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THE RELATIONSHIP BETWEEN THE LEARNING ASSISTANT MODEL AND PERSISTENCE TO GRADUATION

Submitted to: The Learning Assistant Program University of Colorado Boulder

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ABSTRACT

Six-year graduation rates are an important marker of success for institutions of higher education. Although many factors affect whether a student graduates, one roadblock for many is failing large, lecture-style classes (i.e. "gateway courses") that often include hundreds of students. The Learning Assistant (LA) program is designed to facilitate institutional change in ways that help to mitigate the negative relationship between gateway courses and graduation rates. Part of this program includes undergraduate "Learning Assistants" who support students in their learning in several strategically selected STEM gateway courses. In this study, we examine the relationship between participation in these LA-supported courses and six-year graduation rates. We find that taking LA-supported courses is associated with either a statistically significant increase or decrease in the odds of graduating within six years, depending on department. We close by discussing the need for further qualitative analysis in order to properly interpret these differential results.

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The Relationship between the Learning Assistant Model and Persistence to Graduation

Introduction

Science, Technology, Engineering, and Mathematics (STEM) departments at institutes of higher education frequently offer their introductory courses in large lecture-style classes that can serve over a thousand students per semester. This method of course offering is efficient and cost-effective. However, due to the large number of students in these courses, the instructional approach is often lecture-based with little interaction between the instructor and students or among students (Mason & Verdel, 2001; Talbot, Hartley, Marzetta & Wee, 2015). In addition, these courses tend to have relatively high failure rates (Benford & Gess-Newsome, 2006; Twigg, 2003). As a result of these conditions, many students who begin their undergraduate careers with an interest in pursuing a STEM major either switch majors or drop out of college or university without a degree (Crisp, Nora, & Taggert, 2009; Gainen, 1995).

The Learning Assistant (LA) model was established at the University of Colorado Boulder (CU Boulder) in 2001 in response to high failure rates in these courses and other educational issues. Funded by a grant from the National Science Foundation, one goal of the LA program is to assist faculty members in transforming their pedagogy to research-based, conceptual, and learner-centered instruction (Otero, 2015). Part of these course transformations include the use of undergraduate LAs. Faculty members recruit students from math and science majors who have an interest in teaching or who they think would make good peer mentors. LAs get a monthly stipend for working ten hours per week. They also receive training in teaching and learning theories by enrolling in a math and science education seminar taught by discipline-based education researchers. The LA's role within a gateway STEM course is to facilitate group discussions among students, while focusing on developing conceptual understanding of the content. LAs focus on eliciting student thinking and helping students articulate and defend their ideas to others. This is typically done both in the larger lecture section of the course as well as smaller meetings after the weekly lectures, often referred to as recitation. In addition, LAs meet with faculty members once a week to develop deeper understanding of the content, share insights about how students are learning, and prepare for future class meetings (Otero, 2015).

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Undergraduate LAs play an important role in this model of course transformation that is notably different from more traditional graduate student teaching assistants (TAs). While the primary purpose of TAs is to support instructors with teaching, LAs focus on assisting students with learning. Further, as Talbot et al. (2015) point out, "LAs do not grade or have input in evaluating students and are therefore meant to be in a more 'trusted' position" (p. 28). LAs serve as "near peers" to the undergraduates in these STEM gateway courses as they are much closer to the student experience than graduate-level TAs. Researchers hypothesize that connections with LAs help students gain content knowledge through the pedagogical approaches employed by the LAs and also see themselves as capable of mastering the content because they see peers not unlike themselves helping to deliver the content (Otero, 2015; Talbot et al. 2015).

Prior research suggests that STEM gateway courses are one way by which students fail to persist to graduation in college. The LA program began, in part, in an attempt to help assuage this issue. The current study has two aims: 1) to better understand the relationship between the LA program and graduation rates in a local context (CU Boulder), and 2) to serve as a model for how directors of LA programs at other institutions might study the same relationship at their own institutions.

Literature Review

A major purpose of the LA program is to facilitate the transformation of STEM courses from traditional lecture-style instruction, where students passively listen to the instructor's lecture, to learner-centered instruction in which the goal is to engage learners in the active construction of knowledge that leads to conceptual knowledge gain. The LA model facilitates course transformation in a way that allows for students to have more frequent interaction with a content expert, thus increasing not only their own understanding, but also their experience with someone they see as knowledgeable in the field in which they are majoring (Otero, 2015; Talbot et al., 2015)[1].

For example, Pollock (2006) provided evidence regarding the relationship between course transformation including LAs and course outcomes in introductory physics courses by comparing

[1] The current literature review focuses on prior studies of the LA program itself rather than related initiatives or even the theory behind the LA model. For a review of the latter topics, see Handelsman et al., 2004 and Hake, 1998.

three different introductory physics course models. The first model used University of Washington Physics Tutorials materials (McDermott & Shaffer, 2002), peer discussion, lectures and concept tests explicitly connected to the Tutorial content. TAs and undergraduate LAs facilitated Tutorial sessions and attended weekly meetings with the instructor to prepare for Tutorials. These meetings included discussion about content as well as teaching strategies for the specific content. Tutorials took place during recitation sections. Recitation sections divide large gateway courses into smaller groups of students (~20-40) for a secondary meeting outside of lecture. Traditionally, students use this time to ask questions about homework. The Tutorial approach with LAs and TAs puts students into small groups of 3-5 students to work together on research-based materials from the University of Washington Physics Tutorial curriculum. In these groups, the expectation is that LAs and TAs facilitate discussion to aid in conceptual learning without directly providing answers to homework.

A second model used both the Physics for Scientists and Engineers text as well as related workbook (Knight, 2004). This model did not place as much emphasis on peer discussions, but students worked in small groups during recitation to cover material in the Physics for Scientists and Engineers workbook (Knight, 2004). The recitation meetings followed this format for about half of the semester, at which point recitation reverted to more traditional homework review sessions. The TAs who worked in these recitation sections received little training compared to their counterparts in the previous sections of the course. The third model for this course used Knight's (2004) textbook as well. During this term students engaged in peer discussion, but to far lesser extents than in the previous sections. Recitations took on the traditional format with TAs answering questions about homework. Table 1 provides a summary of the three methods of course models described in this study.

