Summer coursework and completing college

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ABSTRACT

The summer school sessions that colleges offer their undergraduates are sometimes considered supplementary activities and are rarely perceived as central to a college's mission or effectiveness. However, analyses of college transcript data that tracked a nationally-representative sample of undergraduates for several years and through multiple colleges show that those undergraduates who attend summer school at the end of their first year of college have better retention rates thereafter and are significantly more likely to complete a degree. This relationship remains statistically significant and of substantial size after controlling for student socio-demographic characteristics and for their academic performance prior to taking summer school, using propensity score matching methods. Moreover, students with lower academic performance and others at higher risk of dropping out who attend summer school also have higher graduation rates, suggesting that administrators should conceive of summer school enrollment as an important tool for improving undergraduate retention and degree completion.

Keywords: summer learning; retention; degree completion; community college.

Acknowledgement: This research was supported by a grant from the Bill & Melinda Gates Foundation.

INTRODUCTION

Rates of college-going are high in the US: nationwide about 62% of Americans aged between 25 and 29 have some post-secondary education (Aud et al., 2012, p. 286). Unfortunately, high rates of access do not translate into high rates of graduation: only 26% of students entering community college degree programs and 63% of undergraduates entering public four-year colleges complete a degree within six years (Becker et al., 2007). This has led to calls from government officials and philanthropies for improvements in degree completion rates (Kanter et al. 2011; Lumina Foundation, 2013).

Researchers have identified multiple factors associated with failure to complete a college degree, including poor high school academic preparation, inadequate financial aid, and the burden of family or work responsibilities (Bozick, 2007; Braxton, 2000; Kuh et al., 2010; Perna, 2010; Seidman, 2005; John et al., 2010; Tinto, 1993). Many of these factors are relatively intractable: undergraduates who work to pay their bills often cannot afford to reduce their work hours; students with parenting obligations are unlikely to escape those responsibilities; and large increases in the level of federal financial aid for undergraduates are unlikely in an era of economic cuts. Policy-makers therefore look for interventions beyond these factors that might have a substantial impact on degree completion.

Educators have undertaken many college-based interventions and reforms aimed at improving graduation rates including changes in curricula, scheduling, support services for students, and mode of delivering courses (Rice &Taylor, 2003; McCormick et al., 2011). Some college-based interventions have shown large treatment effects: for example, the City University of New York's ASAP program increased associate degree graduation rates by 28 percentage points through a mix of block scheduling, smaller classes, intensive counseling and tutoring, and modest financial incentives for students (Linderman & Kolenovic, 2012; Scrivener et al., 2012). However, multifaceted college interventions like ASAP tend to be expensive. ASAP costs an additional $6,612 per FTE student per year (Levin & Garcia, 2012, p.15) compared to a regular annual expenditure per FTE community college student of $7,650 nationwide (College Board, 2012). Consequently, the search continues for less expensive interventions with high impact on college graduation rates, so-called "low hanging fruit."

This paper examines one long-standing feature of college life – summer school – that is not usually viewed by policy makers and education administrators in terms of retention and degree completion. Many colleges offer an optional summer program for undergraduates. Summer courses usually meet for fewer weeks than quarters or semesters in the rest of the year. To balance the fewer weeks, summer courses often meet more frequently or for longer hours, providing a more intensive learning experience compared to regular term time.

Using national data and employing an analytical technique that minimizes selection effects and controls for the influence of prior academic performance and other student variables, the analyses reported below find 7 and 11 percentage point advantages in graduation associated with attending summer school after the freshman year of college, at four-year and two-year colleges respectively. Moreover, summer school attendance is associated with higher graduation rates among several types of students for whom college completion is most problematic. This implies that summer school should not be perceived as a supplementary or peripheral activity, but instead be recognized as a potentially important and relatively inexpensive tool in colleges' efforts to raise graduation rates for undergraduates at risk of failure.

PRIOR RESEARCH AND THEORETICAL FRAMEWORK

There has been very little research about summer enrollment during college, and those few studies were based on a single dataset. Using student transcript data from the NELS88/2000 survey, Adelman (2006) found that taking courses during the summer was associated with higher odds of graduation. He concluded that "Summer-term enrollment works for just about everybody" and that "[For African-American students] earning more than four credits in summer terms offers a stunning boost, narrowing the completion gap vis à vis white students from 15.5 percent to 6 percent" (Adelman, 2006, p.90 & p. 93).

Adelman (2006) employed logistic regression models that did not address selection. However, as documented below, students who take summer coursework differ on background characteristics compared to counterparts who do not enroll in the summer. In a reanalysis of the same NELS transcript data, Author (2011) used propensity score matching methods to reduce selection bias and examined the links between attending summer school immediately after the first year of college and subsequent graduation rates, finding a statistically significant relationship between summer attendance and higher graduation rates, though of smaller magnitude than that reported by Adelman.

The theoretical framework that motivated those two studies involved the concept of academic momentum. That concept suggests that, even after controlling for students' high school preparation and demographic characteristics, undergraduates' experiences in college during the first year set a trajectory for future success. It emphasizes that the manner in which a student progresses during that initial period – the numbers of credits attempted and completed, and the trajectory of grades earned – is important for retention and degree completion. In essence, students who are able to accumulate a full load of credits each semester and attain good grades in their initial semesters, or whose initial grades trend upward, are likely to persist and complete their course of study (Adelman, 2005; Adelman, 2006). Those who do not are less likely to complete a degree. Within a momentum framework, summer school is important because it allows students to gain additional credits towards the required 60 or 120 credits for an AA or BA degree, respectively; summer attendance moves a student closer to the finishing line.

