Seamless Transitions?

Institutional, Demographic, and Course-Specific Effects on Transfer Student Success in Next-In-Sequence Coursework

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Abstract

There are multiple measures of success for transfer students. Initially, it is the number and percent of academic credits successfully transferred in. Ultimately, it is whether or not they complete their degree. This study examines the intermediate, but no less vital, measure of success for students who transfer in credit for one class (e.g., Calculus I) expecting that they are then ready for the next sequential class (e.g., Calculus II). Because curricula between institutions are less aligned than one taken at a single institution, transfer students face additional challenges due to the non-seamless nature of their curriculum.

Introduction

At the University of Minnesota – Twin Cities (UMNTC), approximately one-quarter of newly admitted undergraduate students each year are transfer students. Given their disparate backgrounds, transfer students are more easily defined by what they are not (not direct from high school, not first-time enrollees, not indoctrinated to UMNTC culture and norms by the orientation experience available to traditional first-time full-time freshmen[1]) than what they are. And while transfer students help offset the lost tuition revenue from the departure of non-retained traditional students, the additional resources necessary to contend with the unique issues transfer students face above and beyond those of traditional students softens that benefit. Furthermore, newer accountability measures such as the Voluntary System of Accountability (VSA) are beginning to measure and display transfer student success (e.g., graduation/retention rates), thus bringing to light their previously hidden records[2].

At most institutions, the primary concern for transfer students is that of credit transfer. It is in a transfer student's best economic interest to maximize the percentage of credits transferred thus minimizing the time toward degree by having to repeat or make-up missed or inappropriate course work. The notion that transfer students can save money by taking courses at less-expensive institutions, transfer them in, and proceed seamlessly on toward graduation is laden with false assumptions. These assumptions include the erroneous belief that all credits transferred in will fulfill requirements toward the degree, that the knowledge learned in the accepted courses has adequately prepared the student for the next-in-sequence courses at their new institution that build directly upon that knowledge, and that the remaining universe of non-academic barriers to success particular to transfer students – less social integration, less participation in student-faculty interaction activities such as research (Recruitment & Retention in Higher Education, 2005) – will not interfere with that student's success. In other words, the transfer student planning for a seamless transition from one institution to another must hope that they will not to fall victim to the complex conglomeration of detrimental factors commonly referred to as "transfer shock" (Wyner, 2006, Keeley and House, 1993; Cejda, 1997), a term that oversimplifies the true breadth and depth of the problem to say the least.

To the extent that one accepts Tinto's Model of Institutional Departure (Tinto, 1987 – Figure 1) as a basis for understanding the choices and influences one faces on their progression along their higher education path toward graduation, one can readily see that at any point along the time continuum, transfer students are subject to the same (or at least similar) opportunities for experiences and integrations: entering with similar goals, hoping for similar outcomes, but subject to different experiences by the very nature of their having previous/other post-secondary experiences that they are attempting to weave with their current experiences. And this interweaving is a growing concern as students attempt to combine their experiences at ever more institutions into a single cohesive educational experience. At UMNTC, it is not uncommon for entering transfer students to "swirl" (Recruitment & Retention in Higher Education, 2005) credits from two, three, up to seven separate institutions. The attempted incorporation of each additional institution into their as-yet-incomplete degree program makes it that much more difficult to create a seamless patchwork pathway toward degree completion.

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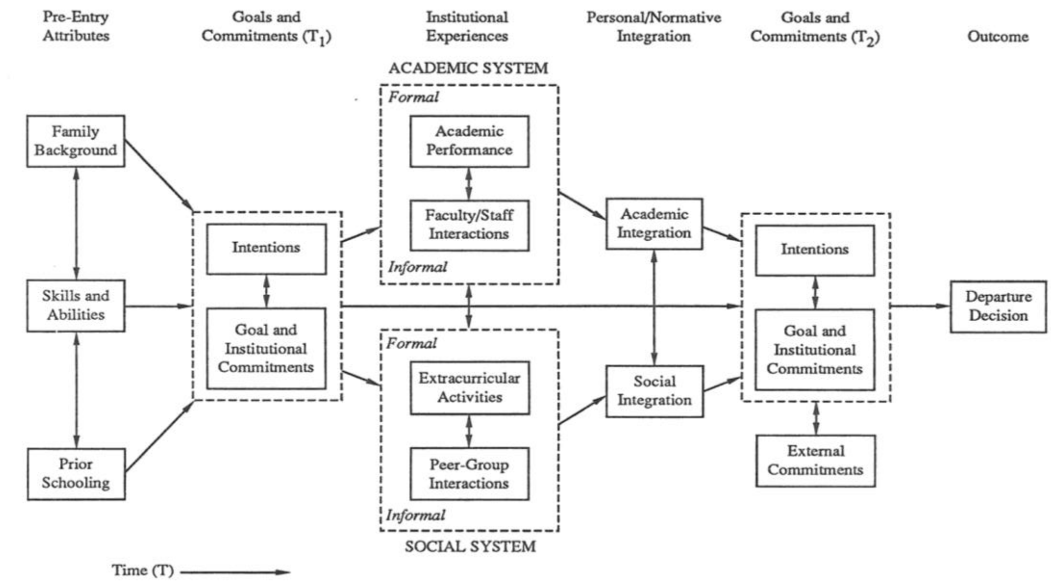
[1] Currently at UMNTC, first year students are offered a two-day orientation plus a one-day parent orientation (http://www.ofyp.umn.edu/fystudents/or/). Transfer students who complete the Online Orientation need only attend a ½ day orientation. (http://www.ofyp.umn.edu/trstudents/or/datesschedule.html)

[2] Popular quality accountability media such as IPEDS and U.S. News & World Report's *America's Best Colleges* focus on first-time, full-time freshmen cohorts.

Figure 1: Tinto's Model of Institutional Departure



Examination of the final credit loads of graduating undergraduates between 2001 and 2007 reveals that traditional students (defined henceforth as first-time fulltime) complete their undergraduate degrees with an average of 137 credits (median = 132) while transfer students who complete their degrees leave with 145 credits (median = 139). While the difference may not be substantial, amounting to roughly the equivalent of two courses, that could be enough to disrupt a student's flow through a degree program, especially if a course repetition interferes with a strict sequence of courses on the path toward degree. For example if a transfer student learns that they are not, in fact, ready for a next-in-sequence course, then they lose one semester having to withdraw from that class and another semester having to retake a course they've already completed elsewhere – one whole academic year of a course sequence gone with nothing new to show. However, as one takes an extended view of success as defined by degree completion, one finds that six years after transfer, the graduation rate for transfer students at UMNTC is the same if not better than that for traditional students eight years after matriculation. In short, transfer students are experiencing the same or similar ultimate success rate, but that success comes at a price of a longer time to degree and more total credits taken before graduating.

