The Effect of AP Participation on Time to College Graduation:

Technical Report

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This technical report accompanies the chapter "Does the Advanced Placement Program Save Taxpayers Money? The Effect of AP Participation on Time to College Graduation," pp. 189-218 in *AP: A Critical Examination of the Advanced Placement Program*, edited by Sadler, P., Sonnert, G., Tai, R., and Klopfenstein, K. Cambridge, MA: Harvard Education Press, 2010. These pages include greater detail about the analysis than was included in the book for the "Data" and "Analysis and Results" sections.

Data

I estimate the effect of AP course experience on time to college graduation by tracking a cohort of Texas students for ten postsecondary semesters using the Texas Schools Microdata Panel (TSMP). Students in the sample graduated from Texas public high schools in spring 1997 and matriculated directly at one of 29 four-year Texas public universities.[1] This cohort of "traditional" college students provides a relatively straight-forward foundation for gaining an initial understanding of the influence of AP on time to degree. Information on students who graduate, transfer to another university, or stop-out for more than two semesters is censored prior to the completion of ten semesters.[2] Of the 32922 students in the original sample, 4220 are missing information on the college attended, major, credit hours, and/or GPA and are dropped from the sample. Thus the final sample in the first semester of college consists of 28702 students.

Accelerated learning, such as that provided by the AP and dual credit programs, facilitate timely (four-year) baccalaureate degree completion by allowing students to start earning college credits while in high school. Table 1 demonstrates patterns of timely degree completion in Texas for the sample of 1997 public college matriculates across demographic groups. The overall four-year graduation rate is 24 percent at Texas public

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[1] The vast majority of students who graduate from college matriculate within one year of graduating from high school. In the Baccalaureate and Beyond Longitudinal Study (B&B:2000/01), 83 percent of first-time bachelor's degree recipients in 2000 attended college less than one year after graduating from high school (Bradburn et al. 2003). Only students who matriculate directly following high school graduation are considered here because students who take time off between high school and college have much higher dropout rates and lower graduation rates (Ahlburg, McCall, and Na 1997).

[2] Students who initially attend two-year schools and transfer to four-year colleges as well as students who transfer between four-year colleges have significantly longer average time to degree (Wirt, et al. 2003). The modeling process used here censors departing students at the time of exit. This prevents circumstances faced by transfer students from confounding estimates of the effect of AP on time to degree, the primary research question of interest here.

universities versus 36 to 39 percent nationally (IPEDS and B&B, respectively).[3] Partly due to the inclusion of private universities in many of the national statistics, four-year graduation rates are lower at Texas public four-year institutions than those nationally. Four-year graduation rates are also underestimated in the Texas data for groups with large rates of out-of-state or private transfer.[4]

Not only do Texas on-time graduation rates tend to be lower than those reported in national data sets, disparities in the on-time graduation rates between stayers and transfers, men and women, and whites and non-whites tend to be larger. Students attending only one public institution graduate on time 53 percent of the time in Texas, more than double the rate of all students. The closest available nationally-representative comparison reflects a 58 percent on-time graduation rate for students from public and private universities combined, and since private schools post higher on-time graduation rates than public schools, the national rate for public schools alone is closer to Texas's 53 percent (B&B). Thus, stayers are 40 percent more likely than all students to graduate in four years nationally compared to 121 percent more likely in Texas.

Nationally, women at public institutions are 42 percent more likely to graduate in four years than are men (IPEDS) while the comparable difference between men and women in Texas public institutions is 69 percent. Nationally, 41 percent of white

[3] Baccalaureate and Beyond Longitudinal Study (B&B) surveyed four-year degree recipients in 2000, and Integrated Postsecondary Education Data System (IPEDS) provides data from four-year degree recipients in 2004 (Knapp, et. al. 2008; Bradburn, et. al. 2003). B&B statistics reported here are from Bradburn ,et. al. 2003, which combines public and private institutions. IPEDS statistics are from Knapp, et. al. 2008, which separates private and public institutions. Both sources include stop-outs in their calculations.

[4] The TSMP sample in Table 2 includes stop-outs and in-state transfers, but students who transferred to out-of-state or private universities cannot be identified separately from stop-outs. Thus, these transfers appear in the denominator but not the numerator, and consequently, four-year graduation rates are underestimated for groups with large rates of out-of-state or private transfer. The magnitude of this sampling error is mitigated in part by the fact that transferring decreases the likelihood of on-time graduation.

students graduated on time versus 29 percent in Texas; 27 percent of black students graduated on time versus 14 percent in Texas; 30 percent of Hispanic students nationally versus 14 percent in Texas; and 43 percent of Asian students nationally versus 31 percent of Asians in Texas (B&B). While the levels are at times starkly different, partly due to the inclusion of private universities in the B&B data, the ordinal rankings of graduation rates are essentially no different nationally than in Texas.

