Moving the Classroom to the Computer Lab: Can online learning with in-person support improve outcomes in community colleges?

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Abstract

Colleges are experimenting with integrating technology into the classroom to improve student learning and reduce costs. While fully online models appear to have negative effects on student learning compared to in-person instruction, there is less evidence about models that blend elements of online and in-person instruction. In this study, I estimate the effect of adopting a blended approach to teaching called the emporium model in which students complete online work in an on-campus lab with instructors onsite to assist. Using a triple difference identification strategy, I find that using the emporium model compared to traditional instruction in remedial math courses in a state community college system reduces course pass rates, retention, and degree attainment. Effects were generally consistent across all three levels of remediation, suggesting there was little variation by students' incoming placement test score.

Keywords: blended learning, community colleges, student performance, college remediation
JEL Codes: I21, I23

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I. Introduction

Over the last ten years, online courses have become prevalent in higher education, particularly at community colleges (Parsad and Lewis, 2008; Allen and Seaman, 2013). Today, one-third of students take at least one course online (Allen and Seaman, 2013). Studies comparing online to face-to-face courses have found predominantly negative effects of online classes on grades, test scores, and progress in college, with larger negative effects for students with lower levels of academic preparation (Figlio, Rush, and Yin, 2013; Xu and Jaggars, 2013; Bettinger, Fox, Loeb, and Taylor, 2017; Alpert, Couch, and Harmon, 2016). While online courses can potentially reduce the cost of administering courses (Deming, et al, 2015), these savings appear to come at a cost to student success.

Blended learning interventions, which mix aspects of online and in-person instruction, might allow colleges to capture some of the cost-savings without worsening students' outcomes. In this paper, I estimate the effect of adopting a lab-based blended learning model in remedial college math courses, compared to in-person instruction, on course pass rates, progress in college, and degree attainment in a midsize, state community college system. Approximately half of all four-year public colleges and two-thirds of all two-year public colleges offer hybrid or blended learning courses (Parsad and Lewis, 2008). However, the literature on the use of blended learning in college is limited to a handful of studies from microeconomics and statistics courses in four-year colleges. This paper will extend this literature by examining the use of lab-based blended learning at scale in a state community college system for a group of students who have less academic preparation.

If entering college students are unable to pass a placement test in math, reading, or writing, they can be assigned to as many as three remedial courses in a given subject, which they must complete before beginning college-level work. Remedial college courses are common. In a study of students beginning college in the 2003-2004 school year, 68 percent of two-year college students and 40 percent of four-year college students took at least one remedial course in reading, writing, or math (Chen, 2016). Math is the most common remedial placement, but also has the highest rates of failure, with only one-third of students completing the sequence of remedial math courses that they have been assigned to (Bailey, Jeong, and Cho, 2009). With the average remedial student taking 2.6 remedial courses, the estimated cost of providing these courses nationally is US$7 billion per year (Scott-Clayton, Crosta, and Belfield, 2014). In order to improve pass rates, increase the speed of remediation, and reduce costs, colleges have begun to experiment with different approaches to integrate technology into remedial courses.

This paper will examine a model of blended learning called the emporium model which consists of online instruction in a lab setting.[1] Under this approach, students spend class time working at their own pace in a computer lab on a series of modularized lessons, practice problems, and assessments. Instead of providing lectures, instructors and teaching assistants are available onsite to provide personalized assistance to students as questions arise (Twigg, 2011).[2] This model is unique from purely online courses, in which students typically do not come to campus or interact in-person with instructors, and is unique among blended learning approaches

[1] When Virginia Tech first adopted this model in 1997, the large computer lab which was used for these courses was called the Math Emporium. The term "emporium model" was later used by the National Center for Academic Transformation to describe this type of course redesign (NCAT, 2013; de Vise, 2012).

[2] Other innovative approaches have included: a) trying to offer remedial instruction to students in high school or the summer before enrolling in college to avoid the need for remediation and b) offering supplemental supports to remedial students, such as advising or tutoring outside of class (Rutschow and Schneider, 2011). In addition, some colleges have switched to a co-requisite model in which students begin in college-level courses immediately, but receive supplemental support at the same time (Belfield, Jenkins, & Lahr, 2016).

in that the online work is performed on-campus with instructors available to students. The emporium model was created at Virginia Tech in 1997 for introductory college math courses, but has spread more widely over the last decade to institutions ranging from state flagship institutions to community colleges (de Vise, 2012; NCAT, 2016). While blended learning models like the emporium model have grown in popularity, there is little evidence on how computer-based approaches to remediation affect students' success in college (Rutschow and Schneider, 2011).

One reason colleges adopt the emporium model is that it can lower the costs of delivering remedial instruction by allowing colleges to raise class sizes, switch to less expensive instructors, or increase the number of sections faculty teach. While not all institutions choose to adopt cost-saving measures while switching to the emporium model, one estimate from 28 institutions found it reduced the cost per student by 20% on average.[3] Advocates for the emporium model also argue that it can improve students' outcomes through several channels (Twigg, 2013). First, the emporium model is modularized and mastery-based. If a student demonstrates proficiency in one part of the course, she can skip that portion and focus on other areas which are more challenging. This could help students to more efficiently address weaknesses. Second, students are allowed to complete the courses at their own pace. A motivated student could complete multiple remedial courses per semester, unlike under the traditional remediation approach. One the other hand, a student who has not mastered all of the material in the first semester can pick up where he left off in the second semester. Third, an alternative mode of instruction which is

[3] Cost savings estimates from the National Center for Academic Transformation (http://www.thencat.org/Guides/DevMath/Cost_Table.html). Note that these estimates ignore equipment and infrastructure costs of establishing the emporium model (e.g. the cost of establishing computer lab space) and are not necessarily a representative sample of all course redesigns involving the emporium model.

student-led and encourages students to take ownership of their own learning may help students who struggle with traditional lecture-based courses.

Between 2009-10 and 2012-13, eleven colleges in the Kentucky Community and Technical College System (KCTCS) adopted the emporium model in at least one of three math courses in the remedial math sequence. I exploit variation in the timing of the adoption of the emporium model across math courses and across institutions.[4] Using a difference-in-difference-in-differences (i.e. triple difference) identification strategy, I estimate the change in outcomes for cohorts of students within the same college and same level of math remediation before and after the adoption of the emporium model while differencing out the change for students in the same level of remediation in comparison colleges and the change for students in different levels of remediation within the same college.

Across KCTCS colleges, students can be required to complete up to three (sequential) remedial math courses before they can begin college-level work. Since students assigned to different levels of remediation are likely to have different outcomes regardless of their remedial course experiences, this design compares students who begin taking the same level of remedial coursework to one another. In addition to controlling for time invariant differences between students in different levels of remediation and students in different colleges, this design also allows me to difference out changes that affected all remedial courses within an institution (e.g. a change in the supports available to students in remedial courses) and changes within a given level of remediation across institutions (e.g. a change in the placement criteria used by KCTCS) that may have occurred at the same time as the introduction of the emporium model.

[4] For example, some institutions adopted the emporium model in one remedial math course, but not the second or third remedial math courses in a sequence in a given year.

I find that using blended learning in a course reduces students' ability to progress through remediation to credit-bearing courses. Students who are taught using the emporium model are ten percentage points less likely to pass their courses in one semester and are five percentage points less likely to take a college-level math course within three years of enrolling. Students are also six percentage points less likely to be enrolled in college by their second year than students taking the same remedial course under traditional instruction. Within three years of enrolling, students taught using the emporium model are five percentage points less likely to earn a degree. Effects were generally consistent across all three levels of remediation, suggesting there is little variation by students' incoming placement test score.

One concern is that it may not be random which courses switched to the emporium model, and that if these differences were time-varying, they could bias estimates of the effect of the emporium model. For example, if colleges adopted the emporium model in a particular course in response to falling pass rates, this could pose a problem. To address this concern, I conduct event study analyses to test if the adopting courses have similar trends to the comparison courses in the pre-adoption period. I find evidence that suggests the timing of the adoption of the emporium model was likely exogenous.

Another concern is that students might switch their level of remediation in response to the introduction of the emporium model. When students first arrive on campus, they are typically given a placement test (or can use scores from a test they took previously) to determine their placement. However, students sometimes can retake the tests or are otherwise able to avoid remedial courses. If students are more (or less) likely to take these steps to adjust their level of remediation or avoid remediation entirely with the introduction of the emporium model, this could bias the results. To address this, I test for changes in enrollment in remedial courses and test for changes in the observable characteristics of students enrolled at each level of remediation and do not find evidence that these change systematically in response to the introduction of the emporium model.

While it is clear that students perform worse in remedial courses with the emporium model, it is not clear why. In the conclusion, I consider reasons why blended learning might have had such a large effect on a student's likelihood of passing their courses, including the possibility that students struggle with self-management and self-pacing. Because the assessment criteria were not necessarily aligned before and after emporium adoption, it is also possible that students were being held to a higher standard of understanding under the emporium model than before. Because the model typically standardizes assessments across classes and requires students to demonstrate their understanding before moving to the next topic, the new approach may have raised the bar on what is required for passing.

This paper contributes to a growing literature on blended learning. Three randomized studies comparing blended learning to purely in-person instruction have found few differences in students' outcomes (Alpert, Couch, and Harmon, 2016; Joyce, et al, 2015; Bowen, Chingos, Lack, and Nygren, 2014). These studies have been limited to introductory microeconomics or statistics courses at large, four-year public colleges. Given that approximately two-thirds of community colleges report using blended or hybrid online courses, this study will expand the literature to a group of colleges that is highly policy relevant (Parsad and Lewis, 2008). Second, while these studies have strong internal validity, two of the three studies use a sample that is limited to students who volunteered to be randomized into a blended learning course – a group who is likely more amenable to taking a blended learning course than the average student. In contrast, this study examines the introduction of blended learning for all students without the option to participate. Third, most blended learning interventions have mixed students' time in a course between an online component that the student can perform off-campus and an in-person section for either a lecture or a discussion section (Alpert, Couch, and Harmon, 2016; Joyce, et al, 2015; Bowen, Chingos, Lack, and Nygren, 2014). This paper examines a model in which students spend all of the course time working online in an on-campus computer lab with instructors available to answer questions.

