2016/13

Updating Tertiary Education Expectations and Choices with Learning

JONIADA MILLA

50 YEARS OF
CORE
DISCUSSION PAPERS

CORE

Voie du Roman Pays 34, L1.03.01

Tel (32 10) 47 43 04

Fax (32 10) 47 43 01

Email: immaq-library@uclouvain.be

<http://www.uclouvain.be/en-44508.html>

Updating Tertiary Education Expectations and Choices with Learning

Joniada Milla*

April 2016

Abstract

I conduct a large-scale analysis on how students revise their educational expectations and change their post-secondary education (PSE) pathways. I find evidence that an important determinant is exposure to unexpected information on the quality of match between their ability and academic difficulty of the program. This relationship is non-linear, and responsive only to unexpected information that signals a mismatch. In Canada about 25% of freshman experience a PSE path disruption, which entails a public and private cost. The findings suggest that policy measures targeting to improve the quality of match through student consultation could be employed to reduce this inefficiency.

JEL Classification: C21, I21

Keywords: Tertiary Education, Major Switch, Drop-out, Expectations, Grades

1 Introduction

Students choose to invest in post-secondary education (PSE) since more education is associated with higher future earnings (Card, 1999), as well as better non-pecuniary job benefits (Oreopoulos and Salvanes, 2009). They undertake this investment at a risk of failing to complete the program and graduate. In fact in the United States, Zafar (2011) reports that 12% of the students at Northwestern University's undergraduate class of 2009 (survey conducted

*While the research and analysis are based on data from Statistics Canada, the opinions expressed do not represent the views of Statistics Canada. I thank Thanasis Stengos, Michael Hoy, and the session participants at the 2013 CEA Annual Meetings and 2014 EEA Annual Congress. An earlier version of this paper has circulated under the title "Tertiary Education Choices under Uncertainty."

November 2006–February 2008) switch their major field of study after freshman year, Arcidiacono (2004) using the nationally representative data from NLS72¹ reports that 18% of undergraduate students switched major and 11% dropped out of college by 1974, and Stinebrickner and Stinebrickner (2012) report that 40% of the students from low-income families at Berea College (survey followed the starting cohort of 2001) drop out of college.

In this paper I use Canadian data from the Youth in Transition Survey (YITS) to study this phenomenon. In the YITS, about 19% of the students who started a PSE program in the 2002–2003 academic year, report to have changed major and 7.8% dropped out after their first year. In Canada, students have to make their choice of the major field of study before they enroll in a PSE program. Differently from the United States, where students (depending on the program) can choose their major field of study as late as their last year, Canadian students are introduced earlier to major-specific courses. Hence, they are likely to realize earlier if their choice is a mismatch with their ability and preferences.

The statistics shown in Table 1 indicate that among the students who report to have switched major after their first year in PSE, about two-thirds (diagonal entries) switch to a major that is within the same major grouping. The students that start in a major in the Education, Arts, Humanities (EAH) group switch to STEM (Sciences, Technology and Trades, Engineering, Math) and SSBA (Social Sciences and Business Administration) majors in almost equal proportions (13.56 and 16.95 %, respectively). However, for the students that initially start in a STEM major, most of the switchers transfer to a SSBA major. Regarding those that start in a SSBA major, the proportion switching to a EAH major is higher than those who transfer to a STEM major. SSBA majors also appear to be the group that retains relatively less students when compared to the other two major groups.

The students that switch to a major not within the bigger groupings, usually have to start the new program from year one because of differences in course content, and so most of the course work completed in their first PSE program may not be credited into the second. In Canada, the government subsidizes more than half of the tuition in post-secondary institutions. Considering the province of Ontario only, for the starting year (2 semesters) in an Arts major the provincial government invests CAD 3,100.00 per student in a university program

¹National Longitudinal Study of the high school senior class of 1972.

Table 1: Percent of students switching major

		Switched Major			Row % Total (Obs. #)
		EAH	STEM	SSBA	
Starting Major	EAH	69.49 (82)	13.56 (16)	16.95 (20)	100 (118)
	STEM	10.12 (17)	67.86 (114)	22.02 (37)	100 (168)
	SSBA	22.14 (31)	15.00 (21)	62.86 (88)	100 (140)
Total (%) (#)		30.52 (130)	35.45 (151)	34.04 (145)	100 (426)

Note: The first number in each cell is a percentage, the number in parenthesis is an observation number. EAH: Education, Arts and Humanities. STEM: Sciences, Technology and Trades, Math and Engineering. SSBA: Social Sciences and Business Administration. The statistics for the majors that do not fall within these categories are not shown in the table.

and CAD 4,400.00 per student in a college² program. The per-student subsidy is higher for business and technology majors, and much higher for the upper university years.³ The investment on the students that drop out after their freshman year, is a loss in net resources. The same is valid for the subsidy invested in those who choose to switch to a different major and have to start a new program from the beginning. Within this framework, for the province of Ontario only, these PSE path disruptions translate on average to a cost of about 48 million CAD per year of public spending. The overall social cost in the economy (public plus the private individual cost) amounts to about 118 million CAD.⁴ Although individuals may still learn something useful (besides that they disliked the program) and improve their skills by

²Differently from the United States, in Canada college and university refer to different academic entities. In Canada, colleges offer vocational trades programs and Bachelor's equivalent degrees in arts and sciences focused on practical instruction. College professors in Canada focus on teaching and have extensive experience in the private sector. Meanwhile, universities offer Bachelor's degrees with research opportunities leading to graduate studies.

³For university Business and Technology majors the subsidy is CAD 5,800.00 and CAD 8,300.00, respectively. For college Business and Technology majors these numbers are CAD 4,400.00 and CAD 5,700.00. For upper university years the subsidy increases to CAD 5,800.00 for Arts and Business majors, and to CAD 8,300.00 for Technology majors (see Trick, 2013, Table 3, p.31).

⁴Author's calculations using data from the Ministry of Training, Colleges and Universities, the YITS and Statistics Canada. I add together the proportion of students in the YITS that drop out and switch program. Then, I multiply this proportion with the total number of 19 year old students in Ontario, Canada that started a post-secondary program in 2004 in a university and college, separately. This results in the total number of students who disrupted their PSE path after their first year in PSE. This number is multiplied by the minimum amount of subsidy that the government of Ontario invests on each new student in their first year of university (CAD 3,100.00) and college (CAD 4,400.00). Similarly, I use tuition rates instead of subsidies to calculate the private cost.

attending the time they did, yet the resources spent are not trivial and not used to their full potential. Obviously, this points to an inefficiency in the economy and to identify policy measures that minimize it, one should look deeper into how students make choices. The PSE path disruptions (dropping out or changing program) are closely related to the uncertainty of graduation (Hussey and Swinton, 2011; Altonji, 1993). In fact, in Canada, the proportion of first year students that graduate varies between 65%–77%. Manski (1989) constructs a model of PSE enrolment and completion where the role of the *ex ante* expected probability of completion is emphasized. Earlier studies use choice data to infer about the way individuals form expectations. This data limitations lead to the use of models that are framed by strong assumptions. So, Manski (2004) highlights the importance of studying expectation formation using subjective expectations and beliefs elicited directly from the respondent.