As described in DesJardins (2003), the dataset used for the survival analysis consists of several smaller datasets merged together. The foundational dataset consists of student characteristics that are measured once during high school, including: sex; race; special education experience; English proficiency; family income; class rank; high school GPA; SAT or ACT scores; AP courses taken; AP exams passed with a score of three or higher; and whether students enrolled in dual credit courses while in high school. A school-level variable is included to account for attendance at a rural high school. This time-constant dataset is then merged with information from the college years, including two time-varying factors, cumulative GPA and whether the student worked each semester (as indicated by social security tax records). Time-constant variables from the college years include admission as an undeclared major and the number of times the student changes major. Table 2 presents descriptive statistics and information about the source of each of these variables.

The number of times students change majors is controlled to account for the fact that changes in major are associated with an increase in time to degree. A dummy variable is included for students who enter as undeclared ("general studies" or "liberal arts major" at some colleges). Changes away from the undeclared major are not included in the total number of major changes since being undeclared necessitates one change in major (only 14 students in the sample graduate undeclared), the effect of which is captured by the *undeclared* dummy.

While there are students who change majors up to six times, frequent major changes are relatively rare. A majority of students carry the same major until they graduate or are censored (52 percent), and 97 percent of students change major two or fewer times.[5] There is no evidence that accelerated learning students, be they AP or dual credit students, are any more or less likely than other students to change their major. However, there is a small negative correlation (-0.10) between having college-level course experience via AP or dual credit and entering with an undeclared major. If undeclared majors are significantly less likely to graduate in four years than other students, as theory would predict, then AP and dual credit experience may decrease time to degree by facilitating early identification of an appropriate major.

The purpose of this paper is to provide a baseline analysis that serves as a model for more detailed work on the impact of accelerated learning on time to degree in the future. AP coursework, AP tests passed, and dual credit coursework are aggregated across subject areas and experience in each of these three accelerated learning opportunities is modeled with a simple dummy variable.[6] Hence, if a student took any

[5] Students who enter undeclared but change to a subject-specific major are included in the 52 percent who do not change major. Among the group of students who enter with a subject-specific major, 48 percent never change major.

[6] Since the AP Spanish Language course and exam are not representative of the AP Program as a whole, they are omitted from the analyses. Although the AP Spanish Language course and exam are designed for non-native speakers, it is common in Texas for native Spanish speakers to take and earn the highest possible score on the AP Spanish Language AP exam. In contrast, Hispanic scores on the AP Spanish Literature test are low relative to non-Hispanic test-takers, so the AP Spanish Literature course is clearly challenging to even native-language speakers. Thus, the course is more reflective of the AP Program as a whole and is included in the analyses.

academic AP course in high school, the AP coursework dummy equals one; if the student passed any AP exam with a score of three or higher, the AP exam dummy equals one; and the dual credit indicator takes a one if a high school student enrolled in credit hours at a junior or senior college between the fall semester of 1995 and spring of 1997. Future research should expand this analysis to consider the number of courses taken by subject area as well as the alignment of AP or dual credit courses taken and AP exams passed with college course-taking patterns.

Figures 1 - 3 show the unconditional smoothed hazard estimates for time to degree (in semesters) for students who took any AP classes while in high school versus those who did not, those who passed any AP exams with a score of three or higher versus those who did not, and those who took any dual credit courses versus those who did not. These hazard functions display the difference in time to degree between students with and without accelerated learning experience when no other differences between the groups are controlled. The null hypothesis for the equality of the survivor functions can be rejected in each case with greater than 99 percent confidence using both log rank and Wilcoxon test statistics. The larger gap in the hazard functions in Figures 2 and 3 relative to Figure 1 is consistent with the fact that taking AP courses alone does not generate college credit while the other two options can and often do. While most students who take the AP exam have taken the relevant AP course, many students take the course but do not take the exam. The simple correlation between taking an AP course and passing at least one AP exam is 0.48.

The driving force in the gaps between time to degree of AP students and others in the above figures is driven to some degree by the self selection of students in the AP

Program and in the quality of the schools that offer AP classes. Especially prior to the surge in AP offerings that began in the mid-to-late 1990s, schools that offered AP were typically white, middle-class, suburban, and well-funded with experienced teachers (Klopfenstein 2004a and 2004b). Therefore, it is important to account for the personal and academic characteristics of students to isolate, to the extent possible from non-experimental data, the causal impact of AP on time to degree. The identification of the causal mechanism is particularly important for scalability. If the impact of AP was specific to the type of students who participated in the program in the early and mid-1990s, then similar benefits will not be observed when the program is expanded to other types of students.

Analysis and Results

As previously mentioned, all analyses are conducted using survival analysis to estimate whether, on average, students who engage in accelerated learning options while enrolled at Texas public high schools graduate with a baccalaureate degree more quickly, ceteris paribus, from Texas public universities than students who do not. The models used here incorporate time-varying independent variables, time-varying coefficients, and controls for unobserved heterogeneity. An explicit treatment for unobserved heterogeneity is potentially important in this instance because as students exit the sample over time, either by dropping out, transferring, or graduating, the average observable *and unobservable* characteristics of students who remain change (DesJardins, et al 2002).

