# Knowledge Decay Between Semesters 

Angela K. Dills<br>Providence College

Rey Hernández-Julian
Metropolitan State University of Denver

Kurt W. Rotthoff
Stillman School of Business, Seton Hall University
Affiliated Researcher, Center for College Readiness

February 2015


#### Abstract

: Given how much is invested in student learning, it is reasonable to examine how knowledge dissipates when class is not in session. One way learning might fade is through summer learning loss. Summer learning loss has been widely studied in K-12 schooling, where the literature has found a range of results. This study expands that literature by analyzing college students taking sequential courses. Some students begin the sequence in the fall semester and have a shorter winter break between the courses. Others begin the sequence in the spring semester and have the two courses separated by a longer summer break. We examine whether the length of that gap explains the students' performance in the subsequent course. Although initial results show that a longer gap is associated with lower grades, including student fixed effects eliminates all of the variation in grades due to knowledge decay except in courses in the languages.


JEL Codes: I21, I28

## 1. Introduction

Although students may not pay attention all the time in every class or remember every lesson, we hope that they at least know more at the end of the class than they did at the beginning. This accumulated knowledge, hopefully, also prepares them for future coursework. We do have evidence that students are likely to forget some, or even most, of the material they learn in class. Deslauriers and Wieman (2011) claim that a majority of factual information is lost within the first year if there is not further relearning or reviewing, and most of that forgetting occurs within the first three months. Although this estimate is useful for understanding the retention of knowledge, it also has implications on the how effective policies could be implemented and on the optimal scheduling of classes. Policy implications are particularly relevant when we consider how to schedule K-12 courses. Schools have recently begun taking shorter breaks between terms in order to avoid what has been termed summer learning loss, with unclear results (Cooper et al,. 1996; Cooper et al., 2003). Some studies show that summer learning loss in elementary and secondary school remains a lingering issue, particularly relevant to children from lower SES households who may receive less academic stimulation over the summer. Other studies find weak evidence that, instead, longer breaks are beneficial for learning, allowing the debate about summer breaks versus year-round schooling to continue.

Although the debate has been limited to K-12 in the past, if summer learning loss exists, it could exist in higher education as well. Our study examines knowledge decay in a previously unexamined group: college students. We analyze student performance in the second course of a collegiate two-course sequence. When courses are sequenced, such as Spanish 101 and Spanish 102, students typically take the sequence in subsequent semesters. However, the semester in which a given student starts a sequence, fall or
spring, determines the amount of time between these courses. Taking the first course in a two-course sequence in the fall means the follow-up course will occur in the spring semester, after a month-long winter break. However, if a student takes the first course in the spring semester but still does the second course in the sequence one semester later (during the fall semester), there is a longer, typically three month, break between the courses. We examine whether this longer break between courses has a detrimental impact on the student's grade in the subsequent course.

We take advantage of a unique data set that allows us to look at detailed student level variation. Since the typical college student completes multiple two-course sequences throughout a college career, we can observe the same student's outcomes in both sequences. This within-student variation allows us to include student fixed effects and control for unobservable student traits that could be correlated with course scheduling choices.

Utilizing 20 years of institutional data from Clemson University, we analyze student-level data that follows students throughout their entire academic careers. We find evidence that longer gaps between the sequenced courses leads to knowledge decay that is measureable and statistically significant. However, this effect disappears with the inclusion of student-level fixed effects in all courses except language courses.

## 2. Background

The debate over knowledge decay has been most prevalent in the K-12 literature. Both traditional school years and year-round schooling include the same number of educational days; however, the traditional school year has a long summer break while year-round schooling schedules several short break periods throughout the year.

The debate focuses on the overall impact of summer vacations - the long annual break-on student learning. This decay in knowledge that happens over the break has been called the summer-learning loss (Kneese, 2000; Cooper, et al., 2003). Some studies have estimated that this loss is large: "the summer loss equaled about one month on a grade-level equivalent scale, or one tenth of a standard deviation relative to spring test scores" (Cooper et al. 1996). Several studies show evidence that summer learning loss exists and occurs disproportionately for disadvantaged and minority students (O'Brien, 1999; Burkam et al., 2003; Downey, Hippel, \& Broh, 2004; Alexander, Entwisle, \& Olson, 2007).