A few studies analyze expectation formation empirically, using data on elicited beliefs about expected earnings (Dominitz, 1998), expected returns to schooling (Dominitz and Manski, 1996) and the choice of contraception method (Delavande, 2008). Two recent papers apply a similar idea to the expectation formation about PSE outcomes. Zafar (2011) finds that students update their beliefs based on the unexpected content of information they receive from the change in their grade point averages (GPA) from the first to the second semester in the first year. Similarly, Stinebrickner and Stinebrickner (2012) confirms this result and finds evidence that the student’s probability to drop out changes with the students’ learning about their academic ability. Both, Zafar (2011) and Stinebrickner and Stinebrickner (2012) use elicited subjective beliefs in probabilistic form. Both papers work with survey data collected in one PSE institution, small sample sizes with little (or no) information about the students before entering the institution. This limits their ability to account for the heterogeneity among individuals. The single-institution surveys do not follow respondents unless they stay within the institution where the survey is conducted. This leads to an overestimate in the proportion of students that drop out and to an underestimate of the proportion of those who switch program.

Differently from these two studies, I use elicited expected behavior variables since the YITS is not built to elicit probabilistic expectations.⁵ However, the analysis in this paper remains

⁵Expected behaviour and probabilistic expectations differ in the following way: In order to elicit probabilistic expectations the question starts by “What do you think is the percent chance that you ...?”. To elicit expected

informative, and most importantly, it provides the first piece of evidence on how learning about own ability influences educational expectation updating and PSE path disruptions as students transition from high school to post-secondary education. Unlike Zafar (2011) and Stinebrickner and Stinebrickner (2012), the dataset I use provides a wealth of information on a representative sample of the Canadian youth from most of the PSE institutions in Canada, and thus big sample advantages. The longitudinal nature of the data allows tracking the students across programs and institutions. I am able to separate among those students that were required to leave the program because of a poor performance during the year. This group were only 2.1 percent of the sample, and are excluded from the analysis. The main specification is conditioned on a set of predetermined variables regarding the individual, their family and socio-economic background. An important addition to this list is the set of variables that describe the experience of the students in their first year of PSE. I estimate the effect that learning about own academic performance, which is imbedded in the unexpected change in GPA between high school and PSE, has on updating expectations about educational attainment. I also investigate the role that learning has on two outcomes related to PSE: (i) the probability to switch the major field of study (program) and (ii) the probability to drop out of PSE.

The results indicate that a drop in the first year PSE grades relative to the high school grades, is a main determinant affecting the revisions of educational expectations. A higher-than-expected drop in grades may be perceived as a signal of a mismatch with the program when students update their perceptions of their own ability to complete learning activities in the program. Also, the probability of a path disruption in PSE increases if the students experience an unexpected drop in GPA. This is not the case for unexpected increases in grades. The students react to their choices only when they think they are making worse progress compared to the average student in the same major and institution as theirs. Even though the paper cannot provide evidence on the rationale behind this asymmetric behavior, as in Dominitz (1998), one presumption that can be deducted from the results and that could apply to this contexts as well may be that a drop in grades beyond what is expected may be viewed as more persistent than an increase.

behavior the question starts by “Do you expect to..(tick one of the increasing categories that applies)...?”.

Based on the evidence provided by this paper, a way of decreasing path disruptions in PSE is by improving the match between the student academic ability and program requirements. Castleman and Goodman (2014) investigate Bottom Line, a college advising program that operates in Boston and Worcester, Massachusetts. This program assists senior year high school students from low-income families to find a PSE institution that is a good match in terms of graduation probability, potential academic success and debt accumulation upon graduation. The authors present compelling evidence that consultation significantly increases access, persistence and completion in higher education. Hence, while the PSE path disruptions cannot be completely eliminated, consultation services for students during high school seems to be a policy intervention that could guide them in making better choices. Consultation sessions could be targeted to inform students about the course content, academic difficulty and job prospects of the different PSE programs. Individual and intensive assistance like Bottom Line provides may be more costly than group information sessions but could potentially be more effective.

The paper is organized as follows. In Section 2, I summarize the model that serves as basis for the main specification. Section 3 describes the data and section 4 discusses the empirical results. Section 5 concludes.

2 Empirical Approach

The empirical specification in this paper is based on the evidence provided by Zafar (2011), that students update their educational expectations through a process that is consistent with a Bayesian updating model. The paper shows that students update their expectations as a result of the signals they derive from changes in their academic performance that is reflected in their grades. The process of educational expectation formation for a rational individual is based on the currently available information, and updated in the interim based on new information obtained. Zafar (2011) argues that, to some extent, a part of the new information can be anticipated by the individual, and separating this from the unanticipated part, enables one to attach a causal explanation to the relationship between unanticipated information and expectations revision.

Expressed in technical terms, expectations updating on the value of a future event, X , can be defined as a function of surprises that the individual encounters between time t and $t + 1$. The surprises are defined as new information, ω_{it+1} , minus its predictable part, $E(\omega_{it+1}|\Omega_{it})$, where Ω_{it} is the information that the individual is exposed to at time t , and assumed to be remembered at time $t + 1$, too. The individuals are assumed to be rational decision makers who use all available information when forming expectations. Any revision on their expectations regarding event X is determined by a function, $\psi(\cdot)$, of unexpected information shocks received at time $t + 1$ that can be summarized by equation (1) as follows.

$$X_{it+1}^e - X_{it}^e = \psi(\omega_{it+1} - E(\omega_{it+1}|\Omega_{it})) \quad (1)$$

In this paper, the Canadian Youth in Transition Survey (YITS) is exploited to build the outcome and independent variables of interest. The outcome of interest for this part of the analysis is expectations about the highest level of education that students plan to attain. X_{it}^e and X_{it+1}^e are their responses two years apart. The survey timeline is shown in Figure 1. In this context, the source of new information equals the unexpected portion of the change in the GPA from high school to PSE. The students were asked in Winter 2002 (January–April) about their high school GPA realized until December 2001. Then, they were interviewed again in Winter 2004 and asked to report the first year PSE grade realized until December 2003. Unlike previous studies that use the change in GPA within the first few semesters in PSE, by using the change in GPA between high school and PSE I capture the initial learning about own ability that students experience during their transition from high school to PSE. Referring to equation (1) above, ω_{it+1} in this case represents the grade change that the younger cohort experiences between high school and first year in PSE, $\Delta GPA = GPA_{PSE} - GPA_{HS}$. Following previous literature, I assume that the only source of information that drives educational expectation updating in this context is deducted from ΔGPA . However, unlike Zafar (2011) that lacks measures for inherent ability, commitment or effort of students during PSE studies, I am able to relax the assumption that the process of expectations updating is independent of these individual characteristics.

