences. The value of financial aid is found to increase strongly with individual discount factors. Risk aversion also has a positive but much smaller effect on willingness-to-pay. After conditioning on individual preferences, family background characteristics only play a relatively modest role in the decision to accept a financial aid offer.

Our findings suggest a number of interesting avenues for future research. First, we believe that more effort should be devoted at eliciting time and risk preferences, and investigating their role in educational financing decisions and schooling choices more broadly. Indeed, our results show that those preference parameters play a crucial role in financial aid acceptance decisions. Second, data availability has confined us to the analysis of financing decisions prior to actual college enrollment. It would be interesting to combine this educational financing experiment with observational data on subsequent outcomes to gain additional insights into the effects of improving higher education financing opportunities on educational as well as future labor market outcomes.

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Appendix (For Online Publication)

A The Millenium Foundation Field Experiment on Education Financing

In this section, we provide additional details on the structure of the field experiment. An extensive discussion of the experiment and the sample is available in [Montmarquette and Johnson \(2015\)](#).

All subjects were presented with the full set of decisions and are 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 three groups. First, young individuals must answer a set of questions aimed at measuring their rate of time preference. Table [A1](#) illustrates the experiment where individuals are offered a choice between two payments of different values to be made at different points in time. This approach originally developed by [Coller and Williams \(1999\)](#), allows to evaluate each subject's willingness to forgo present consumption for future consumption, and provides a measure of the discount rate.

A second set of questions relate to the measurement of risk attitudes. Students are presented with a sequence of binary choices between two lotteries in which risk is objectively stated. Table [A2](#) presents the two strategies used for eliciting risk aversion. Both strategies consists of choosing between a lottery with average payoff and another one with extreme payoff, and identify the cutoff point where an agent switch from the average to the extreme lottery. The major difference between the two strategies lies in the fact that while the first one pins down a cut-off probability, the second identifies a cut-off payoff. These approaches pioneered by [Holt and Laury \(2002\)](#) are standard in the experimental literature to measure the degree of risk aversion.

The third group of questions, which constitutes the most original aspect of the field experiment, is a sequence of choices between a cash payment to be paid within one week from the day the experiment was carried, and the option to use a specific financial aid package covering educational expenses. The financial aid package is to be paid conditional on enrolling in a full-time program at any higher education institution

Table A1: Payoff Table for Measuring Discount Rates

Choice 1		Choice 2		Annual Interest(%)
Payment 1 day	Payment 1 month	Payment 1 day	Payment 1 year	
\$ 75	\$ 75.31	\$ 75	\$ 78.75	5
\$ 75	\$ 75.63	\$ 75	\$ 82.5	10
\$ 75	\$ 76.25	\$ 75	\$ 90.00	20
\$ 75	\$ 78.13	\$ 75	\$ 112.5	50
\$ 75	\$ 81.25	\$ 75	\$ 150.0	100
\$ 75	\$ 87.5	\$ 75	\$ 225.0	200
Choice 3		Choice 4		Annual Interest(%)
Payment 1 week	Payment 1 month + 1 week	Payment 1 week	Payment 1 year + 1 week	
\$ 75	\$ 75.31	\$ 75	\$ 78.75	5
\$ 75	\$ 75.63	\$ 75	\$ 82.5	10
\$ 75	\$ 76.25	\$ 75	\$ 90.00	20
\$ 75	\$ 78.13	\$ 75	\$ 112.5	50
\$ 75	\$ 81.25	\$ 75	\$ 150.0	100
\$ 75	\$ 87.5	\$ 75	\$ 225.0	200