College can also be conceptualized as a set of organizational hurdles. Certain courses cannot be taken unless a student has already passed other prerequisite courses. In addition, students may be unable to take certain courses during the regular school year because of scheduling issues or because they are oversubscribed, and may take that course in the summer instead, in order to 'catch up' (Dainow, 2001; Taylor, 2003; Kretovics et al. 2005) Many colleges require entering undergraduates to take skill or placement tests and direct students with low scores into sequences of remedial or developmental courses (Jaggars & Hodara, 2011). Students may be advised not to proceed into non-remedial courses until they have passed remedial requirements. For some students in this situation, summer school enables them to take courses they need to "get back on track."

Another emphasis, one compatible with the momentum framework, is advanced in the report titled "Time is the Enemy" by the organization 'Complete College America' (2011). It notes that four of every ten undergraduates attend part-time, and that three-quarters of undergraduates are "juggling some combination of families, jobs and school while commuting to class." The result is that "Time is the Enemy of Completion" and "the longer [college] takes, the more life gets in the way of success." Their prescription is to speed up the progress of non-traditional students.

Attending summer school fulfills this agenda in two ways. It allows students to accumulate more credits, but it also avoids a situation where students put aside studying for the summer months and shift their efforts towards other competing obligations: earning money, spending time with family, and so on. If, as the report avers, there is a continual competition for students' attention between education and other life activities, then attending summer school acts to sustain an academic focus and to hold off those other competing demands.

Another possibility is that the intensive class scheduling of summer session courses may be pedagogically more effective for some students. Attending more class sessions per week may help in retaining ideas and building competence. Some students may find it easier to absorb material while taking fewer courses (during the summer) than the multi-class course load in a regular school year semester. Thus summer attendance may improve their academic performance or morale.

Finally, there are certain conceptual parallels between undergraduates attending summer school and previous research on summer learning in K-12 education. Numerous studies have noted large gaps in educational progress between social classes that widen during the summer breaks during K-12 schooling (Murnane, 1974; Heynes, 1978; Entwhistle &Alexander, 1992; Entwhistle &Alexander, 1994; Cooper et al., 1996; O'Brien, 1998; Downey et al., 2004). This well-documented phenomenon known as "summer fallback" refers to a pattern whereby low-SES students fall further behind their more privileged peers over time, not because of differences in the rate of learning during the school year, but largely because of a large gap in the amount of learning taking place over the summer. If similar dynamics were to occur for college-age populations as well as for high school students, one would expect to find that academic skills would atrophy over the summer months among lower-SES undergraduates, while such skills would be preserved over the summer among higher-SES students.

How might enrolling in summer school at college relate to the fallback phenomenon? Comparing students who attend summer school to otherwise similar students do not, one hypothesizes a benefit gained by attending summer school which should be largest for disadvantaged students, because relatively-privileged students accrue or maintain knowledge and skills even when they do not attend college, while relatively disadvantaged students may suffer skill setbacks in summer unless they remain in school. Furthermore one would expect that summer school would have a larger effect on students in institutions where lower SES students predominate, compared to colleges serving more affluent or higher SES students.

Prior studies and this theoretical framing lead to the following research questions:

1. What kinds of students currently opt to take summer coursework? Is there evidence of selection?
2. After correcting for student background characteristics and selection, is summer attendance after the first year of college associated with better retention and graduation prospects?
3. Do differences in outcomes associated with summer attendance vary across institutional type, comparing community college students with four-year college students?
4. Within each type of college, is there heterogeneity of effects: what kinds of students evidence larger differences in educational outcomes than others, related to summer attendance?

These questions are answered using a different source of data than that used in prior studies.

DATA & METHODS

The National Center for Education Statistics, a division of the US Department of Education, funds a longitudinal survey that follows a nationally-representative sample of college freshmen for six years after they first enter college. The latest complete cohort of this survey, known as the Beginning Post-Secondary Survey or BPS, followed a sample from 2003 until 2009. Methodological details are available on-line at http://nces.ed.gov/surveys/bps/about.asp. As a supplementary project, the BPS staff requested transcripts from all the colleges and universities that each student reported they had attended, and coded courses taken, grades received, and exact dates were spent in college.

The following analyses of the BPS transcripts are limited to students who entered into a degree program (AA or BA) in academic year 2003-2004. Only those students attending either a public institution or a private non-profit college are included. Consequently, students at proprietary or for-profit colleges are not present in these analyses. The BPS provides panel weights in order to account for attrition and non-response and replicate weights to correct standard errors for the survey's multi-stage sampling design. Those weights were used in the models reported below. The BPS also replaces missing data through a 'hot-deck imputation' procedure.

The main independent or 'treatment' variable is dichotomous, and indicates whether or not a student enrolled in classes during the summer immediately after his or her first year of college. Summer school attendance was identified from the transcript start-and end-dates of courses. Any term that started in May or later and ended by September was treated as a summer school session. The focus is only on summer school taken immediately after the first year of college. Some students also take summer courses in later years in college, but the analyses in this paper do not address that issue.

Two kinds of statistical models were estimated in order to understand the association between summer school attendance and educational outcomes. The first is multivariate logistic regression. Although the logistic models include many control variables representing potential confounds, their estimates of the coefficient for summer school attendance will be biased to the extent that students who attend summer school differ from students who do not attend summer, in terms of academic, demographic, or other characteristics. (This is termed selection bias.) In order to minimize selection bias, a set of propensity score matched models was also estimated. Propensity-score adjustments can reduce the bias of estimates due to observables and provide a more accurate inference about any 'treatment effect' that may exist (Morgan & Harding, 2006; Guo & Fraser, 2010; Morgan & Winship, 2007; Reynolds & DesJardins, 2009; Shadish et al., 2002).