One working paper to date has examined a computer-based intervention in remedial college courses. Boatman (2012) estimates the effect of three Tennessee colleges' redesigns of their remedial math programs by comparing regression discontinuity estimates of the effect of assignment to remediation before and after the redesign. Two of the colleges' redesigns used modularized, computer-based remediation reforms, similar to the emporium model. In one of these colleges, students were less likely to persist to their second semester after the redesign went into effect; at the other, there were no differences in students' outcomes. This study builds on this study by examining the introduction of the emporium model at scale in a state community college system.

II. Setting and Context

Between 2008-09 and 2013-14, students enrolling in a KCTCS college who had ACT scores below a given threshold or were missing ACT scores were required to take a placement test.[5] Depending on their placement test score, a student could be referred to one of three different levels of math remediation—Pre-Algebra, Basic Algebra, or Intermediate Algebra—

[5] Valid placement tests included COMPASS, ASSET, and KYOTE in addition to the ACT and SAT over the study period.

depending on the KCTCS guidelines.[6] As shown in Figure 1, students assigned to lower levels of remediation were required to complete upper levels of remediation before beginning college-level courses. For example, a student assigned to Pre-Algebra was required to complete Pre-Algebra and Basic Algebra before beginning college-level math. Students can attempt to avoid remediation by taking the placement test an additional time or through other means, such as obtaining a waiver from an administrator or instructor. However, while students have a strong incentive to do this, they are often uninformed about the stakes of the tests (Venezia, Bracco, and Nodine, 2010).

KCTCS offers three different associate's degrees: an associate in applied science (AAS), an associate in arts (AA) or an associate in science (AS). The latter two degrees are transferrable to a four-year institution and are offered in traditional academic subjects, such as history and mathematics. The former is a terminal associate's degree, which tends to cover applied topics such as automotive technology and dental hygiene. Credits from this type of degree are typically not transferrable to four-year institutions in the state. As shown in Figure 1, students who are interested in pursuing a transferrable associate's degree (AA/AS) must have placed out of remediation entirely on a placement test or complete all of their assigned remedial courses through Intermediate Algebra before beginning the gateway college-level math requirements for these degrees. Students who are interested in pursuing a terminal associate's degree (AAS) must either have placed into Intermediate Algebra or above on the placement test or must complete all

[6] KCTCS set course-specific placement criteria based on a student's test score on the COMPASS, ASSET, or KYOTE test. There were some changes to placement criteria over the study period, including the addition of a new placement test (KYOTE) in 2011-12 and a change in the minimum ACT score from 18 to 19 in 2010-11. Importantly, these differences affected all KCTCS institutions within a given year, allowing the research design to difference out any effect these changes might have on student outcomes.

of their assigned remedial courses through Basic Algebra before beginning the college-level math requirement for that degree track.

Like many states, Kentucky has been concerned in recent years about improving students' academic preparation for college and increasing success in remedial college courses. In 2009, the state passed a law (Senate Bill 1) to change the assessment and accountability system in Kentucky in order to improve the rigor of the state's academic standards and increase the number of students who are college ready. The law in part also called for a "unified strategy" to reduce college remediation rates and to increase completion rates for those enrolled in at least one remedial course. In response, the Kentucky Department of Education (KDE) and the Council of Postsecondary Education (CPE) developed four strategies primarily focused on improving students' college readiness in high school, including access to accelerated learning opportunities (e.g. AP, IB, and dual enrollment opportunities), providing targeted interventions to students who fall behind in high school, and increasing access to high quality college and career advising. It also encouraged colleges to adopt summer bridge programs and "accelerated, online, and/or alternative learning formats" to improve success in remedial courses (CPE, 2010).

While much of the response to these changes targeted high schools, colleges also pursued strategies affecting remediation that generally fell into two categories. First, some colleges within KCTCS decided to transform instruction in remedial courses by adopting the emporium model. At least four of the sixteen colleges in KCTCS received funding from a program funded by the Gates Foundation – Change the Equation – to support these efforts. An additional three were funded through a CPE grant to implement initiatives to support Senate Bill 1 (Quillen, 2010). Second, colleges tried partnering with high schools or creating summer bridge programs to reduce the number of students arriving on campus needing remediation (Quillen, 2010).

However, as shown in Figure 2, the rates at which students enrolled in Pre-Algebra, Basic Algebra, and Intermediate Algebra at adopting and non-adopting institutions stayed mostly constant and parallel between fall 2008 and fall 2013. Therefore, the main impact of the bill at the college level appears to be encouraging some institutions to adopt the emporium model.

Figure 3 illustrates the number of colleges using the emporium model in KCTCS colleges between Fall 2008 and Fall 2013.[7] In total, ten out of fifteen colleges adopted the emporium model in Pre-Algebra and Basic Algebra, mostly in the fall of 2011 but some in the fall of 2010 or 2012.[8] Seven colleges in the sample adopted the emporium model for Intermediate Algebra with an almost even number of adoptions each year in fall 2010, 2011, and 2012.[9] Among colleges which adopted the emporium model, there are a few factors which could have driven differences in the timing of implementation. First, it is possible that some colleges simply heard about the emporium model earlier than others, or that staff or faculty members were more interested in adopting the model than others. In addition, implementation delays may have caused variation across sites in the timing of emporium adoption. Implementing the emporium model required several steps, including setting up an appropriate computer lab space, purchasing software, training faculty members, and in some cases, obtaining funding. Some colleges may have had more available computer lab space suited to the task, while others had to establish these spaces.

[7] Some colleges that adopted the emporium model allowed instructors to do a modified emporium model in which they kept some time for lecture. Note that this should attenuate any differences I find between the emporium model and traditional instruction.

[8] One of the sixteen community colleges in KCTCS is excluded from the analysis sample. See the data section below for more details.

[9] All but one college that adopted the emporium model in Pre-Algebra also adopted it in Basic Algebra at the same time. However, the timing of the adoption of the emporium model in Intermediate Algebra differed from the timing of adoption in Pre-Algebra or Basic Algebra in half of the cases in which a college adopted the emporium model in those courses.

III. Data and Sample

I use data from the Kentucky Center for Education and Workforce Statistics (KCEWS) on college course-taking, enrollment, degree attainment, and student demographics for students enrolled in KCTCS colleges between 2008-09 and 2015-16. I also use high school data from KCEWS including high school ACT scores and free and reduced price lunch (FRPL) status which I merge with the college enrollment files. To identify emporium model courses, I constructed a dataset which tracks the adoption of the emporium model at KCTCS colleges for each of the three remedial math courses offered. I first assembled a dataset based on publicly available sources (e.g. grant documentation, old course schedules, public reports) and then reached out to each of the KCTCS colleges to confirm the implementation timeline.

The sample is limited to degree-seeking students who first enroll in a fall semester between 2008-09 and 2013-14 and who take a remedial math course in their first semester.[10] Many colleges which adopted the emporium model began piloting it in a spring semester before using it in all or almost all of their sections in the fall.[11] Students who take remedial courses in the pilot spring would have a choice as to which section to take, thereby allowing students to select into emporium versus traditional instruction. To avoid this, I restrict the sample to students who first enroll in a fall semester and take their first remedial course that semester. Of course

[10] 58% of students who begin college between 2008-09 and 2013-14 first enroll in a fall semester. Three quarters of students who enroll in a remedial math course within three years take it their first semester.

[11] In a few cases, even in the fall a college did not fully implement the emporium model in all sections. Typically, less than 20% of students were affected, so in these cases the college is coded as using whatever the majority of students were using in that semester. The one exception was Bluegrass Community and Technical College, in which approximately 40% of students were enrolled in the emporium model across several fall semesters. This case is discussed below.

students who were already enrolled before the emporium model might adjust the timing of their remedial course-taking to either take remedial courses under the emporium model or avoid the emporium model. However, this would cause remedial enrollments to either grow or shrink when the emporium model is introduced. I test for changes in remedial enrollment in section V and find no evidence that students were adjusting enrollment in response to the introduction of the emporium model.

I also limit the main analysis sample to exclude one college which allowed students to choose between the emporium model and traditional instruction after adopting the emporium model. In this college, after the adoption of the emporium model, approximately 40% of students were enrolled in the emporium model version of the course and the remaining students were in traditional instruction. Because this college could not be clearly classified as adopting or not adopting, I drop it from the sample. However, the main results hold when I include this college as an adopting institution, though are somewhat attenuated.

Summary statistics for the analysis sample are shown in Table 1 for schools which adopted the emporium model in at least one course and those which never adopted it. The first column includes all degree-seeking students who ever enrolled for the first time between 2008-09 and 2013-14 in any term (fall, spring, or summer). The second column limits the first column's sample to students who are enrolled in a remedial math course within one year of enrolling in college. The third and sixth columns limit the sample further to those who first enroll in the fall and take a remedial course their first semester. Together, these columns constitute the analysis sample.

Adopting colleges tend to have larger annual enrollments and serve a more disadvantaged population. Their students tend to come from counties that have higher poverty rates for school age children (26% vs. 21%) and have ACT English and math scores about one point lower on average. While math remediation rates are high in both groups, students in adopting colleges are also more likely to enroll in a remedial math course within one year of starting college (44% vs. 36%), though three year degree attainment rates are similar (20% vs. 21%). Among remedial students, a similar proportion begin remediation in each of the levels. Approximately half take their first remedial course in the lowest level of remediation (Pre-Algebra). Another 40% begin in Basic Algebra, and only 10% begin in Intermediate Algebra. Demographic characteristics across the two groups of colleges are also similar. In both adopting and non-adopting colleges, about 60% of the sample is female, about 80% are white, and 13% are black.