The distinction between ΔGPA_{it+1} and $(\Delta GPA_{it+1} - E(\Delta GPA_{it+1}|\Omega_{it}))$ is crucial. To explain this point, suppose the change in realized GPA, i.e. ΔGPA , is positive. Then we

Figure 1: Timeline of the survey questions

may confound a positive piece of information with a negative one if the first year PSE grades increased by less than the student expected. This highlights the importance of separating out the predictable or expected part of the change in GPA. Unfortunately, the YITS did not ask the students on how much they expect their GPA to change in their first year in PSE relative to their high school GPA. Thus I lack a directly elicited measure for $E(\Delta GPA_{it+1} | \Omega_{it})$. Instead I use a proxy variable to estimate as closely as possible how the students expect their grades will change between high school and PSE. The approach I use assumes that the most important source of information can be retrieved from the older cohort's performance in the exact same institution and similar program. This is a plausible assumption since friends, family and relatives usually share experiences about the difficulty of the program they are following. With this information in mind, and taking into consideration own abilities and commitment to studying, a student may create an educated prediction on the change in GPA that (s)he will likely experience. Hence, I use the average change in grades of the students in the older cohort of YITS to construct the proxy. As long as the PSE institutions are consistent in their selection procedures and thus enroll systematically a similar intake of students each year, approach delivers a reasonable estimate of the expected change in GPA.

I build three different proxy variables. They differ on the extent of similarity between the matches (students from the older cohort) and the matched student (from the younger cohort). The first proxy variable is calculated by the following formula: $\Delta GPA_i^e = \frac{1}{n_{hg}} \sum_j^{n_{hg}} \Delta GPA_j$ where n_{hg} is the number of students in the older cohort of YITS that attended a similar program⁶ h in the same institution g as the reference student from the younger cohort of

⁶The following classification is used to separate majors into similar fields of study groups: (1) Education, (2)

YITS, student i . By matching on the institution and major, I implicitly assume that the students' academic achievement in PSE is independent of their high school grades, which is in practice a strong assumption. In order to relax this assumption I build a second proxy that in addition to major and institution, matches individuals on the high school GPA, too. In that case the proxy is calculated by the following formula: $\Delta GPA_i^e = \frac{1}{n_{h g k}} \sum_j^{n_{h g k}} \Delta GPA_j$ where $n_{h g k}$ is the number of students in the older cohort of YITS that attended a similar program h in the same institution g , that has the same reported GPA category k as the reference student from the younger cohort of YITS, student i . Finally, I construct a third proxy such that $\Delta GPA_i^e = \frac{1}{n_{h g k s}} \sum_j^{n_{h g k s}} \Delta GPA_j$ where $n_{h g k s}$ is the number of students in the older cohort of YITS that attended a similar program h , in the same institution g , that has the same reported GPA category k , and is of the same gender s as the reference student from the younger cohort of YITS, student i . This alternative proxy variable takes into account the achievement gaps between the two genders.

The analysis in the first part of the paper is built around equation (2), which initially assumes a linear functional form for $\psi(\cdot)$ which is then relaxed. Moreover, it allows for heterogeneous individuals and accounts for this heterogeneity by conditioning on a set of individual and family characteristics represented by the vector Z_{it} .

$$\Delta Exp_{it+1} = \beta_0 + \beta_1 (\Delta GPA_{it+1} - \Delta GPA_{it+1}^e) + \gamma Z_{it} + \epsilon_{it+1} \quad (2)$$

where ϵ_{it+1} is a $N(0, \sigma_\epsilon^2)$ idiosyncratic error term. The variables included in Z_{it} are demographic and parental characteristics, and variables that describe the students' experience during their first year in PSE. The later set of variables accounts for the students' commitment and effort during their freshman year. Omitting these variables would otherwise bias upward the coefficient on the (unexpected) change in grades considering the positive effect that effort has on academic performance (Stinebrickner and Stinebrickner, 2008). In the current context, the focus is on the change in grades (rather than its level), thus this correlation is expected to be relatively lower.

Fine and applied arts, (3) Humanities and related fields, (4) Social Sciences and Law, (5) Business and Public Administration, (6) Math and Physics Sciences, (7) Engineering and Applied Sciences, (8) Engineering and Applied Sciences: technologies and trades, (9) Agriculture and biological sciences/technologies, (10) Health professions, sciences and technologies.

3 Data

The Youth in Transition Survey was conducted at the same time on two cohorts of different ages. The younger cohort is first interviewed when 15 years old and then interviewed bi-annually in another four cycles. I am interested in their choices when they are 19 years old. At this age 92% of the students have completed high school, and among these 71% continued their studies into PSE and 29% never enrolled in a PSE program. The analysis in this paper is based mainly on the younger cohort and is complemented by data from the older cohort. The older cohort participants were between the age of 18–20 when first interviewed. Each student in the older cohort is 3 to 5 years older than the students in the younger cohort.

Table 2 shows the student GPA distribution in the YITS. High school GPA is elicited from the following question: *“In your last year of high school, (junior high or elementary school), what was your overall grade average, as a percentage?”*. The GPA in the first year PSE program is retrieved from the following question: *“In your first year, what was your overall grade average as a percentage?”*. The students were asked to check one of the 10 grade point categories listed in the first panel of Table 2. More than 90% of the students report a high school GPA of 70% or higher. The grades are self-reported by the students, and the possibility that they may be overstated can not be ruled out even though the categorical nature of the responses helps mitigate the measurement error. Also, it should be noted that a drop in the PSE grades relative to high school grades, for example from 81% to 79% is recorded as one category drop, and a drop from 89% to 79% is also recorded as a one category drop. Experiencing a drop in grades is common for the younger cohort (55%). Only 32% of the students manage to keep their grades within the 10 grade category of their high school GPA and only 12% experience an increase. Using the data from the older cohort of YITS, I calculate the average change in GPA for each program in the data. On average, in 61% of the PSE programs the students experience a drop. From the last column in panel B of the table, we can see that the chances that students experience an unexpected decrease rather than an increase in GPA are almost twice as high.

The expectations about future educational attainment are elicited by the following question: *“As things stand now, what is the highest level of education you think you will get?”*. The question is carefully formulated to retrieve X_i^e . The students were asked to choose one of

Table 2: Percent of students with reported GPA categories

Panel A: Percentage of students with reported GPA categories, Younger Cohort			
	High School GPA	First year PSE GPA	
90% or above	14.92	6.69	
80-89%	44.40	26.52	
70-79%	33.89	41.71	
60-69%	6.01	20.23	
50-59%	0.49	3.83	
Under 50%	0.29	1.03	
Observations	6504	6504	

Panel B: Percentage of students with negative, zero and positive changes in GPA			
	Younger Cohort ΔGPA	Older Cohort ΔGPA	Younger Cohort $\Delta GPA - \Delta GPA^e$
Negative	55	61	41
Zero	32	22	37
Positive	12	17	22

the following ten levels of education: (1) *Some High School or less*, (2) *High school diploma*, (3) *Some post-secondary education level courses (no diploma or degree)*, (4) *Private business school or commercial school diploma*, (5) *College, CEGEP, or trade/vocational certificate or diploma*, (6) *University degree or certificate below Bachelor's degree*, (7) *University Bachelor's degree*, (8) *University first professional degree (medicine, dentistry, veterinary medicine, law, optometry, divinity)*, (9) *Master's degree or University graduate diploma or certificate (above Bachelor's degree)*, (10) *PhD (or other earned doctorate, D.Sc., D.Ed.)*. In order to organize them in a clear ranking of the educational levels, I re-code as one category the fourth, fifth and sixth category. I also re-code the seventh and eighth category in a single category. Technically, this rearrangement eventually generated seven categories for each of the expectations elicited at age 17 and 19. Using these variables I build the change in expectations, that is simply the difference between the two categorical variables. The difference in practice contains values between $[-4, 4]$. This means that students update upto four categories upwards or downwards. Table 3 contains a tabulation of the responses aggregated to fewer categories at age 17 and 19. One can observe some significant expectations updating after the students go through the first year in PSE given that just about half of the students keep the same expectations.⁷