Table A2: Risk aversion lotteries

Panel 1: Moving probability Lotteries									
			Choice 1		Choice 2		Choice 3		
			L=32	L=2	L=24	L=1.5	L=40	L=2.5	
			H=40	H=77	H=30	H=57.75	H=50	H=96.25	
	Prob L	Prob H	EV	EV	EV	EV	EV	EV	
1	0.90	0.10	32.80	9.50	24.60	7.12	41.00	11.87	
2	0.80	0.20	33.60	17.00	25.20	12.75	42.00	21.25	
3	0.70	0.30	34.40	24.50	25.80	18.38	43.00	30.63	
4	0.60	0.40	35.20	32.00	26.40	24.00	44.00	40.00	
5	0.50	0.50	36.00	39.50	27.00	29.62	45.00	49.38	
6	0.40	0.60	36.80	47.00	27.60	35.25	46.00	58.75	
7	0.30	0.70	37.60	54.50	28.20	40.88	47.00	68.12	
8	0.20	0.80	38.40	62.00	28.80	46.50	48.00	77.50	
9	0.10	0.90	39.20	69.50	29.40	52.12	49.00	86.88	
10	0.00	1.00	40.00	77.00	30.00	57.75	50.00	96.25	

Panel 2: Fixed probability Lotteries											
Choice 1			Choice 2			Choice 1			Choice 2		
L	H	EV	L	H	EV	L	H	EV	L	H	EV
48	48	48	40	64	52	18	90	54	8	104	56
40	64	52	32	80	56	8	104	56	0	112	56
32	80	56	24	96	60	42	42	42	36	60	48
24	96	60	16	112	64	36	60	48	30	78	54
16	112	64	8	120	64	30	78	54	24	96	60
48	48	48	42	66	54	24	96	60	18	114	66
42	66	54	36	84	60	18	114	66	10	122	66
36	84	60	30	102	66	54	54	54	44	68	56
30	102	66	24	120	72	44	68	56	34	82	58
24	120	72	16	128	72	34	82	58	24	96	60
48	48	48	38	62	50	24	96	60	14	110	62
38	62	50	28	76	52	14	110	62	6	118	62
28	76	52	18	90	54						

Notes: (i) EV for expected value, L for Low payoff, H for High payoff. ii) Payoffs are in Canadian \$. iii) Source: SRDC-CIRANO Field Experiment on Education Financing.

in the country (within 2 years). Grants and loans are formally defined as follows.

- 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 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%.

In total, we consider three different types of subsidies: Grants, Loans, and Hybrid Loans which incorporate both a loan and grant component. We use a total of 17 financial decisions, with 5 choices with a single Loan offer, 7 choices with a single Grant offer, and 5 Hybrid offers. These decisions are summarized in Table A3.

In monetary terms, cash alternatives varied from \$25 to \$700, while grants and loans varied from \$400 to \$4,000. The variations in cash, and in the nature and the size of financial aid packages have many advantages. For instance, for a given cash payment offered and manipulating the financial parameters, we can uncover the relative values of a grant and a loan. Suppose instead that the financial aid package is fixed, we can also reveal the willingness to pay for a specific package by manipulating the cash payment. At the outset, it should be clear that these amounts are quite sizeable. Over the period considered, a grant of \$2,000 in 2008 would have covered 65% of yearly fee at University of Western Ontario and Queen's University, and almost 100% at McGill University and Université de Montréal.³⁰ In addition, although tuition fees at vocational college are more dispersed, they are also subject to

³⁰ Those universities are representative of the Canadian Elite schools.

Table A3: Financial aid Lotteries

Type of package	Choices	Cash	Grant	Loan	Aid Take-up
Single Loans	1	25	0	2,000	0.458
	2	300	0	2,000	0.171
	3	700	0	2,000	0.051
	4	300	0	1,000	0.109
	5	300	0	4,000	0.283
Standard Hybrid	6	25	1,000	1,000	0.834
	7	300	1,000	1,000	0.637
	8	700	1,000	1,000	0.389
	9	300	400	400	0.287
	10	300	2,000	2,000	0.727
Single Grants	11	25	1,000	0	0.886
	12	100	1,000	0	0.826
	13	300	1,000	0	0.686
	14	700	1,000	0	0.412
	15	300	500	0	0.384
	16	300	2,000	0	0.764
	17	300	4,000	0	0.835

Notes: i) Amounts are in Canadian dollars, ii) Source: SRDC-CIRANO Field Experiment on Education Financing.

the same regulation and are therefore comparable to those of universities.³¹ Put in 2015 Canadian dollars, the total cost of the experiment is around \$1,000,000.

