Knowledge Decay Between Semesters[*]

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Fall 2015

Abstract:

Summer learning loss has been widely studied in K-12 schooling, where the literature finds a range of results. This study provides the first evidence of summer learning loss in higher education. We analyze college students taking sequential courses with some students beginning the sequence in the fall semester and others in the spring. Those beginning in the fall experience a shorter break between the courses. We test whether the length of that gap explains the students' performance in the subsequent course. Initial results suggest that a longer gap is associated with lower grades. However, including student fixed effects eliminates the observed knowledge decay with a few exceptions: knowledge decay remains for students in language courses, for students with below-median SAT Math scores, and for students with majors outside STEM fields.

JEL Codes: I21, I28

[*] We thank Robert E. McCormick and Michael T. Maloney for their help in obtaining the data. We also thank Jennifer Kohn and participants at the 2015 Eastern Economic Association meetings for their comments.

1. Introduction

The knowledge that students accumulate in a semester should prepare them for better performance in future coursework, particularly in closely related courses. However, students typically retain only a portion of the material they learn. Estimates of how much they retain are mixed. 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. Elementary and secondary school students may also suffer learning loss during the summer. The claim is that, while home from school, students forget academic material more quickly than when in school; this may be particularly true for lower income students (Alexander, Entwisle, and Olson, 2001) with less-enriching summer environments such as camps and lessons. Out of concern for summer learning loss, some K-12 schools have recently begun taking shorter breaks between terms, with mixed results (Cooper et al., 1996; Cooper et al., 2003).

To date, the analysis of summer learning loss has been limited to K-12. We examine this possibility of knowledge decay in a previously unexamined group: college students. We analyze student performance in the second course of a collegiate two-course sequence as a function of the time lapse between the two courses. 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 occurs in the spring semester, after a month-long winter break. When a student takes the first course in the spring semester but still enrolls in the second course one semester later during the fall semester, there is a longer, three-month break between the courses. We examine whether this longer break between courses affects 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. Utilizing 20 years of institutional data from Clemson University, we analyze records of students' entire academic careers. Since the typical college student completes multiple two-course sequences throughout a college career, we observe the same student's outcomes in multiple sequences with differences in the time between the courses. 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.

OLS estimates suggest 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. Only one previous study (McMullen and Rouse, 2012) has been able to estimate knowledge decay both with and without student level fixed effects. Like them, we find that knowledge decay found in the baseline estimates are driven by student-level differences, not the time lapsed between the courses. We do find some situations where knowledge decay still exists with the inclusion of student level fixed effects: in language courses, for students who score below the sample median in SAT Math, and for students with majors outside of the STEM fields.

2. Background

The debate over knowledge decay has been concentrated in the K-12 literature. Studies focus on the overall impact of summer vacations—the long annual break—on student learning. The 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 document declines in student test scores over the summer that are larger for disadvantaged and minority students (O'Brien, 1999; Burkam et al., 2003; Downey, Hippel, & Broh, 2004; Alexander, Entwisle, & Olson, 2007).

The policy-relevant question in K-12 is whether an alternate school calendar would improve student outcomes. Both traditional school years and year-round schooling include the same number of educational days; the traditional school year, however, has a long summer break while year-round schooling schedules several short break periods throughout the year. The calendars differ in their length of breaks as well as in their length of continuous school days. Graves (2010, 2011) makes the point that if there is a difference between a year-round and a traditional school year it must be due to non-linearities in learning, in learning loss, or both. If the non-linearity is in the loss, then year-round schooling is better; if the non-linearity is instead in learning, then longer periods of continuous learning are better, and year-round schooling is worse.

Recent evidence using natural experiments suggests that year-round schooling is no better or may even be worse than a traditional calendar. Graves (2010) estimates that test scores fall when students are on a multi-track year-round calendar, a finding supported by the broader literature summarized in Graves, McMullen, and Rouse (2013). Graves (2011) compares year-round schooling to a traditional school calendar using school-specific trends and finds that the largest drop in performance from year-round calendars is in Hispanics/Latinos and low SES students, the same students who other studies found to be likely to suffer summer learning loss. She remains unable to control for student-level unobservables as she does not observe the same student operating under both environments. However, McMullen and Rouse (2012) observe exactly that: they use a natural experiment in North Carolina with student fixed effects and find zero impact from year-round schools. Schools adopted year-round schooling in a mandatory and staggered manner reducing policy endogeneity concerns. Some of the within-student policy variation also stems from students switching schools, typically as they advance to middle school, to a school using a different schedule. In this case self-selection of students into different middle schools may be problematic. In either case, their identifying variation is always perfectly correlated with a student changing a school or with a school changing its policy, both of which could themselves be relevant predictors of student outcomes.