Table 1. Pollock (2006) Physics I Model Descriptions

Name	Key Traits
#1: Tutorials with LAs and TAs Fall 2003; Spring 2004	Trained TAs and LAs facilitated small group work in recitation sections. Students worked on homework assigned specifically for tutorials. TAs and LAs did not provide answers to the homework as much as guided discussion through questioning techniques to help students construct their own knowledge via discussion.
#2: Workbooks with TAs Fall 2004	TAs facilitated small group work in which students completed exercises in a workbook attached to a course textbook for half of the term. During the last half of the semester recitation was used to review homework in a more traditional fashion, with TAs directly answering questions from the homework assignments. Training for TAs was much more limited.
#3: Traditional TAs Spring 2005	No use of small group work. Recitation sessions oriented around the TA providing answers to homework exercises rather than students working collaboratively to develop conceptual understanding.

Pollock provides two sources of evidence related to student outcomes regarding the relative effectiveness of these three course models. First, he discussed average learning gains on the force and motion concept evaluation (FMCE; Thornton & Sokoloff, 1998) generally. The approach using tutorials with LAs saw an average learning gain of 66% on the FMCE from pre-test to post-test. Average learning gains for the approach using Knight's (2004) workbooks with TAs were about 59% and average learning gains for the traditional approach were about 45%. Pollock further investigated the impact of the different course implementations on higher and lower achieving students on FMCE scores. To do this, he considered students with high pretest scores (those with pretest scores >50%) and students with low pretest scores (those with pretest scores <15%). For both groups of students, the course implementation that included recitation run by trained TAs and LAs had the highest normalized learning gains[2] as measured by the FMCE. Figure 1 illustrates Pollock's findings. The first pair of bars shows that both students with high and low pretest scores had the greatest learning gains from the first form of instruction described in Table 1.

[2] Normalized learning gains are calculated by finding the difference in average post-test and pre-test in a class and dividing that value by the difference between 100 and the average pre-test score. It is conceptualized as the amount the students learned divided by the amount they could have learned (Hake 1998).

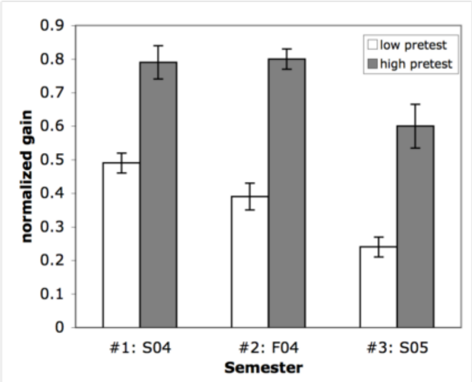

Figure 1. Normalized FMCE Learning Gains for Three Approaches to Physics I
Adapted from Transferring Transformations (p.143), by S. Pollock, 2006.

Pollock's (2006) approach to understanding the impact of course transformation and tutorials with the use of LAs provides some evidence about the relationship between courses including the LA experience and student outcomes. Although Pollock (2006) does not control for potential differences in the groups of students, he does provide evidence that pre-test scores for the three course models were relatively similar, suggesting that there were not large differences in the groups that might be the cause of the different gains seen on the FMCE. Despite this, there might still be other differences between the groups of students. The most obvious differences are that the instructor was different for each course model and the curriculum changed across the different models as well. Confounding variables such as these make it impossible to unambiguously attribute the differential gains to the LA or TA programs.

In another study, Pollock (2009) investigated the potential long-term relationship between exposure to the LA program and conceptual understanding in physics. In this line of inquiry, Pollock compared the Brief Electricity and Magnetism (BEMA; Ding, Chabay, Sherwood, & Beichner, 2006) assessment scores for those upper-division physics majors who did and did not receive LA support in their introductory Physics II course, the course in which electricity and magnetism is first covered. Pollock's results indicate that those students who received LA support in Physics II had higher BEMA scores following upper-division physics courses than those students who did not receive LA support in Physics II. This research provides some evidence to the long-term relationship between exposure to the LA program and conceptual learning.

Goertzen, Brewe, Karmer, Wells, and Jones (2011) investigated the influence of the LA course transformation in introductory physics at Florida International University (FIU). A difference in the

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LA model in physics at FIU from CU Boulder is that the course transformation primarily related to weekly three-hour physics lab meetings and not the regular weekly physics lectures. A few physics education researchers teach fully transformed lecture and lab sections, but these students and sections were eliminated from the current study. In other words, students who went to lab meetings that included LAs in this study did not necessarily receive their weekly lecture from an instructor who was focused on course transformation. In fact, any given lab section is not connected to any particular lecture section for most students at FIU. A single instructor helped to make sure the TAs and LAs fully understood the weekly lab materials, but the course transformation for the LA model did not affect the regular physics lectures. In contrast to Pollock's (2006) study that included University of Washington Tutorials (McDermott & Shaffer, 2002) and Physics for Scientists and Engineers workbook (Knight, 2004), FIU used Open Source Tutorials (Elby, Scherr, Goertzen, & Conlin, 2008) developed at University of Maryland, College Park as the curriculum for the transformed lab courses. Goertzen et al, used the Force Concept Inventory (FCI; Hestenes, Wells, & Swackhamer, 1992) as the outcome of interest in their study. They found that those students exposed to labs transformed by the LA model had a 0.24 increase in mean raw gain in scores from pre-test to post-test while students in classes that were not transformed only saw raw gains of 0.16. They report this translates to an effect size of 0.59.

White, Van Dusen, and Roulades (2016) conducted an investigation of the impacts of the LA model on student learning in physics across institutions. In their study, White et al. used paired pre/post-tests from four concept inventories (FCI, FMCE, BEMA, and Conceptual Survey of Electricity and Magnetism [CSEM]) at 17 different institutions. This study was made possible due to the LA Alliance. The LA Alliance is an international network of institutions that have established or are considering establishing LA programs and have partnered together in this process. Part of the alliance is contributing data to the LA Supported Student Outcomes (LASSO) online assessment. This platform allows for institutions to upload large-scale examination data on several common concept inventories to a central warehouse to make investigation across institutions possible. White et al. limited their sample to include only those students who responded to at least 80% of the items, those who completed both pre- and post-tests, courses with fewer than 10 matched sets of student responses, and those courses with effect sizes calculated to be less than -1 or greater than 4. In order to identify differences in learning gains for students who did and did not receive LA support, White et al. tested differences in course mean effect sizes between the two groups using a two-sample t-test. Across all of the concept inventories, White et al. found average Cohen's d effect sizes 1.4 times higher for LA-supported courses compared to courses that did not receive LA support.