Propensity-score matching proceeds in four stages. First a logistic or probit model is run to predict who undertakes the 'treatment' – in our case who attends summer school after their first year in college. This 'treatment model' or 'propensity score model' contains all available variables including students' demographic background, their high school academic characteristics, their college's characteristics, and the student's academic performance throughout their first year of college. The dependent variable is a dummy variable, with a value 1 for attended summer session, and zero otherwise. Interaction terms are included in the treatment or propensity model. Including predictors that are multicollinear and predictors that are not statistically significant are not problematic for this stage of analysis, since the goal is to determine the predicted probability of treatment, rather than the coefficients of individual predictors (Shadish et al., 2002, p.162). A complete list of predictors used in the propensity score model is provided in the Appendix.

From the logistic model one calculates for each student the probability of taking summer school, given their values on all covariates in the model, a quantity known as the propensity score. The second step involves matching persons who did attend summer school with persons with almost identical propensity scores but who did not attend summer school. This was accomplished through a STATA program called 'psmatch2' that undertakes a form of matching known as nearest neighbor matching with a caliper (Leuven & Sianesi, 2012). In this instance each treated case is matched with three untreated cases whose propensity scores are numerically very close to the treated case's score; the conventional distance or 'caliper' we used is within one quarter of a standard deviation of the treated case's propensity score (Guo & Fraser, 2010, p.147.) The end result is a treatment group and a control group, containing persons matched on the propensity score for treatment.

In propensity score matching, there are typically some extreme cases that cannot be matched. Some individuals have attributes that make it extremely likely that they will attend summer school; they have a very high propensity score as a result. In principle, there might be no individuals with very high propensity scores who did not attend summer school, so there are no untreated cases at this end of the scale to match to the treated cases. Conversely, some individuals may have a very low propensity to take summer school. At this extreme there may be many cases who did not attend summer session, but perhaps no equally-low scorers who did attend summer session. Hence some cases at this extreme cannot be matched.

Propensity score matching and the logic of the Counterfactual model apply to an area of overlap where matching is possible; the term used for this is 'common support.' If large proportions of cases could not be matched, that would raise the issue of whether the matched sample was representative of the larger population of undergraduates (Shadish et al., 2002, p.164). However, in our analyses, as reported in the Appendix, matching proved possible for well over 99% of cases, so this is not a problem. A report of the percent matched is provided there for each covariate.

In experimental studies, random assignment of cases into treatment and control groups ensures that the two groups are balanced in terms of observed and unobserved background characteristics. In a parallel fashion, successful matching on propensity for treatment in a non-experimental study should result in two groups that are closely balanced on all observed characteristics (though not necessarily on unobserved attributes). Consequently it is important to ascertain whether matching did in fact result in balance on covariates (Morgan & Harding, 2006). The Appendix to this paper provides several statistics assessing the degree of balance. The term 'mean bias' refers to the average of the differences between treatment and control group on all covariates, each measured in decimal fractions of a standard deviation, after matching. In our analyses biases were very small, never exceeding 0.05 s.d., indicating a good match. The column titled '% reduction in mean bias' indicates the percentage reduction in that bias, comparing before and after matching. As the Appendix reports, matching reduced bias by 99% or more; in other words, the treatment and control groups became much more balanced than the unmatched sample. Yet another indicator of the quality of the balance is the p value of a t-test comparing the mean value of the treatment group and the control group on each covariate, following matching. If the matching procedure is successful there should be no statistically significant differences on any covariates between treated and untreated groups. (So p values close to 1.0 are desirable.) On these criteria, the matching in our analysis was effective in reducing selection biases.

The third step of a propensity-score matched analysis determines the magnitude of treatment effects and their statistical significance. This is accomplished in the psmatch2 program by calculating a t-test between the treated and untreated groups and reporting estimates for the "average effect of treatment on the treated" or ATT.

A fourth step involves a sensitivity analysis of the ATT results. Propensity score matching cannot rule out the possibility that there might still be unmeasured or unobserved variables which are associated with attending summer school. A sensitivity analysis answers the question: how large would an effect from an unmeasured hypothetical variable need to be to render the results just obtained from a propensity analysis statistically non-significant? The STATA program "mhbounds" was used to calculate this quantity and report and interpret sensitivity values in the findings section below (Becker & Caliendo, 2007).

Causation and the Counterfactual Model of Causal Inference

The use of terms such as 'treatment effect' and 'benefit from attending summer school' may raise concerns that these terms imply causation and violate the credo that 'association is not causation.' In recent years, however, statisticians have argued that under certain carefully specified conditions, observational data can be used to test causal claims and not just association (Guo & Fraser, 2010; Pearl 2000; Shadish et al., 2002). When certain conditions are met, including achieving statistical balance on a range of substantively important covariates, scholars have demonstrated that the Counterfactual Model of Causal Inference, of which propensity score matched models are one application, does permit researchers to make causal inferences, so long as limitations are acknowledged (e.g., Shadish et al., 2002 p.161-163; Morgan & Harding, 2006; Morgan & Winship, 2007; Morgan & Todd 2008; Reynolds & DesJardins, 2009).

FINDINGS

The findings for degree-seeking students at community colleges or two-year institutions contrast in certain respects with those for entrants to four-year colleges, so the following presentation of results is divided by the type of college a student first entered.

1. What kinds of community college students attend summer school?

Table 1, which reports descriptive statistics for the sample, indicates that about 30% of community college students seeking degrees enroll in summer courses at the end of their first year of college. Table 2 provides a multivariate analysis of attendance in summer school for these two-year college undergraduates. Model 1 in Table 2 reveals that female students are more likely to take summer courses than males, and that Asian and Black students have a higher likelihood of taking summer school than Whites. Models 2 and 3 of Table 2, suggest that these demographic differences are not reflections of differences in academic preparation in high school or even academic performance during the first year of college; their coefficients change little after controlling for those factors.

