UNIVERSITY OF CALGARY

Postsecondary Dropouts and Differential Grading Standards: An Empirical Approach

by

Lawrence So

A THESIS SUBMITTED TO THE FACULTY OF GRADUATE STUDIES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ARTS

DEPARTMENT OF ECONOMICS

CALGARY, ALBERTA

AUGUST, 2004

UNIVERSITY OF CALGARY

FACULTY OF GRADUATE STUDIES

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies for acceptance, a thesis entitled "Postsecondary Dropouts and Differential Grading Standards: An Empirical Approach" submitted by Lawrence So in partial fulfillment of the requirements for the degree of Master of Arts.

Supervisor, Dr. M.C. Auld,
Department of Economics

Department Examiner, Dr. Curtis Eaton,
Department of Economics

External Examiner, Dr. James S. Frideres,
Department of Sociology

August 20, 2004

ABSTRACT

Students' performance in course grades can be decomposed into two determinants, namely, grading standards and students' ability. Although grading standards and ability consist of observable characteristics (grading distribution and students' gender, respectively), these variables can also consist of unobservable characteristics. By capturing the heterogeneity in unobservable characteristics of grading standards and students' ability, we find empirical evidence of distortions of postsecondary students' dropout behavior. Particularly, low-ability students benefit from taking courses with lenient grading standards, given that their resulting high grades reduce their probability of dropping out of university. Alternatively, high-ability students are adversely affected by taking courses with difficult grading standards, given that they receive low grades that increase their probability of dropping out. Hence, using a measure of ability that is not influenced by grading standards would better approximate students' ability levels, which can result in a more efficient allocation of schooling resources.

ACKNOWLEDGEMENTS

I would like to thank Dr. M.C. Auld for his support, patience and advice while completing this thesis. His ability to explain difficult concepts and consider a broad range of questions benefited my thesis and my experience in this graduate program. Moreover, the applied econometrics in my thesis would not have been accomplished without his persistent drive to practice *good* econometrics. I would like to thank Dr. B.C. Eaton for introducing and providing the theoretical background to my thesis topic. I would like to acknowledge Dr. Emery, Kevin Gerrits, and Kendra McLeish for providing critical feedback and revisions for my thesis. Dr. Emery's comments gave me new perspective of the overall objective of completing my thesis. Kevin bore the major load of correcting my grammatical errors and created my thesis title. Kendra's rigorous edits with her blue sparkle pen showed me important errors in my thought process that would have gone unchecked otherwise. Their perspectives during critical points in the development of my thesis were invaluable to me. To my family, thank you for your emotional and physical support. I would have never lasted this long in this program without you guys being behind me. Lastly, to all the 2003/2004 economic graduate students, thanks for all your friendship and keeping this year entertaining.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

I. INTRODUCTION

Deciding to drop out of university is a significant decision for a student to make, affecting the student's academic path and the resources tied to his/her enrollment. Hence, determining the factors that affect this decision has been an important research objective across many academic fields. Many researchers (Coleman, 1966; Bayer, 1968; Hanushek, 1986; Pirog, 1997) argue the effect of individual characteristics as the most significant determinant of students' withdrawal decisions, while schooling characteristics are less influential in the decision process. In contrast, others (Goldhaber, 1997; Betts, 2003; Figilo, 2000; Lillard, 2001) argue that schooling characteristics, such as a teacher's experience and grading standards are economically and statistically significant to students' academic outcomes. Resolving the debate concerning the relative importance of these two characteristics has significant education policy implications in so far as the efficiency of the allocation of resources can be improved. That is, if individual characteristics are relatively more important than school characteristics, university administrators can better target individual characteristics and affect dropout rates. For example, if a higher high school Grade Point Average (GPA) deceases the probability of dropping out, university administrators could increase the high school GPA required to gain entry into university. An alternative inference might result if schooling characteristics were found to be relatively more important than individual characteristics. For example, if better instructor qualifications are associated with lower dropout rates, administrators should focus on recruiting better-qualified instructors.

The following literature review will show that a broad range of estimation strategies have been employed in order to answer the above debate. Recent papers (Betts, 2003; Figlio, 2000; Goldhaber, 1997) have worked to account for the unobservable heterogeneity in schooling characteristics that may affect student achievement. Continuing with this line of research, we will decompose grades into course and student heterogeneity, which will be defined as grading standards and ability, respectively. The objective of this decomposition is to investigate whether differential grading standards across academic programs distort students' dropout decisions for different ability levels. Particularly, low ability students who face lenient grading standards may benefit in terms of a reduced probability of dropping out, while high ability students who face difficult grading standards may be disadvantaged in terms of a higher probability of dropping out. An advantage of purging course heterogeneity from grades is that we can generate a measure of ability by capturing the unobservable differences across students. Comparing this measure of ability to other ability measures, such as high school GPA, allows us to identify who should be admitted to university. Moreover, we can use our ability measure to correct the signals sent to students by their university GPA, which would allow students to better assess their ability. Better signals could result in more students streaming into programs that match their aptitude and more students whose aptitude that doesn't match university education dropping out. Thus, school resources can be more efficiently allocated by using this ability measure.

The following paper will be divided into five sections. First, a review of the academic literature on the topic will be presented. This section will introduce the models and estimation strategies used to determine the probability of dropping out. The second section will show how grades can be decomposed into students' ability and grading standards in our empirical strategy. In the third section, a description of the dataset and variables employed will be detailed. The fourth section will include empirical results illustrating the effect of differential grading standards on postsecondary students. Finally, a discussion of how this paper's empirical results relate to the literature and subsequent policy implications will be presented.

II. LITERATURE REVIEW

Although many empirical papers' strategies concerning school dropout determinants vary widely in their details, most of the papers reviewed depict a student's dropout decision as a function of cumulative inputs from individual, family, peer, and school characteristics.[1] The beginning of the literature that investigates the determinants of student performance can be traced to the Equality of Educational Opportunity report (1966) or as it is more commonly known, the Coleman Report. This report surveyed a half million students to determine the most important inputs that affect student performance. In general, the report concluded that school characteristics had little effect on student performance, while student characteristics, such as family and socioeconomic background were more important. This conclusion was, and remains, controversial as it implies increased funding to schools is an ineffective way to improve student performance. As a result of its controversial conclusion, the Coleman Report's methodology has been widely criticized and discredited. Another paper with the same

[1] Eric A. Hanushek (1986) The Economics of Schooling: Production and Efficiency in Public Schools. *Journal of Economic Literature.* (24) 1155.

methodology as the Coleman report is Bayer's 1968 paper. In this paper, Bayer looked at 38 different student and school input variables[2]. Bayer found evidence supporting the Coleman Report, however, the author recognized that his findings were inaccurate due to omitted variable bias. Thus, the paper's conclusions cannot be considered for educational guidance and policy decisions. These earlier papers typically examined combinations of individual and school inputs in an educational production function. Particularly, the production function involved a binary dropout variable being regressed onto general student, family, and school characteristics. A recent paper by Pirog and Magee (1997) used a dataset that contained more information than the above two papers, yet found support for the Coleman Report's findings. This study improved its methodology over earlier counterparts by controlling for school, labor market and individual characteristic variables that were not observed in earlier datasets. The authors concluded that "school quality variables do not have significant impact on educational achievement and are not robust to changes in model specification."[3]

A new construct that emerged from the literature was Tinto's psychosociological model (1975). The model focused on how students' characteristics affect their involvement with their academic institutions and as a consequence, affect their probability of continuing in school. [4] Tinto's model contributes to the body of literature by showing that students begin with a set of background traits and level of commitment

---

[2] Alan E. Bayer, (1968) "The College Drop-out: Factors Affecting Senior College Completion". *Sociology of Education*. (41) 305.
[3] Maureen A. Pirog and Chris Magee. (1997) "High School Completion: The Influence of Schools, Families, and Adolescent Parenting". *Social Science Quarterly* (78) pg. 721.
[4] Claude Montmarquette et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review*. (20) 476.

to school, which affects the degree of their academic and social integration. Indicators of academic and social integration are academic performance and the quality of peer and faculty interactions, which are used to determine students' probability of dropping out. Papers supporting Tinto's model (Pascarella, 1986; Ensminger, 1992; Aitken, 1982; Bean, 1985; Munro, 1985) typically include university GPA, students' pre-university preparedness, prior academic achievements, student-faculty ratios, and time spent in student extracurricular activities, while controlling for students' background characteristics. These papers tend to focus on specific variables that affect integration, such as the paper by Pascarella et al. (1986), which looks at the effect of attending a college orientation program on college persistence. By estimating a simultaneous equation model, Pascarella et al. argue that the indirect effect of the college orientation program has the largest effect on students' decision to continue once enrolled[5]. Other papers (Munro, 1981; Ensminger, 1992; Smith, 2001) supporting Tinto's model broadly interpret their coefficients to provide evidence for Tinto's model. For example, Munro (1981) interpreted the coefficient on her postsecondary GPA variable as indicating academic integration. The conclusion from Munro's study is that academic integration is the primary determinant of dropout behavior, while social integration had no significant effect. [6] Ensminger and Slusarcick (1992) also found evidence of the importance of grades in dropout behavior even though they used methods and a sample significantly different from many other studies of dropout behavior. The Ensminger and Slusarick paper applied a log-linear model to determine the effect of grades on high school dropout

[5] Earnest T. Pascarella, et al. Orientation to College and Freshman Year Persistence/Withdrawal Decisions". *The Journal of Higher Education.* 57(2): 169.
[6] Barbara H. Munro. (1981) "Dropouts from Higher Education: Path Analysis of a National Sample". *American Educational Research Journal.* 18(2): 140.

rates for black elementary students. The paper found that "males who received As or Bs in first grade had over twice the odds of graduating high school as did males who received Cs and Ds, while females with higher grades had over one-and-half times the odds of graduating as had those with lower grades."[7] Smith and Naylor (2001) improved on social integration measures by including variables such as the location of student residence and department sex ratios. [8] Their examination of a student cohort between 1989 -1993 found that higher measures of ability, like those with A level grades were less likely to drop out of university. The conclusion reached in this paper differs from Munro's paper by finding social integration to be economically and statistically significant. That is, Smith and Naylor concluded that because those who lived with their parents or far from campus were less socially integrated, these students were also more likely to drop out.[9] Nevertheless, the underlying trend common to most of the papers supporting Tinto's model is that academic integration measured by grades is found to be economically and statistically significant and that dropping out is a sub-optimal outcome. Hence, personal characteristics, like high school GPA, affecting academic integration and consequently dropout rates should be used to lower enrollment.