⁷In comparison to students that enroll in a PSE program, those that never enroll have very low expectations

Table 3: Transition matrix of percentage of students between prior and posterior educational expectations

		Posterior Expectations (Age 19)				Cell % (Row %) [Column %]
		Less than College Diploma	College Diploma	Bachelor's Degree	Graduate Degree	
Prior Expectations (Age 17)	Less than College Diploma	- (-) [-]	2.90 (63.73) [11.75]	1.65 (36.27) [3.47]	- (-) [-]	4.55 (100) [4.55]
	College Diploma	0.49 (2.53) [41.56]	13.46 (69.07) [54.56]	4.79 (24.60) [10.07]	0.74 (3.8) [2.97]	19.49 (100) [19.49]
	Bachelor's Degree	0.69 (1.41) [58.44]	6.64 (13.50) [26.94]	29.97 (60.88) [62.95]	11.92 (24.21) [44.89]	49.22 (100) [49.22]
	Graduate Degree	- (-) [-]	1.66 (6.2) [6.75]	11.91 (41.84) [23.51]	13.89 (51.93) [52.32]	26.75 (100) [26.75]
	Total	1.19 (1.19) [100]	24.66 (24.66) [100]	47.60 (47.60) [100]	26.55 (26.55) [100]	100 (100) [100]

Note: Each entry is a percentage of the respondents. Sample size is 6504. The educational expectation categories are defined as follows: Less than College Diploma contains: (1) *Some High School or less*, (2) *High school diploma*, (3) *Some post-secondary education level courses (no diploma or degree)*; College Diploma contains: (4) *Private business school or commercial school diploma*, (5) *College, CEGEP, or trade/vocational certificate or diploma*, (6) *University degree or certificate below Bachelor's degree*; Bachelor's Degree contains: (7) *University Bachelor's degree*, (8) *University first professional degree (medicine, dentistry, veterinary medicine, law, optometry, divinity)*; Graduate Degree contains: (9) *Master's degree or University graduate diploma or certificate (above Bachelor's degree)*, (10) *PhD or other earned doctorate, D.Sc., D.Ed.*.

In Table A.1 I present summary statistics for all dependent and independent variables used in the empirical analysis. I group the independent control variables in three groups: Individual level variables, Parental characteristics and First year variables. Individual level variables that include PISA score⁸, Female, Single, Canadian citizen, Province of residence⁹, Rural residency dummies, and Highest education level attended (Bachelor and College program dummies); Parental characteristics that include Parental education category dummies, Parental income and income squared, Parental monetary transfers in the first year PSE; First year variables that include “Sure for type of work”, “Workshops to adjust” dummy¹⁰, “Hours homework”¹¹, “Times thought dropping out”¹². I construct four more variables by using survey questions that ask for Likert-scale responses on the degree of agreement: “The right program”¹³, “Idea for future plans”¹⁴, “Job market skills”¹⁵ and “Sure for type of work”¹⁶. All categorical variables enter in the regression analysis as dummy variables indicating some of the categories as listed in Table A.1.

In the sample, about 56% of the individuals are female, 96 % are single, and 95% are Canadian citizens. In this group, 24% first started their PSE studies in a college and 66% started a program in a university. About a third of the students have a university graduate mother and father. During their first year in PSE, 80% of the students dedicate more than eight hours of studying per week to their homework, 20% of them indicate that they attended

since age 17. About one quarter (27.23%) of this group report that they expect their highest level of educational attainment to be lower than a College diploma, compared to 4.55% in Table 3; 40.97% report a College Diploma, compared to 19.49% in Table 3; and 31.80% report a university degree (Bachelor’s or graduate), compared to 75.97% in Table 3.

⁸Programme for International Student Assessment (PISA) reading test score.

⁹Indicator variables for each of the provinces: Alberta, British Columbia, Manitoba, Saskatchewan, Nova Scotia, New Brunswick, Prince Edward Island, Newfoundland and Labrador. The omitted category is Ontario. Observations from the province of Quebec are excluded due to their CGEP system that can be confounded with a college program by respondents.

¹⁰The survey asks to answer by yes or no to: “*During or before your first year, did you take part in any workshops, programs or courses designed to help you adjust to first-year studies?*”.

¹¹The survey asks students to answer the question by picking one of multiple choice answers (Zero, Less than one hour per week, 1–3 hours, 4–7 hours, 8–14 hours, 15–20 hours, 21–30 hours and More than 30 hours per week) to the question: “*During your first year, about how many hours each week did you spend studying or doing assigned work outside of class?*”

¹²The survey asks students to answer the question by picking one of multiple choice answers to the question: “*How many times per month did you think about dropping out. Was it ...?*” *Never, Less than once a month, Once or twice a month, About once a week, More than once a week.*

¹³The survey question is: “*During my first year, I felt I had found the right program for me.*”

¹⁴The survey question is: “*During my first year, helped me get a better idea of my future plans.*”

¹⁵The survey question is: “*My first year, gave me skills that help me in the job market.*”

¹⁶The survey question is: “*During my first year, I was sure of the type of work I would like to have in the future.*”

workshops to adjust to the PSE experience and about 30% thought at least once per month of dropping out of the program. The PISA score, which serves as a measure of cognitive ability, has a central role in accounting for the inherent heterogeneity among respondents. In the overall sample, the score has a mean (standard deviation) of 560.36 (85.92). Among the major switchers the mean (standard deviation) for the PISA score is actually above the sample average and has a lower variance, 575.74 (78.70), and those who drop out have a lower PISA score on average, 542.55 (81.79), with lower variance than the overall sample. However, the mean differences are statistically insignificant.

4 Results

4.1 Updating educational expectations

Regression estimates of equation (2) are shown in Table 4. The dependent variable is categorical and takes count values between $[-4, 4]$. Positive values indicate an upward revision on educational attainment expectations, zero indicates no change in expectations, and a negative value indicates a downward revision. Figure A.1 plots the empirical distribution of the dependent variable and that of a theoretical normal distribution with the same mean and standard deviation. The Kolmogorov-Smirnov test indicates that the empirical distribution cannot be distinguished from the theoretical normal distribution (p-value=0.743), and hence the choice of least squares estimator. The specification in the first versus the other three panels differ in the independent variable of interest. In Panel 1 the variable that captures learning is the change in GPA. In the other three panels three different definitions of the expected change in GPA, ΔGPA^e , are used to build the unexpected change in GPA, $\Delta GPA - \Delta GPA^e$, which is used separately as the independent variables of interest.