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 positive effects of 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.

Although the education research on summer breaks has focused on K-12 students, our study examines this question utilizing data from a sample of students in higher education. We estimate the impact of break lengths between courses in a sequence. We compare student performance over sequenced courses taken before and after the shorter winter or the longer summer break.

Our paper adds to the literature in two ways: first, it better measures 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. Only one previous study, McMullen and Rouse (2012) incorporates student fixed effects. 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 in environments that are identical. The variation in timing comes from whether the break between courses occurs over the winter or summer. Although the majority of the policy interest centers around K-12 education, no environment exists which can test for knowledge decay while holding constant both the school and the scheduling policy.

Second, we inform the narrower question of scheduling in college courses. By better understanding how the timing of courses 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 differ depending on whether they are taught spring-fall or fall-spring. We also separate the sample to examine whether the results vary by traits of the student or of the course.

3. Model and Data

Students take a variety of course sequences, for example the sequence of Spanish I and Spanish II, during their college tenure. We estimate the effect of the length of time between courses in a sequence on the student's grade in the second 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:

$$(1) \quad \text{grade}_{itjkp} = \beta \text{gap}_{ijtkp} + \alpha \text{prereq grade}_{ikp} + W'_{it}\gamma + \delta_j + \Theta_t + \lambda_k + \sigma_i + e_{ijtp}$$

where W_{it} is a matrix of student and course characteristics including the course level (100-, 200-, 300-, or 400-level course). We also include an indicator for whether the student took the prerequisite course more than once.[1] The department fixed effects, δ_j , control for departmental differences in grading policies. Time dummies for the semester of the follow-on course account for time-varying grade differences such as university-wide grade inflation. Student fixed effects account for time-invariant characteristics of the student such as motivation, ability, socio-economic background, sex, and race.

We focus on β, 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.[2] For students taking the sequence in the fall and then the spring, this gap is five months; for students taking the sequence in the spring and then the fall, it is seven months. Students starting a course sequence in the spring experience a gap between courses that is two months longer. We expect these spring-fall students to experience more knowledge decay between courses, resulting in poorer performance in the follow-up course. The coefficient on *gap* will tell us, in terms of grade points in the subsequent course, how much knowledge is lost from delaying the subsequent course.

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[1] Tafreschi and Thiemann (2015) use a regression-discontinuity design to estimate that students who are required to repeat all of their first-year courses are more likely to drop-out, but also earn higher grades when they re-take a course.

[2] The results are robust for different measures of the time gap between the two courses. 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 included in the larger samples. 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.

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, land grant institution in South Carolina, ranked among the top 100 national universities by U.S. News and World Report. During this period, approximately 69,000 students took undergraduate courses. The primary sample we analyze uses course sequences only occurring in immediately following semesters, either fall-spring or spring-fall. This includes 51,417 unique students. In addition to course grades, we observe individual characteristics for over 90 percent of the students with course sequences in the sample; these include the time-invariant characteristics of SAT score, race, sex, whether they are from South Carolina, and whether a family member attended Clemson. Table 1 summarizes the traits of the students with observed characteristics in our sample.[3]

We follow Dills and Hernández-Julián (2008) and select those courses where, based on the course description, the second course closely builds upon or depends on the knowledge from the first course. About half of the observed course sequences are of science, technology, engineering, or mathematics (STEM) courses, as expected for a university with a science and engineering focus. Other common course sequences are English 101-102 and the four-semester Spanish sequence of 101-102-201-202. Appendix Table 1 lists the course sequences used in our sample.

[3] There are 10 observations with an age at entry to Clemson of 13 or less. We drop these observations from the sample. Course grades and gaps are similar for those students for whom we do not observe personal characteristics such as SAT scores, race, and sex. Personal characteristics of students included in the sample statistically differ from students not included in the sample. Appendix Table 3 displays the means for the two sets of students. Included students have slightly higher SAT scores, were slightly older when starting at Clemson, and are less likely to be in-state, male, or a legacy student. This suggests that the included students are somewhat stronger students than excluded students, likely due to weaker students' leaving Clemson more quickly or transferring credits in to satisfy one of the courses in the sequence. As the results will show, including stronger students makes it somewhat less likely we estimate effects of a gap on student grades.