While there are many avenues for exploration regarding transfer student academic success, going beyond the question of whether or not credits transfer is important because of the false conclusion that transfer students may draw between the number of credits transferred from one institution to the next and their supposed academic readiness to seamlessly continue with their academic plan. Factors that influence the likelihood of a transfer student being retained and/or ultimately graduating hinge principally on their initial academic successes. This study tests the assumption paramount to transfer students attempting to efficiently complete their degree at their new institution: to what extent is it true if a student completes a course at their previous institution and their new institution not only accepts those credits, but awards fully articulated credit for that course, that the student should expect the same probability of passing the next-in-sequence course as a traditional student taking both courses at a single institution?

Data and Methodology

This study examines the differences in success between transfer students and traditional students progressing from one math course to the next-in-sequence math course at the University of Minnesota – Twin Cities Campus from Fall 2000 through Spring 2007. The study is limited to those students who, if they are transfer students, took a math course at another institution prior to transferring to UMNTC and received full-articulation credit for that course (that is, upon transfer, UMNTC awarded them credit for a specific UMNTC course and not just generic transfer credits). For the sake of comparison, a similar course-taking situation for non-transfer students (i.e., traditional – first time, full-time) is examined. Because there obviously is no prior institutional work to compare, this study looked at the first and second math courses taken after enrolling at UMNTC. Both populations were limited to those students enrolling at UMNTC initially between Fall 2000 and Spring 2007. Both populations were further limited to those students whose second math course was "more advanced" than the first. For transfer students, then, the "first" course would be the last math course taken before transferring and their "second" course is the first they took subsequently at UMNTC. For traditional students, the "first" course is the first math course they took at UMNTC and the "second" math course is the second course taken at UMNTC. Both populations are limited to those students whose second math course is more advanced than the first. Determining whether a course is more advanced than another is calculated by subtracting the course number of the first course (or the articulated course equivalent) from the second. If the difference is greater than zero, then the course is more advanced. This is possible because of the sequential nature of mathematics courses at UMNTC (e.g., Calculus II is MATH1272 and Calculus I is MATH1271). Naturally, this study then excludes all those transfer students who repeat courses for which they've already received credit and those students who take math courses less advanced than the last course for which they've received credit. This excludes a none-too-small population of students. Of all the transfer students who received articulated credit for at least one math course and then subsequently enrolled in a math course at UMNTC between Fall 2000 and Spring 2007, 70.5% of them enrolled in a more advanced math course at UMNTC. 6.8% enrolled in the same course for which they received transfer credit, and 22.7% enrolled in a course with a designator lower than that which they transferred in.

Examining math coursework has several distinct advantages from a research perspective. As mentioned above, the course numbering for math classes at UMNTC is sequential, especially at the lower-division level where the preponderance of math transfers occur. Second, in terms of sheer course-taking volume, the Math department has one of the most active credit-generating curricula on campus servicing both math majors as well as the majority of degree seeking students at one time or another. Third, the Math department's courses are frequently on the University's "killer courses" list – that is, the unofficial list of courses with the highest non-pass rate. While obviously not good for the students, from a research point of view, there is enough critical mass of students not passing that it allows for more robust statistical models.

Finally, in order to keep the two populations (transfer and traditional) as balanced as possible for the sake of comparison, only those traditional students who pass their first course with an A, B, C, or S[3] are included in the study. This is because transfer students do not get articulated credit for courses they do not pass, thus there are no "first" courses for transfer students in this study that were not passing grades.

[3] UMNTC uses S/N (satisfactory/not satisfactory) as the equivalent of pass/fail for non-letter grade enrollment options. Typically an S is only achieved if a student would have earned a "C" or higher.

Dependent variable

The dependent variable, PASS_ABCS, is a dummy-coded variable where a value of "1" indicates that the student passed their next-in-sequence ("second") course with an A, B, C, or S. A value of "0" indicates that some other grade was awarded including: D, F, W, N, or I[4].

A binary logistic regression model was chosen because "a dichotomous dependent variable in a linear regression model necessarily violates assumptions of homoscedasticity…and normality…of the error term." (Allison, 1999, p.10) For *k* explanatory variables and *i*=1,…*n* individuals, the model is:

$$\log\left[\frac{p_i}{1-p_i}\right] = \alpha + \beta_1\chi_1 + \beta_2\chi_{i2} + \ldots + \beta_k\chi_{ik}$$

where p_i is the probability that y_i=1. p_i can then be obtained thusly:

$$p_i = \frac{\exp(\alpha + \beta_1\chi_1 + \beta_2\chi_{i2} + \ldots + \beta_k\chi_{ik})}{1 + \exp(\alpha + \beta_1\chi_1 + \beta_2\chi_{i2} + \ldots + \beta_k\chi_{ik})}$$

where β_k is the regression coefficient for variable x_k.

Independent variables

The logistic regression model is run three times each for both transfer students and traditional students. Each run of the model incorporates an additional block of variables. These blocks are divided into groups of variables that account for different effects: institutional effects, personal effects, and other effects.

<u>Institutional variables</u> are those variables that measure the potential effects of a student's previous institution on their likelihood of passing their next-in-sequence math course. Of course, traditional students have no prior institutional experience other than his/her delay between courses.

DELAY represents the number of years between math course enrollments. To calculate DELAY, each calendar year is divided into equal halves, with the Spring and Summer semesters coded as belonging to the first half (e.g., 2003.0) and Fall semester to the second half (e.g., 2003.5). DELAY is then calculated as the difference between in this year-code minus 0.5; thus a person taking math courses in subsequent semesters will have a delay of "0". (e.g., 2003.5 – 2003.0 – 0.5 = 0)

[4] "W" signifies a withdrawal from the course after the day-10 free-drop period but before the end of the semester. "I" indicates an incomplete. Since at least a year has passed from when the latest enrollments occurred and the data for this study were pulled from the data warehouse, an "I" designation remaining on record after this time is included in the not-passing category.

MN is a dummy-coded variable where a value of "1" indicates that the transfer student's last pre-transfer math course was taken at a Minnesota postsecondary education institution. It is assumed that because of articulation agreements between UMNTC and other Minnesota postsecondary institutions, the resultant alignment of curricula would translate to an advantage for in-state transfers.

PVT is a dummy-coded variable where a value of "1" indicates that the transfer student's last pre-transfer math course was taken at a private postsecondary education institution.

TWO-YR is a dummy-coded variable where a value of "1" indicates that the transfer student's last pre-transfer math course was taken at a two-year postsecondary education institution.

Personal variables are those variables that describe the demographics of the student. These measure the effects of innate characteristics that may offer additional insight into factors that help or hinder their academic performance.

PRV_CRS_GRD (previous course grade) is a numerical coding of the grade the student was awarded in their previous math course – or their "first" math course. For transfer students, this is the grade earned in the last math course taken prior to transfer to UMNTC. For traditional students this is the grade earned in their first math course taken at UMNTC. Because this study is limited to students taking next-in-sequence courses, it is not surprising that almost all students' previous course grades are those of a passing grade (A, B, C, or S) since one typically needs to pass the lower course before attempting the next, more advanced course. Letter grades were re-coded according to a 4-point scale with "A"= 4.0, "A-"=3.67, "B+"=3.33, "B"=3.0, etc.