There is also work that focuses on how the LA program affects student outcomes in other STEM fields. For example, Talbot et al. (2015) focused on how transforming STEM gateway courses in biology might influence student satisfaction with an introductory Biology course. Although the focus of this study was primarily on student satisfaction survey data, Talbot et al. also provided minimal analysis with student outcome data. The researchers collected data from the Conceptual Inventory of Natural Selection (CINS; Anderson, Fisher, & Norman, 2002) in two sections of General Biology II, one with and one without LA support. A different instructor taught each section, but both the instructor and the course received relatively similar course ratings. Talbot et al. reported that the average normalized learning gain in the course with no LAs was -0.08 while the gain in the section with LAs was 0.49. Despite these encouraging results, the study design did not control for potential confounding factors that may have also influenced learning gains on the CINS. Similar to the other studies presented, it is possible that the differences in learning gains between LA and non-LA supported courses might have been due to other factors than the LA support itself such as difference in implementation of instruction or difference in class composition.

Although there has been some research on the relationship between the LA program and course-related outcomes, no prior research attempts to examine the relationship between taking LA-supported courses and student outcomes while controlling for variables that may confound this relationship. In addition, while the outcome of interest in the prior work discussed was achievement gains between pre- and post-test scores on concept inventories, in the present study the outcome of interest is six-year graduation rates at CU Boulder. This study thus represents an extension of the previous work both in terms of the methodology and the outcome of interest.

Data

Data for this study comes from administrative records at CU Boulder. We focus on seven cohorts of students who entered the university as full-time students for the first time each fall semester from 2004 – 2010 and took at least one of the STEM courses included in the study. The full dataset includes information for 15,089 students, 10,127 of whom took at least one LA- supported course. Student-level data includes information such as university enrollment term, graduation term, major, race/ethnicity, gender, admissions test scores, transfer student status, first generation status, an indicator for if a student ever received financial aid, and high school GPA. In addition to administrative data, we also have course information for a subset[3] of LA supported courses at CU Boulder in four departments: applied math (APPM), chemistry (CHEM), math (MATH), and physics (PHYS). Table 2 provides a list of the courses included in the present study. Course-level variables include the term in which a student enrolled in a course, the final grade received in the course, and if the particular section of the course included LA support or not.

The current study focuses on these particular courses because each is a gateway course in the respective department. As discussed in the literature review, a relatively high number of students often fail these large, lecture-style classes. From 2001-2014, the average failure rate across all courses was about 18%. This is consistent with the failure rates in such courses documented in previous literature (Twigg, 2003). The study begins with data in all departments listed in Table 2, and ends with a particular focus on the courses in the chemistry and applied math departments, where we can garner the most information about the relationship between the LA program and persistence to graduation.

[3] At the time of this publication, there were a total of 50 LA-supported courses across 12 departments at CU Boulder. We focus on a small subset of STEM gateway courses. For simplicity's sake, we refer to "LA courses" throughout this report, but that phrase only relates to the courses specified in Table 2.

Table 2. Courses in the current study

	APPM	CHEM	MATH	PHYS
Offered alongside sections without LA Support	• Pre-Calculus for Engineers • Calculus 1 for Engineers • Calculus 2 for Engineers	• Introductory Chemistry • General Chemistry 1 • General Chemistry 2		
No contemporaneous sections without LA support	• Calculus 1 with Algebra, Part A • Calculus 1 with Algebra, Part B	• General Chemistry 1 for Chemistry and Biochemistry Majors • General Chemistry 2 for Chemistry and Biochemistry Majors	• Pre-calculus Mathematics • Calculus, Systems, and Modeling • Calculus 1 • Calculus 2	• General Physics 1 • General Physics 2

The purpose of this study is to answer the following question: How do graduation rates compare for students who do and do not take LA-supported courses? The outcome of interest, graduation, is a binary variable: a student graduates in six years or less, or the student does not[4]. Graduation rates are one indicator of how well an institution serves its students, and institutions of higher education are required to annually report their four and six-year graduation rates to the federal government as part of the Students' Right to Know Act[5]. Additionally, the administration at institutions of higher education often set specific six-year graduation rates. For example, the current CU Boulder goal for six-year graduation rate is 80% by 2020 (from 70% in 2016)[6].

[4] A student coded as not graduating in six years can take on any one of three different possible outcomes: (a) the student may never graduate at all, (b) the student may transfer to another institution, or (c) the student may graduate in more than six years.
[5] For more information on graduation rates and the issues with defining them, see the American Council on Education's discussion of Graduation Rates: http://www.acenet.edu/the-presidency/columns-and-features/Pages/Why-Graduation-Rates-Matter%E2%80%94and-Why-They-Don%E2%80%99t.aspx
[6] http://www.colorado.edu/chancellor/campus-priorities/student-success

The student group of interest in this study are those who took any of the courses in Table 2 with LA support, irrespective of department, while enrolled at CU Boulder. Ideally, we would use statistical methods to provide evidence about the causal effect of taking these LA-supported courses on six-year graduation for these students. In order to do this, we would need a second group of students similar to the first in all ways except for exposure to LA-supported courses. If the two groups were not comparable except for this one factor, we would need data necessary to control for any differences between the students in each group that were also related to persistence to graduation. Unfortunately, this not the case in our study.