An alternative view proposed by Manski (1989) counters the idea that dropping out is a sub-optimal outcome. He argues that preventing students from dropping out is not necessarily an ideal outcome if enrolling in school is considered as being part of an

---

[7] Margaret E. Ensminger and Anita L. Slusarcick. (1992) "Paths to High School Graduation or Dropout: A Longitudinal Study of a First-Grade Cohort". *Sociology of Education*. (65) pg. 102.
[8] Jeremy Smith and Robin A. Naylor. (2001) "Dropping out of University: A Statistical Analysis of the Probability of Withdrawal for UK university Students". *Royal Statistical Society* (164) pg. 396.
[9] Ibid., pg. 399.

experiment in which dropping out is just another outcome. [10] Dropping out cannot be deemed as an optimal or sub-optimal outcome because the ex ante expected return of education is needed to make this judgment. For example, "let attending school have cost C and, if completed successfully, benefit B. Second, let P be the probability of completion. Suppose that an observer is told the completion rate of enrolled students, but is not told C, B, or the manner in which P varies across students".[11] Determining the optimality of the enrollment decision cannot be made as the information required to properly evaluate the enrollment decision is not available, i.e. the expected return, $PB - C > 0$ or $E(P|P>C/B)$. Hence, studies that conclude that dropout rates are too high and should be lowered are based on incomplete information and should be considered with caution. According to Manski, dropping out may be an optimal outcome because students can derive valuable information from finding out postsecondary education is not compatible with their interests and abilities.[12]

To model dropping out as an experiment, the determinants of a student's enrollment and dropout decision should be estimated sequentially. Hence, the literature (Montmarquette, 2001; DiPietro, 2004) supporting this view focuses on sequential decision-making rather than student's background characteristics, which affect academic and social integration. These papers are concerned with nonrandom sample bias caused by those who self-selected out of university. That is, the authors used a Bivariate Probit model to simultaneously estimate the decision to drop out of university, conditional on

[10] Claude Montmarquette et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review.* (20) 475.
[11] Manski, C. F. (1989) Schooling as Experimentation: A Reappraisal of the Postsecondary Dropout Phenomenon". *Economics of Education Review.* (8) 306.
[12] Ibid.

the prior decision to continue in the previous semester. Both papers found student characteristics as being important in determining continuance in university. Moreover, in Montmarquette et al.'s paper, a student's prior semester's university GPA was found to be an important determinant of continuance.[13] The authors infer from this coefficient that an academically successful student in the previous semester is likely to continue on with university because "the student can confirm his/her level of ability with respect to the chosen program within a single semester of study".[14] Although the authors interpret this coefficient as an outcome from academic experimentation and the use of grades as a signal of their ability, supporters of Tinto's model interpreted this as an indicator of academic integration. If a course requires greater student involvement, such as more student-teacher interaction, more teaching assistant involvement, etc., students are more likely to receive better grades and therefore less likely to drop out. The main distinction between supporters of Manski's view and earlier papers is it focuses on school characteristics rather than student characteristics that affect academic integration.

As noted in the earlier papers (Coleman, 1966; Bayer, 1968; Hanushek, 1986), the influence of school variables on academic integration was undermined by the economic and statistical significance of student characteristics. Recent papers (Betts, 2003; Figlio, 2000; Goldhaber, 1997; Lillard, 2001) have departed from earlier studies through improving the characterization of school differences by accounting for the unobserved heterogeneity across schools. Estimates from earlier papers suffered from measurement error and/or omitted variable bias because they used variables to proxy these

[13] Claude Montmarquette et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review*. (20): 480
[14] Ibid., pg. 481.

unobservable characteristics. An example is the use of years of teaching experience to proxy unobservable heterogeneity in teachers' motivation or presentational style. A paper that accounts for school heterogeneity is Betts and Grogger's (2003) paper on grading standards. Betts and Grogger use a two-stage estimation strategy to estimate first academic integration, and then its effect on the dropout decision. Rather than looking at GPA as an indicator of academic integration, the authors looked at grading standards. Grading standards were broadly defined to include all unobservable heterogeneity across schools, such as instructor's subjectivity, male-female ratios, number of students in courses or schools, the coarseness of grading distribution, etc. In the first stage of their estimation strategy, the authors regress students' Grade 12 math test scores onto dummy variables representing high schools, the number of math classes taken, and students' GPA in math classes. [15] The estimated coefficients for each high school dummy variable in the first stage regression captured the difference in grading standards across high schools. These coefficients were then used as a regressor in the second stage regression. In the second stage regression, a binary variable for high school completion was regressed onto a vector of student characteristics, school characteristics, and grading standards from the first stage regression. Via this estimation process, Betts and Grogger concluded that heterogeneity in school grading standards was not a significant determinant of high school completion for white students, but has a negative and significant effect on high school graduation rates for blacks and hispanics. [16] The authors attribute this result to the Relative Student Performance hypothesis, which views that "higher standards lead to higher gains for students near the top of the distribution than for students near the bottom;

[15] Julian R. Betts and Jeff Grogger. (2003) "The Impact of Grading Standards on Student Achievement, educational Attainment, and Entry-level earnings". *Economics of Education Review.* (22) pg. 346.
[16] Ibid., pg. 350.

students near the bottom could perceive themselves as falling behind on a relative basis, despite their absolute gain."[17] A similar conclusion was also corroborated by a study completed by Goldhaber and Brewer (1997) using a similar methodology and a different dataset. This paper also found that a random effects model was sufficient to model education production functions because unobservable heterogeneity across schools was not correlated with observable variables.[18]

Following Betts and Grogger's approach to capturing schooling heterogeneity, Figlio and Lucas (2000) investigated the effect of grading standards on students' performance in elementary school. Although they focused on the determinants that affect students' test scores rather than their decision to drop out of school, we see a shift in the literature to using fixed effects models that control for unobservable school heterogeneity. Figlio and Lucas improved on Betts and Grogger's estimation strategy by estimating the effect of grading standards on student achievement, while controlling for student, school, teacher, and time effects. Given the importance of accurately measuring grading standards in their estimation strategies, Figlio and Lucas also investigated potential bias from patterns in teacher-level grading standards over time, and the effect of nonrandom student class-assignment. These authors conclude that the "initially low-performing students appear to differentially benefit from high grading standards when the average ability level of the class is high, and high-performing students appear to differentially benefit from high grading standards when the average ability level of the

[17] Ibid.

[18] Dan D. Goldhaber and Dominic J. Brewer. (1997) "Why don't Schools and Teachers Seem to Matter? Assessing the Impact of Unobservables on Educational Productivity". *The Journal of Human Resources*. 32(3): 519.

class is low."[19] However, this study does not address the effect of grading standards on the probability of dropping out.

In contrast to the last two papers, Lillard and DeCicca (2001) do not control for school heterogeneity, but do choose to use minimum state course requirements as a measure of grading standards. These authors found evidence that higher grading standards cause students to drop out of school, but this conclusion requires a narrow definition of grading standards. This method does not fully account for school quality heterogeneity, which is likely a determinant of academic integration, and consequently a determinant of the probability of students dropping out. Nevertheless, this paper drew comparisons across several different levels of aggregation, i.e. from state level school attrition rates to high school dropout rates, to estimate the effect of grading standards.[20] The paper used fixed and random effects models for their state aggregated data, while for their individual analysis, a Probit model was used on a cross section of high school students. To account for a potential endogeneity bias resulting from omitted variables, the authors used variables that were highly correlated with their omitted variables, e.g. they used earnings for 18-24 year olds and the average unemployment rate as a proxy for students' expected wage rate.[21]

In general, the literature on students' dropout behavior has debated the importance of student characteristics relative to school characteristics. Common across all the

---

[19] David Figlio and Maurice E. Lucas. (2000) "Do High Grading Standards Affect Student Performance?" *NBER Working Paper Series*. (7985) pg. 20.
[20] Dean R. Lillard and Philip P. DeCicca. (2001) "Higher Standards, More Dropouts? Evidence within and Across Time". *Economics of Education Review*. (20) pg. 465.
[21] Ibid., pg. 460.

empirical studies reviewed, as depicted in Table 1, is that the measure of students' ability is negatively related to the probability of dropping out regardless of how this variable is interpreted in relation to their theoretical model. The recent trend has been to account for heterogeneity across schools in order to measure the effect of grading standards, or more broadly, academic integration on the probability of dropping out. This paper will continue with this trend, but will further improve on the decomposition of grading standards. More importantly, this paper also will improve on the measure of ability used to capture the unobservable, idiosyncratic ability of students to attain grades. Measuring the idiosyncratic differences in students' ability levels are typically ignored in the literature, yet we will show they have a significant effect on our estimates. With these two improvements, this paper will show that students' dropout decisions are determined by how the difficulty of course grading standards relates to students' ability levels. The following section will present the estimation strategy used to illustrate the effect of the relationship between grading standards and ability levels.

III. ESTIMATION STRATEGY

A. Decomposing Grades into Ability and Grading Standards

Earlier papers (Coleman, 1966; Bayer, 1968; Hanushek, 1986; Pirog, 1997; Pascarella, 1986; Ensminger, 1992; Aitken, 1982; Bean, 1985; Munro, 1985) typically regressed a measure of student performance onto student, family, and school characteristics. The following equation is typical of the regression completed by earlier papers, where B is a vector of student background variables, like student's age, ethnicity, sex, family income, proxy of ability, e.g., standardized test score and S is a vector of school input characteristics, like class size, teacher experience, teacher-student ratio.

$$Student\ Performance_i = B^T \beta_i + S^T \gamma_i + u_i \tag{1}$$

However, recent papers (Goldhaber, 1997; Betts, 2003; Figilo, 2000) have shown that the school input characteristic vector, S can be modeled as two components. Namely, an observed characteristic component Z_{1j} and unobserved characteristic component Z_{2j}.[22] Since we only have students that attend one school (the University of Calgary) in our dataset, we use course characteristics denoted by j taken by student i to capture school input characteristics. That is:

$$Student\ Performance_{ij} = B^T \beta_i + Z_1^T \gamma_{1j} + Z_2^T \gamma_{2j} + u_{ij} \tag{2}$$

The observed component follows the above examples of school characteristics in Equation 1. The unobserved component in our equation accounts for course heterogeneity that affects student performance, such as instructors' idiosyncratic ability to teach and grade students, classroom distractions, and peer integration. We can then further decompose this equation by separating our student background vector B into observed A_{2i} and unobserved A_{2i} components, which is shown in Equation 3.

$$Student\ Performance_{ij} = A_1^T \beta_{1j} + A_2^T \beta_{2j} + Z_1^T \gamma_{1j} + Z_2^T \gamma_{2j} + u_{ij} \tag{3}$$

[22] Dan D. Goldhaber and Dominic J. Brewer. (1997) "Why don't Schools and Teachers Seem to Matter? Assessing the Impact of Unobservables on Educational Productivity". *The Journal of Human Resources*. 32(3): 508-510.