A range of hazard models with varying assumptions are estimated as a robustness check because there are not "conclusive statistical criteria that can be used for model selection" (Blossfeld, et. al. 2007, p. 268). I examine three estimation processes in turn: a semi-parametric Cox proportional hazard model (Cox 1972), a Weibull model under the proportional hazard assumption, and a discrete mixture model (Heckman and Singer 1984).

The appropriateness of the proportional hazard assumption is analyzed with tests for the constancy of the log hazard-ratio function over time, both globally and for individual variables, using the Schoenfeld residuals from the Cox models. The model without time-varying coefficients fails the proportional hazard assumption miserably, both globally and for the individual accelerated coursework variables. However, once time-varying coefficients are incorporated, all accelerated learning variables individually pass the test, as do all other variables whose effects are allowed to vary over time. Of the 52 variables in the fully specified model, only Limited English Proficient, SAT, and number of major changes individually fail the proportional hazard assumption. These variables are not central to the analysis, so the proportional hazard assumption is deemed to hold for the model with time-varying coefficients.[7]

For all models, estimates are presented as hazard ratios to facilitate the interpretation of coefficient magnitude. The hazard ratio is simply the exponentiated coefficient, so estimates greater than one indicate a positive effect, and the percentage larger than one indicates the magnitude. For example, an estimated hazard ratio of 1.47 on a female dummy variable indicates that females face a 47 percent higher probability of graduation at time t than do males, conditional on not graduating prior to time t. Similarly, an estimated hazard ratio of 1.47 on a continuous variable indicates that a one unit increase in the independent variable increases the probability of graduation at time t by 47 percent, again conditional on not having graduated prior to time t. If the hazard

[7] The results presented below are robust to the exclusion of the variables that fail tests for proportionality.

ratio for the female dummy were 0.80, this would indicate that the probability of graduating at time t for females is 80 percent of that of a similar male. While the coefficient estimates are transformed to hazard ratios, hypothesis tests are conducted using the untransformed values of the coefficients and standard errors.[8]

Each model is considered first with time-constant coefficient estimates and then with coefficient estimates that are permitted to vary by year. Because no students graduate in year 1 and just eight students graduate in year 2, only the estimates for years three through five are displayed for models with time-varying coefficients. With a couple of notable exceptions, which will be discussed, the findings are robust across a wide variety of specifications and modeling assumptions. The accelerated learning variables of interest are remarkably stable across specifications. The control variable estimates are reassuring in that they behave as theory and/or previous research would predict and are essentially unaffected by changes in the modeling assumptions. Appendix A provides estimates for the control variables across models for the models with time-varying coefficients.

Cox proportional hazard models

Tables 3 and 4 provide estimates from a Cox model assuming frailty (unobserved heterogeneity) is gamma-distributed and shared based on the university attended. For a subset of variables, column 1 in Table 3 shows coefficient estimates which, although held constant here, will eventually be allowed to vary. Estimates in Table 3 behave as would be expected based on theory and/or previous research. Despite the failure of tests of the proportionality assumption, the results are presented to provide a comparison with those

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[8] Hypothesis tests conducted on the raw coefficients are asymptotically equivalent to those conducted on the transformed coefficients (Stata v.10 Survival Analysis and Epidemiological Tables p.312).

from the time-varying model. The instantaneous probability of graduating is higher for women and for Asian students, and lower for students who work. Cumulative grade point average has a large positive impact on the likelihood of graduating. Among the accelerated learning variables, neither taking an AP class nor passing an AP exam increases the probability of graduation, although taking a dual credit course increases the instantaneous probability of graduation by 25 percent.

There are intuitive reasons for allowing flexibility for some coefficient estimates, even when a variable itself is time-invariant. For example, minority status may matter most in the early college years as students adjust (or fail to adjust) to a rigorous and diverse learning environment without the immediate support of culturally-similar family and friends. Once the student has adjusted, the impact of race would be markedly diminished. Constraining the effect of race to be constant over time would produce biased estimates if the true effect varies from one year to the next.

Indeed, Table 4 shows that this story provides one possible explanation for why black students who, despite a decreased likelihood of graduation in three years, are equally as likely as white students to graduate in year four. The positive female and Asian effects are largest in the early years, although the possible causal forces are less intuitive. The GPA effect is also largest in the early years although it maintains the largest magnitude of any variable across all five years. A one grade-point increase in GPA (e.g. from a 2.5 to a 3.5) more than quadruples the likelihood of graduating in year three and almost triples the likelihood of graduating in year four.

The value of incorporating time-varying coefficients becomes particularly apparent when examining the accelerated learning variables. While taking an AP class has no statistically significant impact in any single year of the study, passing one or more AP exams increases the likelihood of graduating in year three by 71 percent. The practical significance of this result is limited given that a very small fraction of students graduate in three years (350 out of 14,854 graduates in this sample). This effect decreases to eight percent in year four and is completely dissipated, and even negative, by year five. Interestingly, the effect of taking one or more dual credit classes is to nearly triple the probability of graduating in year three relative to students who did not take such courses. The dual credit effect is 3.5 times the size of the AP exam effect in year four, and unlike the AP exam effect, remains positive and significant in year five.[9]

All Cox models are estimated assuming frailty is gamma-distributed and shared based on the university attended. Shared frailty in this instance is analogous to using random effects in panel data (Cleves, et. al. 2004).[10] The estimated variance of frailty (theta) is 0.09 in Cox models with and without time-varying coefficients.[11] Theta is significantly different from zero in a likelihood-ratio test which suggests that there are some, albeit small, unobserved differences between students attending different postsecondary institutions in Texas. The results of the Cox models without frailty are virtually identical to those with shared frailty, so only the shared frailty model findings are presented here.