On average, students in math remediation appear to have lower test scores and worse outcomes than the average student. Remedial students are about 5 percentage points less likely than an average student to earn a degree within three years and have lower ACT math and English scores than the average student by 2-3 points. However, remedial students' demographics including race, age, and poverty rates in their counties of origin are similar to the average student.

About half of the sample of remedial students first enroll in a fall term and take their first remedial course that semester. These students form the analysis sample. This group appears to be similar to the average remedial student in that they have similar ACT math and English scores and are about as likely to graduate within three years. The proportion of students who first enroll in a given remedial course (e.g. Pre-Algebra, Basic Algebra, or Intermediate Algebra) is also similar. Although they mostly have similar demographics, the analysis sample tends to be younger by a year and a half and are more likely to be enrolled full-time. Given that these students are enrolling in a remedial course in their first term, first enroll in the fall, and a more likely to be full-time, the analysis sample may be somewhat positively selected relative to the average remedial student.

IV. Research Design

I use a difference-in-difference-in-differences (triple difference) design to identify the effect of using the emporium model for math remediation compared to traditional instruction in a student's first remedial math course. I estimate change in outcomes for students assigned to the same level of remediation who started college before versus after the implementation of the emporium model while differencing out two changes: first, the change in outcomes for students in the same level of remediation at comparison colleges, and second, the change in outcomes for students in different levels of remediation in the same college.[12] This strategy eliminates any time invariant differences between colleges and courses which adopted the emporium model and those that did not. It will also difference out any contemporaneous statewide changes (such as changes in college readiness standards or labor market conditions) which could be affecting students' outcomes and contemporaneous changes within adopting colleges that affect all remedial courses (such a change in resources available for remedial courses). Also, by making comparisons of colleges which have either adopted the emporium model for a given remediation level or not, I avoid the problem of student selection into emporium courses which might have biased estimates had I simply compared outcomes for students in emporium courses to students in traditional courses within a college. The assumption underlying this strategy is that the

[12] Students can begin in one of three different levels of remediation. Since the courses are sequential, I assign students to a remediation group based on which of the three levels of remediation they first take. I estimate effects on remedial course outcomes only for a student's first remedial course, since the introduction of the emporium model in one course could affect whether a student takes a later course.

differences in outcomes before and after implementation of the emporium model in a particular course in the comparison schools is the same in expectation as it would have been in adopting schools had they not adopted the emporium model.

I estimate the effect of the emporium model by estimating the following model with OLS:

$$(1)\ Y_{icjt} = \beta\, Treat_{cjt} + \theta_{cj} + \pi_{ct} + \lambda_{jt} + \boldsymbol{\gamma X}_{icj} + \varepsilon_{icjt}$$

Y_{icjt} is student i in remedial course c in college j in year t's outcome of interest.[13] $Treat_{cjt}$ is an interaction between an indicator for whether a college j adopted the emporium model for course c and an indicator for whether the year is after the college's adoption year. β is the coefficient of interest capturing the effect of the emporium model. θ_{cj} are course-by-college fixed effects, π_{ct} are course-by-year fixed effects, and λ_{jt} are college-by-year fixed effects. $\boldsymbol{X}_{icj}$ is a vector of time-invariant student characteristics, including gender, race, ethnicity, and age at entry. Lastly, ε_{icjt} is the idiosyncratic error term. Errors are always clustered at the college-course level, as this is the unit at which the treatment is rolled out (Abadie, Athey, Imbens, and Wooldridge, 2017).

In order to relax the assumption that differences between treated and control courses were constant before and after the emporium model was adopted, I also estimate a less parametric specification which allows the effects of treatment in the pre-treatment and post-treatment time periods to vary by year. Specifically, I use equation (1) but replace the treatment indicator with a set of indicators denoting the year relative to the last pre-treatment year ($m = -1$), which is excluded.

[13] Remedial math courses consist of Pre-Algebra, Basic Algebra, or Intermediate Algebra.

$$(2)\ Y_{icjt} = \sum_{m=-4}^{-2} \beta_m Treat\_m_{cjt} + \sum_{m=0}^{3} \beta_m Treat\_m_{cjt} + \theta_{cj} + \pi_{ct} + \lambda_{jt} + \boldsymbol{\gamma X}_{icj} + \varepsilon_{icjt}$$

The pre-treatment coefficients provide a test of whether there are pre-treatment differences in the trends between treated and control group courses, which could be driving the observed results. The post-treatment coefficients help to answer the question of whether the treatment effect varies depending on the year of implementation. For example, we may expect that a college is able to improve its implementation in subsequent years after the initial adoption year so that the effects of the emporium model become more positive over time. Note that the coefficients on the indicators across years are not estimated with a balanced sample, since not all colleges and courses are observed for the full set of pre- and post-treatment years. As a result, the estimates of the indicators for each year relative to treatment will reflect differences in the effects of the emporium model over time but also differences in the implementation of the emporium model at different colleges and in different courses.

Figure 4 demonstrates how the identification strategy will exploit variation in the timing of the rollout of the emporium model across courses. This figure shows the average rate at which students in a given cohort pass their first remedial course, grouping students by the year in which students in their level of remediation in a given college switched to using the emporium model. (For example, a student who starts in Pre-Algebra would be assigned to the Pre-Algebra course group. If their college adopted the emporium model in Pre-Algebra in 2010, they would be included in the "Adopt 2010" group in the figure). In the years before emporium adoption, the figure shows that cohorts had mostly stable pass rates. However, pass rates fell sharply with the adoption of the emporium model for each group. In contrast, the group of students in courses that were never switched to the emporium model ("Never Adopt") have mostly stable pass rates over this period of time.[14] The following section reports the formal estimates from the triple difference model in equation (1).

V. Results

I estimate the effect of blended learning on a range of student outcomes in Tables 2 and 3. In each outcome in Table 2, there are two regressions. The first regression in column 1 uses the pooled $Treat_{cjt}$ as the independent variable of interest. The second regression in columns 2-4 splits $Treat_{cjt}$ into each remedial course to test for heterogeneity by course, i.e. $Treat\_Pre_{cjt}$, $Treat\_Basic_{cjt}$, and $Treat\_Int_{cjt}$ (For example, $Treat\_Pre_{cjt}$ is an interaction between an indicator for whether a college j adopted the emporium model for Pre-Algebra and an indicator for whether the year is on or after the college's adoption year for Pre-Algebra). From each regression, I report the β from the main treatment variable(s) of interest. The results were not sensitive to the inclusion of demographic controls, so for simplicity, only results with controls are shown.

A. Remedial and College Course Outcomes

[14] Goodman-Bacon (2018) shows that time-varying treatment effects in a two-way fixed effect difference-in-differences model (or triple difference, in this case) can lead to biased results. Specifically, the comparison between early adopters and late adopters where early adopters serve as the comparison group for later adopters will be biased if the treatment effects are time-varying. This figure shows that for the 2011 and 2012 adopters, the effect of switching to the emporium model is mostly time-constant. However, for the 2010 adopters, pass rates continued to decrease in the second year after adoption before levelling off. As a result, the part of the estimate that comes from a comparison of early adopters in 2010 to late adopters in 2011 will be biased upward; part of the negative effect of the emporium adoption for the 2011 adopters will be absorbed by the comparison group's negative change in pass rates from 2010 to 2011. Because the triple difference estimates are a weighted average of many difference-in-difference estimates including this one, the estimates will be somewhat understating the true negative effect of emporium adoption and can be viewed as an upper bound estimate of the true negative effect.

When students take remedial math under the emporium model, they are 10 percentage points less likely to pass the course in one semester, relative to a pass rate of 58 percent with traditional instruction.[15] This large drop in pass rates is similar in magnitude across all three levels of remediation. The decrease in pass rates appears to be driven by the fact that students are more likely (by 10 percentage points) to receive a grade indicating the course is incomplete or still in progress. Under the emporium model, if a student has made progress during the semester but not enough to complete the course, she can receive this grade for the semester and then re-enroll the next semester picking up where she left off. Consistent with this policy, under the emporium model students are also more likely to re-enroll in the same course within their first year by 7 percentage points. This result holds across Pre-Algebra and Basic Algebra, but the point estimate for Intermediate Algebra is slightly smaller (4.7 percentage points) and is not statistically significant. Under the emporium model, students were also 5 percentage points less likely to withdraw from their first remedial course, an effect that was concentrated in the two lowest levels of remediation. This may have been due to this fact that students knew that if they were still struggling to master material at the end of the semester, they could continue taking the course into the next semester without receiving a failing grade.

The fact that students are re-enrolling in the same course the next semester raises the possibility that students are simply taking longer to earn a passing grade under blended learning, but eventually pass the course at the same or an even higher rate compared with traditional instruction. However, even one year later, students taking their first remedial math course under

[15] A student is defined as passing a course in one semester if he earns a P (Passing) or a letter grade of D or better in the course that semester. Students who withdraw (W), get an Incomplete (I), or receive a grade that indicates that the course is still in progress (MP or O) are counted as not passing.

blended learning are still 9 percentage points less likely to have ever passed the course, relative to a pass rate of 62 percent under traditional instruction. These effects are consistent in magnitude across all levels of remediation.