However, the literature is not unanimous on the issue of summer learning loss. Graves (2011) estimates the impact of year-round schooling on academic performance and finds it to have negative impacts on student learning. Graves (2010 and 2011) makes the point that if there is a difference between a year-round and a regular school year it must be due to non-linearities in learning and/or in learning loss. If the nonlinearity is in the loss, then year-round schooling is better; if it is instead in learning, then longer periods of continuous learning are better, and year-round schooling is worse. In addition, Graves (2011) finds that the largest drop in performance from year-round calendars, is in Hispanics/Latinos and low SES students, the same students who in other studies had been found to be likely to suffer summer learning loss. She finds largest positive impacts of traditional calendars in precisely the student populations where other studies have found the largest negative impacts. Graves argues that her results, which counter many of the findings in the education literature, are more credible because of better data and the ability to control for school-specific trends. Although controlling for school-specific trends is an improvement over most of the
literature, she remains unable to control for student-level unobservables as she does not observe the same student operating under both environments.

McMullen and Rouse (2012) are able to do just that: they use a natural experiment in North Carolina with student fixed effects and find zero impact from yearround schools. The within-student source of variation comes from two sources. The first is students switching schools, typically as they advance to middle school, to a school that uses a different schedule. In this case self-selection of students into different middle schools may be problematic. The second is schools switching systems while students stay in the same school; here the widespread, staggered, mandatory adoption of year-round schooling in their sample reduces concerns over internal validity.

Daneshvary and Clauretie (2001) argue that there are significant efficiency improvements associated with the more intensive use of land allowed by a year-round schedule. Graves (2010) and Graves, McMullen, and Rouse (2013) recognize these savings, but argue that they come at a cost in educational achievement: "being on a multi-track year-round calendar results in a drop of $1-2$ percentile points relative to a traditional calendar in national rank on reading, math and language scores." This result could be driven by the selection of school systems that choose to go to year-round schooling, particularly if year-round schooling is primarily introduced where the schools are already performing poorly. McMullen and Rouse (2012) suggest that since there seems to be no difference between the two systems when student effects are included, there may actually be a benefit from the more efficient use of schools that is available through year-round schooling.

Anderson and Walker (2013) revisit the same question on a smaller scale. Instead of thinking about summer-learning loss, they examine learning loss over the weekend. In particular, they look at whether having a four-day school week, as opposed to the
traditional five-day week, impacts learning. Their study finds a positive relationship due to the shorter week and longer break, suggesting that learning loss does not increase over an extra weekend day, and that positive learning non-linearities might exist within a school day.

Most of the research looks at the impact of summer breaks on K-12 students because they are the most policy relevant population. Our study examines this question utilizing data from a sample of students in higher education, in particular the impact of the difference in break lengths between depending on the timing of the course. The use of higher education course sequence differences allows us to analyze student level scores over sequenced courses taken before and after the shorter winter or the longer summer break.

Our paper's main contribution comes through the ability to add student fixed effects, a factor that has only been present in one study of the impact of year-round schooling (McMullen and Rouse 2013). A lingering concern in their study is that some schools may be more able to adapt successfully to the new schedule, and that the change in student learning is capturing otherwise unobserved traits of the school. Our study may provide a cleaner experiment because it examines students, all from one school, operating on environments that are identical except for the timing the sequence of the course.

Our paper adds to the literature in two ways: first, it gives a better measure of how time affects knowledge decay because it allows for student fixed effects in an environment where the school and the school's scheduling policy remain constant throughout the sample. Second, we can inform the narrower question of scheduling in college courses. By better understanding how the order in which courses are taken can affect learning outcomes, we can help universities better advise students. Furthermore,
we can help faculty better understand their students' level of preparation and maybe even consider whether the way that we teach sequenced courses might need to be different depending on whether they are taught spring-fall or fall-spring.

## 3. Model and Data

We estimate the effect of the length of time between courses in a series on the student's grade in the subsequent course. For student $i$ taking an intermediate course in department $j$ in semester $t$, after studying the introductory course $k$ in period $p$, we estimate the following:
(1) grade $_{i t j p}=\beta$ gap $_{i j t p}+a$ prereq $\operatorname{grade}_{i p}+W^{\prime}{ }_{i t \gamma} \gamma+\delta_{j}+\Theta_{t}+\lambda_{p}+\sigma_{i}+e_{i j t p}$ where $W_{i t}$ is a matrix of student and course characteristics including the course level (100-, 200-, 300-, or 400-level course). The department fixed effects, $\delta_{j}$, control for departmental differences in grading policies. Time dummies for both the semester of the prerequisite course and the semester of the follow-on course account for time-varying grade differences such as university-wide grade inflation or differences between fall and spring grading. Student fixed effects account for time-invariant characteristics of the student such as motivation, ability, socio-economic background, sex, and race.