The Weibull Model

The second type of survival model considered is the Weibull. Among parametric survival models, Weibull models are relatively flexible, and they are desirable in the

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[9] Hypothesis tests confirm that the AP exam coefficients are different from the dual credit coefficients at better than one percent in both the time-constant and the time-varying coefficient models.

[10] For technical reasons, it is not possible to model individual-level frailty in a Cox proportional hazard model (Cleves, et al 2004).

[11] For identification purposes, the mean of the frailty parameter is normalized to one.

present framework because, as would be expected for college graduation rates, they allow for the hazard function to increase over time at an increasing rate. Indeed, the estimates for the shape parameter *p* in all Weibull models estimated here are substantially greater than 2 (Table 3, column 2; Appendix A), which confirms that the hazard increases at an increasing rate among traditional single-institution college students who do not take more than two semesters off from school. The Weibull models are estimated in a proportional hazard framework (as opposed to an accelerated failure time framework) to facilitate comparisons with the findings from the Cox models.

Weibull models that account for shared frailty at the postsecondary-institution level fail to converge under either of the two Stata10-supported assumptions that the frailty is distributed either gamma or inverse-Gaussian. Given the evidence from the Cox models that there is some shared frailty within institutions, all standard errors are adjusted using Stata's –cluster– command. These adjustments account for the fact that the unobserved characteristics of students are correlated within universities and that the data do not contain as much information as suggested by the number of degrees of freedom.

Column 2 in Table 3 presents the results of the Weibull model when coefficients are not allowed to vary across time, there is assumed to be individual-level frailty distributed inverse-Gaussian, and standard errors are adjusted. Under this structure of time-invariant coefficients, the estimate of the variance of theta is 3.17. This estimate of theta is not comparable to that from the Cox regression in column 1 since the Cox model assumed shared rather than individual-level frailty.

Time-varying coefficient estimates are reported in Table 5 and show that, as in the Cox models, constraining coefficients to be constant over time obscures meaningful information. Table 5 differs little from Table 4, particularly in year three. In year four, there are changes in sign for working students and those who passed an AP exam, and changes in significance for black students and students who took an AP course. In year five, there are changes in sign for black students and students who passed an AP exam, and changes in significance for Hispanic and working students. Overall, relative to the Cox model, the Weibull model represents the situation of Hispanic students as more dire, of black students as more mixed, the benefits of dual credit as larger, and the benefits of AP exams as smaller.

Comparing the estimate of theta for the Weibull model in Table 3 (3.17) with that in Table 5 (0.0000007) reveals that the source of individual unobserved heterogeneity apparent in the time-constant model is entirely due to misspecification error. When time-varying coefficients are introduced, the estimate of theta drops to essentially zero. Overall, there is evidence of a small degree of shared frailty in the Cox models, but no individual-level frailty in an appropriately specified Weibull model. The possibility of university-level shared frailty in the Weibull model is accounted for by adjusting the standard errors.

Discrete Mixture Model

The preferred estimation technique when modeling college persistence, as evidenced by its frequent use in similar literature, is a Heckman and Singer (1984) model where the frailty is flexibly modeled using a discrete mixing distribution (e.g. DesJardins, et al 1999, DesJardins, et. al. 2002, DesJardins 2003).[12] Unfortunately, mixture models

[12] Criticisms of the mixture model approach appear in Blossfeld, et. al. 2007.

using the complete specification of the Cox and Weibull models previously discussed failed to converge under a variety of maximization techniques and starting values. [13]

A much simplified model that included only SAT score, a time-constant dummy for taking an AP course, and time-varying coefficients for AP exam-taking and dual credit did converge in a continuous-time mixture model assuming gamma-distributed individual-level frailty. The model yielded an estimate of theta approximately equal to zero (0.0000002), and the coefficient estimates followed patterns surprisingly similar to those from the fully specified Cox and Weibull models. The primary reason for using mixture models is to account for individual-level frailty, and the presence of frailty is more likely in the case of omitted variables. Thus, although it was not possible to obtain a complete set of estimation results from a mixture model, the absence of evidence of frailty in this simple model confirms the validity of the findings from the Cox and Weibull models (Blossfeld, et. al. 2007).