Another measure of a student's progress is how quickly she is able to take a college-level math course. Panel B of Table 2 shows that students enrolled in blended learning are 5 percentage points less likely to take college math within three years relative to an average of 38% of students under traditional instruction. The total effect is smaller than the negative effects on pass rates in remedial math because many students "stopout" or dropout of college before they take college math. Still, this result indicates that some students would have taken college math if they were taught using traditional instruction in their remedial courses, but were not able to do so under the emporium model. The negative effects are concentrated among students in Intermediate Algebra, who are 8 percentage points less likely to take college math in their first year under the emporium model. This may be because these students would have been able to move directly to college-level math had they passed Intermediate Algebra, whereas students in lower levels of remediation would have needed to pass other remedial courses before enrolling.[16]

B. College Credits and Retention

Another measure of a student's progress is how many college-level credits he is able to take by the end of his first year. If students are able to progress through their remedial courses more quickly, or if the structure of the emporium model gives students greater flexibility in their schedules, they may be able to take more college-level courses for credit their first year. [17] Table

[16] The exception to this are students in Basic Algebra who do not want to earn an AA or AS degree.

[17] College credits are defined as course credits which count toward students' degrees. These do not include remedial course credits. The typical college course is worth 3 credits.

3 shows there is no change in the number of college credits completed within the first year for students in Pre-Algebra and Basic Algebra. But, students in Intermediate Algebra complete 1.2 fewer college credits (relative to a mean of 11 credits) in their first year. This is consistent with the negative effects on taking college math for this group. If students are unable to pass their remedial math course in their first fall, they are unable to move on to other college courses in their first spring. However, by the end of year three, the average student taught under the emporium model has completed 2.1 fewer college credits than those taught under traditional instruction. The negative effects are largest for students in Intermediate Algebra, who complete 3.7 fewer college credits (relative to the control mean of 22.5 credits), followed by students in Pre-Algebra who complete 1.9 fewer credits.

There is also evidence that students are discouraged from staying enrolled in college due to the emporium model. On average, students are about 6 percentage points less likely to be enrolled in college by the fall after they started (year two), relative to a baseline of 51% of students taught using traditional instruction. The effect is particularly strong for students enrolled in Intermediate Algebra. These students are 11 percentage points less likely to be enrolled by their second year, although the gap drops to 4 percentage points and is no longer statistically significant by the start of the third year. Students starting in the lowest level of remediation—Pre-Algebra – are also 4.8 percentage points less likely to be enrolled by year two, a difference that persists to year three. Results for Basic Algebra students are smaller in magnitude and not statistically significant but are negatively signed. Overall, by year three, students are 4 percentage points less likely to be enrolled.

Together, these results indicate that students are leaving college earlier than they otherwise would have under the emporium model. Of course, this may not be a problem is students are transferring to four-year institutions faster than they otherwise would have. However, there also appears to be no effect on a student's likelihood of transferring to a four-year college (either public or private) within three years on average, and there is a marginally significant reduction in transfer rates of 3.3 percentage points among Intermediate Algebra students.

C. Degree Attainment

Ultimately, students taught under the emporium model are 5 percentage points less likely to have earned any degree (e.g. a certificate, diploma, or associate degree) within three years of enrolling, an effect that is similar in magnitude for students starting in all levels of remediation. Most of this effect is driven by students who would have otherwise earned an associate degree. This was particularly true for Intermediate Algebra students who were six percentage points less likely to earn an associate degree. The negative effects on degree attainment are quite large considering that only 16% earned a degree within three years when taught under traditional instruction. These effects are similar in magnitude to the negative effects on retention, suggesting that students who would have otherwise been able to earn a degree in three years were leaving college as a result of the emporium model.

D. Event Study Effects

Figure 5 plots the β_m terms and the corresponding 95% confidence interval for the main outcomes of interest (The year before emporium adoption ($m = -1$) is the excluded year). Differences in outcomes for treated and control students before the adoption of the emporium model do not appear to be statistically different from one another across the full range of outcomes. However, in the first year of the adoption of the emporium model, students are much less likely to pass their first remedial course by the end of one year. They are also less likely to take and pass a college-level math course within three years and attempt and complete fewer credits within three years. Reflecting the main results, there is also a significant dip in a student's likelihood of re-enrolling in college in their second year and earning a degree within three years in the years after the adoption of the emporium model. These effects are mostly constant in the years following adoption and do not appear to dissipate after colleges have had more time to improve their implementation of the emporium model. While the confidence interval around the point estimates for years after adoption grow larger (likely due to decreasing sample size), the point estimates stay roughly constant or, in the case of retention and degree attainment, appear to grow slightly larger in magnitude in the post-period. Although I cannot track the longer-term outcomes of courses which switched to the emporium model relatively late in the sample, the main results appear to hold over time for courses which switched early. This suggests that colleges have not been able to improve their implementation of the emporium model significantly over time.

E. Treatment Effect Heterogeneity

Next, I explore whether the effect of taking a course under the emporium model differs depending on a students' age, sex, or race. Age is interesting in this context, because younger students might be more comfortable with adopting new technology in the classroom. However, I find that effects of the emporium model are actually less negative for students age 35 and over. As reported in Table 4, students under age 25 and age 25 to 34 have 9 and 12 percentage point decreases in their likelihood of passing their first remedial course within one year of starting college, while students age 35 and older experience no change in outcomes. These differences in treatment effects are statistically significant ($p<0.001$). Long term, students age 35 and older actually earn 4.9 more college credits under emporium instruction. While they are ultimately no more likely to stay enrolled by year 2 or earn a degree within three years, the point estimates on these outcomes are positive (Standard errors are larger for this group because they represent about 20% of the analysis sample). In contrast, students under age 25 and age 25 to 34 earn about two and half fewer credits within three years and are less likely to earn degrees within three years. One theory as to why older students have more positive outcomes could be that these students are more accustomed to managing their time and progress. Since the emporium model requires students to be active learners who manage their own progress and seek help when they need it, older students may have better self-management skills that help them to navigate this environment.

In Table 5, I examine heterogeneity in treatment effects by sex and race. The pattern of results suggests that males and white students experienced larger negative effects of the emporium model. Males were 13.8 percentage points less likely to pass their first remedial course within one year and were 9.2 percentage points less likely to earn a degree within three years. Females experienced smaller decreases in their pass rates (6 percentage points) and degree attainment rates (3 percentage points). White students experienced a 10 percentage point decrease in pass rates as a result of the emporium model and were 7 percentage points less likely to earn a degree within three years. In contrast, black students experienced smaller changes in degree attainment rates on average (The p-value of the difference in the effects on degree attainment for black students compared with white students was 0.079).

VI. Robustness & Validity Checks

While the results indicate that the emporium model is associated with a decrease in pass rates and degree attainment rates, three main threats to validity remain. First, the composition of the students taking remedial courses might have changed at the same time as the introduction of the emporium model. For example, a student may try to avoid remediation by taking the placement test an additional time or by petitioning administrators or faculty. If student effort or college leniency in granting these waivers increased at the same time that the emporium model was implemented, then the observed results may be biased downward.

Table 6 tests for observable changes in remedial enrollment among students who first enroll in college in a fall semester between fall 2008 and fall 2013. If students are more (or less) willing to comply with assignment to remediation under the emporium courses or if schools become more (or less) strict about allowing students to avoid remediation under the emporium model then the introduction of the emporium model should predict a change in enrollment in remedial courses. To test this, I estimate enrollment changes using a basic difference-in-differences model with year and institution-by-course fixed effects using a dataset that is collapsed to the institution-course-year level. I find that the introduction of the emporium model in any course in a college or in a specific course does not affect the number of students enrolling in a remedial course in their first term or within one year.

I also check for changes in the observable characteristics of students in the analysis sample in Panel B of Table 6 by using equation (1) but replacing the outcome with student characteristics. If the introduction of the emporium model coincided with changes in the composition of the student body (e.g. if more well-informed or motivated students choose to take remediation under the emporium model or avoid it), this could be driving the observed results. On average and within individual courses there are few differences in the type of student taking remedial courses after the introduction of the emporium model by sex, race, full-time status, age of entry, ACT math scores, and free-and-reduced price lunch in 12th grade. Students enrolled in Basic Algebra are slightly more likely to be black, but this change does not occur in any other course or on average across courses. Similarly, students in Pre-Algebra are slightly older, but this difference is also not present across other levels of remediation or on average. Lastly, there is an increase in ACT English scores in Pre-Algebra and an increase in average ACT English scores.

However, these few changes are unlikely to drive the observed results. First, given that the pattern of results is typically consistent across all three levels of remediation, it is implausible that changes in specific levels of remediation (such as the increase in student age in Pre-Algebra) are driving the results. Second, the direction of any bias induced by these small changes would likely be positive, as older students and students with higher ACT English scores are more likely to succeed in college. Thus, the observed results would be a lower bound estimate of the true effect. Third, the main specifications control for most of these characteristics (race, sex, age at entry, full-time status) and the findings are not sensitive to the inclusion of controls, as shown in Table A1 in the Appendix. Because only 36% of the sample has ACT math and English scores, I conduct an extra robustness test in which I limit the sample to those with ACT math and English scores and then test for the sensitivity of the estimates to these controls in Table A2 in the Appendix.[18] I find no evidence that the main results are sensitive to the inclusion of test score controls.

A second potential threat to validity is that the timing of the adoption of the emporium model in specific courses at specific colleges may not be random. Colleges which choose to adopt the emporium model may be motivated to make changes in a course in which pass rates have been falling. Because it takes time to establish an emporium center (e.g. prepare a computer

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[18] ACT math and English scores in this sample come from merging community college enrollees with their high school assessment records. Kentucky started statewide ACT testing for 11th graders in 2007-08. By 2009-10, most students enrolling in community college straight after leaving high school have an ACT score. However, because most community college enrollees are much older than 18, many students in the sample are missing testing records.

lab, vet and purchase the software, prepare instructors, pilot the program), most colleges typically have a lag of a year or two between the time when they decide to implement the emporium model on their campus in a given course and when they actually implement it. This provides an opportunity to test if other factors which led a college to adopt the emporium model in a particular course are in fact driving the observed results. To test this hypothesis, I use the event study models in Figure 5. The results show that in the years prior to adopting the emporium model there were not statistically significant differences between the treatment and control group trends, which supports the claim that there were no other changes that occurred in the years before emporium adoption that might be driving the observed results. Instead, across all the main outcomes of interest, there is a sharp change in trends in the first year of emporium adoption. I also examine whether the results would hold if I limit the sample just to institutions which adopted the emporium model in at least one remedial course. The results from this exercise (shown in Table A3) are quite similar to the main results shown in Tables 2 and 3.