We focus on $\beta$, the coefficient on the gap variable. Gap measures the months between the start of the first course to the start of the second course in a given course sequence. ${ }^{1}$ For students taking the sequence from fall to spring, this gap is five months;

[^0]for students taking the sequence in the spring then fall, it is seven months. We expect that students starting a course sequence in the spring are likely to experience more knowledge decay between courses, resulting in lower performance in the follow-up course. The coefficient estimate will tell us, in terms of grade points in the subsequent course, how much knowledge is lost from delaying the subsequent course. We exclude from the sample the students that take the courses in an order that does not follow the recommended sequence.

We observe grades earned in all undergraduate courses taken by Clemson University students between 1982 and 2002. Clemson University is a public, selective, research-intensive institution in South Carolina, ranked among the top 100 national universities by U.S. News and World Report. During this period, approximately 90,000 students took undergraduate courses. In addition to course grades, we also observe SAT scores for over three-quarters of the students who took courses during the period 19822002 and individual-level characteristics such as race, sex, and state of residency. Table 1 summarizes the traits of the students in our sample.

We follow Dills and Hernández-Julián (2008) and select those courses where, based on the course description, we believe that the second course builds upon or depends on the knowledge from the first course. For courses that have multiple prerequisite courses, we use only the higher-numbered prerequisite when defining the prerequisite course. We assume that the lower course number prerequisites are typically taken prior to the higher-number prerequisites. This implies that the prerequisite course with the lower course number course is less likely to be the binding prerequisite course. Instead, the timing of the subsequent course depends on when the student takes the higher numbered prerequisite course. Using this binding constraint allows us to see the
impact of the gap when the student wanted to lower that gap as much as possible, so we focus on the relationship with the higher-numbered prerequisite course.

Students may choose to delay taking the subsequent course. Maybe they have a preference for a particular professor, a course does not fit in their schedule, or they want to wait because they found the material too easy or too difficult. Any potential omitted variable here would have to be a trait of the student that varies from one course pair to the other. For example, suppose a student hates math but has to take a two-course sequence. The same student loves biology and takes a two-course sequence there as well. If the student takes the biology courses closer together than the math courses, the smaller gap might capture their interest in the subject matter, biasing the estimates. To avoid this source of bias, in our main specifications we limit the sample to students who take the subsequent course in the earliest possible semester focusing on those students who follow a fall-spring or spring-fall course sequence. We also present results where we relax this limitation and include the observations where the lag between the courses is longer than the immediately following semester.

There are other predictors of a student's schedule. Students who register late may be less likely to get their desired schedules, or they may have registered for a wrong course or spent a semester abroad, affecting the timing of the courses. These individual traits should be captured by student fixed effects and by limiting the sample to those who take the courses in the immediately following semester. Students may also have some time varying characteristics that are related to their choosing some courses in a fall to spring order and other courses in a spring to fall order. If such a trait exists, and it is correlated with knowledge decay, then we would be capturing its impact in our estimate.

## 4. Results

### 4.1 Baseline Estimates

Table 2 presents estimates of a regression that includes only sequences where the student took the second course in the semester immediately following the semester of the first course. Summer courses are also excluded from this sample. Here, the only possible values of gap are 5 (fall then spring) and 7 (spring then fall). The regression in column (1) does not include student fixed effects. Instead, it includes a dummy variable if the student "took the prerequisite more than once" (with the gap being measured since the more recent course taking), department fixed effects, course-level dummies, term dummies, a dummy for the term when the prerequisite was taken, and the following student characteristics: SAT Math, age entering Clemson, dummy for the student being from in-state, dummy for male, dummy for family member at/from Clemson (legacy), and a series of race dummies (not reported). Standard errors are clustered by student.

This regression estimates in column (1) show a statistically significant estimate of -0.037 on the monthly gap between course start dates. This translates to students having the longer gap between courses (with the first course taken in the spring) have expected grades that are lower by almost 0.08 grade points, or about a quarter of the difference between a $\mathrm{B}+$ and an $\mathrm{A}-$.

The regression in column (2) includes student fixed effects and is limited to the sample for the regression in column (1). Given the student-level fixed effects, the variation comes from a student taking multiple sequenced courses, where the sequences were taken in contiguous semesters, but the gaps between different sequences vary in length. The regression controls for whether the student took the prerequisite more than once (where, like before, the gap is measured since the more recent time the course was
taken), department fixed effects, course-level dummies, term dummies, prereq term dummies, and student fixed effects. Standard errors are again clustered by student.