Synthesis of Findings

Given the finding that AP courses have no impact on the hazard rate, the difference in the hazard functions for AP course-takers relative to other students in Figure 1 is driven entirely by differences in observed characteristics and is not causal. The practical implication of this result is that pressing students into AP classes who are unlikely to take and/or pass the AP exam has no benefit (private or public) in terms of shortening time to college degree. The estimation results suggest that the difference in the hazard function for AP exam-passers seen in Figure 2 is potentially causal in year three (semesters five and six), but the remainder of the difference is certainly due to self

[13] Discrete-time mixture model estimation is possible in Stata using the –hshaz- command. A similar command for continuous-time estimation is –pgmhaz8-. Both are written by Stephen P. Jenkins at University of Essex.

selection. In contrast, there is evidence that the gap between hazard functions for dual credit course-takers and others in Figure 3 is driven by some causal mechanism in years three through five, although the greatest impact, once again, is in year three.

Figure 4 displays predicted hazard functions for a fictional student with the average characteristics of the sample but with different accelerated learning experiences.[14] Predictions are calculated based on estimates generated from the full Weibull model in Table 5. Since students are much more likely to graduate in the spring (even-numbered semesters) than in the fall (odd-numbered semesters), the hazards peak at eight semesters, dip at nine semesters, and spike for the final observation in the tenth semester. The predicted hazard for the average student who passes an AP exam is essentially identical to that for students with no accelerated learning experience, and both are represented by the solid line. Even though the AP effect increases the probability of graduating in year three by almost 50 percent and the dual credit effect by over 200 percent (see Table 5), the probability of graduating in three years is so low that even tripling that probability doesn't create a discernible change in the graduation hazard for the average student. However, an average student with dual credit experience has a higher likelihood of graduation in eight semesters than other students, as well as a higher likelihood at ten semesters (recall that the hazard estimate is conditional on survival to time t).

[14] In the case of a group of dummy variables, the student is defined as having the characteristic of the plurality.

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Figure 1
Unconditional Smoothed Hazard by AP Course-Taking