Identification of the gap effect relies on within student variation in course timing and grades. On average, we observe each student in 4.4 course sequences; we observe two-thirds of the sample in four or more sequences. About half of the sample takes course sequences in both fall-spring and spring-fall. Appendix Table 2 displays the included course sequences for three students taking the Biology 103 and 104 sequence and taking the Spanish 101 and 102 sequence. Students take some course sequences beginning in the fall, and others that begin in the spring. The average within-student standard deviation of course grade is 0.77, somewhat smaller than the sample standard deviation of 1.09. We have 129,501 student level observations over 20 years with an average of 6,475 course observations per year.[4] Fall-spring course sequences are more common: 80 percent of the sample sequences in the baseline sample were taken in fall-spring. Many courses are offered every semester; whether a student takes it fall-spring or spring-fall depends on when the student enrolled in the prerequisite course. Fall-spring sequences are more likely to be freshman-level courses; spring-fall sequences are more likely to be sophomore-level courses.[5]

Some courses have multiple prerequisite courses. We assume that the lower course number prerequisites are typically taken prior to the higher-numbered prerequisites. The lower-numbered prerequisite then is less likely to be the binding prerequisite course. Instead, the timing of the subsequent course depends on when the

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[4] While there are many different combinations of sequenced courses, we see a variety of different outcomes at the student level. Some majors require foreign languages, such as Political Science, English and most B.A. degrees, while others do not such as the engineering programs and most B.S. degrees. Thus, different students have different sequence requirements depending on their majors and interests. (Clemson Undergraduate Announcements, 2000).

[5] Our sample includes 41 different “departments” in the form of different course prefixes. Of these 37 appear in both fall-spring and spring-fall. Four departments, Landscape Architecture, Management, Ceramic & Materials Engineering, and Technology and Human Resources, only appear fall-spring. These four make up 98 of the 129,501 observations in the sample.

student takes the higher numbered prerequisite course. For these course sequences, we define the initial course in a two-course sequence as the higher-numbered of the prerequisites.

Students may choose to delay taking the subsequent course. They might have a preference for a particular professor, a course may not fit in their schedule, or they want to wait because they found the material too easy or too difficult. This self-selection into the timing of the course sequence likely biases cross-sectional estimates of the gap effect. Our inclusion of student fixed effects implies that any potential omitted variable must be a student trait that varies from one course pair to another. For example, suppose a student hates English but is required to take a two-course sequence. The same student loves biology and also takes a two-course sequence in biology. If the student's preference for biology leads him to take the biology courses closer together than the English courses, the smaller gap might capture his interest in the subject matter, biasing the estimates toward finding no effect. Alternatively, if the student takes the English courses closer together to 'get them over with', this biases the gap estimate upwards. 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. It is also possible that faculty teach fall courses different than spring courses. Knowing that students have just come off long breaks, professors may spend more time reviewing prerequisite material in the fall.[6] To the extent instructors compensate for any knowledge decay, this biases our estimates towards finding no effect. We focus on students who follow a fall-spring or

[6] There may be other sources of variation associated with the course's professor. Unfortunately, we cannot identify course professors in the data.

spring-fall course sequence. In later specifications, we present results where we relax this limitation and include the observations where the lag between the courses is longer.[7]

There are other predictors of a student's schedule: students who register late and fail to obtain their desired schedules, students who register for the wrong course, and students who spend a semester abroad. These predictors may correlate with individual traits that also affect one's grades such as responsibility, attentiveness, or curiosity. We mitigate the potential omitted variables bias from unobserved individual characteristics by including student fixed effects and limiting the sample to those who take the courses in the immediately following semester. Any remaining bias must arise from time-varying student characteristics that affect student grades and are related to their choosing some courses in a fall to spring order and other courses in a spring to fall order. For example, students may wait for a specific professor or students later in the college careers may sequence their courses more strategically.[8] If such a trait exists, and it is correlated with knowledge decay, then our estimate captures its impact.

4. Results

4.1 Baseline Estimates

Table 2 presents estimates of regressions using the sample of course sequences where the student took the second course in the regular semester immediately following the semester of the first course in the sequence. Summer courses are excluded from this

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[7] Students who earn AP credit for the first course in a sequence, or who have taken the course at another school and transferred it in, are not included in the regression. The students in the sample have a slightly higher average SAT score than those that are not included.

[8] Including total attempting credits as a measure of course-taking experience at Clemson does not change the results.

sample. Here, the only possible values of gap are 5 (fall then spring) and 7 (spring then fall). Regressions include the student's grade in the prerequisite course, 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, and term dummies. Standard errors are clustered by student to allow for correlation within a student across grade observations.

The regression in column (1) does not include student fixed effects. Instead, it includes the following time-invariant student characteristics: SAT Math score, age entering Clemson, and indicators for whether the student is from in-state, is male, has a family member at or from Clemson (is a legacy), and for race (the coefficients on the race dummies are not reported).[9] Here we find a statistically significant estimate of -0.0368 on the monthly gap between course start dates.