However, prior academic performance in high school does affect the odds of attending college during the summer (Table 2, Model 2). Ceteris paribus, students who had lower GPAs in high school are less likely to take summer school. Similarly, students who performed well academically during their first year at community college were more likely to enroll in the summer (Table 2, Model 3). Two performance measures were included: cumulative college GPA prior to the summer, and cumulative college credits earned, prior to the summer. Both had statistically significant associations with summer school attendance.

This pattern is consistent with Adelman's notion of academic momentum: those students who initially thrive in college, gaining good grades and credits, are drawn into greater levels of involvement, while students who struggle in terms of accruing credits and good grades are less likely to increase their level of involvement and may decrease their academic momentum.

Students who had enrolled in a bridge course between high school and starting college had nearly double the odds of enrolling in summer classes after the end of their first year of college. This is noteworthy because summer bridge programs at community colleges often enroll academically-challenged students, and are often focused on improving basic academic skills; yet taking a bridge program before formally starting college seems to lead such students to enroll once again in summer courses one year later.

2. What outcomes are associated with attending summer school for students at two-year colleges?

Table 3 summarizes a series of conventional regression models and propensity-score matched models predicting important milestones in the academic careers of two-year college entrants. They indicate whether attending summer school at the end of one's first year in college is associated with better outcomes on these milestones. The conventional regression analyses on the left of the table do not correct for selection bias – the fact that students who attend in the summer are systematically different from those who do not attend. The right hand of the column presents propensity matched models that do correct for selection bias.

All of the effects reported in Table 3 came from regression models controlling for the many covariates or potential confounds including: race/ethnicity, gender, age, single parents, US-born, citizenship, student's marital status, having a dependent, whether the student's native language is English, household size, mother and father's educational level, income, home ownership and investments. There were also measures of students' high school academic preparation: student's high school GPA and numbers of credits earned, their SAT quartile and highest level of mathematics taken in high school, and whether they earned any college credits while in high school; whether they lacked a regular high school diploma. The models in Table 3 also controlled for the following college characteristics: total enrollment, percent of students who received federal grant aid, and loan aid, tuition quartile; percent of Black and Latino students at the institution. Finally, several control variables reflected student academic progress and engagement during the freshman year of college, prior to tasking summer school: whether the student viewed themselves as primarily a student working to pay expenses, or primarily a worker who was taking courses in college; whether the student had paid work during the summer; whether the student registered full-time or part-time; the student's cumulative credits earned and cumulative GPA during the first year prior to summer school; the ratio of credits completed to credits attempted in the first year of college; and whether the student took a summer bridge course prior to the Fall semester of their first year. These same variables were used to predict 'treatment' in the propensity matched models in Table 3.

Before detailing the findings in Table 3, however, a potential logical pitfall should be discussed. In principle, summer attendance could be a symptom rather than a cause of retention. Imagine that a student was about to drop out at the end of the first year. That student might be less willing to enroll in summer school at the end of the first year. Hypothetically, therefore, the apparent association of summer attendance with later academic outcomes such as graduation might be spurious, and really reflect the fact that students who are about to drop out of school are much less likely to take summer school at the end of the first year.

To avoid this problem, all the results analyzed in Table 3 are conditioned on a student returning to college for the Fall term of their second year: the analyses only include students who did return after the summer and register for the Fall term of the sophomore year. This conditioning makes a substantial difference to the findings. The apparent effects of summer enrollment were much larger in models that were not conditioned on Fall 2nd year enrollment (models not shown). However, the conditional effects reported in Table 3 remove this potential source of spuriousness, and still indicate that there are summer school effects. This is the most conservative approach.

Table 3 summarizes six different analyses and focuses on the effect sizes for three different outcomes, each of which can be viewed as a milestone in a student's career. The first such milestone, in the first row of table 3, reports whether a student remained enrolled in the Spring of their second year. The conventional regression model reports that 86% of those who took summer school came back for Spring of their second year, compared to 79% of students who did not take summer school, a highly significant difference. Continuing across this first row of Table 3, the propensity model finds that 88% of summer attendees returned to college for the Spring of their second year, compared to 85% of those who did not attend in the summer. The propensity score model did not show a statistically significant effect, implying that the observed difference in reenrolling is partly attributable to background differences between treated and untreated students. A second row in Table 3 shows a similar pattern in estimating the effect of summer school on stopping out of college: conventional regression indicates that summer school reduces stopping out, but propensity analysis suggests this is due to selection.

The most important milestone is whether a student graduated with a degree (AA or BA) within six years of entering a two-year college. The third row of Table 3 shows that students who attended summer school had a 9.79 percentage point higher graduation rate in the conventional regression model. They also had a 10.98 percentage point higher graduation rate in a propensity matched model. Both effects were statistically significant at the 0.001 level. This substantial effect of summer school on degree completion is estimated after controlling or adjusting for high school academic background, and performance in the first year of college, and also for students' demographic characteristics.

The next question to be considered is whether these benefits occur equally for all kinds of students in two-year colleges, or whether summer school attendance has a larger effect size for certain types of students than for others.

3. Heterogeneity in summer effect sizes among two-year-college students.

Heterogeneity in the effects of taking summer school was examined for several subgroups of two-year college students, dividing on age; race; gender; family background; high versus low college GPA; whether or not the student had taken a remedial class; and for high propensity versus low propensity to take summer courses. In each case separate propensity-score matched models for each subgroup determine (a) whether there is a statistically-significant effect of summer for one or both groups and (b) to compare the result- or effect-sizes across the groups. The outcome variable used was graduated with any degree (AA or BA) within six years.