The third threat to validity is that colleges which adopt the emporium model in a particular course might differ from colleges that do not in ways which could affect the results. For example, it could be that instead of choosing to introduce the emporium model, the control colleges decided to implement other changes to improve their students' outcomes. Aside from the emporium model, another reform idea that colleges could have pursued was working with high schools in the area to reduce students' need for remediation before they arrive on campus. First, unlike the emporium model, these changes were aimed at reducing the total number of students in remediation, not changing the instruction in remedial courses. Second, if control colleges were adopting these measures at the same time that the emporium model was being implemented at treated colleges, it would reduce the total number of students needing remediation in the control colleges relative to treated colleges. However, neither Figure 2 nor Table 6 show evidence that the fraction or the number of students enrolling in remedial courses increases with the introduction of the emporium model.

VII. Discussion and Conclusion

This study provides evidence on the effects of using blended learning in college courses. Using a triple difference design, I find that students enrolled in courses using the emporium model are significantly less likely to pass their first remedial course than if they had been taught with traditional instruction. Moreover, the emporium model is associated with a reduction in the number of college credits students earn. In other words, students who are taught using blended learning are kept from progressing to college-level courses that some of these students would have otherwise passed. Students also leave college earlier than they otherwise would have. Three years after enrolling, students are 5 percentage points less likely to have earned any degree (certificate, diploma, or associate's) and 4 percentage points less likely to earn an associate's degree specifically than if they had been taught with traditional instruction.

Jepsen, Troske, and Coomes (2014) estimate that KCTCS graduates with associate's degrees increase their quarterly earnings by $1,484 for males and $2,363 for females approximately five to six years after entering college compared to students who do not earn a degree (as measured in 2008 dollars). Assuming these gains are constant and that a student works for an additional twenty years, the additional income a student could gain would be almost $120,000 for males and $190,000 for females over their lifetimes. For the students who are kept from earning a degree because of the emporium model, these losses are significant.

These results suggest caution in using blended learning approaches with students who are less academically prepared for college. Prior studies of blended learning at the college-level have found no difference between blended and in-person instruction, but have focused on students in four-year public institutions in microeconomics and statistics courses, in some cases with samples of students who volunteer to be randomized. This study extends this literature to students in two-year colleges in remedial math courses, and examines a context in which students do not have a choice of using in-person or blended learning. The results resemble the negative findings from studies comparing online to in-person courses[19] and accord with the general pattern of results from these studies which have found larger negative effects for students with lower levels of academic preparation (Bettinger, et al, 2017; Xu and Jaggars, 2013).[20]

Although it is clear that students struggle to pass their courses under the emporium model, it is not clear why. Three potential mechanisms might be at work. First, online courses appear to require greater self-management skills to direct student learning (Bork & Rucks-Ahidiana, 2013). In a qualitative study of computer-mediated instruction in Tennessee, Fay (2017) finds that colleges treat students as self-managed, autonomous learners, while high schools adopting the same model of instruction provided greater scaffolding to students. Coming

[19] For example, Xu and Jaggars (2013) find students are less likely to stay enrolled to the end of the term (i.e. are more likely to withdraw) by 6.5 percentage points when the course is online compared to in-person, which is somewhat similar to the 4.5 percentage point increase in withdrawals I find. Similarly, Bettinger, Fox, Loeb, and Taylor (2017) find that taking a course online compared to in-person reduces retention to the second year by 10.5 percentage points, while I find a 6 percentage point reduction.

[20] While students in this sample are less academically prepared than the average community college student, they may be somewhat positively selected among all remedial math students because the analysis sample is focused on students who take remedial math in their first term and enroll in a fall term. It is possible that the negative effects would be even larger in magnitude if all remedial students were included in the sample.

from a structured high school environment to college, students may struggle under the emporium model to complete their coursework if they lack supports such as class-imposed deadlines, especially if they know they can just pick up where they left off in the next semester if they do not finish.

Second, the self-directed nature of the emporium model might hurt students' ability to form relationships with other students and professors, which could reduce their attachment to college. Studies of online learning have found that students describe their online instructors as more "distant" and less "personal" than their interactions in a traditional classroom (Jaggars, 2014). Because the emporium model is typically self-directed, students also may not have as many natural opportunities to interact with their peers and understand how they are learning in the classroom. First generation students in particular may be unaware of what is necessary to succeed and may struggle to absorb norms from their peers given a more limited opportunity to interact or observe others' learning (Collier and Morgan, 2008).

Third, it is also possible that fewer students passed under blended learning because students are held to a common standard that might be higher than what they would have experienced in a traditional classroom. Because the emporium model is mastery based, students cannot move on to the next module without passing the previous one. The assessments were also not standardized between the pre-adoption and post-adoption periods, so another possibility is that the assessment became more challenging. However, even if the emporium model is simply holding students to a higher standard before allowing them to enroll in college-level courses, this higher standard appears to keep students from enrolling in college math courses they would have otherwise been able to succeed in. Compared to students in traditional instruction, by their third year students in remedial blended learning courses are five percentage points less likely to take college math, earn 2.1 fewer college credits, are four percentage points more likely to leave college, and are five percentage points less likely to earn a degree. If the standard for passing remedial courses has been raised, it has been raised to a level that keeps students from earning degrees that they otherwise would have been able to obtain.

Overall, the results from this study indicate that blended learning models such as the emporium model may not be as effective as in-person instruction in remedial math courses. Future research should aim to disentangle the mechanisms driving these results and test modifications to the emporium model that might improve students' experiences. For example, colleges have discretion over several elements of the emporium model, such as the student-to-instructor ratio and the type of instructors in the classes (e.g. adjunct faculty, tenured faculty, tutors). Colleges can also choose whether to set specific class times that students must be in the lab or can allow students to drop-in during specific hours. Similarly, instructors can decide how much scaffolding to provide to help students pace themselves through the semester. As colleges try to innovate to improve students' outcomes and reduce the costs of instruction, it is clear that it will be necessary to continue to experiment and rigorously evaluate these efforts to identify blended learning models that might be as effective as in-person instruction for less academically prepared students.

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Table 1. Summary Statistics

	Adopting Colleges			Never Adopting Colleges		
	All Students	Remedial Math Students	Remedial Students Who Enroll in Fall & Take Remedial Math 1st Term	All Students	Remedial Math Students	Remedial Students Who Enroll in Fall & Take Remedial Math 1st Term
Academic year enrollment	8,873			7,961		
	(5,747)			(4,231)		
Earn degree within 3 years	0.20	0.15	0.14	0.21	0.17	0.15
Take remedial math course within year 1	0.44	1	1	0.36	1	1
Enroll in fall and take remedial math 1st term	0.21	0.47	1	0.16	0.45	1
Begin in Pre-Algebra	0.22	0.50	0.51	0.17	0.48	0.47
Begin in Basic Algebra	0.17	0.39	0.39	0.15	0.41	0.41
Begin in Intermediate Algebra	0.05	0.11	0.11	0.04	0.12	0.12
Full time	0.51	0.62	0.75	0.46	0.54	0.69
Female	0.59	0.63	0.63	0.58	0.61	0.61
White	0.81	0.80	0.82	0.79	0.78	0.79
African-American	0.13	0.15	0.13	0.13	0.15	0.14
Other race	0.04	0.04	0.04	0.07	0.06	0.06
Race not reported	0.02	0.01	0.01	0.02	0.01	0.01
County of origin poverty rate (age 5-17)	25.83	26.43	26.94	20.90	20.94	21.19
	(8.64)	(8.68)	(8.80)	(6.01)	(5.80)	(5.83)
Age at entry	28.76	28.27	26.64	28.29	28.71	27.23
	(10.03)	(9.73)	(9.17)	(9.68)	(9.60)	(9.27)
ACT math	17.80	16.10	16.07	18.81	16.08	16.01
	(3.49)	(1.90)	(1.79)	(3.93)	(1.86)	(1.68)
ACT English	17.71	15.98	15.97	18.70	15.94	15.87
	(5.13)	(4.38)	(4.30)	(5.22)	(4.21)	(4.14)

Missing ACT math or English	0.70	0.70	0.62	0.70	0.75	0.66
Colleges	10	10	10	5	5	5
Observations	107,237	47,501	22,204	72,509	26,103	11,846

Notes: Means are reported with standard deviations in parentheses for continuous variables. Sample is limited to degree-seeking students who first enroll in the KCTCS system between the 2008-09 and 2013-14 school years. The second and fifth columns restrict this sample to students who enroll in a remedial math course within one year of starting college. The third and sixth columns limit the sample further to students who first enroll in the fall and take a remedial math course their first semester. Academic year enrollment consists of the total number of students who enroll for the first-time in the fall, spring, or summer of a given year. County of origin poverty rate is missing for a small number of students (less than 5% in all columns). Poverty rates come from the 2009 Small Area Income and Poverty Estimates (SAIPE). Age at entry calculated based on birth year and term-year of entry into college. One college is excluded to match the analysis sample.