Assignment to receiving LA support is not random, so students who take LA-supported courses likely differ from students who do not take LA-supported courses in many ways. For example, during the timeframe spanned in the data, neither the math department nor the physics department offered contemporaneous sections of any of the courses listed in Table 2 with and without LA support. Instead, these departments shifted completely from no LA support for any section of a given course to all sections including LA support at some point during the time span included in our dataset. Thus, in these two departments, there is an historic threat to validity. That is, the results would be threatened by any historic changes that occurred over time such as changes in curriculum or faculty, or even just historical differences in cohorts of students over time. As an example, if we observe that graduation rates for students in the mathematics and physics departments increase after the switch to providing LA support, one interpretation would be that the LA program increases graduation rates. However, we could not rule out the possibility that graduation rates increased due to other factors that also changed over time. It could also be that the university implemented other student supports at the same time, that the types of students recruited to and accepted into the math and physics departments changed, or that the external social environment encouraged more students to persist in school. There is no way to determine conclusively which of these (or other) factors may have caused the changes in graduation rates.

The chemistry department also did not offer contemporaneous sections of courses with and without LA support. Instead, during the span of time in our data, LA support was almost always offered in the “on semester” sections of chemistry. “On semester” indicates Chemistry I in the fall and Chemistry II in the spring. There were few opportunities for those students who took the sequence in the “off semester”, or Chemistry I in the spring and Chemistry II in the fall to receive LA support in these courses.

The most typical reason why students take classes in the “off semester” are that they simply prioritize other courses more in the fall semester, so there is insufficient space to take Chemistry I; they do not feel prepared for Chemistry I in the fall and take a more introductory chemistry class first; or they fail Chemistry I the first time in the fall and re-take Chemistry I in the spring. Although an historical threat to internal validity might not be as much of a concern in the chemistry department as in physics and math, there is still likely selection bias based on the ways students typically end up in “off semester” chemistry courses. We investigate the implications of this assignment to LA support in sensitivity analysis at the end of this report.

The applied math department suffers from a similar threat to internal validity as the chemistry department. Students in every section of the courses in the applied math department had the opportunity to be exposed to LA support as signing up for the support was voluntary. However, those students who are expected to struggle are more strongly encouraged to sign up for the support by both their instructors and advisors. Additionally, instructors suggest that students who are not confident in their math abilities should sign up for the support.

All of these confounds make it difficult to determine whether we might over or under estimate the effect of the LA program on graduation rate. For example, we might overestimate the effect if the university also pursued other student supports to increase graduation rates that similarly influenced those students who received the LA support. This seems plausible given university-level goals for graduation rates. Alternatively, we might also under estimate the effect if the students who struggle the most are in the LA -supported sections. In other words, if the students who receive the LA support would have had lower graduation rates to begin with, the magnitude of the effect might be masked.

The ways in which students find themselves receiving LA support in the chemistry and applied math departments suggest that these students potentially differ on factors such as confidence in their abilities or in their abilities themselves. Prior research suggests that academic self-confidence and general self-efficacy have a stronger relationship to persistence in college than high school GPA and admissions test scores (Bean & Eaton, 2001; Lotkowski, Robbins, & Noeth, 2004). Unfortunately, our data set is limited to a small number of demographic and administrative variables including gender, race/ethnicity and whether a student is a first-generation college student or received financial aid. Additional academic achievement variables in our data include number of credits upon enrollment, high school GPA, and admissions test scores[7,8].

Methods

We begin our analysis with a report of the raw graduation rates for those who did and did not receive LA support in the courses listed in Table 2. This is to provide a baseline description of graduation rates for students who take our courses of interest. We then move on to describe the differences between the two groups with respect to the demographic and administrative variables made available to us. Finally, we use the limited data we have in a logistic regression in an attempt to disentangle some of the relationship between taking LA-supported courses and six-year graduation rates. We not only control for the demographic variables described above (i.e. gender, race/ethnicity, admissions test scores, etc.), but we also include dummy variables for cohort as well as course in later analysis. In other words, we control for observed variables to try to make a fairer comparison and to adjust for the potential confounds mentioned above.

Although regression techniques are typically used in efforts to make causal claims about an intervention, it is important to explicitly state that the purposes of this paper are descriptive rather than causal due to the lack of control group of students as described in the data section. The results presented in this paper are an improvement over raw graduation rates as we control for some differences in student groups, but they do not allow us to make strong causal claims about the direct effect of the LA program on graduation rates. Despite this, it is valuable to understand more about graduation patterns and the relationships between graduation and the LA program. Additionally, this research provides more evidence about the direction of the relationship between exposure to the LA program and propensity to graduate.

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[7] Since not all students take both the ACT and SAT, we use an SAT to ACT concordance table provided by the College Board to place all admissions tests scores on a comparable metric. We take combined SAT Critical Reading and Mathematics scores for students with SAT data and no ACT scores and use the concordance tables to translate SAT total scores to ACT Composite Scores. These scores range from one to thirty-six with a mean of about twenty-seven and a standard deviation of about four. We exclude students with no admissions test scores (about 5% of the population) from the analysis.

[8] All continuous control variables were standardized to have a mean of 0 and a standard deviation of 1 for ease of interpretation

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Results

Raw graduation rates for those students who do and do not take at least one LA-supported course during their tenure at CU Boulder are presented in Table 3. This table includes the number of students who enroll in each of the cohorts included in this analysis as well as the number who graduate in six years or less based on exposure or lack thereof to LA-supported courses. The overall university graduation rate for each cohort is included in the final column of the table for comparative purposes as well.

Students who took at least one LA-supported course had consistently higher graduation rates than those students who did not take at least one LA-supported course. In addition, the graduation rates for those students who took at least one of the LA-supported courses in this study are higher than the campus-wide six-year graduation rate for all cohorts. The average graduation rate, weighted by cohort size, is about 11% higher for those students who took LA-supported courses relative to students who did not.

Although there is a positive association between taking at least one LA-supported course and graduating within six years, there are, of course, other factors that could explain at least some of this association. For example, it might simply be the case that those students who take courses with LA support are inherently different on key factors that influence graduation (e.g. self-confidence, hours spent studying, social and emotional health) from those students who take non-LA-supported courses. Although most of these factors represent information that is not available to us, we present some available demographic and academic achievement information for those students who were and were not exposed to LA support in Table 4.

Students who took courses with LA support are less likely to be female and also less likely to be first generation college students. Additionally, these students had more credits at entry, higher high school GPAs, and higher admissions test scores. Among just these few variables, there are statistically significant differences between those students who took LA-supported courses and those who did not. This suggests that at least some of the differences in graduation rates provided in Table 3 could be explained by factors other than exposure to LA support in STEM gateway courses.