The results of these analyses are reported in Table 4. Comparing students younger than 21 with those 21 or older, attending summer school at the end of one's first year in college was significantly associated with higher rates of graduation for both age groups. The size of the effect was roughly comparable in both age groups.

To examine racial and ethnic subgroups, limited sample sizes constrained the researchers to compare Black and Latino students on the one hand with White, Asian and 'Other Race' students on the other. Statistically significant positive effects of summer school were found for both race/ethnic groups. The size of the summer effect was not significantly different across those racial groups.

Summer school had a positive association with graduation for both men and for women students, of roughly the same magnitude. A similar pattern where both groups benefited about equally was found when comparing students who were 1st generation college goers with students whose parents had attended college.

Two dimensions related to prior academic performance are examined in Table 4. The first contrasted cumulative GPA in college during the first year (prior to summer school). Summer school attendance had a statistically significant positive association with graduation for both higher and lower GPA students. Students were also contrasted according to whether or not they had taken any remedial courses during their first year. Again, both remedial and non-remedial students showed a large positive statistically-significant association between summer school and graduation.

Finally, analyses examined whether students with a high probability to enroll in summer school (based on a multivariate model that contained academic, demographic, and other predictors) exhibited the same graduation boost as students whose profile suggested they were unlikely to take summer school. For both high propensity and low propensity score students, attending summer school was significantly associated with higher chances of graduation.

In sum, heterogeneity was considered on several dimensions: race, sex, age, family background, and academic performance. For all subgroups of two-year college students there was a statistically significant higher graduation rate associated with attending summer school. The effect sizes were not statistically different across subgroups.

Turning to analyses of summer school for students entering four-year colleges, results contrast in important respects with the findings for two-year-college entrants.

4. Which four-year college students attend summer school?

Nationwide, about 21% of four-year college undergraduates enrolled in the summer after their first year, a smaller incidence than among community college students (Table 1). Table 5 indicates that Asian students at four-year colleges have nearly double the odds of enrolling in summer school than those of whites, even after holding numerous other variables constant. Black students are also more likely to enroll in summer school compared to whites. Married students also have statistically significantly higher odds of summer enrollment. Four-year college students whose native language is English are considerably less likely to take summer school than nonnative English speakers, and students with more need-based aid are less likely to enroll in summer school.

Among four-year college students, a stronger high-school academic performance as indicated by a higher GPA is associated with a *lower* probability of enrolling in summer school. However, these effects cease to be significant after controlling for students' academic performance during their first year of college. The higher ones first year college GPA, the more likely one is to enroll in summer school.

As was also the case for community colleges, those students who attended a bridge program in the summer prior to enrolling in college were much more likely to enroll in summer courses at the end of their first year of college: their odds are 2.7 times as high as non-bridge students after controlling for other covariates.

5. What outcomes are associated with attending summer school for four-year college students?

Table 6 reports the correlates of summer school for four-year college students, looking at the same milestones or outcomes as before, and with similar controls. Several outcomes were not statistically significant. However, in both the conventional regression and in the propensity model, there was a statistically significant effect of summer school upon six-year graduation. The magnitude was 3.74 percentage points in the regression model and 6.93 percentage points in the propensity model.

6. Heterogeneity in summer effect sizes among four-year undergraduates.

Table 7 reports on heterogeneity in the relationship between summer school and graduation within six years. Statistically significant positive relationships between summer attendance and the outcomes were found for most subgroups. One exception was that summer school attendance was not associated with better graduation chances for students who had a GPA above the median in their first year of college. It was only positively associated with students who had GPAs below the median in the first year. Taken at face value this suggests that academically high performing students in four-year schools do not benefit from taking summer school, but that summer school is associated with significantly better graduation prospects among academically lower-performing four-year college students.

Older students in four year colleges did not seem to have a significant summer school effect and nor did minority students. Some caution is warranted in interpreting these latter effects, because in both cases, the numbers of cases for the subgroup were smaller, raising issues of statistical power, and because the effect sizes for minorities (for which $p=0.089$) were not statistically different than those for non-minority students, similarly for older versus younger students.

7. Sensitivity Analyses.

In Table 8, for community college students, a non-parametric Mantel and Haenszel test indicates that an unobserved variable would have to change the odds of treatment by a factor 1.5 for the observed effect of summer attendance to be rendered statistically non-significant. Since that would be a quite strong unobserved bias, it seems unlikely that the treatment effect of summer for community college students that we observed is caused by an unmeasured confounder. The same test indicates that for four year college students, a hypothetical unobserved bias that changed the odds of treatment by a factor of 1.15 would negate the observed significant result. An effect of that magnitude suggests that some degree of caution is merited in interpreting the observed impact of summer school among four-year college students, although one should note that a sensitivity analysis does not imply that such a bias actually exists; it simply tests how large a hypothetical bias would need to be before observed results were rendered not significant.

DISCUSSION AND CONCLUSION

Based on prior research and insights from studies of summer fallback, the researchers anticipated that undergraduates who attend summer school after the end of their first year in college might have higher graduation rates than their academically and socially similar counterparts who do not attend summer school. This study supported prior claims made on the basis of different longitudinal data: summer school attendance after the freshman year of college was associated with 7 and 11 percentage point advantages in graduation, at four-year and two-year colleges respectively. Among the many factors controlled for in these analyses was academic performance during the first year in college, as well as various aspects of family background. So these effects of summer enrollment were not simply consequences of students' stronger academic backgrounds or prior performance.