Table 2. Impact of Emporium Model on Course Outcomes

	(1)	(2)			
Dependent Variable	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Control Mean
A. Remedial Course					
Pass in 1st semester	-0.103***	-0.105***	-0.124***	-0.079**	0.58
	(0.024)	(0.030)	(0.031)	(0.036)	
Incomplete/Making Progress in 1st semester	0.099***	0.109***	0.136***	0.049	0.03
	(0.030)	(0.027)	(0.025)	(0.036)	
Withdraw in 1st semester	-0.045**	-0.062***	-0.062***	-0.002	0.12
	(0.020)	(0.020)	(0.020)	(0.040)	
Re-enroll in same course within 1 year	0.073***	0.076***	0.095***	0.047	0.13
	(0.023)	(0.023)	(0.023)	(0.033)	
Pass within 1 year	-0.093***	-0.093***	-0.107***	-0.079**	0.62
	(0.021)	(0.028)	(0.028)	(0.036)	
B. College Math					
Take college math in year 1	-0.031	0.004	-0.036	-0.081*	0.18
	(0.030)	(0.026)	(0.028)	(0.042)	
Take college math within 3 years	-0.047*	-0.024	-0.042	-0.088**	0.38
	(0.025)	(0.025)	(0.027)	(0.034)	

Notes: Each number 1-2 at the top of the table represents a separate regression. In the first regression, point estimates are shown for the main variable of interest (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). The second regression splits this variable into the three possible levels of remediation that a student could take. Standard errors are clustered at the college-course level in parentheses. All regressions have demographic controls and institution-by-year, institution-by-course, and course-by-year fixed effects. Sample is limited to students who first enroll in a fall semester and take a remedial course their first semester between 2008-09 and 2013-14. All regressions have 34,050 observations, except for the following cases: Students missing a grade in their first term remedial course are dropped from the sample for the following outcomes - Pass within 1st semester, Incomplete/Making Progress in 1st semester, Withdraw in 1st semester – yielding a sample size of 32,972. Students who are missing grades for all courses taken in their first year are dropped from the sample for the following outcome – Pass within 1 year – yielding a sample size of 33,092. Almost all of the missing observations come from 3 institutions in the 2008-09 school year which did not report grades in remedial math courses. Excluding students in these institutions in 2008-09, only 0.4% of the sample is missing a grade. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Impact of Emporium Model on College Credits, Retention, & Degree Attainment

	(1)	(2)			
Dependent Variable	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Control Mean
A. College Credits and Retention					
College credits completed in year 1	-0.364	-0.163	0.157	-1.168***	10.66
	(0.271)	(0.310)	(0.339)	(0.432)	
College credits completed within 3 years	-2.136***	-1.878***	-0.958	-3.650***	22.51
	(0.734)	(0.657)	(0.852)	(1.072)	
Retention to year 2	-0.059**	-0.048**	-0.021	-0.113***	0.51
	(0.023)	(0.021)	(0.023)	(0.021)	
Retention to year 3	-0.038*	-0.044**	-0.022	-0.042	0.31
	(0.019)	(0.019)	(0.021)	(0.025)	
Transfer to 4-year within 3 years	-0.003	0.008	0.009	-0.033*	0.13
	(0.015)	(0.015)	(0.015)	(0.019)	
B. Degree Attainment					
Earn any degree within 3 years	-0.051***	-0.047**	-0.049**	-0.057**	0.16
	(0.016)	(0.017)	(0.020)	(0.023)	
Earn associate degree within 3	-0.041***	-0.030*	-0.036**	-0.063***	0.08
	(0.013)	(0.016)	(0.016)	(0.016)	

Notes: Each number 1-2 at the top of the table represents a separate regression. In the first regression, point estimates are shown for the main variable of interest (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). The second regression splits this variable into the three possible levels of remediation that a student could take. Standard errors are clustered at the college-course level in parentheses. All regressions have demographic controls and institution-by-year, institution-by-course, and course-by-year fixed effects. Sample is limited to students who first enroll in a fall semester and take a remedial course their first semester between 2008-09 and 2013-14. All regressions have 34,050 observations. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Impact of Emporium Model by Age

	By Age		
Dependent Variable	<25	25 to 34	>34
A. Course Outcomes			
Pass within one year	-0.091***	-0.120***	-0.006
	(0.027)	(0.040)	(0.041)
Control Means	0.57	0.67	0.70
Observations	18,245	8,525	6,322
B. Later Outcomes			
College credits completed within 3 years	-2.590***	-2.651**	4.907***
	(0.835)	(1.280)	(1.770)
Control Means	20.32	23.19	27.98
Retention to year 2	-0.092***	-0.014	0.068
	(0.022)	(0.042)	(0.051)
Control Means	0.48	0.52	0.59
Earn degree within 3 years	-0.040***	-0.107***	0.016
	(0.010)	(0.029)	(0.042)
Control Means	0.12	0.18	0.24
Observations	18,786	8,786	6,478

Notes: Each column shows the results from a separate regression matching the regression used in column 1 of Tables 2 and 3, but using a sample that is limited to the subgroup noted in the column heading. Point estimates are shown for the main variable of interest (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). Standard errors are clustered at the college-course level in parentheses. All regressions have demographic controls and institution-by-year, institution-by-course, and course-by-year fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Impact of Emporium Model By Sex and Race

	By Sex		By Race	
Dependent Variable	Male	Female	Black	White
A. Course Outcomes				
Pass within 1 year	-0.138***	-0.062**	-0.047	-0.100***
	(0.034)	(0.030)	(0.039)	(0.024)
Control Means	0.56	0.66	0.51	0.64
Observations	12514	20578	4326	26828
B. Later Outcomes				
College credits completed within 3 years	-2.596*	-1.783**	-0.304	-2.228**
	(1.342)	(0.687)	(1.693)	(0.901)
Control Means	20.65	23.62	16.90	23.41
Retention to year 2	-0.050*	-0.067***	-0.052	-0.057*
	(0.029)	(0.023)	(0.037)	(0.029)
Control Means	0.45	0.55	0.44	0.52
Earn degree within 3 years	-0.092***	-0.028*	-0.016	-0.071***
	(0.022)	(0.016)	(0.026)	(0.017)
Control Means	0.13	0.17	0.09	0.17
Observations	12837	21213	4437	27633

Notes: Each column shows the results from a separate regression matching the regression used in column 1 of Tables 3 and 4, but using a sample that is limited to the subgroup noted in the column heading. Point estimates are shown for the main variable of interest (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). Standard errors are clustered at the college-course level in parentheses. All regressions have demographic controls and institution-by-year, institution-by-course, and course-by-year fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Impact of Emporium Model on Enrollment and Student Characteristics

Dependent Variable	(1) Emporium in any course	(2) Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra
A. Enrollment				
# Enrolling in a Remedial Math Course Within 1 Year	-12.586	6.450	-23.028	-24.897
	(11.109)	(14.082)	(18.306)	(15.705)
# Enrolling in Remedial Math Course in First Term	-8.315	2.490	-11.588	-19.136
	(9.080)	(11.037)	(15.121)	(12.010)
B. Student Characteristics				
Female	0.004	-0.016	0.003	0.037
	(0.017)	(0.020)	(0.025)	(0.030)
White	-0.001	-0.005	-0.013	0.017
	(0.013)	(0.011)	(0.015)	(0.017)
Black	0.016	0.018	0.034**	-0.005
	(0.011)	(0.011)	(0.014)	(0.017)
Full time	-0.011	-0.005	-0.017	-0.013
	(0.015)	(0.019)	(0.023)	(0.020)
Age at entry	0.460	1.239**	-0.255	-0.079
	(0.403)	(0.563)	(0.556)	(0.843)
ACT math	0.056	0.065	0.150	-0.020
	(0.092)	(0.103)	(0.123)	(0.177)
ACT English	0.558**	0.785***	0.328	0.479
	(0.246)	(0.276)	(0.362)	(0.320)
FRPL in 12th Grade	0.000	0.001	0.025	-0.017
	(0.021)	(0.028)	(0.032)	(0.040)

Notes: Panel A uses a dataset that is collapsed to the institution-course-year level to estimate the effect of the emporium model on changes in course enrollment in fall terms from fall 2008 to fall 2013. Column 1 regresses enrollment in a remedial math course in a student's first term or within one year on an indicator for a college having adopted the emporium model in a course by that year. This model includes year, institution, and institution-by-course fixed effects. Columns 2-4 repeat this exercise but break out the adoption indicator into the three possible course options. Panel B reports the main variable of interest from equation (1) and uses the analysis sample, i.e. students who enrolled for the first time in a fall semester between fall 2008 and fall 2013 and enrolled in a remedial math course in their first term. Sample size in Panel A is 270 and Panel B is 34,050, except for the ACT math (12,391), ACT English (12,412), and FRPL (10,811) regressions. See Table 1 notes for more details on Panel B variables. Standard errors are clustered at the college-course level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A1. Impact of Emporium Model After Adding Demographic Controls

	(1)	(2)			(3)	(4)			
Dependent Variable	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Control Mean
Pass within 1 year	-0.093***	-0.091***	-0.113***	-0.076**	-0.092***	-0.093***	-0.106***	-0.078**	0.62
	(0.022)	(0.029)	(0.029)	(0.037)	(0.021)	(0.028)	(0.028)	(0.036)	
Re-enroll in same course within 1 year	0.074***	0.077***	0.098***	0.046	0.073***	0.076***	0.095***	0.047	0.13
	(0.023)	(0.023)	(0.023)	(0.033)	(0.023)	(0.023)	(0.023)	(0.033)	
Take college math within 3 years	-0.046*	-0.020	-0.046*	-0.085**	-0.046*	-0.024	-0.040	-0.087**	0.38
	(0.025)	(0.025)	(0.027)	(0.033)	(0.025)	(0.025)	(0.026)	(0.033)	
College credits completed within 3 years	-2.029***	-1.579**	-1.193	-3.520***	-2.048***	-1.877***	-0.785	-3.506***	22.51
	(0.667)	(0.643)	(0.861)	(1.020)	(0.674)	(0.605)	(0.746)	(1.009)	
Retention to year 2	-0.057**	-0.043**	-0.023	-0.109***	-0.058**	-0.048**	-0.019	-0.111***	0.51
	(0.022)	(0.020)	(0.021)	(0.021)	(0.023)	(0.020)	(0.022)	(0.021)	
Earn degree within 3 years	-0.049***	-0.043**	-0.052***	-0.055**	-0.050***	-0.047***	-0.048***	-0.056***	0.16
	(0.014)	(0.016)	(0.019)	(0.021)	(0.013)	(0.016)	(0.017)	(0.019)	
Controls for Student Characteristics					X	X	X	X	