FEMALE is a dummy-coded variable where a value of "1" indicates that the student's gender is female.

IT is a dummy-coded variable where a value of "1" indicates that the student's major is within UMNTC's Institute of Technology, the college-level unit that includes the Department of Mathematics as well as other math- and engineering-related fields.

PELL is a dummy-coded variable where a value of "1" indicates that the student is eligible for Pell funding, a proxy indicator of socio-economic status.

FAFSA is a dummy-coded variable where a value of "1" indicates that the student filled out FAFSA paperwork, another proxy for socio-economic status that encompasses all those who felt they were at least minimally qualified to apply for financial aid.

ASIAN is a dummy-coded variable where a value of "1" indicates that the student's demographics of record is categorized as Asian/Pacific Islander according to 2007 IPEDS classification rules. This racial/ethnic category is separated from other resident non-Caucasian groups due to its members' typically benefiting from "model-minority" effects that include better academic performance (Lee, 1994; Rosser, 1998) rather than the depressed academic performance effects associated with those racial/ethnic categories that correlate with lower socio-economic status.

INT'L is a dummy-coded variable where a value of "1" indicates that the student's visa status identifies him/her as a non-resident alien.

UNDER_REP_MIN (under-represented minority) is a dummy-coded variable where a value of "1" indicates that the student's demographics on record is categorized in the Black/African American, Hispanic/Latino, or American Indian/Alaskan Native categories according to 2007 IPEDS classification rules.

SPR_ENTRY is a dummy-coded variable where a value of "1" indicates that the student's first enrolled term at UMNTC occurred in a spring semester.

Other variables in the model include dummy-codings for academic year of entry and for enrollment in specific math courses. The academic year of entry allows for the possibility that in some years, the students admitted happen to be of significantly better or poorer quality which may affect their overall likelihood of passing their next-in-sequence math course. Likewise, many math courses fall under UMNTC's "killer course" list – courses that have a failure/withdraw rate over 20%. That is, there are certain courses in which the mere act of enrolling significantly decreases one's likelihood of passing with an A, B, C, or S.

There are several key differences in the independent variables between transfer and traditional students that may potentially account for differences in the regression model performance (Table 1). The first is that there is a substantial difference in the mean amount of delay transfer students and traditional student take between their "first" and "second" math courses. Whereas a transfer student's mean delay is 1.24 years (or 2 to 3 semesters), a traditional student typically has almost no delay (0.11 years). The average delay for transfer students is slightly skewed due to its maximum reported value of 20 years. This is not an outlier, however, as there is a continuous progression of values from zero up through this maximum. The fact is, transfer students include adult learners returning after years away from post-secondary education. Taking into account the standard deviation however, the typical transfer student has a delay between math courses of zero to three years.

Another important difference is that transfer students have a higher incidence of being Pell-eligible. 24.3% of transfer students were reported as Pell-eligible compared to just 17.1% of traditional students indicating overall greater financial constraints on transfer students. While this study does not examine students' reasons for transferring rather than enrolling at UMNTC from the outset, one of many possible reasons assumed is that of financial constraint. Many students choose to attend lower-cost, primarily 2-year institutions prior to attending other more expensive institutions in an effort to save money on tuition and cost-of-living expenses. In order for this strategy to be successful, however, two key events must occur: first, the credits taken at the prior institution must transfer to the new institution. Second, the credits transferred must keep the student on the most efficient path toward graduation – that is, the courses transferred must position the student to be exactly where a traditional student would be on the same degree path with the same courses taken. It has been shown, however, that despite entering with more than a year's worth of credits, transfer students who do graduate still take more than three years to graduate and when they do graduate they leave with a larger credit load than traditional students (Goldfine, 2008), meaning that the time/cost savings for transfer students largely disappears due to the additional courses they end up taking post-transfer.

Table 1: Independent Variables in the Logistic Regression Model

	Transfer Students (n=9,972)		Traditional Students (n=1,604)	
Independent Variables	Mean	Std D	Mean	Std D
Delay	1.243	1.881	0.110	0.396
MN	0.703	0.457		
Pvt	0.141	0.348		
Two_Yr	0.555	0.497		
Prv_Crs_Grd	0.306	0.829	2.946	0.903
Female	0.401	0.490	0.385	0.487
IT	0.315	0.465	0.345	0.475
Pell	0.243	0.429	0.171	0.377
FAFSA	0.716	0.451	0.729	0.445
Asian	0.081	0.243	0.125	0.331
Int'l	0.031	0.172	0.017	0.129
Under_Rep_Min	0.075	0.264	0.059	0.236
Spr_Entry	0.265	0.441	0.010	0.110
FY2001	0.075	0.263	0.142	0.349
FY2002	0.080	0.272	0.155	0.362
FY2003	0.107	0.309	0.147	0.354
FY2004	0.209	0.407	0.134	0.340
FY2005	0.179	0.384	0.140	0.347
FY2006	0.179	0.383	0.134	0.340
Calc1	0.177	0.382	0.204	0.403
Calc2	0.169	0.375	0.108	0.310
College Algebra	0.047	0.212	0.003	0.056
IT Calc			0.188	0.390
Lin. Algebra & Dif. Eq. for IT	0.077	0.267		
Lin. Algebra & Diff. Eq.	0.088	0.283		
Pre Calc1	0.019	0.135	0.005	0.073
Pre Calc2	0.088	0.283	0.169	0.374
Short Calc	0.105	0.307	0.115	0.319
PASS_ABCS	0.676	0.468	0.776	0.417

Finally, transfer students are far more likely to enter UMNTC in the Spring semester than traditional students. There are campus policies in place designed to encourage traditional students to enroll in the Fall term as part of a first-time full-time entering cohort, but there are exceptions. Only 1.0% of traditional students enter UMNTC in the Spring compared to 26.5% of transfer students. While the percentage is small, one wonders if this group of traditional students will suffer the same effects transfer students feel of not entering with the traditional cohort of students, not experiencing the same entry and orientation activities, thus beginning their academic career at UMNTC already separated socially from their fellow students.

Results

This logistic regression models for passing next-in-sequence math courses correctly predicted whether or not transfer students and traditional students passed 68.6% and 79.7% of the time respectively (Table 2). This means that overall, the regression model is more accurate at predicting success than a 50-50 coin toss, and is also slightly better than simply assuming that all students will pass. Already, one can see the substantial difference (nearly 10-percentage points) between transfer and traditional students in the percent that pass their next-in-sequence math courses.