The sample was recruited to generate meaningful comparisons by population group, gender, and low-, medium- or high-income status. The original project design called for a minimum sample size of 1,000 urban respondents with the goal of 200 participants per group of interest, with a total sample of 1,248 individuals. Table A4 briefly summarizes the number of participants in several groups of interest.³²

Over the day of the experiment, a numeracy test provided by the Center for Education Statistics was administered to all students. The test was based on the numerical component of the International Adult Literacy and Skills Survey project undertaken by numerous OECD countries between 1995 and 2005. The questions are meant to capture the capacity to perform numerical calculations.³³ Students received a score between 0 and 500, which is used as a cognitive ability measure.³⁴

³¹See Council of ministers of education of Canada.

³²Parental education is defined as the highest level of education of the parent who responded to the survey. Parental income is defined as the total income declared by the respondent, before tax deductions and measured in 2007, of all family members living in the household.

³³More details can be found in [Murray, Clermont, and Binkley \(2005\)](#).

³⁴In our empirical application, individual numeracy test score has been scaled to have variance one, and the mean is 5.1.

Table A4: Descriptive statistics of the sample

Parental	Drop-out	8%
Education	High-school	25%
	Vocational College	7%
	College	61%
Parental	0-20K	5%
Income	20-40K	13%
	40-60K	23%
	60-80K	19%
	80-100K	15%
	+100K	24%
Location	Urban	80%
	Rural	20%
Province	Quebec	30%
	Ontario	29%
	Manitoba	28%
	Saskatchewan	13%
Citizen	Native	94%
	Immigrant	6%
Gender	Male	46%
	Female	54%

Source: SRDC-CIRANO Field Experiment on Education Financing.

B Parametrization

$$\begin{aligned}
c_i^a &= c_0 + c_1 \mathbb{1}_{\text{High-school}}^p + c_2 \mathbb{1}_{\text{Voc college}}^p + c_3 \mathbb{1}_{\text{College}}^p & (11) \\
&+ c_4 \mathbb{1}_{20-40K}^p + c_5 \mathbb{1}_{40-60K}^p + c_6 \mathbb{1}_{60-80K}^p + c_7 \mathbb{1}_{80-100K}^p + c_8 \mathbb{1}_{+100K}^p \\
&+ c_9 \mathbb{1}_{\text{Quebec}} + c_{10} \mathbb{1}_{\text{Ontario}} + c_{11} \mathbb{1}_{\text{Saskatchewan}} + c_{12} \mathbb{1}_{\text{Rural}}^p \\
&+ c_{13} \mathbb{1}_{\text{Female}}^a + c_{14} \mathbb{1}_{\text{Citizenship}}^a + c_{15} \mathbb{1}_{\text{Siblings -18 years}}^a + c_{16} \mathbb{1}_{\text{Siblings +18 years}}^a
\end{aligned}$$