Notes: Each number 1-4 at the top of the table represents a separate regression. In the first and third regressions, point estimates are shown for the main variable of interest in equation 1 (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). The second and fourth regressions split this variable into the three possible levels of remediation that a student could take. The first and second regressions do not include demographic controls (sex, race, age-at-entry, full-time status), while the third and fourth do. Standard errors are clustered at the college-course level in parentheses. All regressions have institution-by-year, institution-by-course, and course-by-year fixed effects. Sample is limited to students who first enroll in a fall semester, take a remedial course their first semester between 2008-09 and 2013-14. The first regression has 32,972 observations, while all others have 34,050 observations (This difference is due to missing grades for a small number of students). *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Impact of Emporium Model for Students Who Have an ACT Math Score

	(1)	(2)			(3)	(4)			
Dependent Variable	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Control Mean
Pass within 1 year	-0.067**	-0.098**	-0.075**	-0.032	-0.069**	-0.099**	-0.080**	-0.031	0.61
	(0.028)	(0.040)	(0.035)	(0.039)	(0.029)	(0.040)	(0.035)	(0.041)	
Re-enroll in same course within 1 year	0.058*	0.061	0.076**	0.042	0.058*	0.061	0.078**	0.041	0.14
	(0.034)	(0.039)	(0.038)	(0.048)	(0.033)	(0.038)	(0.037)	(0.046)	
Take college math within 3 years	-0.081***	-0.066***	-0.081**	-0.097***	-0.082***	-0.067**	-0.085***	-0.096***	0.39
	(0.021)	(0.024)	(0.030)	(0.035)	(0.021)	(0.025)	(0.030)	(0.035)	
College credits completed within 3 years	-2.206	-1.797	-0.380	-3.915**	-2.230	-1.804	-0.500	-3.887**	23.39
	(1.384)	(1.606)	(1.786)	(1.538)	(1.431)	(1.623)	(1.802)	(1.654)	
Retention to year 2	-0.108***	-0.111***	-0.049	-0.148***	-0.109***	-0.111***	-0.050	-0.147***	0.53
	(0.029)	(0.032)	(0.036)	(0.036)	(0.029)	(0.032)	(0.036)	(0.037)	
Earn degree within 3 years	-0.037**	-0.066***	-0.033	-0.013	-0.038**	-0.066***	-0.034	-0.012	0.14
	(0.018)	(0.023)	(0.029)	(0.029)	(0.019)	(0.024)	(0.030)	(0.029)	
Controls for ACT Math					X	X	X	X	

Notes: Each number 1-4 at the top of the table represents a separate regression. In the first and third regressions, point estimates are shown for the main variable of interest in equation 1 (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). The second and fourth regressions split this variable into the three possible levels of remediation that a student could take. The first and second regressions do not include controls ACT math, while the third and fourth do. Standard errors are clustered at the college-course level in parentheses. All regressions have demographic controls and institution-by-year, institution-by-course, and course-by-year fixed effects. Sample is limited to students who first enroll in a fall semester, take a remedial course their first semester between 2009-10 and 2013-14, and have an ACT math score. The first regression has 11,101 observations, while all others have 11,138 observations (This difference is due to missing grades for a small number of students). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table A3. Impact of Emporium Model on College Credits, Retention, & Degree Attainment with Sample Limited to Adopting Colleges

	(1)	(2)			
Dependent Variable	Emporium in any course	Emporium in Pre-Algebra	Emporium in Basic Algebra	Emporium in Intermediate Algebra	Control Mean
A. Course Outcomes					
Pass within 1 year	-0.088***	-0.127***	-0.047	-0.053	0.60
	(0.025)	(0.027)	(0.032)	(0.035)	
Re-enroll in same course within 1 year	0.063**	0.087***	0.061**	0.035	0.13
	(0.027)	(0.020)	(0.025)	(0.051)	
B. Later Outcomes					
Take college math within 3 years	-0.046*	-0.013	0.002	-0.103***	0.38
	(0.023)	(0.013)	(0.024)	(0.037)	
College credits completed within 3 years	-2.462***	-1.821***	-0.633	-3.904***	23.63
	(0.618)	(0.618)	(1.177)	(1.322)	
Retention to year 2	-0.061***	-0.025	0.007	-0.131***	0.54
	(0.019)	(0.016)	(0.021)	(0.029)	
Earn any degree within 3 years	-0.051***	-0.039**	-0.027	-0.073***	0.16
	(0.012)	(0.018)	(0.023)	(0.021)	

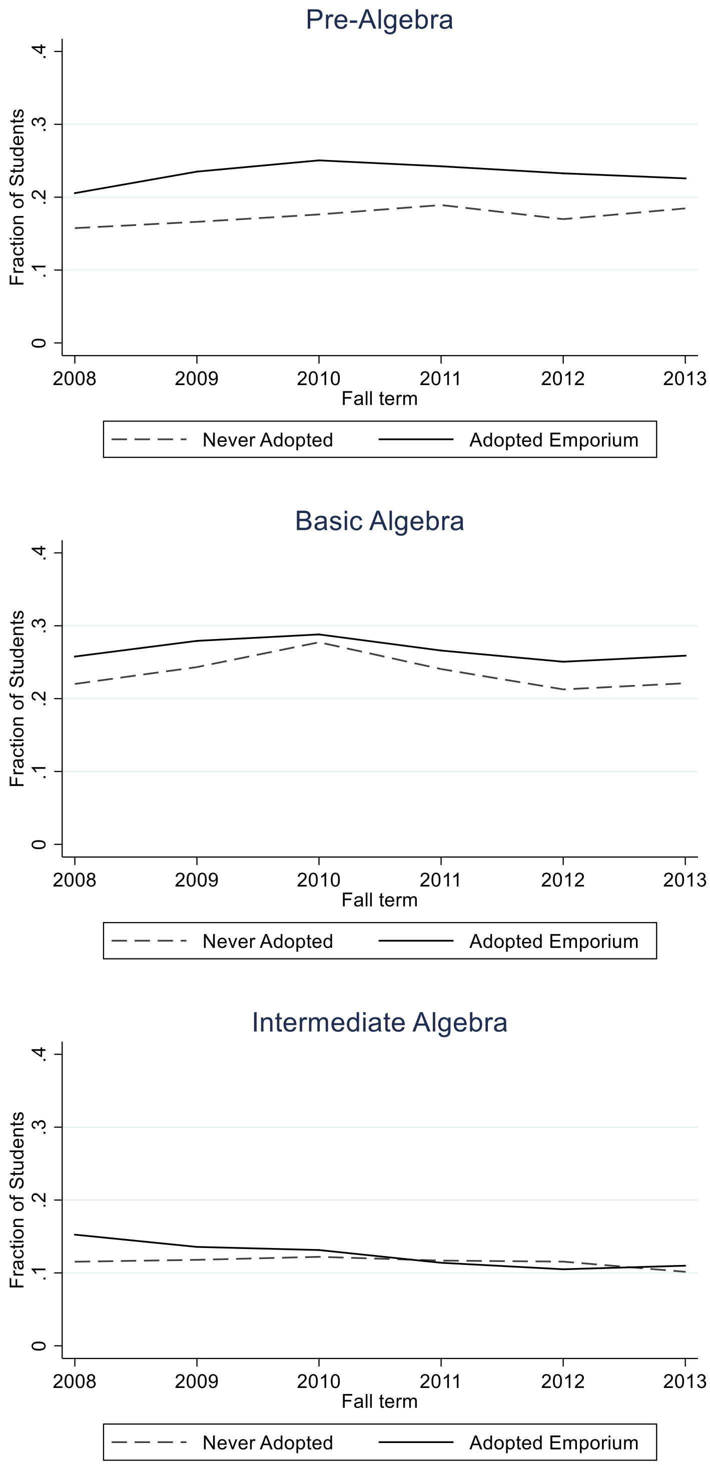
Notes: Each number 1-2 at the top of the table represents a separate regression. In the first regression, point estimates are shown for the main variable of interest (an interaction between an indicator for the post-treatment period and an indicator for being in a treated college and course). The second regression splits this variable into the three possible levels of remediation that a student could take. Standard errors are clustered at the college-course level in parentheses. All regressions have demographic controls and institution-by-year, institution-by-course, and course-by-year fixed effects. Sample is limited to students who first enroll in a fall semester, take a remedial course their first semester between 2008-09 and 2013-14, and are enrolled in a college that adopts the emporium model at some point during this time. In Panel A, the first regression has 21,706 observations and the second has 22,204 due to a small number of students missing grades. All regressions in Panel B have 22,204 observations. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Remedial Placement and College Math Course Eligibility

Remedial Placement on Math Test	Requirements before enrolling in lowest level math required for …	
	AAS Degree	AA or AS Degree
1) No Remediation	None	None
2) Intermediate Algebra	None	Pass Intermediate Algebra
3) Basic Algebra	Pass Basic Algebra	Pass Basic Algebra, then Pass Intermediate Algebra
4) Pre-Algebra	Pass Pre-Algebra, then Pass Basic Algebra	Pass Pre-Algebra, then Pass Basic Algebra, then Pass Intermediate Algebra