Table 2: Predicted vs. Observed Values

Transfer: Pass_ABCS — Predicting Highest Likely Outcome

Observed	Predicted 0	1	% Correct
0	0	514	0.0%
1	0	1090	100.0%
	Overall % Correct:		**68.0%**

≤

Actual Model

Observed	Predicted 0	1	% Correct
0	93	421	18.1%
1	82	1008	92.5%
	Overall % Correct:		**68.6%**

Traditional Pass_ABCS

Observed	Predicted 0	1	% Correct
0	0	2213	0.0%
1	0	7759	100.0%
	Overall % Correct:		**77.8%**

≤

Observed	Predicted 0	1	% Correct
0	519	1694	23.5%
1	331	7428	95.7%
	Overall % Correct:		**79.7%**

As one can see from the logistic regression results in Table 3, limiting the transfer student and traditional student models to institutional variables results in a very weak model. This is not surprising for the traditional model, where DELAY and DELAY ^{2} are the only variables and the average delay is so small. It is interesting to note that in the transfer model, none of the institutional variables other than DELAY and DELAY ^{2} are significant predictors for success. The fact that DELAY and DELAY ^{2} in the transfer student model are both significant, but of opposite signs indicates that the effect is non-linear and that while the effect is initially negative, as DELAY grows (and subsequently as does DELAY ^{2}), the effect eventually reverses. This is illustrated in Figure 2 in the discussion of the full model.

Table 3: Logistic Regression Results for PASS_ABCS

	Block 1				Block 2				Block 3			
	PASS_ABCS				PASS_ABCS				PASS_ABCS			
	NAS		NHS		NAS		NHS		NAS		NHS	
NkR^2	0.016		0.003		0.084		0.245		0.111		0.267	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Delay	-0.211	***	-0.282	***	-0.179	***	0.190	*	-0.159	**	0.054	
$Delay^2$	0.022	**	0.017		0.020	**	-0.080	**	0.018	**	-0.059	
MN	-0.258				-0.108				-0.164			
Pvt	0.172				0.191				0.257			
Two_Yr	0.051				-0.032				0.000			
Prv_Crs_Grd					0.500	****	1.006	****	0.510	****	1.074	****
Female					0.006		0.224	****	0.035		0.185	***
IT					0.420	***	0.722	****	-0.037		0.355	****
Pell					-0.130		-0.910		-0.111		-0.100	
FAFSA					-0.266	*	0.035		-0.266	*	0.051	
Asian					0.196		-0.296	****	0.168		-0.303	****
Int'l					-0.279		0.138		-0.317		0.114	
Under_Rep_Min					-0.114		-0.267	**	-0.033		-0.281	***
Spr_Entry					-0.056		-0.554	**	-0.049		-0.540	**
FY2001									-0.096		0.125	
FY2002									0.283		0.122	
FY2003									0.058		0.064	
FY2004									-0.309		0.017	
FY2005									-0.330	*	-0.079	
FY2006									-0.207		-0.257	*
Crs_Calc1									-0.229		-0.916	****
Crs_Calc2									-0.527	**	-0.895	****
Crs_Col_Alg									-0.648	**	0.316	
Crs_IT_Calc											-0.326	***
Crs_Lin_Alg_Difq_IT									0.576	**		
Crs_Lin_Alg_Difq									0.280			
Crs_Precalc1									-0.234		0.192	
Crs_Precalc2									-0.429	*	-0.473	****
Crs_Shrt_Calc									-0.587	**	-0.990	****
Constant	1.050	****	1.288	****	-0.462	*	-1.870	****	0.020		-1.214	****

*p<0.10; **p<0.05; ***p<0.01; ****p<0.001

When the second block of variables is added to the model, the pseudo R^2 increases[5]. Although not a measure of variance explained, by examining the pseudo R^2 of the two models side-by-side, one is able to get a general impression of the relative strength of the models. In the transfer student model, DELAY and DELAY ^{2} continue to be significant (albeit oppositely signed) predictors of success. In both the transfer student and the traditional student models, a student's previous course grade is a significant and positive predictor of how well that student will do in their next-in-sequence course. In both models, majoring in a department within the Institute of Technology is also a significant and positive predictor of success. This is not surprising as in general, one would hope that a student majoring in a math-intensive field would have a greater affinity for mathematics than others.

It is interesting to note that unlike in the transfer student model, student demographics for traditional students such as being female and being Asian have significant effects (being female being a positive predictor while being Asian is negative). It should be noted that in Minnesota,

[5] Pseudo R^2 is calculated using Nagelkerke R^2.

the Asian population is predominantly a refugee “new wave” population more prone to negative socio-economic status effects opposite that of model-minority stereotypes, (Lee, 1994; Rosser, 1998). To a lesser extent, traditional students classified as under-represented minority and spring entrants suffer negative effects due to these classifications – an effect largely not present in the transfer student model. As predicted, traditional students entering during the Spring term rather than during the Fall term are less likely to pass their next-in-sequence math course, demonstrating the ill-effects of not entering with the traditional Fall cohort.

Moving onto the third model, the DELAY and DELAY^2 variables continue to be statistically significant and with the same signs as within the previous blocks, albeit their power has diminished in the presence of the newly added variables. In the transfer model, previous course grade remains the lone variable still significant at the $p<0.001$ level. The positive effect from majoring in an IT field has diminished to statistical insignificance in the presence of the course-specific variables. That said, one math course demonstrated a significant and positive effect: Linear Algebra and Differential Equations for IT Majors, effectively substituting for the IT variable. The remainder of math courses from this model that are statistically and negatively related to transfer students passing with an A, B, C, or S are Calculus II, College Algebra, and Short Calculus (which is an intensive calculus without a trigonometry component). There is also a minimal statistical and negative effect for Pre Calculus II. Interestingly, neither Calculus I nor Pre Calculus I were statistically significant. Possible reasons for this are discussed in the discussion section of this paper.

For the full traditional student model, the delay effect disappeared – again not surprising given the relatively few traditional students that delay between taking math courses. The same personal variables that were in the 2-block model continue to show up in the full model, with the same directionality. Similar to the transfer student model, Calculus II, Pre Calculus II, and Short Calculus are all significant and negatively related to passing with an A, B, C, or S. Unlike the transfer model, the IT-related course IT Calculus, is significant and negative, possibly helping explain why the IT variable remained significant in the traditional student model while disappearing from the transfer student model. Furthermore, Calculus I was significant and negatively related to passing with an A, B, C, or S in the traditional model but not in the transfer student model.

In order to put the logit coefficients into context, it is helpful to evaluate the impact of changes to the coefficients. Table 4 presents a baseline case for both the full transfer student model and the full traditional student model, depicting a typical student based on mean values in the sample and the effects of changes in baseline values of variables that were statistically significant in the final model to their alternative values, one at a time, and comparison to the probability of what was predicted by the baseline value. The exceptions to this are the course-variables. Since one typically does not take multiple math courses in a single semester, it is necessary to switch the Calculus I variable to “0” before switching any of the others to “1”. Their effect represents this double switch rather than the typical additive effect of changing a single variable. The baseline values for the dichotomous variables were selected based on which response was more prevalent in the sample. For example, since the majority of students in both models were male, the variable Female was initially set to “0”. For the continuous variable Prv_Crs_Grd, the closest natural number to the mean was selected, “3” or a “B”. The alternative “2” or “C” was chosen as being a reasonable alternative value. Similarly, the baseline value for Delay was set to “1” for transfer students but to “0” for traditional students. The value for Delay^2 is dependent on Delay. For dichotomous variables, there exists only one alternative.