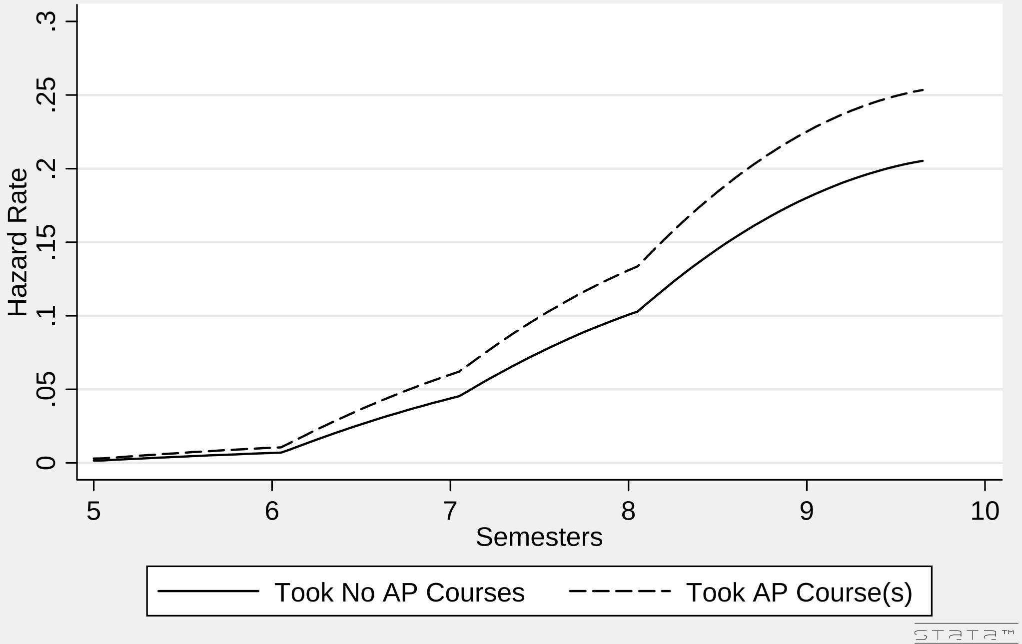


Figure 2
Unconditional Smoothed Hazard by AP Exam-Taking

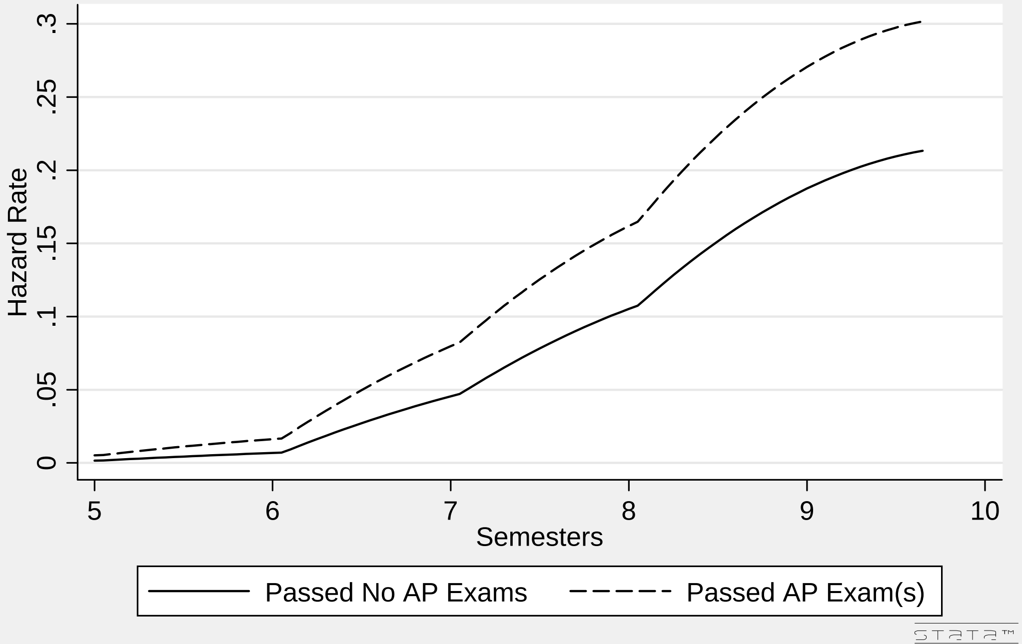
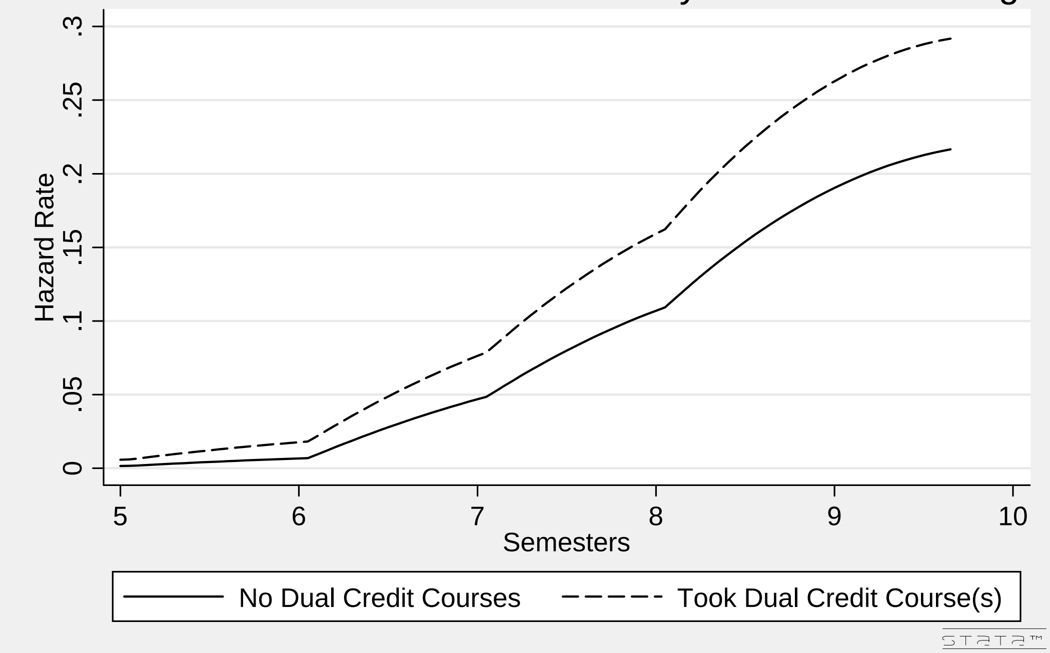