Here the estimated effect of gap is negative, statistically insignificant, and small-less than a third of the magnitude of the estimate in column (1). The change in the estimate that results from including student fixed effects shows that most of the effect in column (1) is captured by observable and unobservable student traits. When the same student takes courses under the two different scheduling regimes, there is no significant difference between the student grades in the courses. The result concurs with findings in the work of McMullen and Rouse (2013) where the negative impact of a longer gap due to potential summer learning loss in K-12 disappears with the inclusion of student fixed effects, and suggests that the bulk of the estimates of summer learning loss are due to differences in selection into the treatment.

Column (3) presents the same regression as column (2) but includes those students without information on all of the student characteristics controlled for in column (1), resulting in a larger sample size. We want to include these students in later regressions so that when we cut the sample we can include a larger number of observations. We add the regression in column (3) to examine whether including these students biases the estimates of the results in column (2). Adding these students to the sample increases the size of the estimates, and potentially biases the estimates in favor of finding a negative estimate. The addition of these students makes it more likely that we find a negative and significant impact of the length of the gap on the student's grade in the subsequent course. Including these students in the regression samples makes finding a negative estimate easier. By using the larger sample we make finding evidence of knowledge decay easier. If we do not find decay in spite of using the larger sample, we take that as supporting evidence against knowledge decay.

Overall, Table 2 shows that the longer the period of time between courses, the lower a student's grade. However, this finding is sensitive to the inclusion of studentlevel fixed effects.

### 4.2 Splitting the sample

Table 3 presents results that split the sample by several student traits in order to more easily identify the students who are vulnerable to the longer gap. Results splitting the sample by sex indicate that any impact of a longer gap is driven by females, but even among them the estimate is not statistically significant at conventional levels (pvalue $=0.105)$. It could be the case that knowledge decays differently between the sexes or that, even when controlling for departmental fixed effects, there is a difference in the way knowledge decays in the courses typically chosen by women and men.

If we split the sample by the grade earned in the prerequisite course, we find that the knowledge decay estimate seems to be larger for the students with the highest grades, and that the students who earned the lower grades have positive estimates, but none of these estimates is significant at conventional levels.

The data provides racial identifiers, but does not specify which identifier belongs to each race. The two largest racial groups in the institution are white and black, so we associate these with the two largest racial groups in the sample. 89.5 percent of the sample falls into the racial group that we consider to be likely whites, and 7 percent of the sample, the second largest group, is the group that we consider to be likely blacks. The next highest racial category is 1.2 percent of the sample. Here we find a slightly larger estimate among likely blacks, but the result is again not significant at conventional levels.

If we split the sample by the number of completed credits into four groups (freshmen defined as having 30 or fewer completed credits; sophomores are those with 31 to 60 completed credits; juniors have 61 to 90 completed credits; and seniors have 91 or more completed credits) we find a negative insignificant coefficient for sophomores and juniors, and a positive insignificant estimate for seniors. Among freshmen, even with student fixed effects included, we find that the longer gap does have a positive impact on grades. It could be that they are still young and the time allows them to learn more about themselves and to be better learners, or that whatever happens in the time in between these courses is beneficial to their education generally. It is also possible that for most students, there is shock in the expectations in a college class relative to their high school classes that makes it harder for them to do well in early courses in their college careers. Once they have remained in college longer, they have adapted to the system, and perform better in those courses taken later in college. Although we are unable to identify a mechanism for the positive estimate on freshmen, it is clear evidence against summer learning loss.

If we split the sample by students that are legacy-meaning they had a sibling, parent, or ancestor attend Clemson-we find that legacies do have larger effects on gap, but these are not significant for either group. We also split the data by the level of the subsequent course. Some courses are prerequisites to a 100-level course. Other courses have are required in other to take a 200-level course (or above). We find the largest effects are found in the 100 -level courses, but again are not statistically significant, possibly due to a similar mechanism to the one present among freshmen. In results not presented, we test whether there the gap may be more important for less academically strong students. Including an interaction term with gap and SAT math, for example, results in a small and statistically insignificant coefficient on the interaction term.