Table 4: Baseline Versus Alternative Results

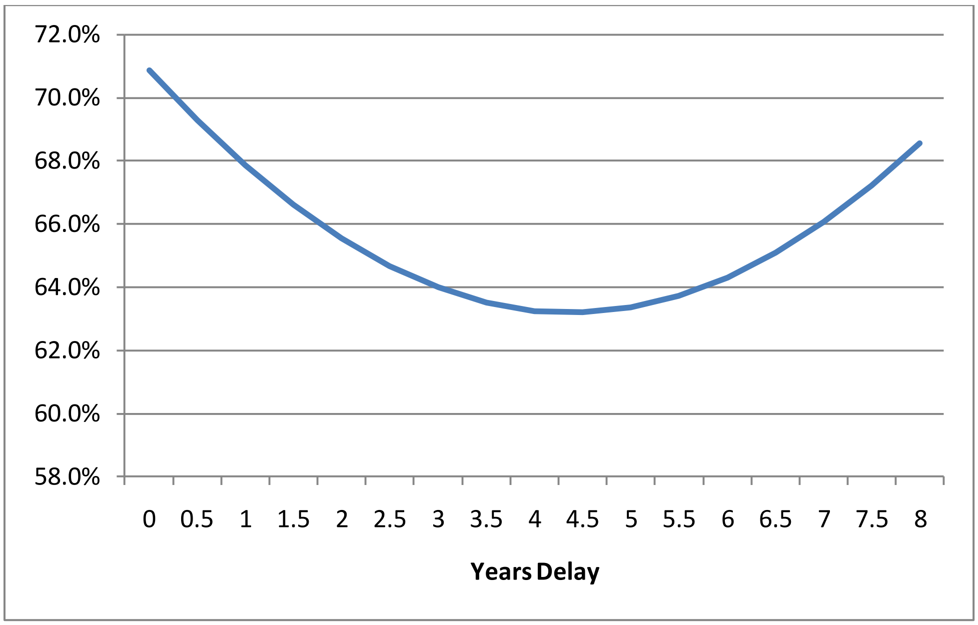
	Transfer Students			Traditional Students		
	Baseline	Alternate	Effect	Baseline	Alternate	Effect
Delay	1	See Figure XX		0		
$Delay^2$	1			0		
MN	1					
Pvt	0					
Two_Yr	1					
Prv_Crs_Grd	3	2	-11.5%	3	2	-24.1%
Female	0			0	1	+3.2%
IT	0			0	1	+5.9%
Pell	0			0		
FAFSA	1			1		
Asian	0			0	1	-6.0%
Int'l	0			0		
Under_Rep_Min	0			0	1	-5.5%
Spr_Entry	0			0	1	-11.2%
FY2001	0			0		
FY2002	0			0		
FY2003	0			0		
FY2004	0			0		
FY2005	0			0		
FY2006	0			0		
Crs_Calc1	1	(0)		1	(0)	
Crs_Calc2	0	1	-6.5%	0	1	+0.4%
Crs_Col_Alg	0	1	-9.3%	0		
Crs_IT_Calc				0	1	+9.2%
Crs_Lin_Alg_Difq_IT	0	1	+9.3%			
Crs_Lin_Alg_Difq	0					
Crs_Precalc1	0			0		
Crs_Precalc2	0			0	1	+7.2%
Crs_Shrt_Calc	0	1	-7.9%	0	1	-1.4%
Baseline Likelihood of PASS_ABCS	70.9%			75.8%		

*p<0.10; **p<0.05; ***p<0.01; ****p<0.001

Thus, as defined by this method, a typical transfer student has a delay of 1 year between math courses; has transferred in from a public, Minnesota, 2-year institution; earned a "B" in their last math course prior to transfer; is male, non-Pell eligible but did fill out a FAFSA; is a resident Caucasian; initially enrolled during the Fall term; and initially enrolled in Calculus I. This aggregate student, according to the full transfer student model has a 70.9% chance of passing their Calculus I course with an A, B, C, or S. Likewise, as defined by this method, a typical traditional student has no delay between math courses, earned a "B" in their first math course; is male, non-Pell eligible but did fill out a FAFSA; is a resident Caucasian; initially enrolled during the Fall term; and their "second" course is Calculus I. This aggregate student, according to the full traditional student model has a 75.8% chance of passing their Calculus I course with an A, B, C, or S.

As one can see from Figure 2, as the delay in years between consecutive math courses increases, the likelihood of a transfer student passing their next-in-sequence math course drops from approximately 71% with no delay down to approximately 63% with a delay of four years. Then an interesting thing happens. Here the effect of $DELAY^2$ reverses the direction of the trend, and beyond a delay of four years, the likelihood of passing rebounds. It is unlikely that this is an effect solely of delaying one's next-in-sequence math course. Rather it is probable that this is an effect caused by the maturity of the student in a situation where there could be a delay of four or more years between classes. This likely represents an older student with more/different life experience and overall more maturity.

Figure 2: Effect of DELAY on Transfer Students in Likelihood of Passing with A, B, C, or S



A transfer student having earned a "B" in their previous math course is 11.5% more likely to pass their next-in-sequence math course (in this case, Calculus I) than a transfer student having earned a "C" in their previous math course. (i.e., a likelihood of 70.9% rather than 59.4%). For traditional students, the likelihood of passing the same next-in-sequence math course if they earned a "B" in their previous math course is 24.1% higher than if they had earned a C in their previous math course. Thus the positive effect of the higher previous grade is much more substantial for traditional students than it is for transfer students. This is explored in greater detail in the discussion section.

For this typical traditional student, entering UMNTC in the Spring term reduces their likelihood of passing their next-in-sequence math course by 11.2%. There was no statistically significant corresponding effect for Transfer students who already experience the social disconnect of not having had entered with a traditional cohort and gone through the same orientation. Other personal characteristics such as gender, majoring in an IT field, being Asian, or being of an under-represented minority demographic all have significant, yet small effects for traditional students.

The course effects must be taken in context. That is, they are not overall effects, rather they are changes in likelihood of passing the next-in-sequence math course relative to their likelihood if they had enrolled in Calculus I. Thus, a typical transfer student enrolling in Calculus II is 6.5% less likely to pass than an otherwise identical transfer student enrolled in Calculus I. Similarly, a typical traditional student enrolling in Calculus II is 0.4% more likely to pass than an otherwise identical traditional student enrolled in Calculus I. This interpretation is different than reading the raw regression results which are a reflection of the likelihood of success in relation to the entire universe of math courses taken by the students included in the model.

The results of the logistic regression models offer some explanation as to why transfer students have a lower success rate in terms of passing their next-in-sequence math courses. Not surprisingly, the longer a student delays (up to a point) between taking their sequential math courses, where the knowledge of one course is necessary for the understanding of the next, the less likely one is to pass that next-in-sequence course. Surprisingly, other than one's grade in their earlier math course, none of the institutional or personal characteristic variables proved to be statistically significant for transfer students. This is good news, in so much as there does not appear to be any systemic or blanket effect based on a student's demographic, economic, or previous college characteristics. Traditional students, as a group, appear more susceptible to these effects – but the reasons for this are beyond the scope of this paper.