Scholars argue that findings from properly-balanced propensity-score models may be read as evidence for a causal relationship, and not just evidence of statistical association (Guo & Fraser, 2010; Morgan & Winship, 2007). The effects reported here are statistically significant and of considerable magnitude, suggesting that summer school may serve as one way to enhance graduation rates. Colleges might consider ways of encouraging more of their students to enroll in summer school. Most especially, community colleges would show the largest gains in graduation if the results reported here are generalizable to interventions designed to pull more students into summer school. One such intervention – a Randomized Control Trial – is currently underway at the City University of New York, but it will be some years before outcomes such as graduation can be assessed.

Finally, one should note that federal policy regarding the provision of summer school has been fluctuating and has recently backed away from supporting summer school attendance. The Higher Education Opportunity Act of 2008 provided, for the first time, a Year-Round Pell Grant that became effective in academic year 2009-2010. Nationwide, about 800,000 undergraduates took advantage of that provision to pay for summer school in that year. However, this year-round or summer Pell grant was subsequently eliminated by a federal statute, the Department of Defense and Full-year Appropriation Act of 2011, following testimony by the Secretary of the US Department of Education that the extra grants "cost 10 times more than anticipated and failed to demonstrate a meaningful impact on students' academic progress" (Kantrowitz, 2011). It is unclear what evidence underlay that statement about lack of academic progress. Several studies cited above, along with the research reported here, suggest that summer school may indeed have ‘a meaningful impact’ on undergraduates’ progress, and one hopes that educational policy-makers will become aware of that evidence.

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APPENDIX

Table 1. Descriptive Statistics of BPS sample (weighted)

	2 year college students in degree programs		4 year college students in degree programs	
	Mean	Std. Err.	Mean	Std. Err.
Treatment				
% attending summer school after one year	.301	.013	.210	.007
Covariates				
Demographic Variables				
Female	.575	.015	.556	.009
Age	22.888	8.426	19.200	4.084
White	.615	.022	.699	.013
Black	.139	.012	.097	.012
Latino	.152	.013	.098	.006
Asian	.041	.005	.057	.003
Other	.050	.004	.047	.004
Student is Married	.137	.008	.025	.003
Have Any Dependent	.217	.010	.037	.004
English as Primary Language	.883	.008	.899	.006
Parental Education Variables				
Parents' Education is Unknown /Less than High School	.105	.008	.040	.003
Parents graduated High School	.304	.011	.174	.006
Parents' Education has less than BA	.297	.013	.218	.007
Parents have BA or higher	.292	.010	.566	.008
SES Variables				
Parents/Student Owns a home	.696	.016	.839	.006
HH Income (log)	10.164	.1.999	10.749	1.551
Total amount of need-based grant aid 2003-2004	920.849	31.274	2591.405	81.716
Academic Variables				
High School GPA				
No GPA info	.317	.011	.082	.006
.5-1.9 (low GPA)	.041	.006	.010	.001
2.0-2.9(mid-low GPA)	.271	.011	.138	.007
3.0-3.4 (mid-high GPA)	.245	.010	.316	.008
3.5-4.0(high GPA)	.124	.009	.451	.009
Remediation				
Didn't take any remediation	.685	.011	.825	.006
Took one or more remediation	.314	.011	.174	.006
Cumulative GPA up to First Summer	2.521	1.179	2.816	.869
Cumulative Credit Earned up to First Summer	14.337	10.316	25.077	9.033
Taking Summer Bridge Program	.092	.008	.060	.006
Full-time status in Fall 2003	.356	.012	.796	.011
Full-time status in Spring 2003	.490	.017	.863	.008
N	4,280		7,390	

Note: For continuous variables (age, income, cumulative GPA up to first summer, cumulative credit earned up to first summer, and ratio of credit earned/attempted up to first summer), a standard deviation is reported instead of a standard error.
Data Source: NCES Beginning Postsecondary Study 2003/2009 cohort, PETS transcript data.

Table 2. Attendance in Summer Courses after the first year of college: Degree-program entrants to Two-year Colleges (weighted)

Odds ratios from logistic regressions predicting First Summer Attendance.

Variables	(1) Demographic and SES	(2) Academic Background in High School	(3) Academic Background in College up to First Summer
Black (*Ref: White*)	1.290*	1.322*	1.773***
Latino	1.029	1.013	1.194
Asian	2.811***	2.649***	2.499***
Other race	0.548**	0.537**	0.620*
Female	1.456***	1.451***	1.389***
Age (centered)	1.042**	1.022	1.011
Age^2 (centered)	0.999*	0.999	0.999
HH Income (log)	0.969	0.973	0.955
Parents' Education is Unknown (*Ref: Parent HS*)	0.914	0.909	0.921
Parents' Education is less than BA	1.075	1.057	1.013
Parents have BA or higher	1.135	1.112	1.005
Home Ownership	1.108	1.143	1.092
Total amount of need-based grant (in thousand$)	1.046*	1.047*	.997
Married	1.185	1.179	1.033
Have Any Dependent	1.076	1.052	1.242
English as Primary Language	0.879	0.889	0.883
No High School GPA Info (*Ref:gpa3.0-3.4*)		1.209	1.375
Low HS GPA (0.5-1.9)		0.468**	0.550*
Medium-low HS GPA (2.0-2.9)		0.854	0.925
High HS GPA (3.5-4.0)		0.971	0.869
Cumulative GPA up to First Summer			1.467***
Cumulative Credit Earned up to First Summer			1.030***
Took Summer Bridge Program			1.973***
Full-time in Fall 2003			0.826
Full-time in Spring 2004			1.231
Number of Observations	4,280	4,280	4,280
Pseudo R-square	.029	.033	.102

*** p<0.01, ** p<0.05, * p<0.1

Note: Pseudo R-square is not valid for logistic regression that use replicate survey weights, so we have computed it instead using sample weights.

Table 3. Logistic regressions and Propensity-Matched Models Predicting Effect of Summer School on Retention and Graduation for students who entered two-year colleges.