In Table 4 we separate the sample by the type of course. It is possible that in some subjects, a second course is very dependent on the first course, while in others the knowledge in the first course is helpful but not essential. Languages seem to be one of the course sequences in the former group. In these courses, a delay in time between the first and second course has a significant and negative impact on the grade in the second course, even when including student fixed effects. ${ }^{2}$

We limit the course series to those where the prerequisite course serves as a prerequisite to only one follow-on course. So, for example, Chemical Engineering 211: Introduction to Chemical Engineering is a prerequisite for three courses: CH E 220 (Chemical Engineering Thermodynamics I), CH E 311 (Fluid Flow), and CH E 319 (Engineering Materials). We exclude courses sequences like the one above as they may reflect less direct connections to course content in the follow-on courses and reflect more a typical sequence of courses for the major. These courses are also slightly more likely to be taken out of order than courses that do not serve as a prerequisite for more than one course ( 1.9 percent of students taking courses with more than one follow-on course take the courses out of order; 1.6 percent of students taking courses with only one follow-on course take the courses out of order). Limiting the sample to those where we believe there is the clearest direct two-course sequence shows no significant impact on gap when looking at the courses that only have one follow-up course. In column (3) we estimate the impact on gap when limiting the sample to only 101-102 sequence courses, in any department. The estimate is larger but not statistically significant.

Students occasionally take course sequences out of order. Column 2 in table 4 drops all of these observations; however, of the almost 183,860 thousand course sequence

[^1]taking that we have, only 2 percent are taken out of the catalog established sequence $(3,910) .{ }^{3}$ We estimate the course sequences where a larger fraction of those courses are taken out of sequence. In column (4) 2e limit the sample to those courses where at least 10 percent of the students took the courses out of sequence and in column (5) where at least 5 percent of the students took the courses out of sequence. Those courses that have a larger number of students taking the course out of sequence continue to find no evidence of knowledge decay between semesters.

### 4.3 Robustness

In Table 5 we separate out those students that take a break in the middle of the course sequence. Column (1) shows gaps between zero and seven months, excluding the students who have a negative gap (because they took the course sequence out of order) and those students who have a gap longer than seven months. Here we find a negative but insignificant estimate. Column (2) includes all positive gaps, column (3) includes gaps between zero months and two years, and column (4) includes at all gaps, including negative ones. In columns two through four we find a positive and significant, although small, impact of course delay on the grade in the subsequent course. Longer gaps could have be capturing the positive impacts due to students maturing or student learning in other courses that are not listed prerequisites. It could also be that as a student advances in an academic career, they perform better in all their courses, even if the prerequisite course was taken a long time before. Here we also find no evidence of knowledge decay.

[^2]A final concern could be that the quality of the professor or the teaching is different in the 'off' semesters. For instance, students may typically take the first two semesters of accounting in a fall/spring sequence (ACC 201 in fall and ACC 301 in spring). There will be many more sections of the course offered in the typical semester than the off-semester, limiting the choices of a student's option of professor and schedule. It could be the case that part of our estimate captures not a difference in grade due to a longer gap; instead, for the student taking the course off-sequence, we are capturing these traits that make the course actually more difficult. We address this concern by adding an indicator for the more typical course offering, either fall to spring or spring to fall. This indicator was interacted with the time gap between the two courses. We then include both these variables in regressions like those estimated previously to answer whether the effect of the gap is different if a course sequence is taken in the off-timed semester. These regressions, available upon request, show these variables have no significant impact in the regression that includes student fixed effects from Table 1 column (3).

## 5. Conclusion

There is continued debate on the implications of school scheduling and it's impact on student learning and learning loss, specifically over summer breaks. The literature using K-12 data is limited in that the researcher typically cannot observe the same student under both kinds of regime. Even with their controls, absent randomized control trials, traits associated with longer delays may also be associated with lower grades. The one study that does include student fixed effects finds no evidence of decay.

We utilize collegiate course sequences at Clemson University to analyze how the timing of these sequences impacts student level outcomes. At first glance, we appear to find evidence of a summer learning loss, known as knowledge decay, at the college level. However, we can include student fixed effects to limit the sample to students who take multiple sequenced courses with different break lengths between them. We find that the estimate of knowledge decay is sensitive to the inclusion of student-level fixed effects. However, this is not consistent across all courses. We do find evidence, even when including student fixed effects, that there is evidence of knowledge decay in language courses.

If the way that college students accumulate knowledge translates to $\mathrm{K}-12$, we find evidence against summer learning loss and argue that concerns over knowledge decay should not factor into K-12 resource allocations, except possibly in the languages. These allocations should, instead, focus on the other costs and benefits of providing year-round schooling relative to a traditional academic calendar.

The significant finding among language courses can be useful for students and advisors. When students are choosing course schedules, in order to increase student success, priority should be given to language courses. Students should take these courses with as small as delay as possible between terms, and students who have a long summer between language courses should participate in relearning and reviewing to reduce knowledge decay.

## 6. References

Alexander, K., Entwisle, D., \& Linda, O. (2007). Lasting consequences of the summer learning gap. American Sociological Review, 72, 167-180.