Figure 3
Unconditional Smoothed Hazard by Dual Credit-Taking



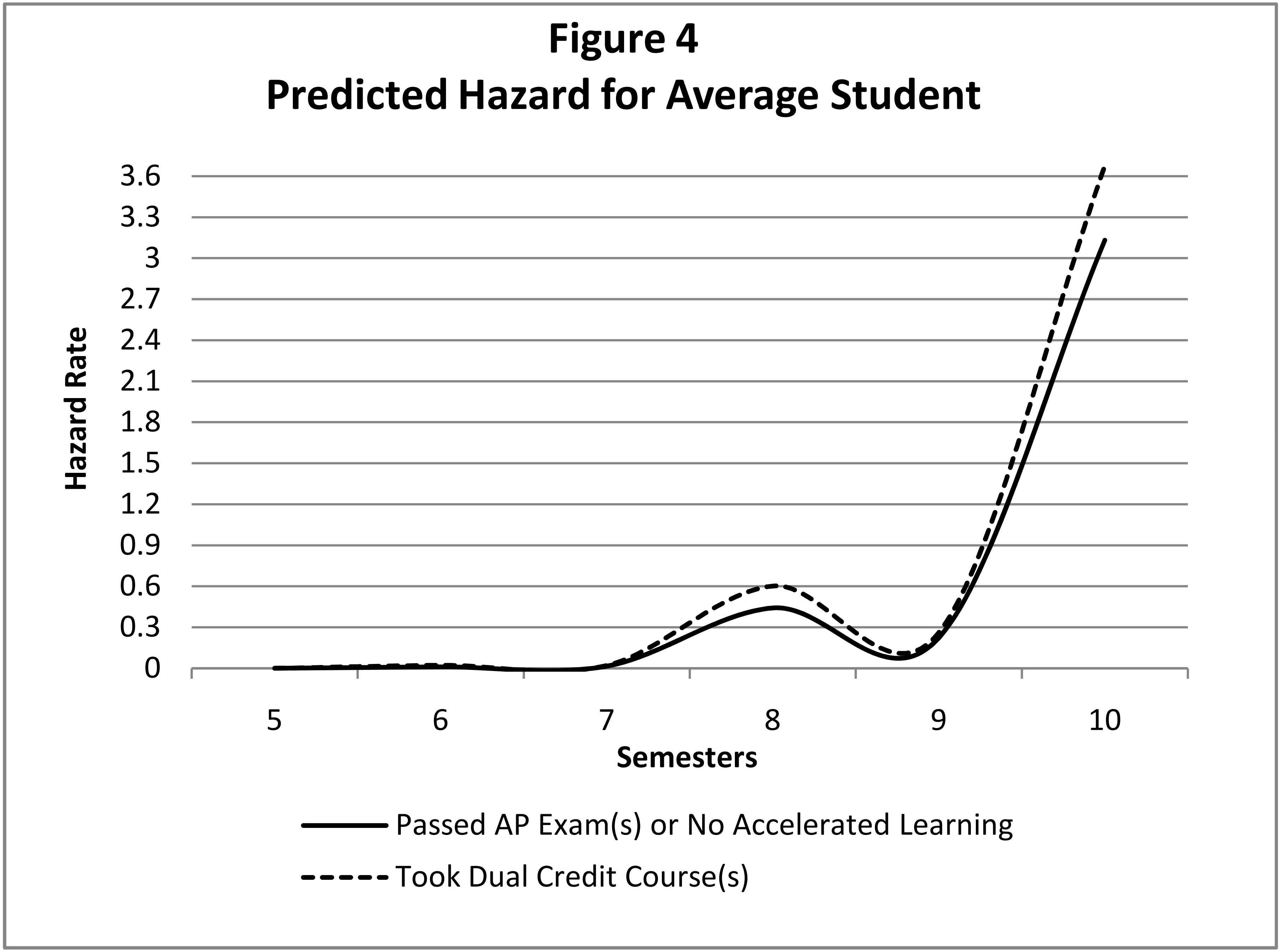


Figure 4
Predicted Hazard for Average Student
Hazard Rate
3.6
3.3
3
2.7
2.4
2.1
1.8
1.5
1.2
0.9
0.6
0.3
0
5
6
7
8
9
10
Semesters
Passed AP Exam(s) or No Accelerated Learning
Took Dual Credit Course(s)

Table 1
Four-year graduation rates at Texas public universities, cohort entering Fall 2007

	percent	numerator	denominator
All	24	6,344	25,946
Women	30	4,269	14,222
Men	18	2,075	11,724
White	29	4,779	16,707
Black	14	366	2,641
Hispanic	14	663	4,865
Asian	31	536	1,733
Stayed at one institution	53	821	1,544

Source: author's calculations using Texas Schools Microdata Panel.

Table 2
Descriptive Statistics[a]

Variable	N	fraction of sample or mean	standard deviation	min	max	Description	Source[c]
Enduring Variables							
Demographic							
female	28702	0.55	-	0	1	female	PEIMS
Asian	28702	0.07	-	0	1	Asian	PEIMS
black	28702	0.10	-	0	1	black	PEIMS
Hispanic	28702	0.18	-	0	1	Hispanic	PEIMS
white	28702	0.65	-	0	1	white	PEIMS
free or reduced lunch	28702	0.21	-	0	1	qualied for free or reduced lunch in any year between 1991 and 1997	PEIMS
special ed	28702	0.02	-	0	1	special education student in any year between 1991 and 1997	PEIMS
Limited English Proficient	28702	0.03	-	0	1	Limited English Proficient in any year between 1991 and 1997	PEIMS
Low income	28702	0.14	-	0	1	parent income less than 15000	FAFSA
Middle income	28702	0.20	-	0	1	parent income between 15000 and 52500	FAFSA
High income	28702	0.10	-	0	1	parent income above 52500	FAFSA
Income missing	28702	0.01	-	0	1	parent income not reported because student not a dependent	FAFSA
No apply	28702	0.55	-	0	1	student didn't apply for aid	FAFSA
rural	28702	0.29	-	0	1	student attended a rural Texas public high school	GIS
Academic							
sat equivalent	28702	1001	192	400	1600	SAT score or, if no SAT, ACT equivalent composite score	CB/ACT
in top 25% in class rank	28702	0.51	-	0	1	=1 if in top 25 percent of graduating high school class	CB/ACT
hs gpa: A	28702	0.53	-	0	1	=1 if report high school gpa is an A	CB/ACT
hs gpa: High B	28702	0.33	-	0	1	=1 if report high school gpa is a B to a B+	CB/ACT
dual credit	28702	0.15	-	0	1	=1 if enrolled in college courses for dual credit while in high school	PEIMS
AP Any dummy	28702	0.43	-	0	1	=1 if took any AP courses	PEIMS
AP Any	12189	2.23	1.51	0.5	10	total AP credits taken (given take an AP course)	PEIMS
AP exam 3 dummy	28702	0.14	-	0	1	=1 if passed any AP exams with score of 3 or higher	CB
AP exam 3	4130	1.76	1.12	1	9	AP exams in which earned a 3 or higher (given take an AP exam)	CB
Undeclared major	28702	0.25	-	0	1	undeclared, liberal arts, or general studies major in first semester	THECB