The observed component consists of the above examples of student background characteristics in Equation 1. The unobserved component is made up of students' idiosyncratic differences that affect their academic performance, defined as ability. If we follow Equation 1's specification, the unobserved heterogeneity across schools and students that affect student performance will end up in the error term. That is, the error term in Equation 1 will be:

$$u_{ij} = A_2^T \beta_{2j} + Z_2^T \gamma_{2j} + \varepsilon_{ij} \tag{4}$$

Omitting either unobserved components may result in two problems. First, the effect of schooling and/or student characteristics will be understated because the unobservables are not included in the explained portion of the variance in student performance.[23] Second, without accounting for these unobservables in the equation, the results are biased for all of our coefficients. The latter problem will not be realized if the unobserved component is uncorrelated with our observed regressors.[24] For example, we have to assume that high school GPA is not correlated with the student's ability, or teacher's experience is not correlated with their motivation to teach. Given that this lack of correlation is highly unlikely, our estimates will be biased if we do not include these unobserved components as a regressor. Past papers (Aitken, 1982, Munro, 1981; Bean, 1985) used proxy variables that are highly correlated with the unobservable variables, such as variables based on survey questions measuring teachers' behavior or teacher's ability. However, with our

[23] Ibid. pg. 508.
[24] Hence, we can use a Random Effects model to account for the effect on our standard errors by this unobserved heterogeneity.

panel data of students by courses, we can capture the unobservable heterogeneity in school and student characteristics by having dummy variables for each student and course. Hence, the following regression will be completed as the first stage of regression:

$$Grade_{ij} = \phi + \sum_{i}^{N} Student_i \alpha_i + \sum_{j}^{T} Course_j \beta_j + \varepsilon_{ij}$$

The ϕ is the constant, α_i represents each students' idiosyncratic ability, and β_j represents the course difficulty for each course. The dependent variable is the grade received by Student i in Course j, which falls in between a 0 to 4.3 grade point scale (for F to A+ grade levels). Student_i is a dummy variable which is equal to one for each unique student and zero otherwise. Course_j is a dummy variable, which is equal to one for each unique course lecture observed in the 2000/2001 school year and zero otherwise. We assume that each student has an idiosyncratic ability that is constant across courses. We also expect to observe the same significant variation across the coefficients for each course dummy variable given that we expect grading standards to differ across courses.

Our fixed effects model[25] is only identified if one category is omitted from the equation, as such an arbitrary category from the course variable is omitted. A problem with this fixed effects model is that we cannot have a characteristic that is constant across courses, like sex, as it will be perfectly collinear with the student dummy variable. However, given that we are interested in identifying the factors that are important in

[25] Although there are other models like the Random effects or differenced effects models that can capture unobserved heterogeneity across students and courses, we used the fixed model because it uses dummy variables to capture unobserved heterogeneity. With these dummies, we can generate a numeric value for each student's ability and a level of course difficulty for each course. Using these two measures, we can infer their relationships with dropout behavior.

determining the probability of dropping out, it is not crucial to our paper to identify the determinants of course grades. Moreover, when we do not include variables that are constant across courses, observable student characteristics are captured by the dummy variable for each student. That is, the coefficient for the $Student_i$ dummy variable represents his/her idiosyncratic ability, and other observable characteristics, such as sex and region of origin. Because of this result, we can reduce the number of coefficients that is estimated by dropping all observable course characteristics. With this fixed effects model, we can capture the unobserved heterogeneity across courses and idiosyncratic student effects that determine course grades. The fixed effects for students can be collapsed across students' courses to generate a measure of ability. This measure serves to purge the unobserved course effects that influence students' grades. In addition, we can also collapse the course effects for each of the students' courses to generate an average course grading standard variable. The grading standard variable captures the level of difficulty in grading standards that each student faced in his/her courses over the 2000/2001 school year.

B. Comparing Ability Measures

With these two new regressors, we can draw comparisons between different measures of ability by looking at their effect on the probability of dropping out. Particularly, we can compare the marginal effect of university GPA to the marginal effect of our estimated ability by running the following Probit models as the second stage of our estimation process:

$$\text{(1)} \qquad \Pr(Dropout)_i = X^T \beta + \gamma GPA_i + u_i$$

$$\text{(2)} \qquad \Pr(Dropout)_i = X^T \beta + \delta \hat{Ability}_i + u_i$$

GPA's marginal effect in Equation 1 differs from estimated ability's marginal effect in Equation 2 by reflecting the effect of course grading difficulty on the probability of dropping out. The magnitude of the difference should tell us how well university grades match students' ability, and whether deviations from ability result in higher attrition rates. If the marginal effect for ability is larger than GPA, we can infer that the slope is steeper in the second equation than the first equation (as shown in Figure 1), ceteris paribus. That is, we can infer that given that grades is larger than ability, low ability students are benefiting by having a lower probability of dropping out than if their grades reflected their ability. Alternatively, grading standards are disadvantaging high ability students by increasing their probability of dropping out. In addition, the variables contained in the $X^T \beta$ vector are important with respect to its correlation to our ability measures. Given that we are interested in determining the relationship between ability, course grading standards and other regressors, we have to be careful with the specification of our equations[26]. Hence, we will complete several specifications to illustrate the negative/ positive relationship between our measure of ability and variables such as sex, age, faculty, number of courses, and average class size.

C. Estimation Strategy Issues

There are two issues with using the estimates from our fixed effects model to generate regressors for our second-stage Probit estimates. First, we have a generated regressor problem because student's ability is estimated and then used in Equation (2) to

[26] We have to be careful with the inclusion of different variables in our specification because our estimated coefficients will reflect not only the relationship of the regressor on the dependent variable but also its relationship with other regressors in the specification.

generate further estimates. Although using generated regressors result in consistent estimates for our ability and grading standard variables, our standard errors and test statistics will be incorrectly estimated. Using generated regressors changes our standard errors because it introduces sampling variation from the first stage regression into the second stage equation, where both equations are estimated from the same random sample. [27] To correct for this problem, we use a re-sampling method such as bootstrapping. This method obtains consistent estimates of the covariance matrix by estimating our two equations B number of times to generate a vector of coefficients, i.e., $\hat{\Theta} = \left[\hat{\vartheta}(1)_m, \ldots\ldots, \hat{\vartheta}(B)_m\right]$) from our sample (with replacement) and then forming the following for our covariance matrix: [28]

$$\text{Estimated Asymptoptic Variance}\left[\hat{\vartheta}\right] = \frac{1}{B}\sum_{b=1}^{B}\left[\hat{\vartheta}(b)_m - \hat{\vartheta}_n\right]\left[\hat{\vartheta}(b)_m - \hat{\vartheta}_n\right]'$$

However, given the computation limitations and complications in bootstrapping our fixed effect model, we will not be adjusting our standard errors.

Second, the dependent variable in the fixed effects model, course grade, is discrete and can be considered count data. That is, we cannot observe grades in between each grade level. For example, we never observe a course grade of 3.31, which is in between the B (3.0) and B+ (3.3) grade levels. Given the nature of our limited dependent variable, we can improve our estimation strategy by using count data models such as a Poisson model, or negative binomial regression. Note that the computational demands of

[27] Wooldridge, Jeffrey M. (2002) *Econometric Analysis of Cross Section and Panel Data*. Massachusetts: MIT Press. pg. 115-117.
[28] William H. Greene. (2003) *Econometric Analysis*. (5th edition). New York: MacMillian Publishing Company. pg. 924.

these models (when applied to our fixed effects model) require us to treat our dependent variable as a continuous variable.

IV. DATASET

A. Description of Data and Variables

From the University of Calgary's Registrar's Office, we have panel data consisting of students by courses. This dataset consists of a panel of 472,349 observations, which details the students' high school and university information over three school years, i.e., 2000 to 2003 (Spring and Summer semesters excluded). Given that we are interested in the behavior of university dropouts, we confine our dataset to only first-year, undergraduate students from the 2000/ 2001 school year. We focus only on first-year students because first-year students have the highest dropout rate at 16.82 percent (738 out of 4,376) compared to a 13 percent dropout rate for second year students. The literature (Smith, 2001; Porter, 1990) also corroborates our relatively high dropout rate for first-year students, finding approximately half of all attrition occurring in the first year. Moreover, according to Tinto, first-year dropouts differ from students in other years because of "the transitional difficulties of adjustment into postsecondary school life".[29] Second, we omit part-time students because we expect that they are more likely to drop out and exhibit poor grades because they are more likely to commit time and effort to alternative opportunities, like work. Particularly, we do not have a measure of expected student wage rate, and consequently, cannot control for the opportunity cost of investing in university while working. Third, we dropped all students from the Faculty

[29] Jeremy Smith and Robin A. Naylor. (2001) "Dropping out of University: A Statistical Analysis of the Probability of Withdrawal for UK university Students." *Royal Statistical Society.* (164): 395.

of Graduate Studies and Environmental Design because we expect that these students' dropout behavior will differ from first-year undergraduate students. We also tested the robustness of our estimates below against dropouts in the Faculty of Law and found no significant differences.[30] We can see from Table 2 that the majority of students (70.98%) are from the Faculty of Communications and Culture and that there is little variation in faculty types as we only have first-year students in our dataset, who did not tend to declare their faculty of interest until later years of their program.

Our dependent variable in the second stage equation is a binary variable indicating if a first-year student is observed in the 2000/2001 school year and is not observed in any year of their program[31] (1 - 5 year of program) in the 2001/2002 school year. Students who dropped out temporarily and re-entered in later semesters were not included in the dataset, given that the determinants of their decision to take time off is different from those who drop out. As shown in Figure 2, in the beginning of the first semester of the school year, there are 4,376 students, but at the end of the semester, 443 students had dropped out, leaving 3,933 students in the Winter 2001 semester. Evidently, a larger proportion of dropouts occurred in the first semester than in the second semester. Given that most of these 4376 students took different course mixes, we have a large number of different courses, i.e. 1444. The result is that we have an unbalanced dataset, where we do not observe every student taking every unique course.

[30] Estimates are available upon request.

[31] Although typically we would assume that first year students will enter the second year of their program the following school year, we found that students in our dataset entered into higher years of their program because of the number of courses taken over the first year, and/or Spring and Summer semester.

Aside from university information, we have information about students' high school backgrounds, as shown in Table 2. Albertans make up the majority of our dataset, representing 79.91 percent (3497 out of 4376 students) of first-year students. Our sex variable is distributed evenly with 45.7 percent males and 54.3 percent females. We have an average high school matriculate average of 76.4 percent for 4168 students. We are missing high school matriculate average for 208 students because we have approximately 5 percent with missing information regarding their high-school background. Our estimates could be biased if this information was not randomly omitted from our dataset. Looking at the university information of these students, we do not see any discernable type for these students in regards to faculty, semester, and age.[32] Moreover, we checked for the robustness of the estimates below by dropping the students without high school information. We found that our estimates did not significantly change when these students were left out.[33] Hence, we conclude that the selection bias from not including high school information for these students is minimal. In addition, some variables were riddled with missing values, such as the students' region of origin. In order to not exclude these students, we generated a missing value category for such categorical variables. Lastly, for ease of interpretation and comparison with the following empirical results, the units for all measures of ability (namely university GPA, high school matriculate average, estimated average ability, and our average course grading standards variable) are in standard deviations.

V. EMPIRICAL RESULTS

[32] These results are unreported.
[33] Estimates are available upon request.

A. Baseline Specification

The economic relationship we are interested in estimating is the difference in marginal effects of a student's GPA and ability on the probability of dropping out. To estimate this relationship, we have to be careful with the variables we include in the regression, given that their correlation to either GPA or ability can change GPA or ability's relationship with the probability of dropping out. Hence, we will estimate several specifications as shown in the tables below, in order to robustly infer the relationship of interest. We will first estimate by regressing our binary variable, dropping out after the 2000/2001school year, onto just students' GPA and then onto the students' estimated ability. Given that our ability measure comes from the fixed effects model, it captures all students' unobservable idiosyncratic abilities to attain grades, while excluding all unobserved course heterogeneity in grading. Since students' GPA is composed of this underlying ability and course-grading standard, the difference between the two equations will reflect the impact of the course-grading standard on the probability of dropping out. Comparing the first two equations shows us that as ability increases by one standard deviation, the probability of dropping out decreases by 10.73 percent, while the same change in GPA is associated with a 10.41 percent decrease in the probability of dropping out (ceteris paribus). We find that this result is statistically significant, finding our p-value for each ability measure, i.e., GPA and estimated ability to be less than 0.00001.