Table 3. Graduation Rates for Fall 2004 - Fall 2010 Traditional cohorts

Students in STEM Intro Courses	# Enrolled	# GRAD in 6 years or less	% GRAD in 6 years or less	% GRAD full CUB campus
Fall 2004 Cohort				
At least 1 LA	701	539	76.9	68
No LA	1311	884	67.4	
Difference			9.5	
Fall 2005 Cohort				
At least 1 LA	941	708	75.2	68
No LA	1034	652	63.1	
Difference			12.1	
Fall 2006 Cohort				
At least 1 LA	1373	1038	75.6	68
No LA	782	480	61.4	
Difference			14.2	
Fall 2007 Cohort				
At least 1 LA	1646	1243	75.5	70
No LA	589	340	57.7	
Difference			17.8	
Fall 2008 Cohort				
At least 1 LA	1811	1351	74.6	70
No LA	460	278	60.4	
Difference			14.2	
Fall 2009 Cohort				
At least 1 LA	1866	1384	74.2	71
No LA	383	256	66.8	
Difference			7.3	
Fall 2010 Cohort				
At least 1 LA	1789	1299	72.6	70
No LA	403	250	62.0	
Difference			10.6	
Cumulative totals				
At least 1 LA	10127	7562	74.7	
No LA	4962	3140	63.3	
Difference			11.4	

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Table 4. Descriptive Statistics for LA and non-LA students

	LA	Non-LA	p-value
	%	%	
Female	36	50	<0.01
Nonwhite	24	24	0.72
First Generation	17	19	<0.01
Receiving financial aid	52	50	0.05
	Mean (SD)	Mean (SD)	
Num. Credits at entry	8 (12)	5 (10)	<0.01
High School GPA	3.66 (0.33)	3.55 (0.36)	<0.01
Test Score	27 (4)	25 (3)	<0.01
N	10127	4962	

Logistic Regression

We next use logistic regression to control for the influence of potentially confounding variables. First, we conduct a regression analysis without any interaction terms (See Model 1 in Table 5). That is, we assume the relationship between the LA program and persistence to graduation to be the same for all groups of students in Model 1. Following that, we consider Models 2 and 3 that include interaction terms. These analyses investigate whether the relationship between exposure to the LA program and likelihood of graduating within six years varies across different groups of students.

The results from Model 1 are shown in the first panel of Table 5. Each column provides the odds ratios (with confidence intervals) for graduating in six years or less for each control variable in the respective model. An odds ratio represents the proportional change in the odds of an event occurring (here graduating in six years or less) for a one-unit increase in an independent variable. An odds ratio equal to 1.0 indicates that changes in the independent variable are not associated with changes in the odds of graduating in six-years or less. Odds ratios less than 1.0 indicate that changes in the independent variable are associated with a decrease in the chances of graduating, while odds ratios greater than 1.0 indicate an increased chance of graduating. Confidence intervals that include 1.0 indicate an odds ratio that is not statistically significant.

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Table 5. Logistic Regression Odds Ratios (Confidence Intervals)

	Model 1	Model 2	Model 3
Intercept	2.75	2.91	2.69
	(2.54, 2.99)	(2.66, 3.19)	(2.47, 2.93)
Exposed to LAs	1.66	1.55	1.71
	(1.56, 1.77)	(1.43, 1.68)	(1.6, 1.84)
Female	1.34	1.19	1.34
	(1.27, 1.42)	(1.08, 1.32)	(1.27, 1.42)
Nonwhite	0.79	0.79	0.88
	(0.75, 0.84)	(0.75, 0.84)	(0.78, 0.98)
First Generation	0.58	0.58	0.58
	(0.54, 0.62)	(0.54, 0.62)	(0.54, 0.61)
Receiving Financial Aid	0.96	0.96	0.96
	(0.91, 1.01)	(0.91, 1.01)	(0.91, 1.01)
Standardized entry credits	1.25	1.25	1.25
	(1.21, 1.29)	(1.21, 1.29)	(1.21, 1.29)
Standardized HS GPA	1.45	1.45	1.45
	(1.41, 1.48)	(1.41, 1.48)	(1.41, 1.48)
Standardized Test Score	0.96	0.96	0.96
	(0.93, 0.99)	(0.93, 0.99)	(0.93, 0.99)
2005 Cohort	0.86	0.86	0.86
	(0.78, 0.94)	(0.78, 0.94)	(0.78, 0.94)
2006 Cohort	0.86	0.86	0.86
	(0.78, 0.94)	(0.78, 0.94)	(0.78, 0.94)
2007 Cohort	0.8	0.8	0.8
	(0.73, 0.88)	(0.73, 0.88)	(0.73, 0.88)
2008 Cohort	0.82	0.82	0.82
	(0.74, 0.90)	(0.74, 0.9)	(0.74, 0.9)
2009 Cohort	0.81	0.81	0.82
	(0.74, 0.9)	(0.74, 0.9)	(0.74, 0.9)
2010 Cohort	0.78	0.77	0.77
	(0.70, 0.85)	(0.70, 0.85)	(0.70, 0.85)
LA Exposure*Female	---	1.17	
		(1.05, 1.32)	---
LA Exposure*Nonwhite	---	---	0.88
			(0.77, 0.99)
N = 15089			

The results in Table 5 indicate that taking LA-supported courses has a positive and statistically significant association with graduation. Specifically, holding constant all other variables in Model 1, students who take at least one LA-supported course have odds of graduating in six years or less that are 66% greater than those of students who do not take LA-supported courses. Female students have 34% greater odds of graduating than males, nonwhite students 21% lower odds of graduating in six years than white students, first generation students have 42% lower odds than those who are not the first in their families to go to college, and those receiving financial aid have 4% lower odds of graduating than those who do not receive aid. Furthermore, students who entered CU with credits one standard deviation higher than average had 25% greater odds of graduating than those who entered with the average number of credits. Similarly, those students with one standard deviation higher high school GPA had 45% higher odds of graduating in six years or less than those with average high school GPAs, while those students with one higher standard deviation in admissions test scores had 4% lower odds of graduating in six years or less than those with average admissions test scores.