In both cases the coefficients are positive and statistically significant suggesting an increase in the expected level of education if the students' GPA in first year PSE increases by one category relative to their high school GPA. In order to account for the heterogeneity in expectation formation, I condition on a set of variables. The step-wise addition of the individual, parental and first year variables leads to a better fit for the model. The third column in each table represents the common specification used in the literature so far (Za-

far, 2011; Stinebrickner and Stinebrickner, 2012) that incorporates several basic demographic characteristics in the estimation. However, unlike previous literature I have available for use a measure for inherent ability (PISA score measured at age 15), and several variables that inform about the effort and commitment of students during their first year in PSE. These are incorporated in the specifications shown in columns (4) and (5) of the table. Based on the results of the first panel, a one category increase in GPA change increases the revisions of educational expectations by a modest 0.09 categories. In column (5) I add in interaction term of the ΔGPA with a dummy variable that indicates negative values of ΔGPA . The estimates indicate that if students experience an increase or no change in GPA (positive values of ΔGPA) they do not revise their expectations (coefficient is statistically insignificant). However, they revise their expectations when faced with decreases in GPA. For the negative values of ΔGPA , a one category decrease (as ΔGPA becomes more negative) leads to a downward revision of 0.17 categories in educational expectations. This relationship can be more easily seen in Figure 2(a).

Note that when we compare coefficients of Panel 2 to those of Panel 3 and 4 the coefficients are reduced in magnitude. In comparison to Panel 2, the unexpected change in GPA is less prone to measurement error when Proxy 2 and 3 are used for ΔGPA^e because they match younger cohort to older cohort students based on their GPA, and on both GPA and gender, respectively, in addition to the PSE institution and similar major field of study. As a result there is a consistent decrease in the coefficient estimates from Panel 2 to 4. The differences between the estimates of Panel 1 and Panel 4 indicate that when using unexpected change in GPA the effect on revising expectations is much smaller, and the difference between coefficients is statistically significant. Since ΔGPA is an imperfect measure of a shock in how the GPA of the students evolves, by subtracting the anticipated part of it the measure $\Delta GPA - \Delta GPA^e$ gets closer to the true value of the shock. Hence using the former may lead to an overestimate of the effect if we observe a ΔGPA that is much smaller than $\Delta GPA - \Delta GPA^e$, and an underestimate if vice versa. If ΔGPA^e was elicited directly from the students, the bias would depend on how optimistic are students in forming expectations about their GPA changes.

Next, I consider a nonlinear functional form for $\psi(\cdot)$ and I use partially linear regression

Table 4: ΔExp as a function of changes in GPA

	(1)	(2)	(3)	(4)	(5)
Panel 1: Change in GPA					
ΔGPA	0.076*** (0.020)	0.079*** (0.021)	0.082*** (0.022)	0.093*** (0.026)	-0.024 (0.051)
Interaction					0.168** (0.067)
Joint Test (p-value)					0.000
Pseudo R^2	0.004	0.006	0.007	0.027	0.028
Sample Size	6504	6504	6504	6504	6504
Panel 2: Unexpected Change in GPA, Proxy 1 used for ΔGPA^e					
$\Delta GPA - \Delta GPA^e$	0.119*** (0.020) ^c	0.121*** (0.020) ^c	0.121*** (0.020) ^c	0.100*** (0.021)	0.047* (0.028)
Interaction					0.102*** (0.038)
Joint Test (p-value)					0.000
Pseudo R^2	0.010	0.012	0.013	0.028	0.031
Sample Size	6504	6504	6504	6504	6504
Panel 3: Unexpected Change in GPA, Proxy 2 used for ΔGPA^e					
$\Delta GPA - \Delta GPA^e$	0.072*** (0.025)	0.076*** (0.026)	0.079*** (0.027)	0.082*** (0.030)	-0.037 (0.073)
Interaction					0.158* (0.088)
Joint Test (p-value)					0.000
Pseudo R^2	0.003	0.006	0.009	0.027	0.031
Sample Size	6326	6326	6326	6326	6326
Panel 4: Unexpected Change in GPA, Proxy 3 used for ΔGPA^e					
$\Delta GPA - \Delta GPA^e$	0.036** (0.016) ^c	0.034** (0.017) ^b	0.034** (0.017) ^b	0.033* (0.017) ^b	0.006 (0.021)
Interaction					0.073** (0.037) ^c
Joint Test (p-value)					0.028
Pseudo R^2	0.001	0.003	0.005	0.023	0.025
Sample Size	6326	6326	6326	6326	6326
Individual Variables		✓	✓	✓	✓
Parental Variables			✓	✓	✓
First Year Variables				✓	✓

Note: Robust standard errors in parenthesis. Statistical significance: ***1%, **5%, *10%. The interaction term refers to an interaction variable between the (unexpected) change in GPA and a dummy indicator for negative values of this variable. The “Joint test” is a chi-squared test on the joint significance of the two parameters reported for each regression. The different definitions of the ΔGPA^e proxies are as follows: Proxy 1 matches on the the exact PSE institution and similar major field of study; Proxy 2 matches on the the exact PSE institution, similar major field of study and high school GPA category; Proxy 3 matches on the the exact PSE institution, similar major field of study, high school GPA category, and gender.

to estimate the relationship between the update in expectations and the information shocks. In Figure 2 I show this relationship. Graph 2(a) shows regression estimates using ΔGPA , and graph 2(b) plots in addition to 2(a) the regression using $(\Delta GPA - \Delta GPA^e)$ as the independent variable. Similar to the results of Table 4 column (5), Figure 2 suggests that educational expectations revisions are responsive only to unexpected negative changes in GPA. Students are indifferent to positive, or no changes in GPA.

Figure 2: Expectations updating as a function of (unexpected) change in GPA

Note: The variable plotted in the y-axis is the fitted residual of specification (4) in Table 4 excluding change in GPA as a covariate. This ensures that all heterogeneity from other observed factors is netted out of the ΔExp , except for the variable of interest. The figure shows the local polynomial regression (third degree polynomial, Epanechnikov kernel, and unit bandwidth) of the fitted residuals on the (unexpected) change in GPA. The proxy variable for ΔGPA^e used in the construction of the unexpected change in GPA is Proxy 1 that matches on the the exact PSE institution and similar major field of study.

Although the dependent variable, ΔExp , aims to use all available information by exploiting all the individuals together without splitting the analysis into subsamples, however, it is important to note that the meaning carried by each of the categories of the variable (indicated by the integers $[-4, 4]$) is complex. For instance, a value of “1” in the dependent variable, ΔExp , indicates a mechanical one category upward revision in educational expectations. Its meaning could represent a revision from a Bachelor’s degree to a Master’s for one student, but also a revision from a College Diploma to a Bachelor’s Degree. For that reason, I consider other alternatives to the dependent variable definition that refer to one type of revision at a time. I firstly aggregate the educational categories in the same fashion as in Table 3. Then I define eight dummy variables that indicate an educational expectation by “1” and no revision by zero. The definition of the variables is included in the footnote of Table A.2,

that also contains the regression estimates. The reported coefficients are the marginal effects of probit regressions, and represent a change in the probability of revising expectations as indicated by the dependent variables. The dependent variables in columns (2), (3), and (6) indicate upward revisions in expectations to a higher educational category. The rest indicate downward revisions in expectations to a lower educational category. The fit of the regressions is much higher than those in Table 4. Overall the results are consistent with those shown in Table 4 – with an increase in the unexpected shock the probability to revise expectations upwards increases and the probability to revise them downwards decreases. In most of the cases results indicate that the students revise expectations more as a result of negative shocks and are indifferent to positive shocks.