Evident from this result is that the slope of ability is basically identical to the slope of GPA. When we plot this result in Figure 3, we can see that the X's representing the estimated ability match the squares representing GPA. This result contradicts our expectation that GPA's slope would be flatter than Ability's slope because we expected students to have a different probability of dropping out if their ability was measured with GPA rather than ability. Particularly, we expected low ability students to have a lower probability of dropping out if their ability was measured with GPA than ability because they receive grades higher than their ability. Alternatively, we expected high ability students to have a higher probability of dropping out because the grades they receive are lower than their ability. However, this result did not occur because it is likely that we have the opposite result also occurring. That is, we have low ability students who have a high probability of dropping out given their low grades, while we have high ability students who have a low probability of dropping out given their high grades. Hence, these students balance our expected flatter slope for GPA. Given that the effect of grading standards are masked in this specification, we have to introduce controls for course heterogeneity.

B. Controlling for Course Heterogeneity (Specifications 2 & 3):

We can control for course heterogeneity by introducing faculty dummy variables to our specification. Starting with no control for ability, we see in the first two columns of Table 4 that all faculties except for the Faculty of Fine Arts are less likely to drop out than students in the Faculty of Communications and Culture. However, these estimates reflect the effect of the differences in both course heterogeneity and ability across faculties. First, when we introduce the ability measure, university GPA, we should be able to approximately control for the differences in ability in our faculty dummy estimates. Consequently, the faculty dummies should reflect only the difficulty of courses given course heterogeneity across faculties. With this change to Specification 2, we can see that the Engineering faculty is negatively related to university GPA, as the marginal effect of this dummy variable further decreases relative to the specification without controlling for GPA. In contrast, the probability of dropping out increases for students in the Faculty of Fine Arts relative to the Faculty of Communications and Culture, increasing to 9.83 percent (ceteris paribus). We can infer from this result that if we have two students with the same GPA, e.g., at 90 percent, the student in the Faculty of Engineering has a lower probability of dropping out than the student in Faculty of Fine Arts. This result occurs because we cannot control for the underlying ability by using GPA as a measure of ability. That is, Engineering students have lower probability of dropping out than Fine Art students even though they have the same GPA because Engineering students have higher ability than Fine Art students. Particularly, Engineering students have high ability with an average of 0.39 standard deviations relative to Fine Arts students who have an average ability of –0.16 standard deviations (which is shown in Table 12). This result is evidence of differential grading standards because we found that an Engineering student can have higher ability than a Fine Arts student even though they have the same grades.

When we introduce our other ability measure, estimated ability allows us to actually control for students' underlying ability, so the estimates for the faculty dummy variables should only reflect course difficulty across faculties. Our results from this estimation tell us a corroborative story to the previous paragraph's inference that there is evidence of differential grading standards. When we introduce our ability measure, we find that Engineering students are 2.78 percent more likely to drop out relative to the Communications and Culture students, (ceteris paribus). The change in the ability measure significantly altered our result, changing the sign of the marginal effect from negative to positive. Given that Engineering students have the most difficult courses with an average course difficulty of 1.41 standard deviations (based on our average course grading difficulty measure from the fixed effects model) and the highest probability of dropping out, we can infer that Engineering students are more likely to drop out due to the difficulty of their courses. This relationship is consistent for our estimates for the Fine Arts students, where we found that students are less likely to drop out due to the ease of their faculty's grading standards, i.e., an average course difficulty of -1.59. The probability of dropping out for Fine Arts students decreases from 9.83 percent to 1.94 percent when we change our ability control from university GPA to the estimated ability variable (ceteris paribus). Our results show that if we took two people with the *same* GPA and placed one student in a more difficult grading faculty, like Engineering, and the other into a more lenient grading faculty, like Fine Arts, the Engineering student is *less* likely to dropout than the Fine Arts student. In contrast, if we took two people with the same *estimated ability* and placed one in the Engineering faculty and the other in the Fine Arts faculty, the Engineering student is *more* likely to drop out than the Fine Arts student. This result occurs because when we control for ability using university GPA, the underlying ability is still different, i.e., Engineering students are less likely to drop out when we control for their GPA because the marginal effect is still reflecting their relatively high underlying ability that is lowering their probability of dropping out. Thus, we found that differential grading standards across faculties are associated with different probabilities of dropping out for different ability levels.

The problem with using faculty dummy variables to control for the level of course heterogeneity is that it controls for little course variation when we only have few faculty controls. That is, 70.98 percent of our students have not declared their intended faculty and chose the general studies faculty by default, i.e., the Faculty of Communications and Culture. By controlling for students' majors rather than faculties, we can further control for course heterogeneity, and make a better judgment of whether this relationship remains consistent under this specification. We see in Table 5 that Biomechanics majors are 1 percent less likely to drop out of university than Art History majors, when we control for GPA, (ceteris paribus). However, when estimated ability is controlled, we find that the probability of dropping out for Biomechanics majors is 1.87 percent higher probability of dropping out than Art History majors (ceteris paribus). In contrast, for Music majors, we find that when we control GPA, they have a higher probability of dropping out relative to Art History majors at 8.3 percent (ceteris paribus). With the different ability control, i.e., using estimated ability, we see that the probability of dropping out switches signs, decreasing to 0.62 percent less likely to drop out relative to Art History majors, (ceteris paribus). Given that we find Biomechanics majors have relatively high ability and high course difficulty, while Music majors have the opposite characteristics, our previous inference holds when we further disaggregate our control for course heterogeneity with dummy variables for majors.

Another method to control for course heterogeneity and to illustrate these relationships is to use the average of the coefficients from the course dummy variables for each student in our fixed effects model to generate an average course grading difficulty variable.[34] Hence, larger values of this variable are associated with more difficult course grading standard, while lower numbers are associated with more lenient grading standards. For the GPA controlled equation, we find in Table 6 that the average course difficulty variable has a negative marginal effect on dropping out, showing that a one standard deviation increase in course difficulty, there is a 2.65 percent decrease in probability of dropping out, (ceteris paribus). In contrast, the ability-controlled equation shows the opposite relationship, that students are more likely to drop out at 1.97 percent for a one standard deviation increase in course difficulty, (ceteris paribus). When we regress our dropout variable onto just the average course difficulty variable, there is a 0.62 percent decrease in the probability of dropping out for a one standard deviation increase in average course difficulty, (ceteris paribus). We can infer that the GPA variable is negatively related to the average course difficulty variable given the large lower probability of dropping out in the GPA controlled equation. By the same reasoning, we find our estimated ability is positively related to the course difficulty variable. This result illustrates that when we do not properly control for ability by using university GPA, the underlying ability in the average course difficulty variable lowers the probability of dropping out. Using our estimated ability, we find that this relationship is no longer found, finding that students taking courses with harder grading standards are more likely to drop out.

C. Identifying Student and Course Characteristics (Specification 4)

[34] Initially, the course effects from the fixed effects model reflect the course leniency in grading standards. For ease of interpretation, we multiplied this variable by negative one and changed the units to standard deviations to generate a course grading difficulty variable.

A problem with the above specifications is that the marginal effects for both our ability and course difficulty variables do not identify specific course and student characteristics, such as class size, age, sex, number of university courses, and region of origin that affect dropout behavior. The marginal effects of these variables meet most of our expectations on their effect on the probability of dropping out, given our review of the literature. First, we find in Table 7 that males are less likely to drop out than females for both equations. We find a 3.4 percent lower probability for males than females when controlling for GPA and 2.77 percent lower probability for males than females when controlling for ability (ceteris paribus). Second, our age (or birth date) variable shows that as students get older, they are more likely to drop out. Both equations estimated small effects, as students get one year younger, there is a 0.17 and 0.25 percent increase in the probability of dropping out for the GPA and estimated ability controlled equations, respectively (ceteris paribus). This minimal effect is likely to be explained by the small variation in the age variable for first-year students, where 79.13 percent of first-year students are between the ages of 18-20. We also find that the age variable is not statistically significant, finding p-values of 0.84 and 0.225 for the age variable in the GPA and estimated ability controlled equations, respectively. Third, the marginal effects for the dummy variables representing each student's region of origin show that for both equations, students from distant regions are more likely to drop out than students from Alberta. The only two regions with students that were less likely to drop out of university than Alberta students are Nova Scotia and Yukon with marginal effects of –2.27 and -5.27 percent, respectively (ceteris paribus). Students originating from the United States have the highest probability of dropping out of university with a marginal effect of 37.32

percent, (ceteris paribus). Fourth, the effect of the number of courses taken by students in the 2000/2001 school year shows that for both equations, as students take more courses, the less likely students will drop out. For example, in the GPA controlled equation, when the number of courses increases by one course, the probability of dropping out decreases by 2.42 percent (ceteris paribus) and is statistically significant with a p-value less than 0.00001. The inclusion of this variable has a significant effect on the marginal effects for GPA and estimated ability as this variable is a another measure of ability. The positive correlation between the number of courses taken and the measures of ability is evident when both the marginal effects for GPA and ability decrease in magnitude by approximately 2 percent. An interesting effect from including the Number of Courses variable is that in both equations, we find the marginal effect on the Engineering dummy variable increases, changing from a negative to positive probability of dropping out in the GPA controlled equation. This change in sign shows us that when we control for Engineering students taking relatively more courses (an average of 9.56 courses) than other faculties (an average of 7.57 courses for all other faculties), we find that Engineering students are more likely to drop out. Lastly, when we introduce the course characteristics (class size and its square), we find that as class-size increases, students are less likely to drop out. For both ability-controlled equations, we find the same negative effect, 0.14 percent on the probability of dropping out for a one student increase in class size for both equations at an increasing rate (ceteris paribus). The interesting effect of controlling for class-size is its relationship to our faculty dummies. Specifically, we found that when we control for the fact that the Faculty of Fine Arts has small class-sizes (an average of 30.43 students) relative to other faculties (an average of 94.68 students), the sign and magnitude changes from 1.94 percent to –2.24 percent in the ability-controlled equations (ceteris paribus). We can infer that the relatively lower average class sizes in the Faculty of Fine Arts increases the probability of dropping out when class-size is not controlled in the specification.

D. Investigating Nonlinear Ability Measures (Specifications 5, 6, & 7):

The last specification issue is determining whether the GPA or ability variables have a nonlinear relationship with the probability of dropping out. To determine if this relationship exists, we first include the squares of our ability measures, i.e., GPA-squared and ability-squared variables in our two equations. When we add the square of GPA to the model, we find in Table 8 that there is a negative relationship between GPA and its square because the marginal effect on GPA increases from –8.4 to –33.06 percent, (ceteris paribus). Moreover, given that the marginal effect is positive at 7.2 percent (ceteris paribus) for the GPA squared variable, we can infer that the effect of GPA on the propensity to dropout is decreasing at an increasing rate. The opposite result can be inferred for the ability-controlled equation, i.e., the marginal effect is smaller for ability, increasing from –8.37 to –6.32 percent (ceteris paribus). Hence, given that the magnitude decreased, there is a positive relationship between ability and its square.

