The Effects of Concurrent Enrollment on the College-Going and Remedial Education Rates of Colorado's High School Students

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Introduction

In Colorado, concurrent enrollment refers to programs at public high schools through which students in grades 9 through 12 can take free college-level courses (CDE, 2010). The courses are taught by postsecondary instructors and take place either at the high school or at a higher education institution (CDE, 2010). Concurrent enrollment programs have grown rapidly since legislation was enacted in 2009 that expanded access and clarified funding streams (House Bill 09-1319). Those in favor of concurrent enrollment argue that it increases academic preparation for college and provides momentum toward degree attainment by giving students the opportunity to enter college with credits already accumulated (An, 2013). Prior research has found positive associations between concurrent enrollment participation and college success (Karp, Bailey, Hughes, & Fermin, 2007; Morrison, 2008).

The empirical analysis conducted here seeks to discover if similar positive associations can be found using Colorado's data. The following research questions will be used to guide this study:

(**RQ1**) How does participation in concurrent enrollment affect the college-going rates of Colorado's high school students?

(**RQ2**) How does participation in concurrent enrollment affect the remedial education rates of Colorado's high school students?

Literature Review

Prior studies that have sought to identify predictors of college enrollment and success have generally focused on three components: 1) academic achievement, typically measured by standardized test scores and high school grade point average (GPA); 2) demographic factors, such gender, race/ethnicity and family income; and 3) pychosocial factors, which can include motivation, self-management, study skills, and academic engagement (Robbins et al., 2004).

Many studies have substantiated the validity of both standardized test scores and high school GPAs in predicting first-year college GPAs and retention rates (Allen & Robbins, 2010; Radunzel & Noble, 2012; Robbins, Allen, Casillas, Peterson, & Le, 2006). Most educational achievement studies include both variables in models because prior research has found some unique value to each one. One study, for example, found that ACT composite scores and high school GPAs better predict first-year GPAs together than separately (Sawyer, 2010). Researchers have postulated that GPAs are more of an indicator of academic motivation (e.g. turning in assignments on time) while ACT or SAT scores are more of an indicator of intellectual ability (Allen & Robbins, 2010). GPAs, however, do have disadvantages in that they do not account for differences in the competitiveness of schools or for grade inflation (Bassiri & Schulz, 2003; Ziomek & Svec, 1995). An advantage of the ACT or SAT is that they are national, standardized tests, which provide a more consistent measurement of academic aptitude (Radunzel & Noble, 2012).

Demographic variables are essential to include in education studies because research has consistently shown that low-income, minority students have lower levels of academic achievement than their peers. Test score data from the National Assessment of Educational Progress (NAEP) shows that African American and Hispanic students score two grade levels below white students when taking the NAEP exam in 4th and 8th grades (National Center for Education Statistics, 2009, 2011). Children from low-income families are more likely to have low reading abilities by the third grade, which makes them four times more likely to drop out before high school graduation than their peers (Hernandez, 2011). Low-income and minority students are less likely to enroll in or graduate from college than their white, affluent peers (An, 2012).

Education researchers—including those specifically studying concurrent enrollment—often do not include indicators of motivation into educational achievement models because of the difficulty of measuring motivation and the resulting dearth of available data (An, 2012; Le, Casillas, Robbins, & Langley, 2005). This leads to significant problems of selection bias. To prevent selection bias problems, some recent psychology-based studies have used a "Student Readiness Inventory", or SRI, to measure psychosocial factors that are relevant to college enrollment and success. A recent study by Robbins et al. (2006) using data from the SRI survey instrument found that motivation added "considerable value beyond traditional predictors (i.e., demographic and achievement) for all three types of [college] outcomes: GPA, retention, and success in specific courses" (p. 612-613).

Data

Data were collected through the Colorado Department of Higher Education's (DHE) Student Unit Record Data System (SURDS). Currently, SURDS includes comprehensive data on students enrolled at all public colleges and universities in the state, as well as those enrolled at the University of Denver, Regis University, and Colorado Christian University. The DHE supplements SURDS with data from the National Student Clearinghouse (NSC) to provide information on out-of-state enrollment and enrollment at private institutions. The NSC has a coverage rate of 96 percent of all students enrolled in a U.S. public or private college (NSC, 2013). Thus, the dataset used in this study covers nearly all Colorado high school graduates who attended college, whether in-state or out-of-state, at a public or private institution.