Anderson and Walker (forthcoming). "Does Shortening the School Week Impact Student Performance? Evidence from the Four-Day School Week," with Mary Beth Walker. Education Finance and Policy.

Burkam, D., Ready, D., Lee, V., \& LoGerfo, L. (2003). Social class differences in summer learning between kindergarten and first grade: Model specification and estimation. Sociology of Education, 77(1), 1-31.

Cooper, H., Valentine, J., Charlton, K., \& Melson, A. (2003). The effects of modified school calendars on student achievement and on school and community attitudes. Review of Educational Research, 73(1), 1-52.

Cooper, H., Nye, B., Charlton, K., Lindsay, K., \& Greathouse, S. (1996). The Effects of Summer Vacation on Achievement Test Scores: A Narrative and Meta-Analytic Review. Review of Educational Research, 66(3), 227-268.

Daneshvary, N. \& Clauretie, T. M. (2001). Efficiency and costs in education: year-round versus traditional schedules, Economics of Education Review, 20(3), 279-287.

Deslauriers, L. and Wieman, C. (2011). Learning and retention of quantum concepts with different teaching methods. Physical Review ST Physics Education Research 7, 010101. Published 31 January 2011.

Dills, Angela K. and Rey Hernández-Julián (2008) Transfer College Quality and Student Performance Eastern Economic Journal 34, 172-189.

Downey, D., Hippel, P., \& Broh, B. (2004). Are schools the great equalizer? Cognitive inequality during the summer months and the school year. American Sociological Review, 69, 613-635.

Graves, J. (2010). The Academic Impact of Multi-Track Year-Round School Calendars: A Response to School Overcrowding. Journal of Urban Economics, 67, 378-391.

Graves, J. (2011). Effects of Year-Round Schooling on Disadvantaged Students and the Distribution of Standardized Test Performance. Economics of Education Review, 30(6), 1281-1305.

Graves, J., McMullen, S. \& Rouse, K. (2013). Multi-Track Year-Round Schooling as Cost Saving Reform: Not just a Matter of Time. Education Finance and Policy, 8(3), 300-315.

Kneese, C. (2000). Teaching in year-round schools. ERIC Digest (Report No. EDOSP-2000-1). Washington, DC: ERIC Clearinghouse on Teaching and Teacher. Education (ERIC Document Reproduction Service No. ED449123).

Louis Deslauriers and Carl Wieman (2011) Learning and retention of quantum concepts with different teaching methods. Phys. Rev. ST Phys. Educ. Res. 7, 010101 Published 31 January 2011

McMullen, Steven C., and Kathryn E. Rouse. (2012). "The Impact of Year-Round Schooling on Academic Achievement: Evidence from Mandatory School Calendar Conversions." American Economic Journal: Economic Policy, 4(4): 230-52.

O'Brien, D. (1999). Family and school effects on the cognitive growth of minority and disadvantaged elementary school students. University of Texas, Dallas. Texas Schools Project, Working Paper 09.

Table 1: Coming soon.

Table 2: Length of time between prerequisite and follow-up course and course grade

|  | (1) <br> without student fixed effects | $\overline{(2)}$ <br> with student fixed effects | (3) <br> with fixed effects, larger sample |
| :---: | :---: | :---: | :---: |
| months between |  |  |  |
| courses | $\begin{gathered} -0.0365^{* *} \\ (0.0166) \end{gathered}$ | $\begin{gathered} -0.00928 \\ (0.0182) \end{gathered}$ | $\begin{aligned} & -0.0156 \\ & (0.0181) \end{aligned}$ |
| grade in prerequisite | $\begin{aligned} & 0.600^{* * *} \\ & (0.00327) \end{aligned}$ | $\begin{aligned} & 0.319^{* * *} \\ & (0.00585) \end{aligned}$ | $\begin{aligned} & 0.320^{* * *} \\ & (0.00555) \end{aligned}$ |
| took prerequisite $>1 x$ | $\begin{gathered} -0.514^{* * *} \\ (0.0220) \end{gathered}$ | $\begin{gathered} -0.196^{* * *} \\ (0.0344) \end{gathered}$ | $\begin{gathered} -0.203^{* * *} \\ (0.0335) \end{gathered}$ |
| SAT Math | $\begin{gathered} 0.00948^{* * *} \\ (0.000370) \end{gathered}$ |  |  |
| age | $\begin{gathered} 0.0121^{* * *} \\ (0.00146) \end{gathered}$ |  |  |
| instate | $\begin{gathered} -0.0461^{* * *} \\ (0.00595) \end{gathered}$ |  |  |
| male | $\begin{aligned} & -0.142^{* * *} \\ & (0.00563) \end{aligned}$ |  |  |
| legacy student | $\begin{gathered} 0.0298^{* * *} \\ (0.00614) \end{gathered}$ |  |  |
| Observations | 117,878 | 117,878 | 129,519 |
| R-squared | 0.380 | 0.708 | 0.705 |