To further investigate this nonlinear relationship, we drop our measure of ability variables in Specification 6 and add dummy variables for a given percent range, e.g., we generate a dummy variable for those students with GPAs in the 1-2 standard deviations range. Estimating with these new dummy variables matches our previous results, showing that as the GPA range increases, the probability of dropping out decreases in magnitude until our last range, which shows a smaller lower probability of dropping out. The increase in the probability of dropping out for the last range is likely reflecting the higher opportunity cost of higher GPA students who decide to drop out. For example, these students may have more opportunities to progress in their non-academic careers or academic careers at other institutions than students with a lower GPA. For the ability-controlled equation, we see that the negative effect on the probability of dropping out is larger across all intervals than the intervals for the GPA-controlled equation. Moreover, the changes between each percent range are large, depicting a slightly steeper curve relative to GPA-controlled equation. This result is evident in Figure 4 where we can see that the black Xs representing ability are mostly below the gray Squares representing GPA for high ability students. Evident also from the graph is how the scatter plot follows a step function because of the use of dummy intervals to represent continuous measures of ability.

We can better illustrate the changes in probability by using a Spline variable for both GPA and ability in each equation. The marginal effect for each interval in the Spline variable is a measure of the slope for that interval rather than showing the levels as in Specification 6. Using a Spline variable, we can identify for both equations that the slope for students at the interval of the GPA/Ability –2 is the steepest, while we find that the slope for the following intervals are flatter (which we can see in Figure 5). Moreover, at this interval, the difference in the probability of dropping out between the ability-controlled equation and the GPA controlled equation disappears. At the slope for the 2 interval, the two equations begin to diverge. That is, given the positive slopes for last two intervals of the ability-controlled equation, high ability students are more likely to drop out than high GPA students. Thus, given the non-linearities in the GPA and ability variables shown across our specifications, we will include the square of each variable in our specification.

VI. DISCUSSION

A. Drawing Similarities with the Literature

Drawing direct comparisons between our results and the literature is difficult because of the differing estimation strategies, datasets, and/or interpretation of coefficients rather than marginal effects. Nonetheless, comparing the results of Specification 5 to the literature shows that some of our estimates' magnitudes and directions match the literature. Specifically, we concur with the negative coefficient on the dummy variable for sex obtained by Montmarquette et al.'s paper.[35] Our age variable indicates that older students are more likely to drop out of university. That is, similar to DiPietro's paper, which found students who are 24 years old or older are 19 percent more likely to drop out than 22-year-old students (ceteris paribus).[36] Montmarquette et al. arrived at a similar result, finding a lower probability of continuing onto the next semester with age. Comparing the average class size and average class size squared variables, we find that the signs of our variables match Montmarquette's et al. paper. Particularly, students become less likely to drop out, at a slightly increasing rate, for each

[35] Claude Montmarquette et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review*. (20) 480.
[36] Giorgio DiPetro. (2004) The Determinants of University Dropout in Italy: A Bivariate Probability Model with Sample Selection. *Applied Economics Letters*. (11) 190.

one-student increase in average class size (ceteris paribus).[37] Lastly, the negative marginal effect of our ability measures matches previous results. All the papers reviewed demonstrated that the probability of dropping out decreases as the ability measure increases marginally. Regardless of how the measure of ability is defined in the literature, be it current GPA, prior semester's GPA, Grade 10 math scores, all the papers reviewed found a negative sign to their respective ability measure. Although we find similarities between our estimates and inferences in the literature, we also find significant discrepancies between the literature and this paper regarding the effect of grading standards on the probability of dropping out.

B. Comparing Measures of Course Grading Standards

Four papers that investigated the effect of grading standards on the probability of dropping out are papers by Betts & Grogger, Figlio & Lucas, Lillard & DeCicca, and Smith & Naylor. Betts and Grogger's paper uses a similar estimation strategy to ours by generating a regressor for their grading standard in the first stage equation. The authors used dummy variables for each student's high school class rather than dummy variables for each university course.[38] As well, the authors controlled for differences in student ability by including the number of math courses the student had taken as well as the student's high school GPA, which differs from our use of dummies for each student in the first stage. With this estimation strategy, Betts and Grogger (2003) found that "grading standards have their greatest effect among the students who are most likely to

[37] Claude Montmarquette et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review.* (20) 480.
[38] Julian R. Betts and Jeff Grogger. (2003) "The Impact of Grading Standards on Student Achievement, educational Attainment, and Entry-level earnings". *Economics of Education Review.* (22) pg. 345.

graduate, i.e., the effects of grading standards at the bottom quartile are relatively small".[39] Particularly, Betts and Grogger found that the coefficient on their grading standard variable to be small, which they concluded that grading standards have an insignificant effect on high school completion. Specifically, there is a 0.47 percent decrease in the probability of dropping out as grading standards increase by one standard deviation (ceteris paribus).[40] The magnitude of our grading standards variable is larger, i.e., there is a 2.64 percent decrease in the probability of dropping out as average course difficulty increase by one standard deviation in our GPA-controlled equation (ceteris paribus).[41]

Betts and Grogger further investigated the effect of grading standards by introducing ability measures and the effect of ethnicity. An interesting result is that as they include students' 10th grade math scores and schools' average 10th grade math scores, their grading standard's coefficient switched signs. That is, a one standard deviation increase in grading standards resulted in a 0.23 percent increase in the probability of dropping out (ceteris paribus).[42] They found this result to be robust for both blacks and hispanics. This result is inconsistent with their conclusion that higher grading standards have a positive effect on high ability students' completion decisions. The authors explained this contradiction in terms of the Relative Performance Hypothesis. That is, although "higher standards lead to higher gains for students near the top of the distribution than for students near the bottom, students near the bottom could perceive

[39] Ibid., pg. pg. 348.
[40] Ibid., pg. pg. 347.
[41] Ibid.
[42] Ibid., pg. Pg. 349.

themselves as falling behind on a relative basis, despite their absolute gains."[43] However, the change in sign of their grading standard's coefficient is consistent with our results. We found that when we introduced students' unobserved ability, students were more likely to drop out as grading standards increased. Although our results illustrate this relationship, we infer that differential grading standards affect different ability levels rather than inferring the Relative Performance Hypothesis. In Betts and Grogger's initial specification, low ability students' dropout decisions are negatively effected by higher grading standards, while high ability students' dropout decisions are positively effected by higher grading standards. In our paper, low ability students' probability of dropping out is lowered by lenient grading standards, while the opposite outcome applies to high ability students.

We differ from Betts and Grogger's and other papers accounting for school heterogeneity (Figlio & Lucas, 2000; Lillard & DeCicca, 2001; and Smith & Naylor, 2001) because our fixed effect model further disaggregates school heterogeneity by controlling for course heterogeneity. That is, we have panel data of student by courses rather than panel data of students by schools or by teacher. In addition, our departure from Betts and Grogger's result is likely due to their focus on high school students rather than postsecondary students. Investigating high school students causes discrepancies as high school students are forced to comply with an academic curriculum, while postsecondary students can self-select into different courses to better match their aptitude. Students selecting into courses to match their aptitude is an ideal outcome if grading standards are identical across all programs. However, because students can self-select

[43] Ibid., pg. 350.

into a course mix without knowing whether grading standards are high/low, they can receive incorrect signals about their ability from their grades. Since low ability postsecondary students can receive higher grades than their ability and high ability students can receive lower grades than their ability, dropout decisions may be distorted.

Figlio and Lucas's paper found similar empirical evidence to Betts and Grogger. Figlio and Lucas found that high ability students are more positively effected by student achievements than low ability students in a below average ability class. However, like Betts and Grogger's paper, they also focus on the school performance of students whom are required to follow a mandatory program, namely elementary students. Nevertheless, they find evidence of the Relative Performance Hypothesis. Particularly, "they found that high standards lower the *safety* for high-achievers in low-achieving classes and may generate more effort and greater learning, as might high standards increase the *risk* for low achievers in high achieving classes."[44] This inference was deduced from trying several different grading standards in their analysis to determine the robustness of their results. While using teacher fixed effects from a first stage regression as a measure of grading standards and controlling for student and school heterogeneity in their second stage estimation, the authors found that for a one standard deviation increase in grading standards, students' change in math test scores increased by 3.135 percent (ceteris paribus).[45] Our paper contradicts this result, showing that increasing grading standards negatively influences high ability students as poor grades signal that their ability is lower than expected, potentially encouraging them to withdraw from university.

---

[44] David Figlio and Maurice E. Lucas. (2000) "Do High Grading Standards Affect Student Performance." *NBER Working Paper Series*. (7985): 19-20.
[45] Ibid., Table 7.

However, this contradiction is likely the result of Figilo and Lucas investigating the effect of grading standards on students' performance rather than school completion, and their focus on students that are required to comply with an academic program.

Comparing Lillard and DeCicca's paper with ours, we find that the direction of their grading standard's variable matches our paper. Lillard and DeCicca's paper finds that as course graduation requirements (or grading standards) are increased, students are more likely to drop out, given the positive sign on their graduation requirement's coefficient. [46] However, their research differ from ours and the two papers mentioned earlier by not using a fixed effects model to estimate their grading standards. Lillard and DeCicca chose state mandated high school graduation requirements to capture the difficulty of courses in high school. [47] In contrast, we generated regressors for both ability and grading standards, allowing our estimates to benefit from capturing all unobservable effects across courses and students that would be lost if we decided to aggregate or proxy the variables. Smith and Naylor also did not use a fixed effects model to capture student or course heterogeneity in their study. Instead, they chose to use dummy variables for Subject Degrees because these dummy variables can control for variation in grading standards from different programs. [48] To account for differences in student ability, this paper used dummies for different grade levels and included a pre-determined measure of ability (i.e. the number of failed courses taken by subject). Because the measure of ability is determined before students make their withdrawal decision, this decision is not directly

[46] Lillard, Dean R. and Philip P. DeCicca. (2001) "Higher Standards, More Dropouts? Evidence within and Across Time". *Economics of Education Review*. (20) pg. 465.
[47] Ibid., pg. 460.
[48] Jeremy Smith and Robin A. Naylor. (2001) "Dropping out of University: A Statistical Analysis of the Probability of Withdrawal for UK university Students." *Royal Statistical Society*. (164): 389-405.

effected by differential grading standards. With this specification, they found subjects like Mathematics (presumably with high ability students) to have a higher probability of dropping out at 5.92 percent than subjects (presumably low ability students) like Humanities with a probability of dropping out at –0.02 percent (ceteris paribus).[49] Hence, the results by Naylor and Smith corroborate our results.