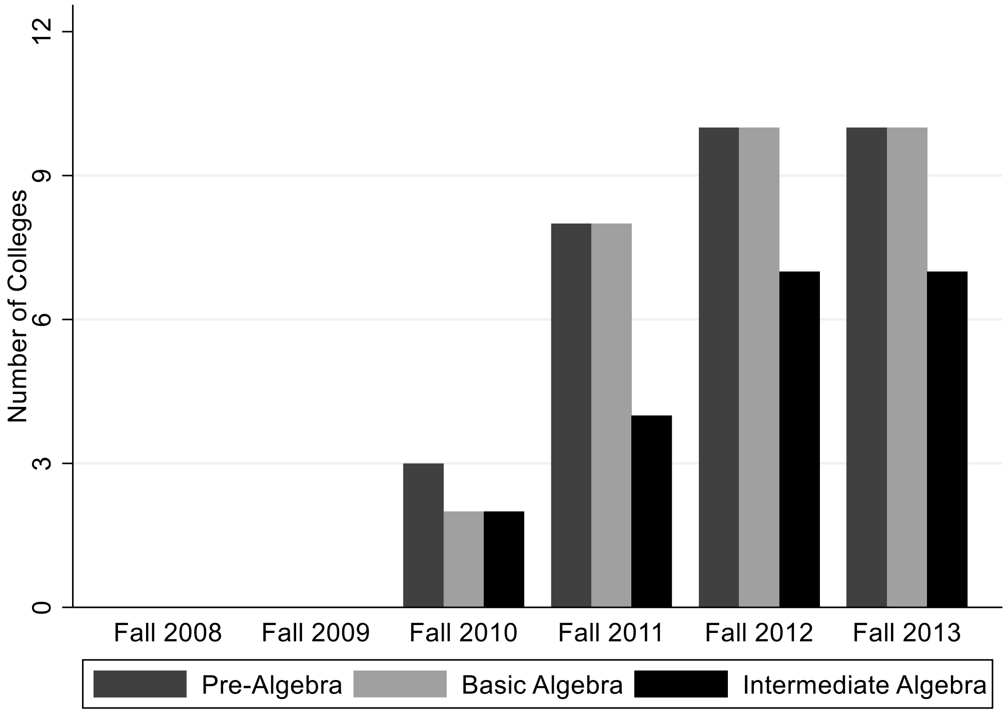
Notes: Darker shading indicates a lower initial placement on the placement test. AAS degree indicates an Associate of Applied Science, AA indicates Associate of Arts, and AS indicates Associate of Science.

Figure 2. Fraction of Entering Students Taking a Remedial Math Course at Adopting and Non-Adopting Institutions, Fall 2008 to Fall 2013



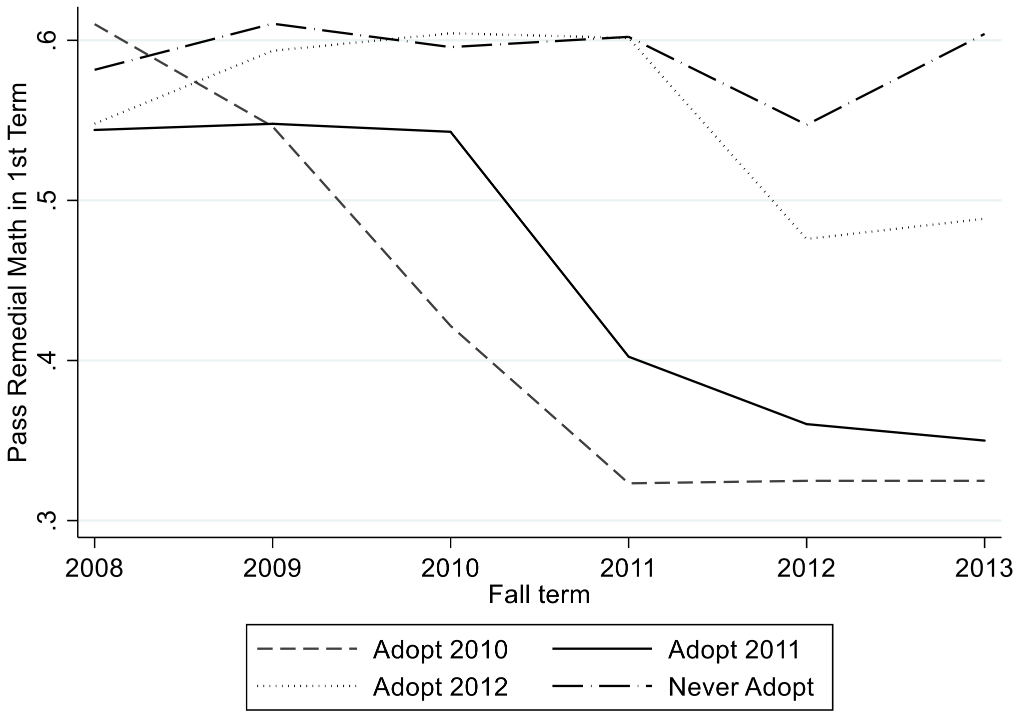
Notes: Sample includes all students who enroll in the fall between 2008-09 and 2013-14 at adopting and non-adopting institutions. Students are counted as taking a particular remedial math course if they enroll in that remedial math course by the fall after first enrolling in college. Bluegrass Community and Technical College is excluded to match the analysis sample.

Figure 3. Number of Colleges Using the Emporium Model



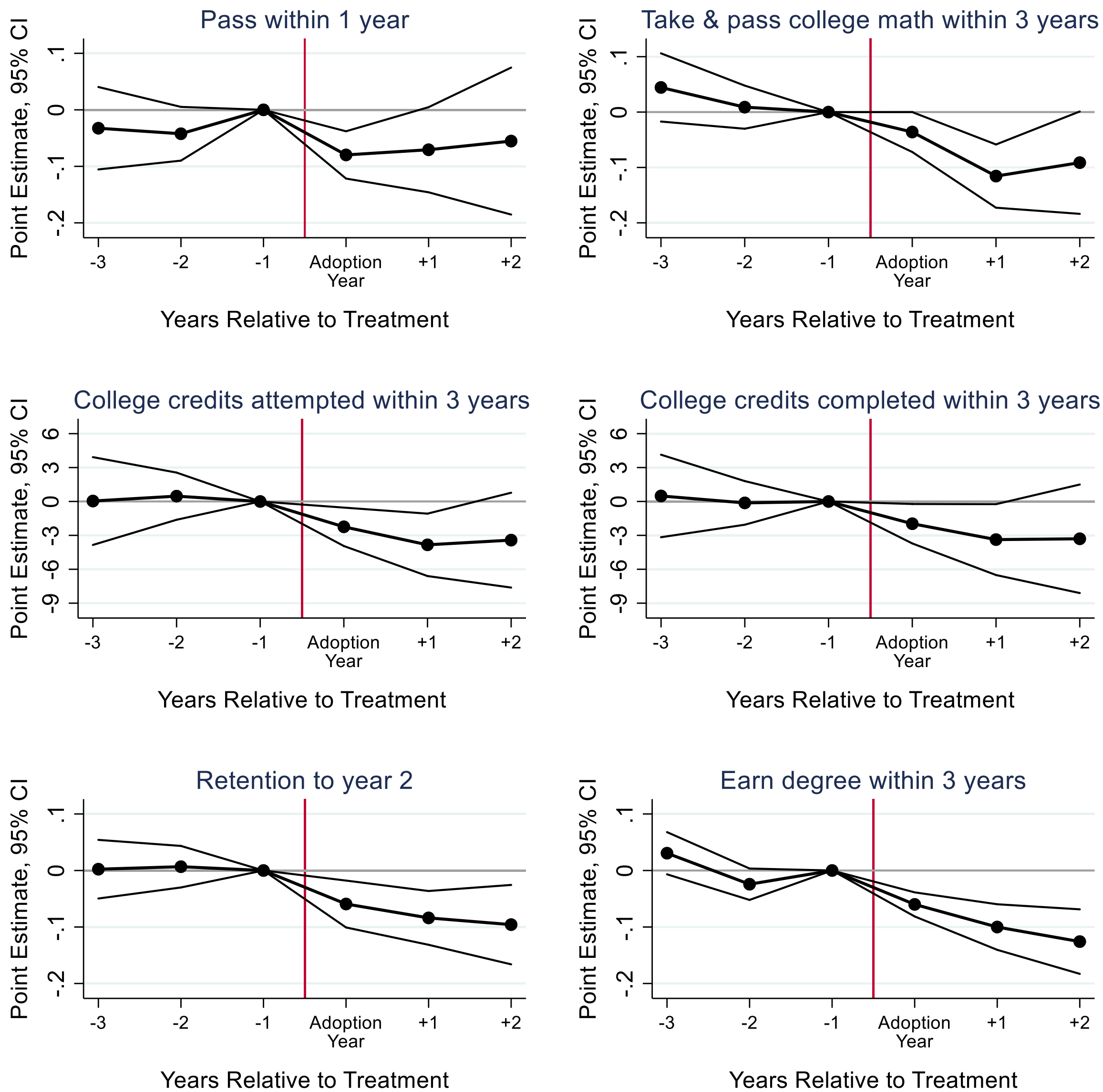
Notes: Each bar corresponds to the number of colleges which are using the emporium model as of that semester in each course. Bluegrass Community and Technical College is excluded to match the analysis sample.

Figure 4. Pass Remedial Math in First Term by Adoption Timing Group



Notes: This figure plots the pass rates for students in their first remedial course splitting the sample by when a given course and college adopted the emporium model (Adopt 2010 indicates courses that switched to the emporium model in Fall 2010). The sample matches the main analysis sample and includes all students who first enroll in a fall semester and take a remedial course their first semester between 2008-09 and 2013-14.

Figure 5. Effects of the Emporium Model by Year



Notes: Each marker indicates the estimated β_m from the event study model in equation (2). The omitted year in each regression is the year just before adoption. The lighter lines on either side of the centered line represents the 95% confidence interval for each estimated coefficient. The analysis sample is the same for each outcome as noted in Tables 2 and 3. Note that the panel is unbalanced; there are fewer treated institutions near -3 and 2 years relative to treatment than in the years closer to the adoption year. Four years before treatment and three years after treatment have been trimmed from these figures due to the small number of treated units.