In column (2), we include student fixed effects and estimate the regression on the same sample as the regression in column (1). Given the student fixed effects, the variation comes from a student taking multiple sequences of different course pairs, some in the fall-spring and some in the spring-fall. The regression continues to control 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, and term dummies. Standard errors are again clustered by student.

The estimated effect of the gap in column (2) is negative, statistically insignificant, and small. When the same student takes courses under the two different

[9] Legacy is included as a rough proxy for students that potentially have inside information, or the ability to get inside information, about the college process generally and Clemson specifically.

scheduling regimes, there is no significant difference between the student grades in the courses. The change in the estimate that results from including student fixed effects shows that most of the effect in column (1) is captured by time-invariant student traits. The result concurs with findings in the work of McMullen and Rouse (2012) 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.

In Column (3) we present estimates from the same regression as in column (2) but including those students for whom we do not possess information on all of the student characteristics controlled for in column (1). These time-invariant characteristics are captured by the student fixed effects. In later specifications, we cut the sample in a variety of ways; the larger baseline sample allows for larger samples in later regressions. A comparison of the estimates using this larger sample in column (3) to those in column (2) shows that the estimate in the larger sample is slightly larger in magnitude. Using the larger sample in the later regressions potentially biases the estimates towards finding a negative effect, making finding a negative estimate of knowledge decay easier than would the smaller sample.

In an ideal experiment we would observe a student taking the same course sequence more than once but with a different time gap between the courses. That experiment, though ideal in theory, is only observable for students who fail a course, and as a result are not representative of the typical student. Instead we compare the within-student, across-course differences in the time between courses, controlling for the course pair, as the best possible approximation to that perfect experiment. These results are presented in column (4) of Table 2. Here, we add course-pair fixed effects to directly compare students that are taking the same course sequence. Again, the results are statistically insignificant although the point estimate is now positive.

Previous research on summer learning loss suggests that academically weaker students may experience more knowledge decay. Students with a less extensive knowledge base may struggle to recall previously learned information more than better-prepared students. We allow for this possibility by including an interaction term of the gap length and the grade the student received on the prerequisite course. Column (5) of Table 2 presents these results. In this specification the gap is positive and statistically significant and the interaction term is negative and statistically significant. The effects for each prerequisite grade are graphed in Figure 1. Students who perform poorly in the prerequisite benefit from a longer gap; students who perform well in the prerequisite benefit from a shorter gap.

Overall, the estimates presented in Table 2 suggest that, on average, the length of time between courses has no impact on a student's grade once student-level fixed effects are included. With the inclusion of student fixed effects, the estimated knowledge decay is small, negative, and statistically insignificant. This effect differs by the student's grade in the first course. Students who earn higher grades in the prior course are more likely to earn a lower grade in the subsequent course when there is a longer gap between the courses; students who did worse in the prior course do better with longer gaps between courses. Although the mean effects are not statistically significant, different sub-groups appear to respond differently to the gaps they face in course taking. To address these possible differences within groups, we stratify the sample in the next section.

4.2 Splitting the sample by student type

The results in Table 2 suggest that the gap between courses may be more important for some subgroups of students. We consider, in particular, students who are potentially more vulnerable to a longer gap. Table 3 presents these results.

We begin by splitting the sample by math SAT score. In columns (1) and (2) the estimates indicate that the gap is more harmful for students who are academically weaker. For students with below median SAT math scores, the gap matters: taking courses spring-fall instead of fall-spring is associated with a grade 0.2 points lower.[10] The gap has no significant effect on above median SAT math scorers.

Clemson University is a land-grant college; about half of the students in our sample major in a STEM field. In columns (3) through (6) we separately examine the students who have registered as a STEM major at least at some point and those who have never registered as a STEM major. In columns (3) and (4) we include all courses in the sample. In columns (5) and (6) we only examine performance in courses in STEM fields. The gap in course sequence does not matter for those that are STEM majors, but has a significant, negative impact for those students who have never been a STEM major. The impact of gap for non-STEM majors is larger in STEM courses then it is for all courses; indicating that the gap seems to matter more for students outside of their chosen major.

4.3 Robustness

In Table 4 we separate the sample by the type of course. Dividing by course demands more of the data than does dividing by student characteristics. When stratifying by course type, identification relies on students taking more than one course

[10] Dividing the sample by quartiles of SAT math scores leads to similar conclusions. The gap is more important for students scoring lowest quartile on the math SAT.

series of that type. In some cases, this is common. For example, in languages many students take the first four semesters of a language; science and engineering majors take many sequences in STEM fields. These course sequences also likely meet curricular requirements for these students.