Comparing the percentages of summer attendees and non-attendees on various outcomes: Conditioned on fall 2004 enrollment

	Regression Model (%)			Propensity Model (%)		
	Summer	No Summer	Difference	Summer	No Summer	Difference
Outcome						
Reenrolled Spring 2nd Year	86.15	79.17	6.98***	88.08	84.89	3.18
Ever Stopped Out	30.86	41.10	10.24***	29.88	33.39	3.50
Graduated within 6 years	45.83	36.04	9.79***	53.28	42.30	10.98***
N		3,020			2,960	

*** p<.001; **p<.01; *p<.05

These models include controls for students' demographic and family background, high school academic preparation, academic performance during the first year of college, and other factors. See text for a complete list.

Table 4. Heterogeneity Tests of Summer Effects on Graduation among Two-year College Students Conditioned on fall 2004 enrollment

	Graduated in 6 years					
	Treated	Controlled	Difference	S.E.	P	P of differences between groups
Age (mean=20.85, median=19)						
Younger (younger than 21)	.4327	.3254	.1072	.0424	.011	
Older (21 or older)	.5790	.4754	.1036	.0289	.000	.944
Race						
Minority (Black and Hispanic)	.4142	.2454	.1688	.0435	.000	
Non-Minority (White, Asian, Others)	.5708	.4601	.1106	.0280	.000	.260
Gender						
Male	.5398	.4166	.1231	.0395	.001	
Female	.5263	.4206	.1057	.0307	.000	.728
Remediation						
Took at least one remediation	.4929	.3813	.1116	.0284	.000	
Didn't take any remediation	.6503	.5437	.1066	.0512	.037	.932
Family background						
1^{st} generation college-goer	.5025	.3884	.1141	.0338	.000	
Not a 1^{st} generation college-goer	.5623	.4331	.1292	.0368	.000	.762
Cumulative GPA up to First Summer						
Low GPA (GPA is Below 2.97)	.3360	.2560	.0800	.0362	.027	
High GPA (GPA is 2.97 or higher)	.6312	.5091	.1220	.0304	.000	.374
Propensity of Taking First Summer						
Low Propensity	.4690	.3756	.0933	.0381	.014	
High Propensity	.5478	.3933	.1544	.0296	.000	.205

Table 5. Attendance in Summer Courses after the first year of college: Entrants to Four-year Colleges (weighted)

Odds ratios from logistic regressions predicting First Summer Attendance.

Variables	(1) Demographic and SES	(2) Academic Background in High School	(3) Academic Background in College up to First Summer
Black (*Ref: white*)	1.342*	1.401**	1.345*
Latino	1.156	1.192	1.189
Asian	2.092***	2.031***	1.947***
Other race	1.009	1.009	1.033
Female	1.193**	1.168**	1.118
Age (centered)	1.005	0.992	0.998
Age^2 (centered)	1.001	1.001	1.000
HH Income (log)	0.956	0.957	0.954
Parents' Education is Unknown (*Ref: Parent HS*)	0.779	0.773	0.748
Parents LT Bach	1.013	1.005	0.986
Parents have BA or higher	1.221	1.194	1.158
Home Ownership	1.043	1.048	1.032
Total amount of need-based grant (in thousand$)	0.962***	0.961***	0.961***
Married	1.866*	1.869*	1.884*
Have Any Dependent	1.155	1.140	1.113
English as Primary Language	0.649***	0.658***	0.664***
No High School GPA Info (*Ref: GPA 3.5-4.0*)		1.064	1.038
Low HS GPA(0.5-1.9)		1.847	1.885
Medium-low HS GPA(2.0-2.9)		0.724**	0.809
Medium-high HS GPA(3.0-3.4)		0.856*	0.926
Cumulative GPA up to First Summer			1.232***
Cumulative Credit Earned up to First Summer			0.998
Taking Summer Bridge			2.676***
Full-time in Fall 2003			0.928
Full-time in Spring 2004			1.098
Observations	7,390	7,390	7,390
Pseudo R-square	0.023	0.026	0.040

*** p<0.01, ** p<0.05, * p<0.1

Table 6. Logistic regressions and Propensity-Matched Models Predicting Effect of Summer School on Retention and Graduation for students who entered four-year colleges.

Comparing the percentages of summer attendees and non-attendees on various outcomes: Conditioned on fall 2004 enrollment

	Regression Model (%)			Propensity Model (%)		
	Summer	No Summer	Difference	Summer	No Summer	Difference
Outcome						
Reenrolled Spring 2nd Year	94.83	93.92	0.91	95.87	93.78	2.08**
Ever Stopped Out	14.49	16.37	1.88	14.16	17.03	-2.86
Graduated in 6 year	73.94	70.20	3.74*	76.40	69.47	6.93*
N		6,620			6,600	

*** p<.001; **p<.01; *p<.05

These models include controls for students' demographic and family background, high school academic preparation, academic performance during the first year of college, and other factors. See text for a complete list.