C. Policy Implications

The objective of this paper is to investigate how differential grading standards distort postsecondary students' dropout decisions at different levels of ability. Because we found that unobservable grading standards significantly affect students' dropout decisions, we can also infer that school input characteristics are important in determining student outcomes. However, we find the economic and statistical significance of grading standards to be smaller than our estimated ability measure. Resolving the relative importance of school to student characteristics has important policy implications because it determines how much funding should be allocated to school resources. We can infer from our results that the heterogeneity in schooling (or course) characteristics that affect student performance is an important determinant of postsecondary students' withdrawal decisions. However, because our grading standard variable captures both observable and unobservable characteristics, we cannot identify the effect of the components making up the grading standards variable without more detailed information. Hence, further research is needed to determine how to better target school funding.

[49] Ibid., pg. 396.

Although we cannot definitively answer which schooling characteristic should receive funding priority, our improvement in modeling ability helps us to identify which high school students should enroll in university. This result has important policy implications because the number of students that enroll in university affects the strain placed on university resources. If students who ought to withdraw from university (based on their low ability) remain in university due to lenient grading standards, university resources may be inefficiently allocated. In order to make policy recommendations, we have to construct a better relationship between our estimated ability measure and how students are admitted to university. The problem with our ability measure is the difficulty in properly interpreting it, given that it captures many unobservable, idiosyncratic differences in students' ability levels. An ability measure that is often interpreted and used for university enrollment decisions is students' high school matriculate average. Hence, we can use students' high school matriculate average as a measure of ability in the above specifications to draw comparisons with our estimated measure of ability. An important characteristic of this measure of ability is that it is determined prior to university education, and consequently, not affected by university grading standards. However, high school grading standards influence high school matriculate average, e.g., a difference in grading standards between Math and English teachers. Nevertheless, this measure is a better proxy of ability than university GPA because high school students are required to take subject requirements and have standardized tests.

C.1. Empirical Results from Relating High School Matriculate Average to Ability

We can use Specification 3 and replace the ability measure with matriculate average to draw comparisons with our prior results of university GPA and estimated ability. As shown in Table 11, the direction of average course difficulty marginal effect, when controlling for matriculate average, follows the same direction as the marginal effect in the estimated ability controlled equation. Particularly, a one standard deviation increase in average course difficulty is associated with a 0.13 percent increase in the probability of dropping out (ceteris paribus). This positive marginal effect shows that the correlation between matriculate average and grading standards is similar to the relationship between estimated ability and grading standard. Particularly, like our estimated ability variable, university grading standards do not influence matriculate average. The main difference between matriculate average and estimated ability is the small magnitude of average course difficulty in the matriculate average-controlled equation relative to the marginal effect in the estimated ability controlled equation, as shown in Table 11. The relatively minimal effect of matriculate average can be explained by differential grading standards in high schools and the significance of our ability variable to capture unobservable idiosyncrasies across students. Moreover, if we have matriculate average as the only determinant of the probability of dropping out, we find that this measure of ability has the smallest negative effect on the probability of dropping out relative to all our ability measures. That is, for a one standard deviation increase in matriculate average, the probability of dropping out decreases by 0.81 percent (ceteris paribus).[50] Nevertheless, these results provide further evidence that increasing the course difficulty in grading standards increase the probability of dropping out when ability is properly controlled.

[50] Results are available upon request.

A simpler method than using econometrics to demonstrate the relationship between matriculate average and our ability measure is to look at the averages for each measure of ability across faculties. Although this method offers a rough approximation of the above relationship, i.e., this method does not control for the effect of differences in student and course characteristics like in our above econometrics, we find that faculties with students of high ability and matriculate averages have low university GPAs due to difficult grading standards. For example, we can see in Table 12 that Engineering students have one of the highest matriculate averages and ability at 0.15 and 0.388 (standardized units), respectively, but the poorest GPA due to the hardest grading standards at –0.20 and 1.41 (standardized units), respectively. In contrast, we can see that Fine Arts students have one of the lowest matriculate averages and ability at -0.091 and -0.16 (standardized units), respectively, but the highest GPA due to the easiest grading standards at 0.516 and –1.593 (standardized units), respectively.

Given that matriculate average is a strong indicator of students' unobserved ability, a policy implication that arises is to use matriculate averages to identify low ability students that should not persist in university. University administrators can reduce the enrollment of low ability students by having higher matriculate average requirements for faculties with lenient grading standards. By raising the high school matriculate average required to enter lenient grading faculties, the overall enrollment of low ability students will be reduced. Hence, a more efficient allocation of resources can be achieved. That is, presently low ability students are incorrectly encouraged by their high university grades to remain in school, which incorrectly decreases their opportunity cost of continuing with their university degree. For example, low ability students are forgoing employment income or alternative postsecondary schooling by attending university because they are falsely misled by their high university grades. Moreover, resources used by low ability students could be redirected to higher ability students if low ability students are not competing for resources. Another problem with retaining low ability students in university is that because university education tends to signal high ability to employers, incorrect signals are sent about students' abilities to employers. Preventing low ability students from entering university will benefit employers, allowing them to hire a high ability student with greater certainty rather than running the risk of hiring a low-ability student with *high* grades. The main problem with this approach is that we still have high ability students dropping out and relatively low ability students remaining in university because the signals received from their respective grades are incorrect. To correct for this problem, we can use the course effects in our fixed effects model to re-weight grades. For example, students taking courses with lenient grading standards are allocated negative course weights to lower their overall GPA. Hence, students will receive the correct signals about their ability, and make better decisions regarding whether university education or withdrawing from university is a better fit for their aptitude.

VII. CONCLUSION

We went through several specifications in the estimation process, but each specification told a consistent story about the relationship between ability, course difficulty, and GPA on the probability of dropping out. That is, we found that differential grading standards across academic programs are associated with distortions in students' dropout decisions. When we can control for the underlying ability with our estimated ability, we found that as we increase course difficulty, we found a higher probability of dropping out. Hence, grades allocated to low ability students in their courses lower their probability of dropping out, signaling to them that they have a higher ability level than their actual ability level. For high ability students, we find that their assigned course grades increase their probability of dropping out because it signals to them that they have lower ability than their actual ability. We can identify which faculties have high ability students who are dropping out by switching from controlling for their GPA to controlling their ability. For example, Engineering students, who have relatively high ability, were shown to be less likely to drop out than Communication students when we controlled for their GPA. However, when we controlled for their ability, we find that they have positive probability of dropping out relative to Communication students. This relationship was also found to be consistent for low ability students. Thus, Montmarquette et al. are correct in inferring that "a high GPA after the first semester is the most important and almost the sole determinant of persistence at the university".[51] However, GPA masks the underlying factors, i.e,. course difficulty in grading standards and students' ability levels that determine students' decisions to withdraw from postsecondary schools. When GPA is not decomposed into these variables, the magnitude, direction, and relationship between GPA and other regressors will result in misleading inferences about their effect on students' decisions to drop out.

[51] Claude Montmarquette et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review*. (20) 481.

The problem with this result is that because there are differential grading standards across academic programs, universities retain more low ability students and fewer high ability students than universities without differential grading standards. Resources are allocated inefficiently because students, who should have dropped out if grading standards were constant across courses, are forgoing employment and education opportunities that might be a better match, given their aptitude, than university education. Alternatively, high ability students that dropped out may be underemployed relative to career opportunities had they completed university. University funds could be better allocated to high ability students rather than to low ability students. For example, scholarships and admission to graduate programs could be better awarded once differential grading is corrected. Particularly, a potential tool to improve resource allocation is to use high school matriculate averages in order to identify faculties with low ability students and subsequently work at reducing their enrolment. Moreover, university GPAs could be re-weighted by the course effects generated by our fixed effects model to better send the correct signals about students' abilities.

Although we furthered the analysis on the relationship between ability and grading standards and the probability of dropping out, there are several shortcomings in our analysis. First, as noted in the above Estimation Strategy section, we did not correct for our count data in the fixed effects model. Because we treated our dependent variable as a continuous variable, we can improve on our estimates by using either a Poisson regression model or Negative Binomial regression model. Second, we did not control for students who switched faculties or majors. These students might affect our estimates because students who find their courses to be too difficult may switch faculties or sort into the appropriate faculty rather than dropping out. Using a Chow test, we can determine whether we should estimate our specification with the data segmented into two groups i.e., those who switched faculties and those who didn't switch faculties, and/or include a dummy variable for those who switched in our specification. Third, we have a problem with self-selection as students can choose their courses rather than being randomly assigned to each course. The result is that we may have biased estimates in our fixed effects model because the unobserved propensity of each student to select himself or herself into any given course will be captured by the error term. This in turn will be correlated with the course dummy variable regressors. However, we expect our bias to be minimal because the bias coming from students selecting courses based on their aptitude, like Mathematics, is likely to balance the bias from students selecting courses based on other aptitudes, like English. Nevertheless, we can improve on our estimates by identifying and potentially correcting for this biasness in our estimation strategy. Last, our conclusions might be improved if we can identify the determinants within our average course difficulty variable that affect the probability of dropping out. For example, it will be interesting to find out the relative importance of observable and unobservable variables on students' dropout behavior, like instructors' salaries and instructors' presentation style, respectively. Given these shortcomings in our paper, further research should be conducted to refine our estimates and inferences on the behavior of postsecondary dropouts.

BIBLIOGRAPHY

Auld, Christopher. (2003) "Causal effect of early initiation on adolescent smoking patterns". *Working Paper*. 1-52.

Barrington, Byron L. and Bryan Hendricks. (2001) "Differentiating Characteristics of High School Graduates, Dropouts, and Nongraduates". *University of Wisconsin Center at Wausau*. 309-319.

Bayer, Alan E. (1968) "The College Dropout: Factors Affecting Senior College Completion". *Sociology of Education*. (41) 305-316.

Betts, Julian R. and Jeff Grogger. (2003) "The Impact of Grading Standards on Student Achievement, educational Attainment, and Entry-level earnings". *Economics of Education Review*. (22) 343-352.

Bound, J. Et al. (1995) "Problems with Instrumental Variable Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak". *Journal of the American Statistical Association*. (90): 443-450.

DiPetro, Giorgio. (2004) "The Determinants of University Dropout in Italy: A Bivariate Probability Model with Sample Selection". *Applied Economics Letters*. (11) 187-191.

Eaton, Curtis and Mukesh Eswaran. (2001) "Grades and Student Incentives: A Human Capital Approach". *Working Paper*. 1-31.

Ensminger, Margaret E. and Anita L. Slusarcick. (1992) "Paths to High School Graduation or Dropout: A Longitudinal Study of a First-Grade Cohort". *Sociology of Education*. (65): 95-113.

Figlio, David and Maurice E. Lucas. (2000) "Do High Grading Standards Affect Student Performance." *NBER Working Paper Series*. (7985): 1-31.

Goldhaber, Dan D. and Dominic J. Brewer. (1997) "Why don't Schools and Teachers Seem to Matter? Assessing the Impact of Unobservables on Educational Productivity". *The Journal of Human Resources*. 32(3): 505-523.

Greene, William H. (2003) *Econometric Analysis*. (5th edition). New York: MacMillian Publishing Company.

Hanushek, Eric A. (1986) "The Economics of Schooling: Production and Efficiency in Public Schools". *Journal of Economic Literature*. (24): 1141-1177.

Harding, David J. (2003) "Counterfactual Models of Neighborhood Effects: The Effect of Neighborhood Poverty on Dropping Out and Teenage Pregnancy". *American Journal of Sociology*. (109): 676-719.