$$\begin{aligned}
\psi_{iq}(g_q, \ell_q) &= \psi_0 + \psi_1 g + \psi_2 g^2 + \psi_3 \ell + \psi_4 \ell^2 + \psi_5 \ell \times g \\
&+ \psi_6 \beta + \psi_7 \theta + \psi_8 \beta \times g + \psi_9 \theta \times g + \psi_{10} \beta \times \ell + \psi_{11} \theta \times \ell \\
&+ \psi_{12} \text{NU} + \psi_{13} \text{NU}^2 + \psi_{14} \text{NU} \times \beta + \psi_{15} \text{NU} \times \theta + \psi_{16} \text{NU} \times g + \psi_{17} \text{NU} \times \ell \\
&+ \psi_{18} \mathbb{1}_{20-40K}^p + \psi_{19} \mathbb{1}_{40-60K}^p + \psi_{20} \mathbb{1}_{60-80K}^p + \psi_{21} \mathbb{1}_{80-100K}^p + \psi_{22} \mathbb{1}_{+100K}^p \\
&+ \psi_{23} \mathbb{1}_{\text{High-school}}^p + \psi_{24} \mathbb{1}_{\text{Voc college}}^p + \psi_{25} \mathbb{1}_{\text{College}}^p + \psi_{26} \mathbb{1}_{\text{Quebec}} + \psi_{27} \mathbb{1}_{\text{Ontario}} + \psi_{28} \mathbb{1}_{\text{Saskatchewan}} \\
&+ \psi_{29} \mathbb{1}_{\text{QC}} \frac{g}{2180} + \psi_{30} \mathbb{1}_{\text{ON}} \frac{g}{5667} + \psi_{31} \mathbb{1}_{\text{SK}} \frac{g}{5064} + \psi_{32} \mathbb{1}_{\text{QC}} \frac{\ell}{2180} + \psi_{33} \mathbb{1}_{\text{ON}} \frac{\ell}{5667} + \psi_{34} \mathbb{1}_{\text{SK}} \frac{\ell}{5064} \\
&+ \psi_{35} \mathbb{1}_{20-40K}^p \times g + \psi_{36} \mathbb{1}_{40-60K}^p \times g + \psi_{37} \mathbb{1}_{60-80K}^p \times g + \psi_{38} \mathbb{1}_{80-100K}^p \times g + \psi_{39} \mathbb{1}_{+100K}^p \times g \\
&+ \psi_{40} \mathbb{1}_{20-40K}^p \times \ell + \psi_{41} \mathbb{1}_{40-60K}^p \times \ell + \psi_{42} \mathbb{1}_{60-80K}^p \times \ell + \psi_{43} \mathbb{1}_{80-100K}^p \times \ell + \psi_{44} \mathbb{1}_{+100K}^p \times \ell \\
&+ \psi_{45} \mathbb{1}_{20-40K}^p \times \theta + \psi_{46} \mathbb{1}_{40-60K}^p \times \theta + \psi_{47} \mathbb{1}_{60-80K}^p \times \theta + \psi_{48} \mathbb{1}_{80-100K}^p \times \theta + \psi_{49} \mathbb{1}_{+100K}^p \times \theta \\
&+ \psi_{50} \mathbb{1}_{20-40K}^p \times \beta + \psi_{51} \mathbb{1}_{40-60K}^p \times \beta + \psi_{52} \mathbb{1}_{60-80K}^p \times \beta + \psi_{53} \mathbb{1}_{80-100K}^p \times \beta + \psi_{54} \mathbb{1}_{+100K}^p \times \beta \\
&+ \psi_{55} \mathbb{1}_{\text{HS}}^p \times g + \psi_{56} \mathbb{1}_{\text{VC}}^p \times g + \psi_{57} \mathbb{1}_{\text{CO}}^p \times g + \psi_{58} \mathbb{1}_{\text{HS}}^p \times \ell + \psi_{59} \mathbb{1}_{\text{VC}}^p \times \ell + \psi_{60} \mathbb{1}_{\text{CO}}^p \times \ell \\
&+ \psi_{61} \mathbb{1}_{\text{HS}}^p \times \beta + \psi_{62} \mathbb{1}_{\text{VC}}^p \times \beta + \psi_{63} \mathbb{1}_{\text{CO}}^p \times \beta + \psi_{64} \mathbb{1}_{\text{HS}}^p \times \theta + \psi_{65} \mathbb{1}_{\text{VC}}^p \times \theta + \psi_{66} \mathbb{1}_{\text{CO}}^p \times \theta & (12)
\end{aligned}$$

C Background consumption

Table A5: Background consumption (financial aid questions)

	Estimates	St. errors
Const	1.84	0.01
High-school	-0.09	0.02
Vocational College	0.63	0.01
College	-0.05	0.01
20-40K	-0.91	0.03
40-60K	0.39	0.04
60-80K	0.51	0.04
80-100K	-0.46	0.04
+100K	-0.27	0.05
Urban	0.03	0.01
Male	0.90	0.02
Native	-1.75	0.00
Quebec	-0.33	0.04
Ontario	0.45	0.03
Saskatchewan	0.39	0.01
Siblings less than -18	-0.11	0.01
Siblings more than 18	0.02	0.01