We first consider these two types of subjects that make up the majority of our observations: languages and STEM courses. It could be that in some subjects, the second course depends a lot 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.[11] Interestingly, for sciences, this effect is reversed: longer gaps between courses in the sequence are associated with higher grades. This result could be driven by similar knowledge being presented in multiple courses, helping students build on courses that are not formal pre-requisites. The result could also be driven by selection. Students in the sciences may be likely to switch majors after an unsuccessful attempt in an initial course than students in other majors.

We then split the data by the level of the subsequent course. Freshman-level courses and sophomore-level subsequent courses may be more closely tied to the material of the perquisite. We focus on course sequences ending in a 100-level (freshman) or a 200-level (sophomore) course. 100- and 200-level courses are also more likely to be required course sequences for a student's major. We find similar estimates among the 100- and 200-level courses as in the full sample (column 3). If we specifically target series numbered 101 and 102, typical course numbering for an introductory two-

[11] Clemson offered seven languages in our sample: American Sign Language, Chinese, German, Italian, Japanese, Russian, and Spanish.

semester sequence, the estimated effect of the gap is larger (-0.1) although statistically insignificant.

There are some course sequences where the prerequisite serves as a prerequisite for a variety of courses. 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 limit the course series to those where the prerequisite course serves as a prerequisite to only one follow-on course. 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.

Students will occasionally take course sequences out of order; sequences students are allowed to take out of order likely rely less on the knowledge gained in the prerequisite. We estimate the effect of the gap for courses where most people take the courses in sequence. In column (6) we include only those courses where 10 percent or fewer students took the courses out of sequence; in column (7) where 5 percent or fewer students took the courses out of sequence. Those courses that have fewer students taking the course out of sequence continue to find no evidence of knowledge decay between semesters.

In Table 5 we expand the sample to include students taking a course sequence in timings other than the immediate fall-spring and spring-fall. For these specifications, we include time dummies for the semester in which the prerequisite course was taken.[12] Column (1) includes sequences with gaps between zero and ten months. This incorporates students enrolling in summer school for one of the courses in the sequence. Here we find a positive and significant estimate. Column (3) includes gaps between zero months and two years, column (3) includes all positive gaps, and column (4) includes all gaps, including negative ones. In columns (2) through (4) we continue to find a positive and significant, although small, impact of course delay on the grade in the subsequent course. Longer gaps could capture positive impacts due to students maturing or student learning in other courses that are not listed prerequisites. It could also be that as students advance in an academic career, they perform better in all their courses, even if the prerequisite course was taken a long time before.[13] Here we also find no evidence of knowledge decay.

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). More sections of the course will be offered in the typical semester than the off-semester, limiting the choices of a student's professor and schedule. Part of our estimate may capture not a difference in grade due to a longer gap but rather traits that make the course 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

[12] When only considering courses that immediately follow each other, the prerequisite course term dummies are perfectly collinear with the subsequent course term dummies.

[13] Adding a variable for the number of credits the student has completed successfully does not significantly change the regression results.

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 estimates, available upon request, show these variables have no significant impact.

5. Conclusion

Debate continues on the implications of school scheduling and its impact on student learning and learning loss, specifically over summer breaks. This paper provides the first evidence on learning loss in higher education. Students enroll in a variety of course sequences in college. Using administrative data from Clemson University, we focus on course sequences taken two semesters in a row, either fall-spring or spring-fall. Sequences taken fall-spring offer a shorter gap between courses than do courses taken spring-fall.

In specifications controlling for time-invariant student characteristics, we appear to find evidence of a summer learning loss, also known as knowledge decay, at the college level. Because students who take multiple sequenced courses with different break lengths between them, we can include student fixed effects. The estimate of knowledge decay is sensitive to the inclusion of these student-level fixed effects. We find that, on average, grades are no different for sequences taken fall-spring instead of spring-fall. In addition to providing new evidence on knowledge decay in higher education, we confirm the importance of controlling for student fixed effects shown by McMullen and Rouse (2012) in elementary and middle school. Even with a wide set of controls, traits associated with longer delays may also be associated with lower grades.

Knowledge decay, however, is not consistent across all courses or all students. Students with lower math SAT scores and students who never declare a STEM major at this land grant university experience knowledge decay in all their courses. Scheduling sequential courses fall-spring and encouraging academically weaker students to take subsequent courses closer to their prerequisites would improve these students' grades. Language courses also evince knowledge decay; it is particularly important to sequence language courses closer together. These findings can be useful for students and advisors. When students are choosing course schedules, priority should be given to lower-scoring students and to language courses to increase student success. These students should take these courses with as small a delay as possible between terms, and students who have a long summer between courses should participate in relearning and reviewing to compensate for the knowledge decay.