In an attempt to better clarify the independent variables' effects, the dependent variable was next redefined so that success is defined as passing with an A or a B (students taking their courses pass/fail are excluded from this model as there is no indication of whether the "S" earned is equivalent to an A, B, or C.) to measure the independent variables effect on not just passing, but passing with a better than average grade. Yet, the results for this analysis are remarkably similar to the original (Table 5). In addition to being a stronger model as evidenced by the larger pseudo R^2 values (demonstrating relative model strength, not variance explained), the only difference of note are that DELAY and $DELAY^2$ no longer appear to be statistically significant for transfer students – indicating that the effect of delaying one's next-in-sequence math course appears to primarily affect the borderline (that is, "C") students likelihood of passing, and not the likelihood of students earning an A or a B. For whatever reason, it also appears that traditional students entering in FY2003 were also slightly more likely to earn an A or B in their next-in-sequence math course than students from other entry years.

So it appears that the single greatest predictor of whether or not a student passes their (more advanced) next-in-sequence math course is the grade they earned in their previous math course. Unfortunately, looking at the mean Prv_Crs_Grd scores for transfer and traditional students (Table 1), the mean score for transfer students is practically equal – actually just a bit better – than that of traditional students (3.1 and 2.9, respectively). Furthermore, as was shown by the baseline versus alternative results, the effect of a change in grade is much more substantial for traditional students than it is for transfer students. Thus, closer examination of the relationship between previous course grade and next-in-sequence course grade is warranted.

Table 5: Logistic Regression Results for PASS_AB

	PASS_ABCS				PASS_AB			
	NAS		NHS		NAS		NHS	
NkR^2	0.111		0.267		0.169		0.372	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Delay	-0.159	**	0.054		-0.017		0.336	***
$Delay^2$	0.018	**	-0.059		0.005		-0.073	*
MN	-0.164				-0.040			
Pvt	0.257				0.218			
Two_Yr	0.000				-0.144			
Prv_Crs_Grd	0.510	****	1.074	****	0.709	****	1.370	****
Female	0.035		0.185	***	0.136		0.348	****
IT	-0.037		0.355	****	-0.024		0.432	****
Pell	-0.111		-0.100		-0.027		-0.098	
FAFSA	-0.266	*	0.051		-0.177		0.048	
Asian	0.168		-0.303	****	0.223		-0.191	**
Int'l	-0.317		0.114		-0.048		0.080	
Under_Rep_Min	-0.033		-0.281	***	-0.131		-0.097	
Spr_Entry	-0.049		-0.540	**	0.066		-0.469	**
FY2001	-0.096		0.125		-0.371		0.087	
FY2002	0.283		0.122		0.194		0.175	
FY2003	0.058		0.064		0.245		0.245	**
FY2004	-0.309		0.017		-0.113		0.114	
FY2005	-0.330	*	-0.079		-0.186		0.196	
FY2006	-0.207		-0.257	*	-0.012		-0.155	
Crs_Calc1	-0.229		-0.916	****	-0.711	***	-1.000	****
Crs_Calc2	-0.527	**	-0.895	****	-0.680	***	-0.789	****
Crs_Col_Alg	-0.648	**	0.316		-1.070	***	-1.209	**
Crs_IT_Calc			-0.326	***			-0.357	****
Crs_Lin_Alg_Difq_IT	0.576	**			0.625	***		
Crs_Lin_Alg_Difq	0.280				0.024			
Crs_Precalc1	-0.234		0.192		-0.019		-0.459	
Crs_Precalc2	-0.429	*	-0.473	****	-0.266		-0.725	****
Crs_Shrt_Calc	-0.587	**	-0.990	****	-0.988	****	-1.110	****
Constant	0.020		-1.214	****	-1.968	****	-3.847	****

*p<0.10; **p<0.05; ***p<0.01; ****p<0.001

Taking a closer look at a single course then, such as Calculus II (Table 6), some interesting differences between transfer and traditional students begin to emerge. Of the transfer students in this study whose first math class at UMNTC was Calculus II, 92.5% of them took Calculus I as their last math class before transferring (or received Calculus I course credit). Similarly, of the traditional students whose second math class taken at UMNTC was Calculus II, 98.4% of them took Calculus I immediately prior. While both percentages are high demonstrating little deviation from this direct path, almost 1 in 10 transfer students enter into Calculus II through some other path while traditional students have almost no deviation.

Table 6: Paths of Success for Calculus II

Previous Course		% passing (or getting credit for) this previous course before enrolling in Calculus II	N	% passing Calculus II with an A, B, C, or S
Calculus I	Traditional Students	98.4%	1,264	76.3%
	Transfer Students	92.5%	260	60.8%
Short Calculus	Traditional Students	0.9%	11	54.5%
	Transfer Students	4.3%	12	41.7%
Other Courses	Traditional Students	0.7%	9	44.9%
	Transfer Students	3.2%	9	77.8%

And even for those on this same, most direct path between Calculus I and Calculus II, there are differences in their success rate – 60.8% of transfer students moving from Calculus I to Calculus II passed with an A, B, C, or S whereas the success rate for traditional students on the same path was 76.3%. One might expect that the success fall-off for transfer students might be due to the borderline or “C” students (Calculus I) being the ones to account for the difference in success rate. But as Table 7 demonstrates, this is not true. For the students who earned a “C” in Calculus I and subsequently enrolled in Calculus II, the difference in success (defined as passing Calculus II with an A, B, C, or S) between transfer and traditional students is marginal (53.2% versus 54.7% respectively). On the other hand, the success rate differences between transfer and traditional students for those who earned either a “B” or “A” in Calculus I are far more substantial – differences of approximately 20 percentage points in both cases.

Table 7: Success Rates for Specific Course Paths by Earlier Course Grade

Grade in prior class		Pre Calculus I to Pre Calculus II	Pre-Calculus II to Calculus I	Calculus I to Calculus II
A	Transfer	64.7%	86.1%	73.5%
	Traditional	93.5%	91.0%	94.2%
B	Transfer	75.8%	72.3%	56.4%
	Traditional	84.4%	75.2%	77.9%
C	Transfer	48.2%	46.7%	54.7%
	Traditional	58.1%	48.1%	53.2%

This same pattern exists in the Pre Calculus II path. Table 8 shows that 79.0% of traditional students enrolling in Pre Calculus II as their second-in-sequence math course took Pre Calculus

I immediately prior. For transfer students taking Pre Calculus II as their first post-transfer math course, only 62.2% took Pre Calculus I as their last pre-transfer math course. Even within this same path of Pre Calculus I to Pre Calculus II, the success rate for transfer students is significantly lower than that of traditional students.