Lee, Valerie E. and David T. Burkham. (2003) "Dropping Out of High School: The Role of School Organization and Structure." *American Educational Research Journal*. (40): 353-393.

Light, Audrey and Wayne Strayer. (2000) "Determinants of College Completion: School Quality or Student Ability"? *The Journal of Human Resources*. (35): 299-332.

Lillard, Dean R. and Philip P. DeCicca. (2001) "Higher Standards, More Dropouts? Evidence within and Across Time." *Economics of Education Review*. (20): 459-473.

Manski, C. F. (1989) "Schooling as Experimentation: A Reappraisal of the Postsecondary Dropout Phenomenon". *Economics of Education Review*. (8): 305-312.

Montmarquette, Claude et al. (2001) "The Determinants of University Dropouts: a Bivariate Probability Model with Sample Selection". *Economics of Education Review*. (20): 475-484.

Munro, Barbara H. (1981) "Dropouts from Higher Education: Path Analysis of a National Sample". *American Educational Research Journal*. 18(2): 122-141.

Pascarella, Earnest T. et al. Orientation to College and Freshman Year Persistence/Withdrawal Decisions". *The Journal of Higher Education*. 57(2): 155-175.

Pirog, Maureen A. and Chris Magee. (1997) "High School Completion: The Influence of Schools, Families, and Adolescent Parenting". *Social Science Quarterly*. (78): 710-724.

Sabot, Richard and John Wakeman-Linn. (1991) "Grade Inflation and Course Choice". *The Journal of Economic Perspectives*. 5(1): 159-170.

Smith, Jeremy and Robin A. Naylor. (2001) "Dropping out of University: A Statistical Analysis of the Probability of Withdrawal for UK university Students." *Royal Statistical Society*. (164): 389-405.

Staiger, Douglas and James H. Stock. (1997) "Instrumental Variables Regression with Weak Instruments". *Econometrica*. (65): 557-586.

Wooldridge, Jeffrey M. (2002) *Econometric Analysis of Cross Section and Panel Data*. Massachusetts: MIT Press.

Table 1: Summary of Literature Review

Selected Studies	Dataset	Estimation Strategy	Study's Focus	The Effect of a Measure of Ability
Betts and Grogger (2003)	High School and Beyond (HSB) 1980-92	Two Stage Fixed effects	School Characteristics	-0.0086
Lillard and DeCicca (2001)	High School and Beyond (HSB) 1980-92	Probit	Student Characteristics	-0.045
Montmarquette et al. (2001)	Universite de Montreal longitudinal student data	Bivariate Probit	School Characteristics	-0.6148
Di Pietro (2004)	Italian National Statistical Centre (2001)	Bivariate Probit	School Characteristics	-0.292
Smith and Naylor (2001)	United Kingdom Universities - Cohort of students from 1989-93	Probit	School Characteristics	-1.38
Pirog and Magee (1997)	National Longitudinal Survey of Labor Market Experience (NLSLME) 1979-91	Probit	Student Characteristics	-5.305
Goldhaber and Brewer (1997)	National Educational Longitudinal Study of 1988	Random Effects	School Characteristics	Not Shown
Light and Strayer (1999)	National Longitudinal Survey of Labor Market Experience (NLSLME) 1979-91	Binomial Probit model	Student Characteristics	-0.243

Table 2: Summary Statistics for Variables

Variables	Frequency	Average
Student Characteristics		
Sex		
Female	2,376	-
Male	2,000	-
Birth Date	-	1980.472
Region of Origin		
Alberta	3,497	-
British Columbia	309	-
Manitoba	46	-
NWT	12	-
Ontario	56	-
Saskatchewan	181	-
Missing	235	-
Hong Kong	1	-
New Brunswick	7	-
Nova Scotia	9	-
Prince Edward Island	3	-
United States	6	-
Yukon	8	-
New Foundland	5	-
Quebec	1	-
University Characteristics		
Faculty		
Communications	3,135	-
Engineering	560	-
Fine Arts	141	-
Kinesiology	176	-
Law	70	-
Nursing	291	-
Social Work	3	-
Measure of Ability		
University GPA	-	-3.07E-10
Average Estimated Ability	-	-2.33E-10
High School Matriculate Average	-	-8.56E-09
Average Course Difficulty	-	5.54E-10
Average Class-size	-	92.61
Average Class-size Squared	-	10000.15
Number of Courses	-	7.822

Table 3: Specification 1 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts

Controlled Equaton	GPA		Ability	
	Marginal Effects	T-stat	Marginal Effects	T-stat
Measure of Ability				
GPA	-0.1041	19.4200 *	-	-
Average Estimated Ability	-	-	-0.1073	-19.5000 *
Sample Size	4376		4376	

Note: The top category for each variable is the reference category for categorical variables

The units for GPA, Matriculate Average, Average Estimated Ability and Average Course Difficulty are in standard deviations.

* Indicates Significance at the 95 percent Confidence Level

Table 4: Specification 2 – Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Faculty Heterogeneity

Controlled Equation	No Ability Control		GPA		Ability	
	Marginal Effects	T-stat	Marginal Effects	T-stat	Marginal Effects	T-stat
University Characteristics						
Faculty						
Communications	-	-	-	-	-	-
Engineering	-0.0216	-1.3100	-0.0381	-2.4300 *	0.0278	1.5700
Fine Arts	0.0138	0.4400	0.0983	2.8500 *	0.0194	0.6400
Kinesiology	-0.0442	-1.6100	0.0316	1.0500	0.0116	0.4000
Law	-0.1302	-3.0600 *	-0.0962	-2.1300	-0.0163	-0.2700
Nursing	-0.1207	-5.5300 *	-0.0675	-2.8000 *	-0.0894	-4.0500 *
Social Work	-	-	-	-		
Measure of Ability						
GPA	-	-	-0.1035	-18.8900 *	-	-
Average Estimated Ability	-	-	-	-	-0.1058	-18.9200 *
High School Matriculate Average	-	-	-	-	-	-
Sample Size			4373		4373	

Note: The top category for each variable is the reference category for categorical variables
The units for GPA, Matriculate Average, Average Estimated Ability and Average Course Difficulty are in standard deviations.
* Indicates Significance at the 95 percent Confidence Level

Table 5: Specification 2 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Major Heterogeneity

Controlled Equation	No Ability Control		GPA		Ability		
	Marginal Effects	T-stat	Marginal Effects	T-stat	Marginal Effects	T-stat	
Major							
Art History	-	-	-	-	-	-	
Art	-0.0049	-0.05	0.0358	0.3300	0.0152	0.1400	
Biomechanics	-0.05789	-0.49	-0.0100	-0.0800	0.0187	0.1400	
Conjoint Nursing	-0.1274	-1.8800	-0.0962	-1.4200	-0.1012	-1.5300	
Dance and Art	0.0653	0.4300	0.1014	0.6700	0.0661	0.4600	
Dance Education Activity/Theory	-0.0326	-0.3300	-0.0814	-1.0400	-0.0533	-0.6100	
Dance	-0.0860	-0.6700	-0.0378	-0.2700	-0.0698	-0.5600	
Drama	0.0127	0.1100	0.0088	0.0800	-0.0369	-0.3800	
Exercise and Health Physiology	-0.0903	-1.0300	-0.0443	-0.4800	-0.0317	-0.3300	
General	-0.0293	-0.3100	-0.0036	-0.0400	-0.0003	0.0000	
General Studies	-0.0034	-0.0400	-0.0364	-0.4500	-0.0280	-0.3400	
Humanities	0.0427	0.4200	0.0189	0.2000	0.0251	0.2700	
Kinesiology	-0.0368	-0.3200	-0.0115	-0.1000	-0.0001	0.0000	
Management	-0.0603	-0.7200	-0.0838	-1.1500	-0.0718	-0.9600	
Mind Science	-0.1096	-1.0000	-0.0540	-0.4400	-0.0543	-0.4400	
Music	0.0000	0.0000	0.0830	0.4100	-0.0062	-0.0300	
Pre-Optometry	0.0000	0.0000	0.0045	0.0300	0.0567	0.3800	
Pre-Program Management	0.1212	0.4900	0.0557	0.2500	0.0783	0.3300	
Pre-Veterinary Medicine	-0.0982	-1.1000	-0.1162	-1.6700	-0.0924	-1.1300	
Science	-0.0189	-0.2100	-0.0601	-0.7600	-0.0165	-0.2000	
Social Science	0.0167	0.1800	0.0032	0.0400	0.0102	0.1100	
Social Work	0.0848	0.6100	0.0755	0.5800	0.0751	0.5700	
Secondary School Drama	-0.0292	-0.1800	0.1086	0.5700	0.0361	0.2100	
Undeclared	0.0141	0.1500	-0.0208	-0.2500	-0.0014	-0.0200	
Missing	-0.0459	-0.5300	-0.0767	-1.0300	-0.0025	-0.0300	
Measure of Ability							
GPA	-	-	-0.1051	-19.1600 *	-	-	
Average Estimated Ability	-	-	-	-	-0.1066	-19.1800	*
Sample Size	4367		4367		4367		

Note: The top category for each variable is the reference category for categorical variables

The units for GPA, Matriculate Average, Average Estimated Ability and Average Course Difficulty are in standard deviations.

* Indicates Significance at the 95 percent Confidence Level

Table 6: Specification 3 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Average Course Difficulty

Controlled Equation	GPA		Ability	
	Marginal Effects	T-stat	Marginal Effects	T-stat
Measure of Ability				
GPA	-0.1081	-19.8100 *	-	-
Average Estimated Ability	-	-	-0.1112	-19.8100 *
Average Course Difficulty	-0.0265	-4.6900 *	0.0197	3.4900 *
Sample Size	4376		4376	

Note: The top category for each variable is the reference category for categorical variables
The units for GPA, Matriculate Average, Average Estimated Ability and Average Course Difficulty are in standard deviations.