Odds ratios are difficult to compare to the associations implied in Table 3 as those graduation rates are expressed in terms of percentage of graduates. Additionally, because of the nature of logistic regression, the results must always be interpreted for a particular group of students. To facilitate a comparison to Table 3, we can express the results from the logistic regression in terms of the marginal difference in the probability of graduating for specific groups of students who are and are not enrolled in courses with LA support. One group of students we might consider are those who are male, white, non-first generation college students, do not receive financial aid, have the mean number of credits at entry, mean HS GPA, mean admissions test scores, entered college in 2004 and are not exposed to LA-supported courses. These students take on values of 0 for all variables in Model 1. The change in probability of graduating for these students who only differ in that they have taken LA-supported courses compared to those who do not is an increase in the probability of graduating in six years or less of 0.09, from 0.73 to 0.82. In other words, these students have an 9% higher chance of graduating in six years or less[9]. Note that after controlling for potential confounding variables the increased probability of graduating (0.09) in the logistic regression is smaller than nearly all of the differences in graduation rates presented in Table 3. In other words, after controlling for potential confounding variables, the association between graduating in six years or less and exposure to LA support decreases, though it remains a statistically significant relationship. Something to note is that this adjusted association varies as a function of a student's high school GPA. For the same group of students with high school GPA one standard deviation

[9] The Appendix provides details regarding the process for converting the results from a logistic regression into probability estimates.

below or above the mean, the difference in probability of graduating when exposed to LA support is 10% or 7% respectively.

Table 6 contrasts four student profiles and provides the difference in predicted probability of graduating for students who take LA-supported courses in each profile relative to students who do not take LA-supported courses. These particular profiles are presented because students' gender and race/ethnicity are two of the strongest predictors of six-year graduation rate. We also discuss how the marginal difference in probabilities change for students with different high school GPAs below.

Table 6. Graduation rates for different profiles of students

Key Contrast	LA?	Probability of Graduating (CI)	Difference
White Males	No	0.73 (0.72, 0.75)	0.09
	Yes	0.82 (0.80, 0.84)	
White Females	No	0.79 (0.76, 0.81)	0.07
	Yes	0.86 (0.83, 0.88)	
Nonwhite Males	No	0.69 (0.66, 0.72)	0.09
	Yes	0.78 (0.75, 0.82)	
Nonwhite Females	No	0.75 (0.71, 0.78)	0.08
	Yes	0.83 (0.79, 0.86)	

Note: Reference categories for contrasts above are non-first generation college students who do not receive financial aid and enrolled as Freshmen in fall 2004. All continuous predictors are fixed at their mean values.

The results in Table 6 suggest that the marginal difference in probability of graduating (or the change in probability of graduating after controlling for the covariates in the model) is about 8% across the different student profiles. However, high school GPA is the strongest predictor of six-year graduation rate, aside from exposure to the LA program, after controlling for the other variables in the model. Thus, it is important to know how these marginal probabilities change based on the value of high school GPA. Each of the differences in probability of graduating in six years or less shown in Table 6 increases by 1-2% points when students have high school GPAs one standard deviation below average and decrease by about 1-2% when students have high school GPAs one standard deviation above average. This suggests that taking an LA-supported course is associated with a greater increase in graduation rates for students who had lower high school GPAs than those who had average or above average GPAs, but the differences are relatively small, albeit statistically significant. In general, the marginal change in probability of graduating in six years or less for being exposed to the LA program ranges from 7 – 12% depending on the group of students under consideration.

Following estimation of Model 1, we moved on to investigate the potential interactions or additional relationship between receiving LA support and three other factors: being female, nonwhite, or a first-generation college student. Only the interactions between being female or nonwhite and receiving LA support were statistically significant, so these are the only models reported in Table 5.

Models 2 and 3 investigate whether the relationship between taking an LA-supported course and 6-year graduation rate varies across student gender or race/ethnicity. The statistically significant interaction effects in each model indicate that the relationship does differ. Being exposed to LA-supported courses increase the odds of graduating by 55% for male students, but the increase is 82% for female students (OR 2.16, CI [1.62, 2.93]). This suggests taking an LA-supported course increases the likelihood of graduating within six years by a greater amount for female students. We also find that taking an LA-supported course is associated with a greater increase in the likelihood of graduating within 6 years for white students than it is for non-white students. Exposure to the LA program increases the odds of graduating by 71% for white students and increases the odds for non-white students by 50% (OR 1.32 CI [0.96, 1.79]).

Department-level analysis

These initial results suggest that taking LA-supported courses has a significant and positive association with six-year graduation for various kinds of students. However, recall that although this analysis includes treatment cases in all four departments (i.e. math, applied math, chemistry, and physics), there are only contemporaneous control cases in the applied math and chemistry departments.

The graduation rates for students in our sample who took LA-supported courses in only one department are 75% and 68% in physics and math respectively, while the graduation rates for students who took LA-supported courses in only the applied math and chemistry departments are 52% and 70% respectively. Since students who took the physics and math department courses have higher graduation rates, it is possible that the estimated relationship between taking LA-supported courses and six-year graduation rates from this logistic regression are inflated. Table 7 shows the number of students in the treatment and control conditions in both applied math and chemistry. Since the number of students in the treatment case in applied math is small in comparison to the overall sample size, and since the chemistry graduation rate is similar to that of physics and math, it is unlikely that the lower graduation rates in applied math have a large impact on the results presented to this point. Regardless, it is important to investigate if these initial results might be misleading.

Table 7. Distribution of LA vs. no LA exposure in applied math and chemistry

	Applied Math	Chemistry	Total
LA Exposure	201	1669	1870
No LA exposure	714	2579	3293
N	915	4248	5163

We next turn to the logistic regression from Model 1 with only those students exposed to LA-supported courses in either the applied math or chemistry departments. Only students who took either chemistry or applied math courses with or without exposure to LA support appear in both data sets. This approach restricts the sample size as we not only eliminate all students from the math and physics departments, but we also eliminate any student who took LA-supported courses in *both* the applied math and chemistry departments so that we account for any potential spillover effects of LAs from multiple departments.