DHE has established a partnership with the Colorado Department of Education that permits the linkage of postsecondary data with K-12 data using the State Assigned Student

Identifier (SASID). This study relies on the SASID-linked databases to create a panel dataset that follows cohorts of students as they move through the K-12 system and into higher education. The high school graduating cohorts of 2010, 2011 and 2012 are included in this study, providing a total of 129,196 observations for the first research question. Due to limitations in the availability of data, only 2010 and 2011 high school graduates who attended a public college in Colorado are included in the analysis of the second research question, providing a sample size of 43,943 students.

Dependent Variable

The dependent variable in the first research question is college enrollment, which was measured by considering those students who enrolled in college in the fall immediately following high school graduation. Students who enrolled in college anywhere—at an in-state, out-of-state, public or private institution—are captured. This is a dichotomous variable; students who enrolled in college were coded as a 1. The dependent variable in the second research question is students' need for remedial education in college, which includes both students assessed as needing remediation and those enrolled in remedial courses who did not have an assessment score on file. Only students who enrolled in a public college in Colorado are captured in the calculation of remedial rates (CDHE, 2013). This is also a dichotomous variable; students who needed remedial education in college were coded as a 1.

Independent Variables

The key explanatory variable for both research questions is participation in concurrent enrollment. High school students are eligible to participate in concurrent enrollment courses in grades 9 through 12. This study employed a dichotomous measure of participation, in which students who graduated high school with any type of or amount of concurrent enrollment credits were coded as a 1.

The empirical analyses included demographic and academic control variables that, based on prior research, are thought to influence concurrent enrollment participation, college-going behavior and remedial education need. These measures included gender (male = 1), high school free and reduced-price lunch (FRL) status (1 = received FRL), race/ethnicity and ACT scores. FRL status is reported by high schools to the Colorado Department of Education and indicates that the high school graduate received free or reduced-price lunch. Race/ethnicity is self-reported by students and was measured here using dummy variables for Asian, American Indian/Alaskan Native, African American, and Hispanic students, with white students being the baseline group. There are few missing values for race/ethnicity—about 0.91 percent of all students (n=1, 426).

The composite ACT score was used as a proxy control for academic achievement. ACT subject scores (reading, writing, math and science) also were collected, but in the effort to achieve a more parsimonious model, composite scores were used.[1] Colorado has required all high school juniors to take the ACT since 2001 (ACT, Inc., 2009). The test is provided free to students, and one day of the academic year for juniors is devoted to taking the ACT.

Nonetheless, some students skip school and do not take the ACT. For the 2010, 2011 and 2012 high school graduating cohorts, 25,558 students, or 16.4 percent, had missing ACT scores. List-wise deletion was used to eliminate the observations with missing ACT data. This method has its disadvantages because the population of students with missing data differed from the general population. Those with missing data were less likely to attend college (24.0%) than the students with ACT scores (63.9%), and they were less likely to participate in concurrent enrollment (9.6% compared to 19.8%).

Methods

To address the first research question, linear probability models (LPMs) were estimated using the dichotomous fall enrollment and concurrent enrollment variables as the dependent and key independent variables, respectively (see Table 1). The second research question is estimated using LPMs and logistic regression with the dependent variable being the need for remedial education and the key independent variable remaining as concurrent enrollment (see Table 2). Both research questions were estimated using a progression of linear probability models. Initially, bivariate models with the dependent variables and the key independent variable were run. The second models added demographic (gender, FRL status, race/ethnicity) control variables, and the third models added the control for academic achievement (ACT composite score).

The fourth and final linear probability models addressed concerns about omitted variables. In particular, school-specific features—such as the availability of college guidance counselors, the presence of a college preparatory culture, and school location (e.g. rural, urban)—vary greatly and could have a confounding effect on the model. Similarly, there could be unique effects that occur during each cohort's time in school. Thus, in "Model 4," a variable for high school graduation year was added to the regression model (as time fixed effects) and school fixed effects were absorbed. Model 4 was considered the preferred model specification in both the college enrollment and remedial education estimations, and the results from those models are discussed below.

In addition, the researcher used logistic regression for the second research question to estimate the effects of concurrent enrollment on the need for remedial education. The logistic regression equation included all of the variables from the fourth linear probability model with the

[1] Models that were run with subject scores did not vary much from the models run with the composite score.

exception of school fixed effects. The results section reports findings from the marginal effects analysis, which was run after the logistic regression.