Table 7. Heterogeneity Tests of Summer Effects on Graduation among Four-year College Students

Conditioned on fall 2004 enrollment

	Graduated in 6 years					
	Treated	Controlled	Difference	S.E.	P	Difference of differences
Age (mean =19; median=18)						
Younger (younger than 21)	.7816	.7155	.0661	.0158	.000	
Older (21 or older)	.5000	.5131	-.0131	.1232	.914	.524
Race						
Minority (Black and Hispanic)	.6405	.5693	.0711	.0418	.089	
Non-Minority (White, Asian, Others)	.7946	.7441	.0505	.0166	.002	.646
Gender						
Male	.7113	.6501	.0612	.0267	.022	
Female	.7953	.7396	.0556	.0192	.003	.865
Remediation						
Took at least one remediation	.6592	.5930	.0661	.0298	.026	
Didn't take any remediation	.8201	.7756	.0444	.0176	.011	.530
Family background						
1st generation college-goer	.7113	.6086	.1026	.0330	.001	
Not a 1st generation college-goer	.7877	.7329	.0548	.0180	.002	.203
Cumulative GPA up to First Summer						
Low GPA (GPA is Below 3.0)	.6788	.5517	.1270	.0248	.000	
High GPA (GPA is 3.0 or higher)	.8416	.8356	.0059	.0184	.746	.000
Propensity of Taking First Summer						
Low Propensity	.7862	.7001	.0861	.0234	.000	
High Propensity	.7510	.7121	.0389	.0214	.068	.136

Table 8. Sensitivity Analysis for the Effect of Summer School on Graduation

Conditioned on fall 2004 enrollment, ATT

	2 year college		4 year college	
Estimated Difference	10.98%		6.93%	
	Gamma	P-value	Gamma	P-value
	1	P<.000	1	P<.000
	1.1	P<.000	1.05	.003
	1.2	P<.000	1.1	.020
	1.3	.004	1.15	.072
	1.4	.041	1.2	.185

1.5	.185	1.25	.360
1.6	.456	1.3	.466
1.7	.292	1.35	.280
1.8	.107	1.4	.144
1.9	.028	1.45	.064
2	.005	1.5	.024

Table 9. Predictors for the Propensity Score Matching Model

Demographic background	race*female, age, dependency status, single parent status, citizenship status, has any dependents, whether the student's native language is English, household size, housing status (whether a student live on campus, off campus, or living with parents), degree of urbanization
SES background	mother and father's educational level, non-traditional household status, homeownership status, homeownership*dependency status, whether parents or students have significant investments status, investment status*dependency status, income (log), income*dependency status, percentage of loan out of total aid
Students' high school academic preparation	SAT math quartile, whether students earned any college level credits while in high school, high school GPA, whether they lacked a regular high school diploma, highest level of mathematics taken in high school
College characteristics	institutional enrollment size (log), percent received federal grants at institution, percentage of black and Latino at institution, tuition quartile, institutional sector
Student academic progress and engagement during the freshman year of college	whether the student viewed themselves as primarily a student working to pay expenses or primarily a worker who was taking courses in college, whether the student had paid work during the summer, hours worked per week while enrolled in 2004, whether the student registered full-time or part-time, whether the student took a summer bridge course prior to the Fall semester of their first year, the student's cumulative credits earned and cumulative GPA during the first year prior to summer school, the ratio of credits completed to credits attempted in the first year of college

Note: For the analyses of 4-year college students, a measure of college selectivity was added to these predictors in the propensity models.

Table 10. Statistics for Propensity Score Matches involving Two-year students

	N	% Matched	% Reduction in Bias after matching	P-value of T Test for Treat-Control	Mean Bias of covariates after matching
Table 3 (ATT: In condition of fall 2004 enrollment)	2,960	99.46	99.9	0.990	.025
Table 4 (ATT: In condition of fall 2004 enrollment, Heterogeneity Tests)					
Age					
Younger (younger than 21)	739	96.34	99.9	0.994	.038
Older (21 or older)	2,186	98.95	99.9	0.985	.033
Race					
Minority (Black and Hispanic)	776	95.33	99.8	0.977	.034
Non-Minority (White, Asian, Others)	2,156	99.72	99.9	0.989	.025
Gender					
Male	1,203	99.91	100	0.997	.031
Female	1,757	99.15	99.8	0.973	.029
Remediation					
Took at least one remediation	2,175	99.45	99.7	0.960	.037
Didn't take any remediation	784	99.36	99.7	0.971	.058
Family background					
1st generation college goer	1,494	99.13	99.9	0.986	.040
Not a 1st generation college goer	1,398	99.64	99.7	0.971	.037
Cumulative GPA up to First Summer					
Low GPA (GPA is Below 2.97)	1,241	99.59	99.9	0.990	.040
High GPA (GPA 2.97 or higher)	1,715	99.13	99.8	0.977	.026
Propensity of Taking First Summer					
Low Propensity	1,314	99.31	99.9	0.995	.030
High Propensity	1,606	97.15	99.9	0.988	.026

Table 11. Statistics for Propensity Score Matches involving Four-year students

	N	% Matched	% Reduction in Bias after matching	P-value of T Test for Treat-Control	Mean Bias of covariates after matching
Table 6 (ATT: In condition of fall 2004 enrollment)	6,598	99.93	100	0.997	.023
Table 7 (ATT: In condition of fall 2004 enrollment, Heterogeneity Tests)					
Age (mean =19; median=18)					
Older (19 or older)	236	93.28	99.5	0.950	.096
Younger	6,341	100	99.9	0.990	.023
Race					
Minority	1,106	99.01	100	1.000	.030
Non-Minority	5,483	99.96	99.9	0.989	.018
Gender					
Male	2,817	99.75	99.9	0.992	.027
Female	3,775	99.92	100	1.000	.024
Remediation					
Took at least one remediation	2,061	99.56	99.8	0.980	.023
Didn't take any remediation	4,524	99.82	99.9	0.992	.021
Family background					
1st generation college goer	1,791	99.72	99.9	0.992	.033
Not a 1st generation college goer	4,748	99.93	100	0.996	.019
Cumulative GPA up to First Summer					
Low GPA	3,058	99.70	99.9	0.996	.026
High GPA	3,526	99.74	99.9	0.990	.026
Propensity of Taking First Summer					
Low Propensity	3,273	100	99.8	0.987	.021
High Propensity	3,321	99.87	99.9	0.994	.025