4.2 PSE outcomes

Arcidiacono (2004) and Stinebrickner and Stinebrickner (2012) find that students change their PSE path as they learn about their academic ability through academic performance. In fact in the YITS, when asked “*What is the main reason you changed it[major]?*”, 41% of the students responded by “*Didn’t like it/not for me*” and 38% of the students answered by “*Interest in new subject*”. I use the specification in equation (3) to test whether an unexpected change in grades affects the probability of switching major and dropping out of PSE.

$$P(Y_{it+1} = 1) = \beta_0 + \beta_1 (\Delta GPA_{it+1} - \Delta GPA_{it+1}^e) + \gamma Z_{it} + \nu_{it+1} \quad (3)$$

where Y is the outcome, Z_i the vector of control variables (defined in Section 2) for each respondent i and ϵ_{it+1} is a normally distributed $N(0, \sigma_\nu^2)$ error term. The estimation results are summarized in Tables 5 and 6. For both outcomes the step-wise addition of the control variables contributes to a better fit of the regression model, but also more than halves the coefficient on the independent variable of interest. Referring to column (4) in Table 5, the estimates indicate that an unexpected increase of one category in GPA decreases the probability to switch major by 2.6 percentage points. When the unexpected change in GPA is used this coefficient drops to 1.7–1.9 percentage points, even though they are statistically indistinguishable. As we can see from column (5), including the change in expectations variable in

this regression does not affect the coefficient on the (unexpected) change in GPA. However, this is affected by the addition of the interaction variable. In all three panels in column (6) it loses statistical significance, but the joint significance tests with the interaction term indicate they are jointly different from zero.

Figure 3: Probability to switch major and drop out as a function of (unexpected) change in GPA
Note: The variable plotted in the y-axis is the fitted residual of specification (4) in Tables 5 and 6, respectively, excluding change in GPA as a covariate. This ensures that all heterogeneity from other observed factors is netted out of the dependent variable, except for the covariate of interest. The figure shows the local polynomial regression (third degree polynomial, Epanechnikov kernel, and unit bandwidth) of the fitted residuals on the (unexpected) change in GPA. The proxy variable for ΔGPA^e used in the construction of the unexpected change in GPA is Proxy 1 that matches on the the exact PSE institution and similar major field of study.

The results presented in Table 6 suggest a decrease of 1.7 percentage points for a one category increase in the ΔGPA . When I use the unexpected change in GPA the coefficient drops, but the difference is statistically insignificant except for Panel 3. Differently from Table 5, the change in expectations variable (ΔExp) has a consistent and statistically significant effect on the probability to drop out of PSE in Panels 2–4. This is not the case in Panel 1. The addition of the interaction term allows for the coefficient on the GPA change to differ for negative variable values. As shown in column (6) this difference is not statistically significant. In Figure 3 I allow for a non-linear relationship between (unexpected) change in GPA for both outcomes separately. For the probability of switching major, the choice of the variable in the x-axis seems to matter given the differences in the graphical representation of the non-linear regression. However, this is not the case for the graph (b) where the plots almost overlap.

Table 5: Probability to switch major and changes in GPA

	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Change in GPA						
ΔGPA	-0.066*** (0.007)	-0.059*** (0.006)	-0.056*** (0.007)	-0.026*** (0.008)	-0.026*** (0.003)	-0.018 (0.018)
ΔExp					0.002 (0.005)	0.002 (0.005)
Interaction						-0.009 (0.021)
Joint test (p=value)						0.004
Pseudo R^2	0.034	0.050	0.056	0.132	0.133	0.133
Sample Size	5275	5275	5275	5275	5275	5275
Panel 2: Unexpected Change in GPA, Proxy 1 used for ΔGPA^e						
$\Delta GPA - \Delta GPA^e$	-0.049*** (0.007) ^b	-0.043*** (0.007) ^b	-0.041*** (0.007) ^b	-0.017** (0.007)	-0.017*** (0.007)	-0.010 (0.011)
ΔExp					0.002 (0.005)	0.002 (0.005)
Interaction						-0.011 (0.012)
Joint test (p=value)						0.036
Pseudo R^2	0.019	0.043	0.053	0.149	0.149	0.149
Sample Size	5275	5275	5275	5275	5275	5275
Panel 3: Unexpected Change in GPA, Proxy 2 used for ΔGPA^e						
$\Delta GPA - \Delta GPA^e$	-0.034*** (0.007) ^a	-0.035*** (0.007) ^a	-0.035*** (0.007) ^b	-0.018** (0.007)	-0.019*** (0.007)	-0.004 (0.011)
ΔExp					0.003 (0.005)	0.003 (0.006)
Interaction						-0.022* (0.012)
Joint test (p=value)						0.000
Pseudo R^2	0.009	0.038	0.049	0.150	0.150	0.152
Sample Size	4697	4697	4697	4697	4697	4697
Panel 4: Unexpected Change in GPA, Proxy 3 used for ΔGPA^e						
$\Delta GPA - \Delta GPA^e$	-0.036*** (0.007) ^a	-0.035*** (0.007) ^a	-0.034*** (0.007) ^b	-0.019*** (0.006)	-0.019*** (0.006)	-0.009 (0.009)
ΔExp					0.003 (0.006)	0.003 (0.006)
Interaction						-0.018 (0.012)
Joint test (p=value)						0.004
Pseudo R^2	0.012	0.035	0.045	0.149	0.149	0.150
Sample Size	4697	4697	4697	4697	4697	4697
Individual Variables		✓	✓	✓	✓	✓
Parental Variables			✓	✓	✓	✓
First Year Variables				✓	✓	✓

Note: The coefficient estimates are marginal effects from probit regressions. Robust standard errors in parenthesis. Statistical significance: ***1%, **5%, *10%. The interaction term refers to an interaction variable between the (unexpected) change in GPA and a dummy indicator for negative values of this variable. The “Joint test” is a chi-squared test on the joint significance of the (unexpected) change in GPA and the Interaction parameters. The different definitions of the ΔGPA^e proxies are as follows: Proxy 1 matches on the the exact PSE institution and similar major field of study; Proxy 2 matches on the the exact PSE institution, similar major field of study and high school GPA category; Proxy 3 matches on the the exact PSE institution, similar major field of study, high school GPA category, and gender.