Results

College Enrollment

On average, participation in concurrent enrollment is associated with a 22.9 percent increase in the likelihood of enrolling in college immediately after high school graduation, holding gender, income, race/ethnicity and ACT scores constant. The coefficient was somewhat sensitive to changes in model specification, including the addition of fixed effects. Adding ACT scores to the regression equation attenuates the effect of concurrent enrollment participation on college enrollment. This is not a surprising finding given that prior research has found positive correlations between standardized test scores and college attendance and success (Radunzel & Noble, 2012). Adding fixed effects to the model slightly increases the effect of concurrent enrollment on college enrollment indicating that there are some meaningful differences occurring within schools around concurrent enrollment. The coefficient for high school graduation year is negative because college enrollment overall has declined from 2010 to 2012.

The final model (Model 4) includes all variables within the available dataset that are believed to affect college enrollment in some way, and therefore the result it produces—a 22.9 percent increase in college-going rates—is the most valid result of the four models displayed. However, there is still the known omitted variable of motivation (as well as any unknown omitted variables), which means this finding is most likely overestimated. If a measure of motivation were included, we would expect the coefficient to decrease because motivation is thought to be positively associated with both the independent variable of interest and the dependent variable. In other words, some concurrent enrollment students were likely to be intrinsically motivated to both take concurrent enrollment courses and to enroll in college, and thus their decision to enroll in college cannot be directly tied to the effect of taking concurrent enrollment courses.

To further explore the potential selection bias problem, a LPM was estimated with concurrent enrollment as the dependent variable and the other variables as the independent covariates. For all students, a one point increase in ACT scores was associated with a 0.27 percent ($p<.01$) increase in the probability of participating in concurrent enrollment. This estimation indicates some selection bias, but the magnitude is quite small. Furthermore, the coefficient on FRL status was positive and statistically significant; FRL students were 4.8 percent more likely to participate in concurrent enrollment than non-FRL students. Research indicates being of low-income status is negatively associated with college enrollment (Fry, 2011), which means there is at least some evidence that the bias of selecting into concurrent enrollment programs is nuanced. One plausible explanation could be that while low-income students are less likely to attend college, of those who do plan to attend they will be more inclined to select into concurrent enrollment programs because they are able to earn college credits for free.

Table 1. Linear Probability Models estimating the effect of concurrent enrollment participation on college enrollment

VARIABLES DV=College Enrollment	(Model 1) Bivariate	(Model 2) Includes demographics	(Model 3) Includes demographics & ACT	(Model 4) Full model w/ time and school fixed effects
Concurrent Enrollment	0.305***	0.295***	0.207***	0.229***
	(0.003)	(0.003)	(0.003)	(0.005)
Male		-0.073***	-0.064***	-0.064***
		(0.002)	(0.002)	(0.002)
Free and Reduced Price Lunch		-0.137***	-0.094***	-0.075***
		(0.003)	(0.003)	(0.004)
American Indian/ Alaskan Native		-0.180***	-0.064***	-0.049***
		(0.012)	(0.013)	(0.013)
Asian		0.084***	0.074***	0.068***
		(0.006)	(0.006)	(0.006)
African American		-0.045	0.099	0.106***
		(0.006)	(0.006)	(0.006)
Hispanic		-0.170***	-0.033***	-0.024***
		(0.003)	(0.003)	(0.004)
ACT Composite Score			0.031***	0.027***
			(0.000)	(0.000)
High School Graduation Year				-0.012***
				(0.001)
Constant	0.519***	0.630***	0.012**	24.832***
	(0.001)	(0.002)	(0.006)	(2.962)
Observations	155,975	154,549	129,196	129,196
R-squared	0.056	0.110	0.192	0.219

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Another limitation of this estimation technique is that in LPMs not all predicted values fall in a range of 0 to 1, even though the probability of the dependent variable occurring must fall in that range. Of the predicted values from the preferred model, 10,157 values are less than or greater than 1. This constitutes only 6.6 percent of the observations, however, which could be considered acceptable. Nonetheless, to be cautious, a probit regression model was estimated using maximum likelihood. The direction and statistical significance of the concurrent enrollment variable remained the same across the LPM and probit models, which lends support to the findings of the LPMs.

Remedial Education

Overall, participation in concurrent enrollment is associated with a 9.0 percent decrease in the likelihood of needing remedial education in college, holding gender, income, race/ethnicity and ACT scores constant. As in the college enrollment estimation, the coefficient on concurrent enrollment was sensitive to changes in model specification, particularly when ACT scores were added to the regression equation.