D Model fit

Table A6: Model Fit

Choices	Empirical Frequencies	Predicted Probabilities
c_{25} VS g_{1000}	0.90	0.89
c_{100} VS g_{1000}	0.84	0.83
c_{300} VS g_{1000}	0.64	0.69
c_{700} VS g_{1000}	0.28	0.41
c_{300} VS g_{500}	0.41	0.39
c_{300} VS g_{2000}	0.82	0.76
c_{300} VS g_{4000}	0.78	0.84
c_{25} VS ℓ_{2000}	0.63	0.46
c_{300} VS ℓ_{2000}	0.19	0.17
c_{700} VS ℓ_{2000}	0.04	0.05
c_{300} VS ℓ_{1000}	0.18	0.11
c_{300} VS ℓ_{4000}	0.28	0.28
c_{25} VS $\ell_{1000} + g_{1000}$	0.89	0.83
c_{300} VS $\ell_{1000} + g_{1000}$	0.60	0.64
c_{700} VS $\ell_{1000} + g_{1000}$	0.24	0.39
c_{300} VS $\ell_{400} + g_{400}$	0.35	0.29
c_{300} VS $\ell_{2000} + g_{2000}$	0.74	0.73

Note: c , g and ℓ stand for cash, grant and loan, respectively. For example c_{25} VS g_{1000} refers to the choice between \$25 cash and \$1,000 grant, while c_{25} VS $\ell_{1000} + g_{1000}$ refers to the choice between \$25 cash and the hybrid package (\$1,000 loan and \$1,000 grant).

E Spatial heterogeneity

In Table A7 below, we report the distribution of the willingness-to-pay for a \$1,000 loan, a \$1,000 grant and a hybrid financial aid package containing a \$1,000 loan and a \$1,000 grant, separately for Ontario and Québec. These two provinces, which are the most populated in Canada, are characterized by markedly different levels of tuition fees. Specifically, Québec has low average annual tuition (\$2,180 over the period of interest), while Ontario has significantly higher tuition rates (\$5,667 on average over the period of interest). Québec and Ontario do not only differ in terms of higher education tuition fees, but also in terms of financial aid generosity. The average amount of financial aid offers per student, as well as the fraction of the total financial aid that takes the form of grants is significantly higher in Québec than in Ontario.³⁵ For a Québec resident, the median value of securing a \$1,000 loan is estimated to be \$54. On the other hand, the median young Ontarians, who are faced with higher tuition rates, would pay a higher amount (\$71). More generally, the distribution of the willingness-to-pay in Ontario dominates almost everywhere the distribution in Québec.³⁶ For instance, at the third quartile, the values indicating the willingness-to-pay are equal to \$137 for Ontario and \$100 for Québec.

Students from Ontario also attach higher values to grants as well as hybrid loans than students from Québec. The median Ontarian high school student in our sample is willing to forego \$458 to secure a \$1,000 grant (45.8 cents per dollar), while the median student from Québec is willing to trade \$360 against a \$1,000 grant (36 cents per dollar). Differences for hybrid loans are of similar magnitude, with the median willingness-to-pay for a hybrid (\$1,000 loan, \$1,000 grant) package in Ontario being equal to \$432, against \$334 in Québec. These findings are consistent with the existence of significantly higher levels of (net) tuition fees in Ontario than in Québec.

³⁵For more details regarding financial aid parameters in Canada, see [Belley et al. \(2014\)](#).

³⁶In particular, the first quartile, the median and the third quartile of the distribution of the willingness-to-pay are all significantly higher in Ontario than in Québec at the 5% level.

Table A7: The distribution of the willingness-to-pay by province

	$c_i^m(\ell_{1000})$		$c_i^m(g_{1000})$		$c_i^m(\ell_{1000} + g_{1000})$	
	ON	QC	ON	QC	ON	QC
1st Dec.	8.2	3.4	174	104	180	110
1st Quart.	28	22	310	226	300	214
Median	71	54	458	360	432	334
3rd Quart.	137	100	618	487	569	448
9th Dec.	191	159	776	580	707	530

Notes: (i) QC: Quebec, ON: Ontario. ii) Amounts are in Canadian dollars.