We separate the analysis by department in order to avoid any conflation of results due to the differential enactment of the LA program. Additionally, we add dummy variables for the two largest courses in each department: Calculus I and II for applied math and Chemistry I and II for chemistry. Qualitative data suggests that the use and implementation of LAs is not consistent across departments, so it is important to understand if the association between taking LA-supported

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courses and probability of graduating is different in applied math versus chemistry. If it were the case that the LA experience had the same average association across departments, then there would be similar regression results for each subsample. The results presented in Table 8 prove this not to be the case.

Holding constant all other variables, students who take at least one LA-supported course have a 26% lower odds and a 62% higher odds of graduating in six years or less in applied math and chemistry respectively. Thus, we see that although the relationship between taking LA supported gateway courses in both of these departments and six-year graduation rates is statistically significant, the direction of those associations are in opposite directions. Recall that the range in marginal change of probability of graduating in Model 1 for the full data set indicated an increase in graduation rates from 7-12%. In applied math, the marginal change in probability is a decrease of 5-7%. In chemistry, we observe an increase of 6-14%. Thus, the results in the chemistry department largely align with the results from the overall analysis, but the applied math results are quite different.

Investigation of the same three interactions previously described indicated that the interaction between female and receiving LA support remains statistically significant and positive in applied math. However, this same relationship is non-significant in chemistry. Further, the interaction between being a first-generation college student and taking LA-supported courses is statistically significant and positively associated with six-year graduation rates in the chemistry department. Finally, there was no statistically significant relationship between the Nonwhite and LA exposure interaction and graduation rates in either the applied math or chemistry departments.

Table 8. Odds ratios (confidence intervals) for APPM and CHEM

	APPM	CHEM
Intercept	2.02	2.95
	(1.55, 2.64)	(2.54, 3.44)
Exposed to LAs	0.74	1.62
	(0.56, 0.98)	(1.44, 1.83)
Female	1.59	1.19
	(1.21, 2.08)	(1.07, 1.33)
Nonwhite	1.00	0.78
	(0.77, 1.31)	(0.70, 0.88)
First Generation	0.35	0.62
	(0.26, 0.47)	(0.55, 0.71)
Receiving Financial Aid	1.14	1.06
	(0.91, 1.43)	(0.96, 1.18)
Standardized entry credits	1.51	1.22
	(1.32, 1.74)	(1.14, 1.3)
Standardized HS GPA	1.3	1.38
	(1.15, 1.46)	(1.31, 1.46)
Standardized Test Score	0.85	1.03
	(0.76, 0.97)	(0.97, 1.09)
2005 Cohort	0.65	0.72
	(0.48, 0.87)	(0.61, 0.84)
2006 Cohort	0.73	0.79
	(0.50, 1.06)	(0.66, 0.94)
2007 Cohort	0.58	0.57
	(0.39, 0.86)	(0.47, 0.68)
2008 Cohort	0.82	0.59
	(0.56, 1.19)	(0.48, 0.72)
2009 Cohort	0.47	0.82
	(0.29, 0.74)	(0.67, 1.02)
2010 Cohort	0.59	0.59
	(0.37, 0.94)	(0.48, 0.72)
CALC I	0.78	---
	(0.61, 0.99)	
CALC II	1.22	---
	(0.90, 1.66)	
CHEM I	---	1.06
		(0.94, 1.18)
CHEM II	---	1.85
		(1.60, 2.15)
N	915	4248

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Sensitivity Analysis

We finally consider two sensitivity analyses to test the robustness of the findings in Table 8. First, we limit the sample to those students who took the courses in Table 2 with or without LA support in their first year at CU Boulder. Ideally, students take these large gateway courses in their first year on campus, so in many ways, these students are the target audience for the LA program. Thus, this analysis serves as a way of understanding if the relationship between taking LA-supported courses and graduating in six years or less is potentially different for those students who take the courses in their first year as students. Odds ratios for exposure to LA support for this subset of students appear alongside the odds ratios for all students in Table 9.

Table 9. LA-Exposure Odds Ratios by Department and Sample

		Full Sample	First Year
APPM			
	Odds Ratio	0.74	0.81
	Confidence Interval	(0.56, 0.98)	(0.60, 1.10)
	N	915	864
CHEM			
	Odds Ratio	1.62	2.05
	Confidence Interval	(1.44, 1.83)	(1.74, 2.42)
	N	4248	3075

In the applied math department, there is a statistically significant and negative relationship between exposure to the LA program and six-year graduation across all students who take LA-support applied math gateway courses. However, this relationship is just below the statistically significant cutoff (i.e. the confidence interval misses 1.0 by 0.02). For those students who take the applied math gateway courses in their first year, there is no statistically significant relationship between exposure to LAs and six-year graduation rates. For chemistry, we see a positive and statistically significant relationship between taking LA-supported gateway courses and six-year graduation rates, regardless of when the gateway courses are taken. However, the association is stronger when students take the gateway courses in their first year.

Finally, recall that the method by which students receive LA support in chemistry is predominantly if they take the “on-semester” chemistry sequence. As explained in the data section of this report, it is possible that those students who take the “off-semester” sequence may be more likely to have less confidence in their abilities or self-efficacy, which has been linked to success in college. Thus, as a final sensitivity analysis, we conduct the same chemistry department regression analysis with only those students who took the off-semester sequence in chemistry.

Table 10. Chemistry Off-Semester LA-Exposure Odds Ratios

	Off-semester
Odds Ratio	1.03
Confidence Interval	(0.75, 1.41)
N	1141

The results in Table 10 indicate that there is no statistically significant relationship between exposure to LA-supported chemistry courses in the off-semester and six-year graduation rates. The results from the sensitivity analyses do not negate the potential relationship between exposure to LAs and graduation rates, but they do indicate a need for further research as the sample of students used in the regression yields differential results regarding the relationship between exposure to LAs and graduation. In order to gain a clearer understanding of the variation in results, it is necessary to gain more information regarding factors such as student self-efficacy and the types of students in each department and LA exposure condition.