Table 8: Paths of Success for Pre Calculus II

Previous Course		% passing (or getting credit for) this previous course before enrolling in Pre Calculus II	N	% passing Pre Calculus II with an A, B, C, or S
Pre Calculus I	Traditional Students	79.0%	1,663	75.0%
	Transfer Students	62.2%	97	63.9%
Other Courses	Traditional Students	21.0%	441	69.4%
	Transfer Students	37.8%	59	62.7%

Again, a closer examination of the grades of the students in their immediately previous math course (in this case, Pre Calculus I) shows that at all levels, traditional students are out-performing their transfer student counterparts, not just the so-called “borderline” students who entered Pre Calculus II having only earned a “C” in Pre Calculus I. To illustrate the effect of this, imagine two students, one transfer, one traditional, both having passed Pre Calculus I with an “A” grade, and both enrolling at UMNTC in Pre Calculus II. The traditional student has a 93.5% chance of passing Pre Calculus II whereas the transfer student only has a 64.7% chance of passing. Granted, transfer students take a year off on average between math courses, but as we saw from Figure 2, the impact for transfer students taking a delay of 0 and a delay of 1 year is only about 5%.

While this pattern is consistent in the part 1 to part 2 course paths (e.g., Calculus I to Calculus II, or Pre Calculus I to Pre Calculus II), it does not hold up when moving from Pre Calculus II to Calculus I. Like in the other models, transfer students are more likely to take a less-direct path into Calculus I than from the traditional Pre Calculus II. However, unlike the previous models, both transfer and traditional students had about the same success rate when moving from Pre Calculus II to Calculus I (66.9% and 69.9% respectively). And when one examines their previous course grades (Table 9), one sees nearly identical success rates regardless of the grade they earned in Pre Calculus II.

Table 9: Paths of Success for Calculus I

Previous Course		% passing (or getting credit for) this previous course before enrolling in Calculus 1	N	% passing with an A, B, C, or S
Pre Calculus II	Traditional Students	59.6%	1,447	69.9%
	Transfer Students	45.9%	133	66.9%
Intensive Pre Calculus	Traditional Students	25.4%	616	71.9%
	Transfer Students	15.9%	46	63.0%
Other Courses	Traditional Students	15.0%	363	56.5%
	Transfer Students	38.2%	108	71.3%

Other Findings

One surprising result of this study was the lack of any statistical significance (positive or negative) in any of the transfer student models of the institutional characteristics. The negative assumptions about transfers from two-year institutions or the supposed benefit from transferring from a private institution – with regards to math transfers, at least – did not pan out. It is reassuring to know that students are not penalized due to the general characteristics of the school from which they transferred.

Another interesting finding was the disappearance of statistical significance of the personal characteristics (with the exception of previous-course-grade) when the third block was added to the transfer student models. Given the obstacles transfer students already face, it must come as no small relief that in the full model, differences by race and gender washed out and statistically, all transfer students were in the same boat, figuratively speaking. These personal characteristic differences, however, were present in the traditional student model (positive effect for being female and for majoring in an IT field; negative effect for being non-Caucasian (but not international)). Interesting as this finding is, the reasons and the implications for this are beyond the scope of this paper.

Discussion

As stated at the outset of this paper, the root causes behind "transfer shock" are many and diverse. The difficulties transfer students face stem from a combination of academic, social, and temporal factors that traditional students have more resources and programs with which to counteract. This paper sought to focus in on one specific assumption regarding transfer student academic progression: the lack of a seamless curricular transition from their previous institution into their new one. That is, why do transfer students who are on identical curricular path as their traditional student counterparts still demonstrate lower success rates when attempting to continue on from where their previous institution's curriculum left off?

While the results above do not answer this question directly, they do offer important insight into the curricular environment and barriers transfer students face when attempting to move onto more advanced course work they feel they are prepared for based on their previous academic success. When a student is awarded fully articulated credit for a specific course such as Calculus I, there is no reason why that student wouldn't assume that they are academically prepared for Calculus II – at least no less ready than a traditional student who completed the same course for which they just received credit.

That said, the results of this study indicate three distinct curricular barriers to their academic success: (1) transfer students are more likely to experience (longer) delays between sequential courses; (2) transfer students are less likely to adhere to the most direct sequential curricular path; (3) transfer students are more likely to be less academically prepared for their next-advanced course than the grade they received in the previous course suggests, especially when the transfer interrupts a curricular sub-sequence (e.g., Calculus I to Calculus II, and Pre Calculus I to Pre-Calculus II).

With regards to the first point, mathematics, like any cumulative knowledge/skills curriculum such as language acquisition depends on the continual review and application of learned skills. Just as one would not expect someone to attempt 4th semester Spanish after a year of not speaking Spanish at all and still pass (or at a minimum, not struggle to succeed), one would not expect a math student who has not taken a math course in a year to jump into the next-in-sequence math course and do well. The logistic regression model demonstrates this with a decrease in the likelihood of passing one's next-in-sequence math course with each year away from the field – at least initially. As the delay becomes more extreme (beyond four years), other factors begin to play a role and the trend reverses itself. It would be folly to interpret this by saying, "if you're going to delay taking a math course, you should delay six, seven, or even eight years." Clearly, the relatively few students who do in fact wait this long draw on other skills to overcome the negative effects of extended delay between courses.

Transfer students, on average, have a delay of 1.24 years between math courses, with a standard deviation of 1.88. That means the typical transfer student spends from one to three years not doing any academic math work from the point they complete their last math course at their previous institution to their first at UMNTC. That alone could account for an approximately 8% drop in their likelihood of passing their next-in-sequence math course. Conversely, a typical traditional student has between no delay and one semester between their first and second math course at UMNTC, and this has no statistical effect on their likelihood of passing their next-in-sequence math course.

With regards to the second point, that transfer students are less likely to adhere to the most direct sequential curricular path, this is exemplified best by looking at the what previous courses students took (or got credit) immediately prior to their enrollment in Calculus II. Of the traditional students taking Calculus II only 1.6% of them did not have Calculus I as the course immediately prior. For transfer students, 7.5% of them took (or got credit for) some other class than Calculus I prior to taking Calculus II at UMNTC. While this percentage is still relatively small, the fact remains that there is practically no deviation from the most direct path for traditional students. This trend is prevalent throughout the mathematics curriculum. 79.0% of traditional students who enrolled in Pre-Calculus II as their second-in-sequence math course took Pre-Calculus I immediately prior compared to just 62.2% for transfer students.

Finally, the third point highlights the most serious curricular barrier to success for transfer students. Whereas one would assume that borderline "C" students would be the ones to feel the brunt of the lack of alignment between institutional curricula, the fact is transfer students who get a “C” in their last pre-transfer course are largely no less likely to pass their next-in-sequence math course than traditional students who got a “C” in their first-in-sequence math course, at least in the Pre Calculus II-to-Calculus I and Calculus I-to-Calculus II sequences. While it is overall true that the lower one’s grade in their previous course, the lower one’s likelihood of passing their next-in-sequence math course, transfer students who break a subsequence (Calculus I-to-Calculus II or Pre Calculus I-to-Pre Calculus II) are substantially less likely to pass their next-in-sequence math course than their traditional student counterparts, regardless of their previous course grade. This effect, however, is not present where the curriculum breaks naturally (Pre Calculus II-to-Calculus I). This is likely due to the fact that there is relative uniform consensus as to what defines the beginning of “Calculus.” It is more ambiguous as to where the dividing line exists between Calculus I and Calculus II. Each institution in constructing its curriculum has the freedom to structure the content of the Pre Calculus and Calculus contents as they see fit, understanding that these curricula typically extend over two semester (or three quarters). Furthermore where the curricular break between parts 1 & 2 (& 3 in the case of institutions on quarters) exists is ambiguous from institution to institution. The sum total of the content, however, of Pre Calculus or Calculus is less ambiguous and a student moving from completion of the Pre Calculus sequence into the beginning of Calculus sequence is more likely to experience a relatively seamless transition.