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Figure 1: Effect of gap by grade in prerequisite course

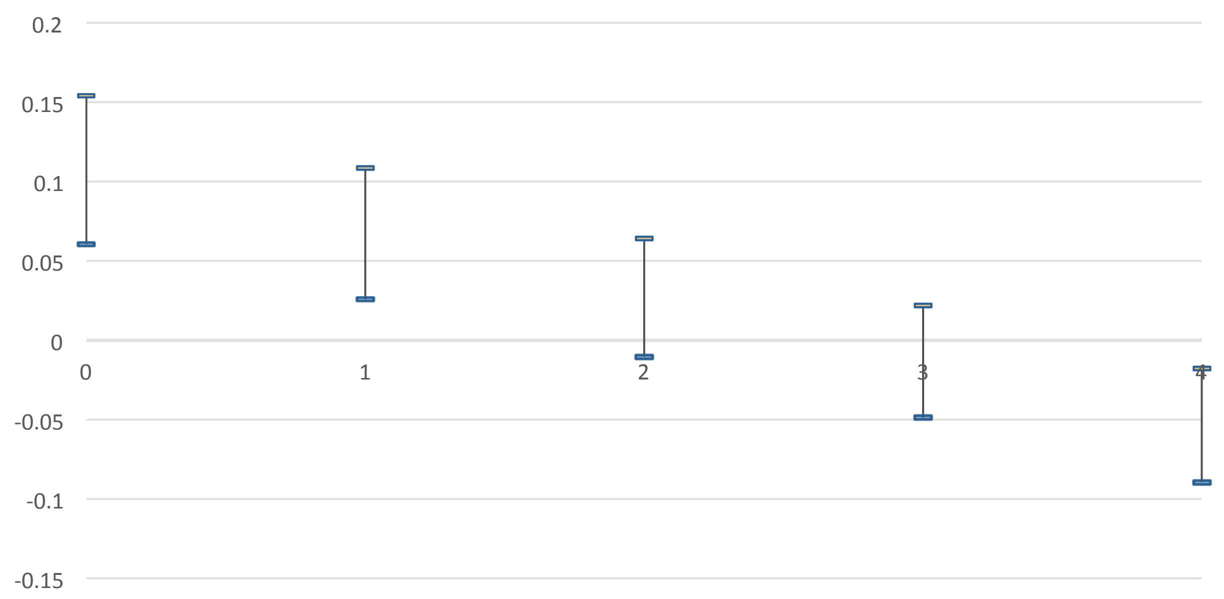

Table 1: Summary Statistics
(n = 117,861)

Variable	Mean	Std. Dev.	Min	Max
grade	2.7	1.1	0	4
gap between courses	5.4	0.8	5	7
grade in pre-requisite	2.797	0.903	0	4
took prerequisite twice	0.019	0.138	0	1
SAT math	565.00	83.80	240	800
Age at Clemson entry	19.715	1.959	15.4	47.6
In-state student	0.680	0.466	0	1
Male	0.547	0.498	0	1
Family/Legacy	0.278	0.448	0	1

Table 2: Course grade and length of time between pre-requisite and follow-up course, fall-spring and spring-fall only

	(1)	(2)	(3)	(4)	(5)
gap	-0.0368**	-0.00939	-0.0156	0.0210	0.107***
	(0.0166)	(0.0182)	(0.0181)	(0.0187)	(0.0238)
grade in prerequisite	0.600***	0.319***	0.320***	0.311***	0.540***
	(0.00327)	(0.00585)	(0.00555)	(0.00552)	(0.0259)
gap*grade in prerequisite					-0.0402***
					(0.00468)
took prerequisite twice	-0.514***	-0.196***	-0.202***	-0.141***	-0.210***
	(0.0220)	(0.0344)	(0.0335)	(0.0331)	(0.0335)
SAT math (in 10s)	0.00948***				
	(0.000370)				
Age at Clemson entry	0.0122***				
	(0.00146)				
in-state student	-0.0462***				
	(0.00596)				
male	-0.142***				
	(0.00563)				
family/legacy	0.0296***				
	(0.00614)				
Student fixed effects included	No	Yes	Yes	Yes	Yes
Course-pair fixed effects included	No	No	No	Yes	No
Observations	117,861	117,861	129,501	129,501	129,501
R-squared	0.380	0.708	0.705	0.717	0.705

All regressions include whether the student took the prerequisite more than once (gap is measured since the more recent course taking), department fixed effects, course-level dummies, and 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. Columns (2)-(4) include student fixed effects. Column (4) additional includes dummies for each course-pair sequence. Robust standard errors clustered by student in parentheses. This sample only includes fall-spring and spring-fall (those courses immediately following each other). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Does the gap matter more for weaker students?