Regressions include whether the student took the prerequisite more than once (with the gap measured since the more recent course taking), department fixed effects, course-level dummies, term dummies, and prerequisite term dummies. In addition to the variables reported in column (1), column (1) contains indicators for whether the student belongs to one of 10 race categories. Robust standard errors clustered by student in parentheses. This sample only includes fall-spring and springfall (the suebsequent course immediately follows the prerequisite course).
${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$

Table 3: Length of time between prerequisite and follow-up course and course grade, stratified by various categories

|  | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Panel A | by sex |  | by grade in prerequisite course |  |  |  |
|  | males | females | D's | C's | B's | A's |
| months between courses | 0.0179 | -0.0467 | 0.279 | 0.0711 | -0.0341 | -0.0427 |
|  | (0.0234) | (0.0288) | (0.551) | (0.0908) | (0.0485) | (0.0315) |
| grade in prerequisite | $0.310^{* * *}$ | $0.320 * * *$ |  |  |  |  |
|  | (0.00797) | (0.00860) |  |  |  |  |
| took prerequisite $>1 x$ | $-0.184^{* * *}$ | $-0.220^{* * *}$ | 0.197 | -0.0756 | $-0.243^{* *}$ | -0.373 |
|  | (0.0419) | (0.0591) | (0.414) | (0.0923) | (0.105) | (0.232) |
| Observations | 64,490 | 53,388 | 9,591 | 36,866 | 50,420 | 32,388 |
| R-squared | 0.701 | 0.712 | 0.921 | 0.799 | 0.758 | 0.787 |
| Panel B | by race |  | by completed credits |  |  |  |
|  | likely blacks | likely whites | freshmen | sophomores | juniors | seniors |
| months between |  |  |  |  |  |  |
| courses | -0.0789 | -0.00552 | $0.693^{* * *}$ | -0.0602 | -0.0745 | 0.0208 |
|  | (0.0804) | (0.0196) | (0.0341) | (0.183) | (0.0880) | (0.124) |
| grade in prerequisite | $0.347^{* * *}$ | $0.315^{* * *}$ | $0.384^{* * *}$ | $0.370 * * *$ | $0.103 * * *$ | $0.162^{* * *}$ |
|  | (0.0227) | $(0.00618)$ | (0.0138) | (0.0183) | (0.0303) | (0.0442) |
| took prerequisite $>1 x$ | $-0.204^{* * *}$ | -0.182*** |  | -0.137 | -0.0132 | -0.110 |
|  | $(0.0782)$ | (0.0397) |  | (0.269) | (0.164) | $(0.145)$ |
| Observations | 8,235 | 105,448 | 47,117 | 30,069 | 25,394 | 15,298 |
| R-squared | 0.712 | 0.707 | 0.845 | 0.844 | 0.883 | 0.896 |
| Panel C | by legacy status |  | by level of follow-up course |  |  |  |
|  | legacies | non-legacies | 100-level | 200-level | $300-\mathrm{level}$ | 100 or 200 |
| months between |  |  |  |  |  |  |
| courses | -0.0260 | -0.00249 | -0.0177 | -0.0110 | 0.0286 | -0.0146 |
|  | (0.0341) | (0.0214) | (0.0734) | (0.0546) | (0.273) | (0.0197) |
| grade in prerequisite | $0.306 * * *$ | $0.324^{* * *}$ | $0.414^{* * *}$ | $0.0724^{* * *}$ | 0.0871 | $0.322^{* * *}$ |
|  | $(0.0111)$ | $(0.00688)$ | (0.00932) | (0.0169) | (0.0850) | (0.00598) |
| took prerequisite $>1 x$ | -0.104 | -0.228*** | $-0.236^{* * *}$ | 0.0855 | 0.0617 | -0.206*** |
|  | (0.0690) | (0.0396) | (0.0767) | (0.0807) | (0.362) | (0.0371) |
| Observations | 32,736 | 85,142 | 79,568 | 39,647 | 10,304 | 119,215 |
| R-squared | 0.712 | 0.707 | 0.805 | 0.832 | 0.943 | 0.720 |

All regressions include whether the student took the prerequisite more than once (with the gap measured since the more recent course taking), department fixed effects, course-level dummies, term dummies, prerequisite term dummies, and student fixed effects. Robust standard errors clustered by student in parentheses
${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$