* Indicates Significance at the 95 percent Confidence Level

Table 7: Specification 4 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Student and Class Characteristics

Controlled Equation	GPA			Ability		
	Marginal Effects	T-stat		Marginal Effects	T-stat	
Student Characteristics						
Sex						
Female	-	-		-	-	
Male	-0.0343	-3.0400	*	-0.0277	-2.46	*
Birth Date	0.0017	0.8400		0.0025	1.21	
Region of Origin						
Alberta	-	-		-	-	
British Columbia	0.0611	2.8000	*	0.0597	2.74	*
Manitoba	0.0329	0.6200		0.0294	0.55	
NWT	0.1070	1.0100		0.1041	0.99	
Ontario	0.0065	0.1400		0.0082	0.17	
Saskatchewan	0.0888	3.1200	*	0.0875	3.09	*
Missing	0.1546	5.0200	*	0.1523	4.94	*
Hong Kong	-	-		-	-	
New Brunswick	0.1079	0.7900		0.1033	0.76	
Nova Scotia	-0.0227	-0.2100		-0.0181	-0.16	
Prince Edward Island	-	-		-	-	
United States	0.3732	1.9500		0.3874	2.02	*
Yukon	-0.0527	-0.4200		-0.0455	-0.36	
New Foundland	-	-		-	-	
Quebec	-	-		-	-	
University Characteristics						
Faculty						
Communications	-	-		-	-	
Engineering	0.0312	1.6500		0.0940	4.56	*
Fine Arts	0.0247	0.7800		-0.0226	-0.79	
Kinesiology	0.0133	0.4600		-0.0005	-0.02	
Law	-0.1236	-3.5000	*	-0.0927	-1.95	
Nursing	-0.0800	-3.3200	*	-0.0946	-4.21	*
Social Work	-	-		-	-	
Measure of Ability						
GPA	-0.0840	-14.6600	*	-	-	
Average Estimated Ability	-	-		-0.0837	-14.41	*
Average Course Difficulty	-	-		-	-	
Class-size	-0.0014	-2.5700	*	-0.0014	-2.46	*
Class-size Squared	0.0000	2.0900	*	0.0000	2.11	*
Number of Courses	-0.0242	-9.2900	*	-0.0247	-9.51	*
Sample Size	4363			4363		

Note: The top category for each variable is the reference category for categorical variables
The units for GPA, Matriculate Average, Average Estimated Ability and Average Course Difficulty are in standard deviations.
* Indicates Significance at the 95 percent Confidence Level

Table 8: Specification 5 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Squared Terms

Controlled Equation	GPA			Ability		
	Marginal Effects	T-stat		Marginal Effects	T-stat	
Measures of Ability						
GPA/Avg. Est(Ability)	-0.3306	-12.1700	*	-0.0632	-10.0900	*
GPA Squared/Avg. Est(Ability) Squared	0.0721	9.5000	*	0.0305	8.0900	*
Sample Size	4363			4363		

Table 9: Specification 5 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Measures of Ability Dummy Variables

Controlled Equation	GPA			Ability	
	Marginal Effects	T-stat		Marginal Effects	T-stat
Categories for Ability Measures					
GPA/ Ability <-4	-	-		-	-
GPA/ Ability -4 to -3	-	-		-0.1477	-0.260
GPA/ Ability -3 to -2	-0.0330	-0.62		-0.1650	-0.260
GPA/ Ability -2 to -1	-0.1517	-5.01	*	-0.3291	-0.310
GPA/ Ability -1 to -0	-0.2994	-8.16	*	-0.8449	-0.340
GPA/ Ability 0 to 1	-0.3431	-8.21	*	-0.9015	-0.350
GPA/ Ability 1 to 2	-0.2145	-8.1	*	-0.4361	-0.360
GPA/ Ability 2 to 3	-	-		-0.1555	-0.340
Sample Size	4363			4363	

Table 10: Specification 5 - Probit Estimates by Maximum likelihood of the Effects of Ability Measures on Postsecondary Dropouts While Controlling for Spline Variables

Controlled Equation	GPA			Ability		
	Marginal Effects	T-stat		Marginal Effects	T-stat	
Spline Variables						
GPA/ Ability Change -5	-	-		-	-	
GPA/ Ability Change -4	-0.0134	-0.100		0.1333	0.98	
GPA/ Ability Change -3	-0.0127	-0.190		-0.1086	-1.57	
GPA/ Ability Change -2	-0.3931	-11.810	*	-0.3039	-9.27	*
GPA/ Ability Change -1	0.0120	0.540		-0.0361	-1.67	
GPA/ Ability Change 0	-0.0461	-2.040	*	-0.0373	-1.6	
GPA/ Ability Change 1	0.0773	1.670		0.0211	0.5	
GPA/ Ability Change 2	-	-		0.0453	0.28	
Sample Size	4363			4360		

Note that for all the above tables : the top category for each variable is the reference category for categorical variables

The units for GPA, Matric Average, Average Estimated Ability and Average Course Difficulty are in Standard Deviations

* Indicates Significance at the 95 percent Confidence Level

All Regressions in this Table Control For Gender, Age, Faculty, Class-Size, Class-Size Squared, Number of Courses, and Provinces.

Specification 7 uses a Spline variable, where each interval represents the slope of that interval

Table 11: Specification 3 – Probit Estimates by Maximum Likelihood of the Effects of High School Matriculate Average While Controlling for Average Course Difficulty

Controlled Equation	GPA			Ability			Matriculate Average		
	Marginal Effects	T-stat		Marginal Effects	T-stat		Marginal Effects	T-stat	
Measure of Ability									
GPA	-0.1081	-19.8100	*	-	-		-	-	
Average Estimated Ability	-	-		-0.1112	-19.8100	*	-	-	
Average Course Difficulty	-0.0264	-4.6800	*	0.0197	3.4900	*	0.0013	0.2300	
Matriculate Average	-	-		-	-		-0.0133	-2.4400	*
Sample Size	4376			4376			4376		

Note: The top category for each variable is the reference category for categorical variables

The units for GPA, Matriculate Average, Average Estimated Ability and Average Course Difficulty are in standard deviations.

* Indicates Significance at the 95 percent Confidence Level

Table 12: Means of Measures of Ability and Difficulty in Grading Standards

Faculty	Communications	Engineering	Fine Arts	Kinesiology	Law	Nursing	Social Work
Course Difficulty	-0.1201	1.4102	-1.5926	-0.5547	2.5339	-0.9415	1.8546
GPA	-0.0793	-0.2034	0.5159	0.5407	0.3751	0.5683	1.0181
Ability	-0.1270	0.3877	-0.1590	0.2954	1.4167	0.1616	1.7597
Matriculate Average	0.0540	0.1504	-0.0908	-0.0846	-1.1363	-0.6382	-3.0665

Figure 1: The Effect of GPA vs. Ability on the Probability of Dropping out

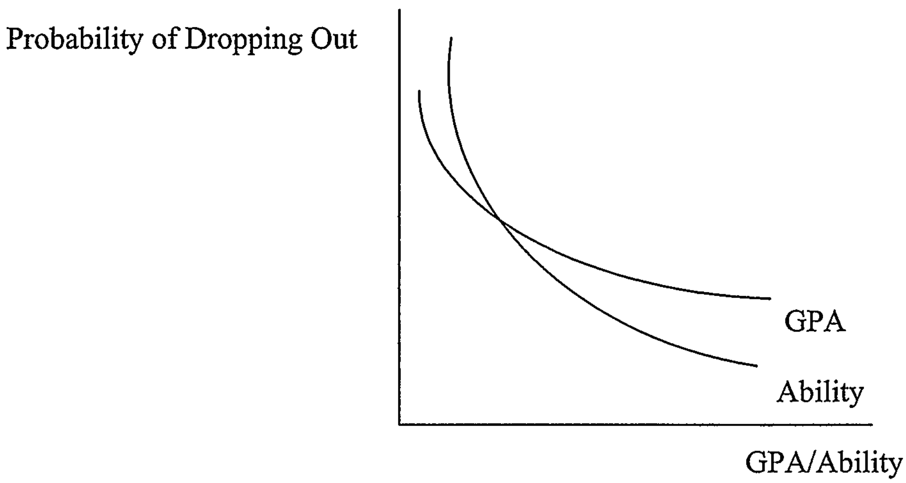

Figure 2: Sequence of Dropouts for the 2000/2001 School Year

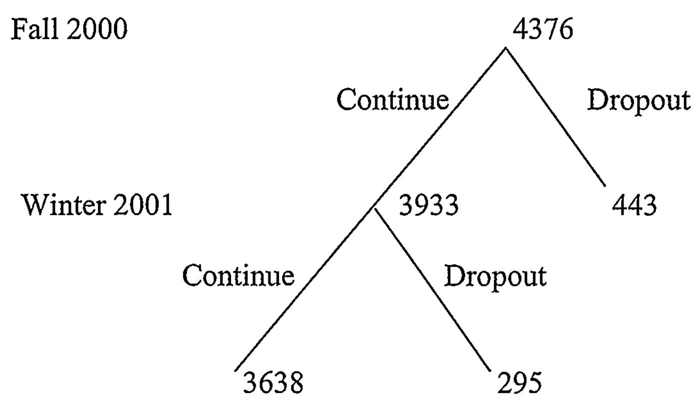

Figure 3: The Effect of GPA and Ability on the Probability of Dropping out Without Student or Course Controls

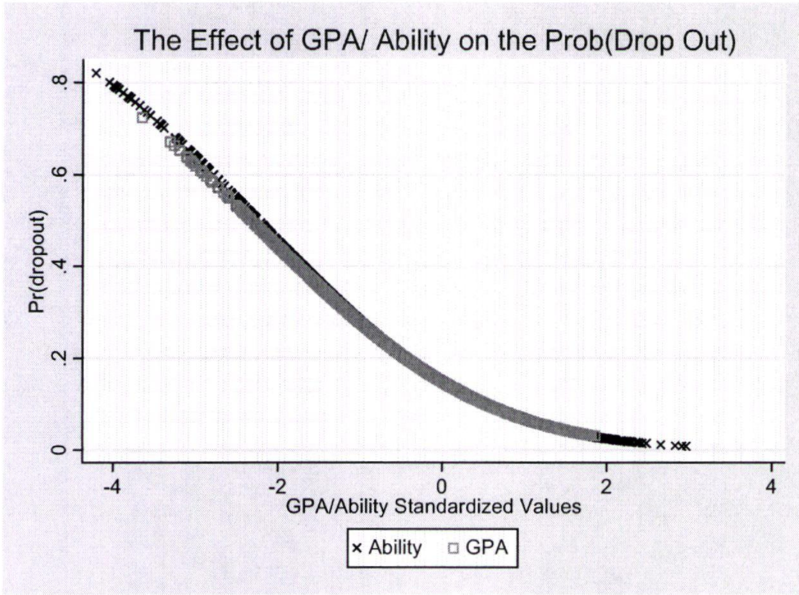

Figure 4: Specifying the Ability Measures with Dummy Variables

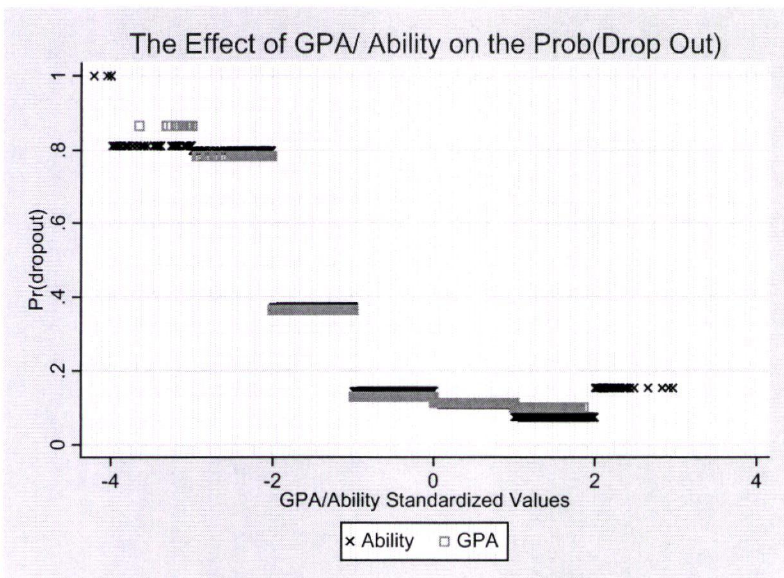

Figure 5: Specifying the Ability Measures with Spline Variables