	(1)	(2)	(3)	(4)	(5)	(6)
	by SAT math		STEM major?		STEM courses only	
	below median	above median	ever	never	ever STEM major	never STEM major
gap	-0.107**	0.0124	0.0258	-0.0757**	0.0387	-0.0918**
	(0.0420)	(0.0197)	(0.0221)	(0.0308)	(0.0280)	(0.0404)
grade in prerequisite	0.320***	0.311***	0.321***	0.313***	0.230***	0.202***
	(0.00840)	(0.00748)	(0.00774)	(0.00794)	(0.0123)	(0.0138)
took prerequisite twice	-0.157***	-0.234***	-0.211***	-0.149**	-0.0813	-0.0144
	(0.0484)	(0.0466)	(0.0371)	(0.0740)	(0.0494)	(0.141)
Observations	59,219	70,282	64,013	65,488	42,598	42,363
R-squared	0.701	0.702	0.703	0.711	0.777	0.774

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

Table 4: Does the gap matter more for different types of course sequences?

	(1) languages	(2) STEM course	(3) 100-or 200-level courses	(4) only 101/102	(5) no duplicate prereqs	(6) % taken out of order < 10%	(7) % taken out of order < 5%
gap	-0.0898*	0.0366	-0.0147	-0.0994	-0.0109	-0.0156	-0.0125
	(0.0509)	(0.0301)	(0.0197)	(0.107)	(0.0219)	(0.0181)	(0.0184)
grade in prerequisite	-0.245***	0.238***	0.322***	0.437***	0.330***	0.320***	0.321***
	(0.0216)	(0.0123)	(0.00598)	(0.0150)	(0.00700)	(0.00555)	(0.00564)
took prerequisite twice	0.371*	-0.0841	-0.206***	-0.198*	-0.287***	-0.203***	-0.207***
	(0.202)	(0.0530)	(0.0371)	(0.114)	(0.0411)	(0.0335)	(0.0340)
Observations	15,582	65,723	119,198	60,478	104,020	129,452	127,241
R-squared	0.853	0.813	0.720	0.859	0.741	0.705	0.711

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

Table 5: Does the effect of the gap differ when we consider a wider variety of course-taking behavior?

	(1)	(2)	(3)	(4)
	0 < gap <= 10	0 < gap <= 24	gap > 0	all
gap	0.0119***	0.00774***	0.00455***	0.00318***
	(0.00426)	(0.00137)	(0.00116)	(0.00109)
grade in prerequisite	0.306***	0.273***	0.267***	0.263***
	(0.00504)	(0.00436)	(0.00426)	(0.00421)
took prerequisite twice	-0.180***	-0.183***	-0.177***	-0.197***
	(0.0254)	(0.0199)	(0.0193)	(0.0179)
Observations	143,710	172,042	176,956	180,787
R-squared	0.683	0.646	0.639	0.638

All regressions include whether the student took the prerequisite more than once (gap is 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table 1: Course sequences in fall-spring or spring-fall sample

Course	*Prerequisite*	*N*
Accounting 303	Accounting 204	7
Accounting 301	Accounting 201	177
Accounting 307	Accounting 202	2,300
Applied Economics 302	Applied Economics 202	190
American Sign Language 102	American Sign Language 101	49
American Sign Language 201	American Sign Language 102	47
American Sign Language 202	American Sign Language 201	27
Anthropology 301	Anthropology 201	56
Anthropology 320	Anthropology 201	40
Architecture 152	Architecture 151	91
Architecture 251	Architecture 152	78
Architecture 252	Architecture 251	68
Architecture, Arts, & Humanities 102	Architecture, Arts, & Humanities 101	14,03
Architecture, Arts, & Humanities 203	Architecture, Arts, & Humanities 102	687
Architecture, Arts, & Humanities 204	Architecture, Arts, & Humanities 203	693
Architecture, Arts, & Humanities 205	Architecture, Arts, & Humanities 102	105
Architecture, Arts, & Humanities 206	Architecture, Arts, & Humanities 205	133
Astronomy 302	Physics 221	11
Astronomy 303	Physics 221	1
Biological Science 100	Biology 103	1
Biological Science 102	Biology 110	467
Biological Science 205	Biology 103	115
Biological Science 223	Biological Science 222	1,335
Biology 102	Biology 101	940
Biology 104	Biology 103	13,121
Biology 111	Biology 110	2,536
Ceramics & Material Engineering 222	Ceramics & Material Engineering 221	15
Chemical Engineering 220	Chemical Engineering 211	193
Chemical Engineering 311	Chemical Engineering 211	94
Chemical Engineering 312	Chemical Engineering 311	2
Chemical Engineering 321	Chemical Engineering 220	250
Chemistry 102	Chemistry 101	14,363
Chemistry 106	Chemistry 105	144
Chemistry 201	Chemistry 102	186
Chemistry 205	Chemistry 102	12