Table 6: Probability to drop out and changes in GPA

	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Change in GPA						
ΔGPA	-0.019*** (0.005)	-0.025*** (0.005)	-0.029*** (0.005)	-0.017*** (0.004)	-0.014*** (0.004)	-0.021** (0.011)
ΔExp					-0.003 (0.002)	-0.011*** (0.003)
Interaction						0.007 (0.013)
Joint test (p=value)						0.002
Pseudo R^2	0.010	0.048	0.074	0.214	0.280	0.280
Sample Size	5804	5804	5804	5804	5804	5804
Panel 2: Unexpected Change in GPA, Proxy 1 used for ΔGPA^e						
$\Delta GPA - \Delta GPA^e$	-0.026*** (0.005)	-0.029*** (0.005)	-0.031*** (0.005)	-0.016*** (0.004)	-0.015*** (0.004)	-0.012** (0.006)
ΔExp					-0.010*** (0.003)	-0.010*** (0.003)
Interaction						-0.004 (0.007)
Joint test (p=value)						0.036
Pseudo R^2	0.019	0.056	0.079	0.215	0.223	0.224
Sample Size	5804	5804	5804	5804	5804	5804
Panel 3: Unexpected Change in GPA, Proxy 2 used for ΔGPA^e						
$\Delta GPA - \Delta GPA^e$	-0.015*** (0.004)	-0.017*** (0.004) ^c	-0.018*** (0.004) ^b	-0.010*** (0.003) ^c	-0.009*** (0.003)	-0.007* (0.004)
ΔExp					-0.009*** (0.003)	-0.009*** (0.003)
Interaction						-0.005 (0.011)
Joint test (p=value)						0.118
Pseudo R^2	0.010	0.045	0.065	0.213	0.221	0.221
Sample Size	5528	5528	5528	5528	5528	5528
Panel 4: Unexpected Change in GPA, Proxy 3 used for ΔGPA^e						
$\Delta GPA - \Delta GPA^e$	-0.023*** (0.005)	-0.023*** (0.004)	-0.022*** (0.004)	-0.012*** (0.004)	-0.011*** (0.004)	-0.008*** (0.004)
ΔExp					-0.010*** (0.004)	-0.010*** (0.004)
Interaction						-0.005 (0.007)
Joint test (p=value)						0.006
Pseudo R^2	0.012	0.069	0.087	0.226	0.238	0.239
Sample Size	5528	5528	5528	5528	5528	5528
Individual Variables		✓	✓	✓	✓	✓
Parental Variables			✓	✓	✓	✓
First Year Variables				✓	✓	✓

Note: The coefficient estimates are marginal effects from probit regressions. Robust standard errors in parenthesis. Statistical significance: ***1%, **5%, *10%. The interaction term refers to an interaction variable between the (unexpected) change in GPA and a dummy indicator for negative values of this variable. The “Joint test” is a chi-squared test on the joint significance of the (unexpected) change in GPA and the Interaction parameters. The different definitions of the ΔGPA^e proxies are as follows: Proxy 1 matches on the the exact PSE institution and similar major field of study; Proxy 2 matches on the the exact PSE institution, similar major field of study and high school GPA category; Proxy 3 matches on the the exact PSE institution, similar major field of study, high school GPA category, and gender.

5 Conclusion and discussion

Post-secondary education in Canada is partly subsidized by the provincial government. When faced with high proportions of dropouts and major switchers, even for a single year, the cost can be significant. Students (or their parents) invest in PSE uncertain of whether they will complete the program. Rational decision-makers rely on all possible sources of information to form expectations about the probability of graduating from a post-secondary education program. This paper investigates how students update their higher educational expectations. I find evidence that the main driving force behind expectation revisions is the information that students derive from unexpected changes in their academic performance, which is measured by the difference in the GPA between high school and the PSE freshman year. Through this information they learn about their own academic ability and its match with the difficulty of the program that they are attending. I demonstrate that the relationship between the unexpected change in grades and expectation updating is non-linear. Students revise their educational expectations when they experience an unexpected drop in GPA, but they are indifferent to positive changes in GPA. This paper also tests whether the unexpected change in grades affects the dropout decision and the decision to switch major. An unexpected one category increase in this variable leads to a decrease of 1.9 percentage points in the probability to switch major, and to a decrease of 1.2 percentage points in the probability to drop out a PSE program.

Students may be conscious of their ability, but they may not be well informed about how their skills fit with the different programs. The findings in this paper indicate that a signal of mismatch between the student's background and the difficulty of the program increases the probability of a path disruption. The unexpected change in grades may be not the only factor influencing educational expectations and outcomes, preferences could also have an important role. However, they may be thought as interrelated. In one hand a student that does not enjoy the courses will not be motivated to work hard for the exams, and on the other hand a student that is not achieving performance levels above average of their peers will question their choice of major. It is not in the scope of this study to separate the two channels, and the effect estimated in this paper reflects a composite effect. Recent literature (Castleman and Goodman, 2014) provides evidence that student consultation during the

last year of high school improves the quality of match between the student (preferences and ability) and the program of study, and leads to higher retention rates in PSE. These type of policy interventions seem to matter in decreasing the likelihood of path disruptions, which will consequently diminish the inefficiencies in the public cost of education.

References

- Joseph G. Altonji. The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics, Part 1: Essays in Honor of Jacob Mincer*, 11(1): 48–83, 1993.
- Peter Arcidiacono. Ability sorting and the returns to college major. *Journal of Econometrics*, 121(1-2):343–375, 2004.
- David Card. The causal effects of education on earnings. In O. Ashenfelter and David Card, editors, *Handbook of Labour Economics*, volume 3, chapter 30, pages 1801–1863. Elsevier Science B.V, 1999.
- Benjamin Castleman and Joshua Goodman. Intensive college counseling and the college enrollment choices of low income students. *HKS Faculty Research Working Paper Series RWP14-031*, (July), 2014.
- Adeline Delavande. Pill, patch or shot? subjective expectations and birth control choice. *International Economic Review*, 49(3):999–1042, 2008.
- Jeff Dominitz. Earning expectations, revisions, and realizations. *Review of Economics and Statistics*, 80:374–88, 1998.
- Jeff Dominitz and Charles F. Manski. Eliciting student expectations of the returns to schooling. *Journal of Human Resources*, 31(1):1–26, 1996.
- Andrew J. Hussey and Omari H. Swinton. Estimating the ex ante expected returns to college. *American Economic Review: Papers & Proceedings*, 101(3):598–602, 2011.
- Charles F. Manski. Schooling as experimentation: a reappraisal of the postsecondary dropout phenomenon. *Economics of Education Review*, 8(4):305–312, 1989.
- Charles F. Manski. Measuring expectations. *Econometrica*, 72(5):1329–1376, 2004.
- Philip Oreopoulos and Kjell G. Salvanes. How large are returns to schooling? hint: Money isn’t everything. *NBER Working Papers 15339*, National Bureau of Economic Research, Inc., 2009.

- Ralph Stinebrickner and Todd R. Stinebrickner. The causal effect of studying on academic performance. *The B.E. Journal of Economic Analysis and Policy*, 8(1):1–55, 2008.
- Todd R. Stinebrickner and Ralph Stinebrickner. Learning about academic ability and the college dropout decision. *Journal of Labor Economics*, 30(4):707–748, 2012.
- David Trick. College-to-university transfer arrangements and undergraduate education: Ontario in a national and international context. *Toronto: Higher Education Quality Council of Ontario*, 2013.
- Basit Zafar. How do college students form expectations? *Journal of Labor Economics*, 29(2): 301–348, 2011.