Conclusion and Limitations

In this study, we attempt to disentangle the relationship between taking at least one LA-supported STEM gateway course and six-year graduation at University of Colorado Boulder. Although we controlled for several student-level variables, we surely missed key variables that contribute to a student's propensity to graduate. For example, if students have to work one or multiple jobs to support themselves in college, a student's proximity to campus, the hours a student spends studying, overall cost of attending college, a student's emotional health, and family socioeconomic status all influence graduation rates (Lotkowski, Robbins, & Noeth, 2004). Additionally, perhaps one of the biggest potential confounding variables in this study is the instructor. Those instructors who seek out course transformation including LAs are likely different from those who do not, and this might significantly influence the relationship between taking LA-supported courses and six-year graduation rates. Additionally, instructor might also be an important variable in the chemistry-specific analysis. It might be that the instructors who are assigned to off-semester chemistry sections are different from those who teach in the on-semester sequence, thereby additionally confounding the results presented here. Despite this limitation, the regression analysis represents an improvement over an unadjusted comparison of mean graduation rates, and even after controlling for the available variables, we do see a positive association between taking LA-supported gateway courses in the chemistry department generally and six-year graduation rates. This is promising news, but the inverse findings in the applied math department for implementation of supposedly the same program is cause for further research.

The knowledge that the use of LAs and assignment to receive exposure to LAs is different across and within departments indicates a need for further qualitative work. It is necessary to understand if it is reasonable to compare the relationship between LA-supported courses and six-year graduation rates across these departments. Implementation of the LA program may be so different across applied math and chemistry that comparing the relationships to six-year graduation rates between the two is like comparing apples to oranges. A more detailed understanding of the conditions under which students find themselves in the LA-supported versus non-LA-supported experiences in each department as well a deeper understanding of the differential ways the LA program is enacted in each department are necessary in order to know how to best interpret the results of this study. In addition to this qualitative work, future investigation should focus on the potential relationship between LA support and course grades. It is difficult to understand the relationship between experiences that occur during a student's first few semesters in college to a long-term outcome such a six-year graduation rate. However, the connection between the LA program and course grade is much more direct and influenced by fewer confounding variables.

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Appendix

Results from the logistic regression are reported in odds ratios in this report for ease of interpretation. However, most statistical software reports the results from logistic regression in log odds. This appendix provides a full results table for Models 1-3 in the full dataset as well as an example of the calculations necessary to transform the output into probabilities as presented in Table 6 of this paper.

Table A1. Logistic Regression Log Odds Estimates

	Model 1	Model 2	Model 3
Intercept	1.01	1.07	0.99
Exposed to LAs	0.51	0.44	0.54
Female	0.29	0.18	0.29
Nonwhite	-0.23	-0.23	-0.13
First Generation	-0.55	-0.55	-0.55
Receiving Financial Aid	-0.04	-0.04	-0.04
Standardized entry credits	0.22	0.22	0.22
Standardized HS GPA	0.37	0.37	0.37
Standardized Test Score	-0.04	-0.04	-0.04
2005 Cohort	-0.15	-0.15	-0.15
2006 Cohort	-0.16	-0.16	-0.16
2007 Cohort	-0.22	-0.22	-0.22
2008 Cohort	-0.20	-0.20	-0.20
2009 Cohort	-0.20	-0.21	-0.20
2010 Cohort	-0.25	-0.26	-0.26
LA Exposure*Female	---	0.16	---
LA Exposure*Nonwhite	---	---	-0.13
N = 15089			

Any log odds can be transformed into a probability through exponentiation. In this explanation, we consider the transformation for students who are white, male, non-first generation college students, who do not receive financial aid, and have an average value for number of credits at entry, high school GPA, and admissions test scores and do not receive LA support and began at CU Boulder in 2004. In order to transform the log odds of 1.01 to a probability of six-year graduation, we make the following calculations

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$$P(\text{Grad6=1}) = \frac{e^{Intercept}}{1+e^{Intercept}} = \frac{e^{1.01}}{1+e^{1.01}} = \frac{2.75}{3.75} = 0.73$$

The exponentiation shown in the example transforms a log odds of 1.01 into a 0.73 probability of graduating in six years or less. If we now want to contrast this probability with a different student profile, we simply change one or more of the control variables. For example, if we want to find the amount of change in the probability of graduating in six years or less by being exposed to an LA supported course for the same type of students as considered above, we make the following calculations

$$P(\text{Grad6=1}) = \frac{e^{Intercept+LA(1)}}{1+e^{Intercept+LA(1)}} - \frac{e^{Intercept+LA(0)}}{1+e^{Intercept+LA(0)}} = \frac{e^{1.01+0.51(1)}}{1+e^{1.01+0.51(1)}} - \frac{e^{1.01+0.51(0)}}{1+e^{1.01+0.51(0)}} =$$

$$= 0.82 - 0.73 = 0.09$$

This means that a student who has a zero for all covariates in Model 1 of Table 5 except exposure to an LA-supported course has a 9% higher chance of graduating in six years or less over a similar student who was not exposed to an LA-supported course. Although not shown, both of these calculations assume that all the other point estimates from the logistic regression are multiplied by 0 and thus not included in the calculation. The variables only appear in the calculation if there is an interest in understanding a contrast for a particular student profile that requires changing the value of the predictor from 0 to 1.

Now consider a more complex comparison, again from Model 1 in Table 5. Suppose we want to know the difference in probability of graduating for nonwhite females, holding all other control variables constant at zero. The following calculations would be necessary:

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$$P(Grad6=1) = \frac{e^{Intercept+Female(1)+Nonwhite(1)+LA(1)}}{1+e^{Intercept+Female(1)+Nonwhite(1)+LA(1)}} - \frac{e^{Intercept+Female(1)+Nonwhite(1)+LA(0)}}{1+e^{Intercept+Female(1)+Nonwhite(1)+LA(0)}} =$$

$$= \frac{e^{1.01+0.29(1)-0.23(1)+0.51(1)}}{1+e^{1.01+0.29(1)-0.23(1)+0.51(1)}} - \frac{e^{1.01+0.29(1)-0.23(1)+0.51(0)}}{1+e^{1.01+0.29(1)-0.23(1)+0.51(0)}} =$$

$$0.83 - 0.74 = 0.09$$

Here we are interested in a different group of students, and so the variables for female and nonwhite are “turned on”, so to speak. These variables are now included in the calculations because a value of 1 is used instead of 0 as in the above calculations. Similar calculations can be made to understand the marginal difference in probability of graduating for any group of students in the data exposed to LA support or not.