Chemistry 223	Chemistry 102	1,608
Chemistry 224	Chemistry 223	2,324
Chinese 102	Chinese 101	19
Chinese 201	Chinese 102	13
Chinese 202	Chinese 201	8
Chinese 204	Chinese 203	1
Computer Science 102	Computer Science 101	1148
Computer Science 220	Computer Science 120	148
Computer Science 270	Computer Science 120	124
Construction Science Management 202	Construction Science Management 201	778
Construction Science Management 205	Construction Science Management 203	156
Construction Science Management 301	Construction Science Management 202	569
Design 152	Design 151	347
Design 251	Design 152	237
Design 252	Design 251	366
Design 351	Design 252	274
Design 352	Design 351	325
Economics 314	Economics 211	135
Economics 315	Economics 212	92
Electrical & Computer Engineering 212	Electrical & Computer Engineering 211	586
Electrical & Computer Engineering 262	Electrical & Computer Engineering 202	627
Electrical & Computer Engineering 321	Electrical & Computer Engineering 320	1,370
Engineering Mechanics 202	Engineering Mechanics 201	2,384
English 102	English 101	34,034
Finance 312	Finance 311	2,824
Forestry 102	Forestry 101	122
Forestry 205	Forestry 102	89
Geology 102	Geology 101	1,206
Geology 112	Geology 101	997
German 102	German 101	775
German 201	German 102	411

German 202	German 201	348
General Communications 207	General Communications 104	665
Industrial Engineering 201	Engineering 120	133
Italian 102	Italian 101	360
Italian 201	Italian 102	194
Italian 202	Italian 201	199
Japanese 102	Japanese 101	274
Japanese 201	Japanese 102	173
Landscape Architecture 152	Landscape Architecture 151	23
Latin 102	Latin 101	213
Latin 201	Latin 102	173
Latin 202	Latin 201	187
Legal Studies 313	Legal Studies 312	1,146
Management 315	Marketing 314	14
Mechanical Engineering 303	Mechanical Engineering 203	333
Packaging Sciences 102	Packaging Sciences 101	278
Packaging Sciences 202	Packaging Sciences 102	228
Parks, Recreation, and Tourism Management 205	Parks, Recreation, and Tourism Management 101	789
Physics 208	Physics 207	4,410
Physics 221	Physics 122	7,326
Physics 222	Physics 221	3,291
Physics 311	Physics 222	21
Physics 321	Physics 221	7
Russian 102	Russian 101	140
Russian 201	Russian 102	71
Russian 202	Russian 201	71
Sociology 303	Sociology 201	65
Spanish 102	Spanish 101	5,154
Spanish 201	Spanish 102	3,480
Spanish 202	Spanish 201	3,768
Technology and Human Resource Development 160	Technology and Human Resource Development 110	48
Textile Engineering 201	Textile Engineering 176	261
Textile Engineering 202	Textile Engineering 201	324

Appendix Table 2: Sample student schedules with sequenced courses for three students with the BIOL 103-104 sequence and a SPAN sequence

Student 1:		Student 2:		Student 3:	
BIOL 103	Fall 1982	BIOL 103	Spring 1991	BIOL 103	Fall 1996
BIOL 104	Spring 1983	BIOL 104	Fall 1991	BIOL 104	Spring 1997
ENGL 101	Fall 1982	ENGL 101	Fall 1990	ENGL 101	Fall 1996
ENGL 102	Spring 1983	ENGL 102	Spring 1991	ENGL 102	Spring 1997
SPAN 101	Fall 1982	SPAN 101	Fall 1990	SPAN 101	Spring 1998
SPAN 102	Spring 1983	SPAN 102	Spring 1991	SPAN 102	Fall 1998
SPAN 201	Fall 1983	SPAN 201	Fall 1991	SPAN 201	Fall 1999
SPAN 202	Spring 1984	SPAN 202	Spring 1992		

Appendix Table 3: Comparison of included students to not-included students

	students in sample		students not in sample		
Variable	N	mean	N	mean	ttest
SAT math	47,273	558.3	22,119	544.3	-19.6***
Age at Clemson entry	47,273	19.66	16,600	19.59	-3.8***
In-state student	47,273	0.69	16,600	0.76	17.4***
Male	47,273	0.54	16,600	0.57	5.7***
Family/Legacy	47,273	0.28	16,600	0.43	34.8***