Table 4: Different course samples

| VARIABLES | (1) <br> languages | (2) <br> single prereq courses | $(3)$ $\text { no } 101 / 102$ | (4) poutoforder $<$ 0.1 | (5) <br> poutoforder $<$ $0.05$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| months between |  |  |  |  |  |
| courses | $\begin{gathered} -0.0898^{*} \\ (0.0509) \end{gathered}$ | $\begin{aligned} & -0.0109 \\ & (0.0219) \end{aligned}$ | $\begin{aligned} & -0.0994 \\ & (0.107) \end{aligned}$ | $\begin{aligned} & -0.0156 \\ & (0.0181) \end{aligned}$ | $\begin{aligned} & -0.0125 \\ & (0.0184) \end{aligned}$ |
| grade in prerequisite | $\begin{gathered} -0.245^{* * *} \\ (0.0216) \end{gathered}$ | $\begin{aligned} & 0.330^{* * *} \\ & (0.00700) \end{aligned}$ | $\begin{gathered} 0.437^{* * *} \\ (0.0150) \end{gathered}$ | $\begin{aligned} & 0.320^{* * *} \\ & (0.00555) \end{aligned}$ | $\begin{aligned} & 0.321^{* * *} \\ & (0.00564) \end{aligned}$ |
| took prerequisite $>1 x$ | $\begin{aligned} & 0.371^{*} \\ & (0.202) \end{aligned}$ | $\begin{gathered} -0.287^{* * *} \\ (0.0411) \end{gathered}$ | $\begin{gathered} -0.198^{*} \\ (0.114) \end{gathered}$ | $\begin{gathered} -0.203^{* * *} \\ (0.0335) \end{gathered}$ | $\begin{gathered} -0.207^{* * *} \\ (0.0340) \end{gathered}$ |
| Observations | 15,585 | 104,036 | 60,483 | 129,462 | 127,251 |
| R-squared | 0.853 | 0.741 | 0.859 | 0.705 | 0.711 |

All regressions include whether the student took the prerequisite more than once (with the gap measured since the more recent course taking), department fixed effects, course-level dummies, term dummies, prerequisite term dummies, and student fixed effects. Robust standard errors clustered by student in parentheses
${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$

Table 5

|  | $(1)$ | $(2)$ | $(3)$ <br> $0<$ gap $<=$ <br> 24 | $(4)$ |
| :--- | :---: | :---: | :---: | :---: |
|  | $0<$ gap $<=7$ | gap $>0$ |  | all |
|  |  |  |  |  |
| months between | -0.103 | $0.00456^{* * *}$ | $0.00774^{* * *}$ | $0.00250^{* *}$ |
| courses | $(0.171)$ | $(0.00116)$ | $(0.00137)$ | $(0.00107)$ |
| grade in prerequisite | $0.313^{* * *}$ | $0.267^{* * *}$ | $0.273^{* * *}$ | $0.258^{* * *}$ |
|  | $(0.00517)$ | $(0.00426)$ | $(0.00436)$ | $(0.00419)$ |
| took prerequisite $>1 x$ | $-0.174^{* * *}$ | $-0.176^{* * *}$ | $-0.183^{* * *}$ | $-0.198^{* * *}$ |
|  | $(0.0266)$ | $(0.0193)$ | $(0.0199)$ | $(0.0178)$ |
| Observations | 139,968 | 177,008 | 172,081 | 181,907 |
| R-squared | 0.691 | 0.639 | 0.646 | 0.635 |

All regressions include whether the student took the prerequisite more than once (with the gap measured since the more recent course taking), department fixed effects, courselevel dummies, term dummies, prerequisite term dummies, and student fixed effects.
Robust standard errors clustered by student in parentheses
${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$


[^0]:    ${ }^{1}$ The results are robust for different timing measures. The results hold if we measure the gap as from the end of the first course to the beginning of the second course or the middle of the first course to the middle of the second course. Although these other measures give similar results, we have a noisy measure of the end and midpoint of some of the summer courses. To keep our gap measure as clean as possible, we measure the gap from the beginning of the first course to the beginning of the subsequent course.

[^1]:    ${ }^{2}$ Clemson offered 9 languages in our sample: American Sign Language, Chinese, French, German, Italian, Japanese, Russian, Spanish, and Portuguese.

[^2]:    ${ }^{3}$ Most of these are from a sequence of Geology courses (GEOL 102- and GEOL103; 94 percent of the 1,109 students taking GEOL 103 take it before GEOL 102).