The concerns over the appropriateness of using a LPM as the estimation technique are more pronounced in the case. Approximately 29 percent of the predicted values fall outside of the 0 to 1 range. The LPM estimation assumes a linear relationship between the independent and dependent variables. It may be the case there is a non-linear relationship between taking concurrent enrollment courses and the likelihood of needing remedial education in college.

This study used logistic regression as an alternate estimation method (see Table 3). The coefficient on concurrent enrollment remains statistically significant and negative in direction, which supports the LPM findings. The logit coefficient cannot be interpreted as representation of the change in the probability that the dependent variable will occur, however. Therefore, the researcher conducted simulations using the logit model output in order to estimate the marginal effects of concurrent enrollment on the likelihood of needing remedial education in college. The results predict that taking concurrent enrollment courses reduces the need for remedial education by 11.2 percent.

Table 2. Linear Probability Models estimating the effect of concurrent enrollment participation on the need for remedial education in college.

VARIABLES DV=Remedial Education Need	(Model 1) Bivariate	(Model 2) Includes demographics	(Model 3) Includes demographics & ACT	(Model 4) Full model w/ time and school fixed effects
Concurrent Enrollment	-0.129***	-0.136***	-0.080***	-0.090***
	(0.005)	(0.005)	(0.004)	(0.004)
Male		-0.043***	-0.017***	-0.016***
		(0.004)	(0.003)	(0.003)
Free and Reduced		0.182***	0.054***	0.035***
Price Lunch		(0.006)	(0.005)	(0.005)
American Indian/ Alaskan Native		0.179***	0.061***	0.044**
		(0.024)	(0.020)	(0.020)
Asian		-0.026**	-0.049***	-0.050***
		(0.011)	(0.008)	(0.009)
African American		0.302***	0.055***	0.045***
		(0.009)	(0.008)	(0.009)
Hispanic		0.232***	0.040***	0.025***
		(0.006)	(0.005)	(0.005)
ACT Composite Score			-0.065***	-0.063***
			(0.000)	(0.000)
High School Graduation Year				-0.003
				(0.003)
Constant	0.436***	0.366***	1.784***	8.078
	(0.003)	(0.004)	(0.009)	(6.953)
Observations	47,578	47,578	43,943	43,943
R-squared	0.014	0.107	0.450	0.465
Adj. R-squared	0.014	0.107	0.450	0.460

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Table 3. Logistic regression model estimating the effect of concurrent enrollment participation on the need for remedial education in college.

VARIABLES DV=Remedial Education Need	(Model 1) Full model w/ time fixed effects
Concurrent Enrollment	-0.643***
	(0.033)
Male	-0.214***
	(0.028)
Free and Reduced Price Lunch	0.307***
	(0.039)
American Indian/Alaskan Native	0.430**
	(0.147)
Asian	-0.573***
	(0.071)
African American	0.235***
	(0.063)
Hispanic	0.131***
	(0.038)
ACT Composite Score	-0.569***
	(0.006)
High School Graduation Year	-0.050*
	(0.028)
Constant	111.92**
	(56.69)
Observations	43,943
R-squared	0.465
Adj. R-squared	0.460

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Discussion

While concurrent enrollment programs have been around for a long period of time, they have only recently been expanded in Colorado, and only recently have researchers begun to study the potential of such programs to improve postsecondary outcomes. This study found positive, statistically significant and substantively large effects of concurrent enrollment participation on college enrollment for all Colorado high school graduates. Selection bias is a threat to the study and thus the effect size is most likely overestimated. However, with an increase of 22.9 percent in the probability of enrolling, there is a good chance that some portion of that effect is due to concurrent enrollment participation.

The second part of this study focused on the effect of concurrent enrollment on remedial education rates. The first regression method found that concurrent enrollment decreased the probability of needing remedial education in college by 9 percent. There were reasons to be concerned that the estimation technique was not a good fit, however, so a second regression method was run. The second model found that concurrent enrollment students were 11.2 percent less likely to need remedial education in college. The similar results from the two different estimation methods lends confidence to the finding that concurrent enrollment is associated with a decrease in the need for remedial education.

These are promising findings, and future research by the Colorado Department of Higher Education will further explore this issue and will attempt to address selection bias more effectively. Additionally, future research will continue to follow this cohort of students to track the effect of concurrent enrollment on retention and degree completion rates, as well as on other postsecondary success measures such as grade point average and credit accumulation.

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