Appendix

Figure A.1: Kernel estimate of the ΔExp distribution plotted against a normal distribution

Table A.1: Summary statistics

	Variable	Obs	Mean	Std. Dev.
Dependent variables				
	ΔExp	6504	0.072	1.388
	Major Switch	5275	0.193	0.395
	Drop out	6106	0.078	0.268
Independent control variables				
	PISA score	6504	560.359	85.915
	Female	6504	0.559	0.496
	Single	6504	0.960	0.193
	Citizen	6504	0.947	0.223
	Rural	6504	0.336	0.472
<i>Province of Residence:</i>				
	Newfoundland	6504	0.101	0.302
	Prince Edward Island	6504	0.072	0.259
	Nova Scotia	6504	0.135	0.342
	New Brunswick	6504	0.126	0.331
	Manitoba	6504	0.093	0.291
	Saskatchewan	6504	0.086	0.280
	Alberta	6504	0.085	0.279
	British Columbia	6504	0.104	0.306
<i>Mother Education:</i>				
	Some College	6504	0.077	0.267
	College	6504	0.319	0.466
	First Professional degree	6504	0.040	0.198
	Bachelor's	6504	0.176	0.381
	Graduate	6504	0.047	0.211
<i>Father Education:</i>				
	Some College	6504	0.062	0.242
	College	6504	0.295	0.456

Table A.1: Summary statistics (cont.'d)

Variable	Obs	Mean	Std. Dev.
First Professional degree	6504	0.033	0.179
Bachelor's	6504	0.166	0.372
Graduate	6504	0.099	0.299
Family Income	6504	355.985	243.028
Parental Monetary Transfers	6504	2296.742	3914.900
<i>Highest Education Level Attended:</i>			
Bachelor's Equivalent	6504	0.659	0.474
College Equivalent	6504	0.236	0.424
<i>Times thought dropping out:</i>			
Less than once a month	6504	0.126	0.332
Once or twice a month	6504	0.128	0.334
About once a week	6504	0.031	0.174
More than once a week	6504	0.024	0.154
<i>The right program:</i>			
Agree	6504	0.554	0.497
Strongly Agree	6504	0.203	0.402
<i>Idea for future plans:</i>			
Agree	6504	0.637	0.480
Strongly Agree	6504	0.224	0.417
<i>Job market skills:</i>			
Agree	6504	0.555	0.496
Strongly Agree	6504	0.152	0.359
<i>Sure for type of work:</i>			
Agree	6504	0.478	0.499
Strongly Agree	6504	0.125	0.330
Workshops to adjust	6504	0.198	0.399
<i>Hours of homework:</i>			
8 to 14 hours	6504	0.323	0.467
15 to 20 hours	6504	0.305	0.460
21 to 30 hours	6504	0.144	0.352
More than 30 hours per week	6504	0.064	0.245

Table A.2: Probability of changing expectations as a function of $(\Delta GPA - \Delta GPA^e)$

	(1) Coll to lessColl	(2) Coll to Bach	(3) Coll to Grad	(4) Bach to lessColl	(5) Bach to Coll	(6) Bach to Grad	(7) Grad to Coll	(8) Grad to Bach
Panel 1: Change in GPA								
ΔGPA	0.004 (0.007)	0.003 (0.014)	-0.000 (0.005)	0.007 (0.005)	0.017* (0.009)	0.034** (0.014)	-0.016* (0.008)	-0.051** (0.021)
Interaction	-0.029* (0.017)	-0.029 (0.030)	0.022* (0.012)	-0.012* (0.006)	-0.042*** (0.012)	0.000 (0.019)	0.024** (0.010)	0.023 (0.025)
Joint Test (p-value)	0.171	0.570	0.069	0.132	0.003	0.003	0.056	0.015
Pseudo R^2	0.367	0.329	0.608	0.346	0.367	0.076	0.625	0.139
Sample Size	830	1184	875	1667	2375	2717	1009	1627
Panel 2: Unexpected Change in GPA, Proxy 1 used for ΔGPA^e								
$\Delta GPA - \Delta GPA^e$	0.004 (0.007)	0.003 (0.014)	-0.000 (0.005)	0.007 (0.005)	0.017* (0.009)	0.034** (0.014)	-0.016* (0.008)	-0.051** (0.021)
Interaction	-0.029* (0.017)	-0.029 (0.030)	0.022* (0.012)	-0.012* (0.006)	-0.042*** (0.012)	0.000 (0.019)	0.024** (0.010)	0.023 (0.025)
Joint Test (p-value)	0.171	0.570	0.069	0.132	0.003	0.003	0.056	0.015
Pseudo R^2	0.367	0.329	0.608	0.346	0.367	0.076	0.625	0.139
Sample Size	830	1184	875	1667	2375	2717	1009	1627
Panel 3: Unexpected Change in GPA, Proxy 2 used for ΔGPA^e								
$\Delta GPA - \Delta GPA^e$	0.003 (0.006)	0.013* (0.008)	-0.010 (0.007)	-0.005 (0.004)	0.008 (0.012)	0.037* (0.022)	0.009 (0.009)	-0.017 (0.025)
Interaction	-0.026 (0.018)	-0.030 (0.028)	0.035*** (0.012)	0.004 (0.005)	-0.034** (0.014)	-0.007 (0.024)	0.001 (0.011)	0.013 (0.028)
Joint Test (p-value)	0.475	0.198	0.006	0.486	0.012	0.079	0.327	0.793
Pseudo R^2	0.558	0.358	0.771	0.360	0.395	0.093	0.632	0.161
Sample Size	808	1149	851	1619	2307	2640	985	1590
Panel 4: Unexpected Change in GPA, Proxy 3 used for ΔGPA^e								
$\Delta GPA - \Delta GPA^e$	0.005 (0.006)	-0.001 (0.009)	-0.006 (0.007)	-0.008* (0.005)	0.004 (0.008)	0.033* (0.018)	0.007 (0.009)	-0.022 (0.021)
Interaction	0.033* (0.018)	-0.043 (0.029)	0.028 (0.009)	0.006 (0.006)	-0.030** (0.012)	-0.019 (0.023)	-0.003 (0.011)	0.015 (0.025)
Joint Test (p-value)	0.141	0.206	0.006	0.162	0.013	0.129	0.675	0.556
Pseudo R^2	0.393	0.323	0.760	0.340	0.363	0.092	0.612	0.134
Sample Size	808	1149	851	1619	2307	2640	985	1590

Note: The coefficient estimates are marginal effects from probit regressions. Robust standard errors are reported in parenthesis. Statistical significance: ***1%, **5%, *10%. The interaction term refers to an interaction variable between the (unexpected) change in GPA and a dummy indicator for negative values of this variable. The "Joint test" is a chi-squared test on the joint significance of the two parameters reported for each regression. The different definitions of the ΔGPA^e proxies are as follows: Proxy 1 matches on the the exact PSE institution and similar major field of study; Proxy 2 matches on the the exact PSE institution, similar major field of study and high school GPA category; Proxy 3 matches on the the exact PSE institution, similar major field of study, high school GPA category, and gender. The educational expectation categories are defined as follows: **lessColl** includes: (1) *Some High School or less*, (2) *High school diploma*, (3) *Some post-secondary education level courses (no diploma or degree)*; **Coll** includes: (4) *Private business school or commercial school diploma*, (5) *College, CEGEP, or trade/vocational certificate or diploma*, (6) *University degree or certificate below Bachelor's degree*; **Bach** includes: (7) *University Bachelor's degree*, (8) *University first professional degree (medicine, dentistry, veterinary medicine, law, optometry, divinity)*; **Grad** includes: (9) *Master's degree or University graduate diploma or certificate (above Bachelor's degree)*, (10) *PhD or other earned doctorate, D.Sc., D.Ed.*. Each of the dependent variables (indicated at the top of each column) take a value of zero if the student makes no revisions and takes a value of one if they make the indicated revision. For example, the variable "Coll to lessColl" takes a value of zero if the students in both age 17 and 19 report one of the educational categories grouped under "Coll", and takes a value of one if the students revise educational expectations from a category within the "Coll" grouping to a category within the "lessColl" grouping.