Limitations

The most notable limitation of this study is its reliance on data from a single institution. This could not be avoided since course-specific transfer and institutional data is unavailable on a broader scale. This limitation is offset somewhat by the large sample size covering seven years of data.

The second limitation of this study is its specific focus on students attempting next-in-sequence course work within the field of mathematics. The potential scope of this research includes the entire range of course taking by transfer students, including success in courses that transfer students repeat upon transfer as well as instances where transfer students regress to lower-level coursework than the last course taken prior to transfer. Furthermore, the focus on mathematics was chosen due to the linear nature of the course designators as well as the volume of course taking through that department. That said, given the range of course taking options, mathematics represents a small, albeit representative sample. At the outset of this study, course taking patterns from the English department were examined as well but were ultimately eliminated from analysis. This was due to the non-linear nature of the English course designators (e.g., British Literature I has a lower designator than British Literature II, but British Literature I is generally considered the more advanced course given the additional language barriers). At best, English courses designators could only be categorized at the 1xxx, 2xxx, 3xxx, etc., levels for determination of whether one course was more advanced than another. This severely limited the sample size and the majority of courses transferred in fell at the 1xxx level. Unexpectedly, it was also discovered that when transferring credits in, the majority of students complete their English course requirements at their previous institution, thus not needing to take further English courses at UMNTC. The final problem with including English course work in the study was the lack of grade differentiation – that is, few students failed to pass their English courses. While this is good news for students transferring to UMNTC, it makes for a weak statistical model when 85% of transfer students pass their next-in-sequence English courses.

Implications

Rather than attempting to tackle the universe of social and academic issues that transfer students must face, this study focused on the specific issue of students completing a course at one institution, getting fully-articulated credit for that course at their new institution, and then finding that they are not as prepared for the next-in-sequence course as they expected. This is but one of a myriad of issues transfer students must face. For example, Sereeta, et al (2009) recently demonstrated that one-fifth of transfer students in a study at the University of California – Berkeley reported that they concealed the fact that they were transfer students. So clearly, the psychological and social issues transfer students face cannot be ignored.

That said, this study's findings offer insight into a part of the problem that can be addressed through institutional and national policy choices, and at a minimal cost. On the institutional side, transfer students should be better advised about breaking a course sub-stream (i.e., parts I and II of a course sequence) across multiple institutions. If this situation is necessary or unavoidable, it is imperative that the student find out what level of knowledge is expected to succeed in the next-in-sequence course. Blind acceptance of the fact that credit transferred only gives a student a false assumption of their readiness. Unfortunately, even the best articulation agreements between institutions or within a system cannot cover 100% of the minutiae within a single course's curriculum.

Laird (2009) notes that "The lack of a standardized course-numbering system among higher-education institutions…and the lack of common requirements from one institution to another often add layers of confusion to the transfer process." (p.B23) But, a common course-numbering system only goes so far. Without taking the impractical leap of recommending the adoption of a national standardized curriculum, it does behoove the postsecondary mathematics community to come to some agreement as to what constitutes the minimum expected curricular skills that should be addressed in at least the first part of a multi-part course sequence. This can merely be a set of agreed upon guidelines designed to help better elucidate the expected sequence of progressive knowledge as one moves through a multi-term course. This would have the additional benefit of helping students who transfer from a quarter-based academic calendar to a semester-based calendar (or vice-versa) to have a better understanding of exactly where they fall within their new institution's sequence.

The second recommendation is for better advising for students who delay between sequential courses. Like any language acquisition, a student should not expect to "pick up where they left off" after delays upwards of a year and expect no problems – especially in fields where the knowledge is as cumulative as it is in mathematics. It is up to both the student as well as the institution to acknowledge that the erosion of skill and knowledge over time can seriously impact one's chances of success and that steps should be taken to make up for that knowledge shortfall. Such a remedy could be as simple as meeting with the instructor of the next-in-sequence course and finding out what specific skills are expected. Instructors need to be made aware of the fact that a significant portion of their students are entering their classes from a variety of curricular directions. Even the ones that received credit for the most direct path into their class may be less prepared than they expect. Making basic expectations available before the beginning of the term will save many students the hardship of having to drop or withdraw from a class for which they clearly were not ready. Being more open with communicating expectations also has the benefit of avoiding other more intrusive remedies such as requiring students to pass a skills test at every level of a sequence.

Conclusion

While it is clear that the academic background of transfer students is but one piece of the complex array of factors that work to the detriment of their academic success, it is nevertheless an important part and one that is easily addressed – with just a little extra effort on the part of advisors, faculty, and the transfer students themselves. Transfer students must take ownership of their different situation, despite their best efforts to merge their prior institution's curriculum seamlessly into their new one. Not even the best articulation agreement will ever be as seamless as taking all of one's courses at the same institution. Articulation agreements, meant to smooth the transfer of credits from one institution to another, clearly have their place, but they should not absolve students and their institutions from the responsibility of understanding the less-than-perfect match of even fully-articulated courses to the actual courses offered by the new institution.

Greater visibility of transfer student success through vehicles such as the Voluntary System of Accountability will soon shine a public light on the difficulties transfer student face in their attempt to seamlessly merge the curricula from their myriad of attended institutions. This study has demonstrated that the key barriers to academic success for transfer students attempting to pass next-in-sequence courses (specifically math courses, but the results are generalizable) are that (1) transfer students are more likely to have longer delays between math courses than traditional students which has a negative effect on their ability to succeed in their next-in-sequence coursework, (2) transfer students are more likely to either take a course sequence upon transfer or be awarded articulated credit for courses that are off the most direct and efficient curricular path, resulting in a lower likelihood of being adequately academically prepared for their next-in-sequence math course, and (3) despite feeling adequately prepared academically for next-in-sequence coursework based on prior-coursework performance, transfer students face a curricular disconnect by the mere fact of having taken their previous course at another institution that negatively affects their chances of success.

Elaborate remedies are not needed to address these shortcomings. Simply having a better understanding of the nature of the academic barriers transfer students face and then working to address potential curricular shortcomings before the start of the academic term could be enough to either steer transfer students to more appropriate coursework or to have them work before the start of the term toward addressing the areas where the course they took and the course for which they received credit do not overlap.

With a little extra effort, institutions can begin dispel the myth of "transfer shock" and work toward addressing the concrete aspects of the problem.

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