number major changes	13782	1.38	0.63	1	6	number of times changed major away from anything other than undeclared	THECB
censored due to stopout or transfer	28702	0.33	-	0	1	not enrolled for more than two consecutive semesters or transfer to another Texas public four-year	THECB
graduate	28702	0.46	-	0	1	graduate in ten semesters or less	THECB
graduate, given do not stopout or transfer	19121	0.70	-	0	1	graduate in ten semesters or less given do not stopout or transfer	THECB
time to degree (in semesters), given graduate	13444	8.80	1.0	4	10	time to degree for graduates	THECB
Time-Varying Variables [b]							
cumulative college GPA	28702	2.51	0.97	0	4	college grade point average on a four-point scale	THECB
working	28702	0.50	-	0	1	earned income in a social-security covered sector	TWC

[a] For dummy variables, the mean represents the proportion of the sample reporting a "one."

[b] For time-varying variables, the reported mean reflects the value in semester 1 (Fall 1997).

[c] Guide to source abbreviations: PEIMS= Texas's Public Education Information Management System; FAFSA=Free Application for Federal Student Aid; GIS=author's calculations using Geographic Information System; CB=College Board; ACT=ACT, Inc.; THECB= Texas Higher Education Coordinating Board; TWC= Texas Workforce Commission

Table 3
Time Constant Hazard-Ratio Estimates

	Cox, shared gamma frailty		Weibull, unshared frailty	
Female	1.26	***	1.62	***
	(0.02)		(0.15)	
Asian	1.07	*	1.08	
	(0.04)		(0.11)	
Black	1.07		0.96	
	(0.05)		(0.14)	
Hispanic	0.97		0.71	**
	(0.03)		(0.11)	
Working	0.96	**	0.90	**
	(0.02)		(0.04)	
Cumulative GPA	2.49	***	5.00	***
	(0.05)		(0.59)	
Took AP course(s)	1.01		1.05	
	(0.02)		(0.03)	
Passed AP exam(s)	1.02		1.14	
	(0.03)		(0.11)	
Took Dual Credit	1.25	***	1.64	***
	(0.03)		(0.09)	
Theta,	0.09		3.17	
variance of frailty	(0.03)		(0.35)	

Standard errors in parentheses. Shared frailty (Cox) and variance clustered (Weibull) based on universityattended.

Table 4

Time-Varying Hazard-Ratio Estimates, Cox Model with Gamma Shared Frailty[a] on University

	Year3		Year4		Year5	
Female	1.56	***	1.37	***	1.16	***
	(0.19)		(0.04)		(0.03)	
Asian	1.65	***	1.12	**	0.98	
	(0.29)		(0.06)		(0.05)	
Black	0.54		1.02		1.11	**
	(0.21)		(0.06)		(0.06)	
Hispanic	0.83		0.97		0.98	
	(0.18)		(0.04)		(0.04)	
Working	0.94		0.95	*	0.97	
	(0.11)		(0.03)		(0.02)	
Cumulative GPA	4.73	***	2.73	***	2.26	***
	(0.58)		(0.07)		(0.05)	
Took AP course(s)	1.06		1.04		1.00	
	(0.13)		(0.03)		(0.03)	
Passed AP exam(s)	1.71	***	1.08	**	0.91	***
	(0.22)		(0.04)		(0.03)	
Took Dual Credit	2.89	***	1.27	***	1.16	***
	(0.33)		(0.04)		(0.04)	

[a] Theta, the estimated variance of frailty, equals 0.09.

Standard errors in parentheses

Table 5

Time-Varying Hazard-Ratio Estimates, Weibull Model with Unshared Inverse-Gaussian Frailty[a] and Variance Clustered on University

	Year3		Year4		Year5	
Female	1.76	***	1.46	***	1.18	***
	(0.28)		(0.14)		(0.04)	
Asian	1.97	**	1.28	***	0.81	***
	(0.58)		(0.10)		(0.04)	
Black	0.72		1.26	***	0.80	**
	(0.24)		(0.11)		(0.08)	
Hispanic	0.90		1.01		0.67	***
	(0.20)		(0.12)		(0.05)	
Working	1.14		1.12	***	0.79	***
	(0.09)		(0.03)		(0.02)	
Cumulative GPA	17.03	***	5.65	***	1.59	***
	(1.62)		(0.43)		(0.16)	
Took AP course(s)	1.17		1.10	***	0.99	
	(0.13)		(0.04)		(0.04)	
Passed AP exam(s)	1.47	**	0.98		1.01	
	(0.25)		(0.07)		(0.04)	
Took Dual Credit	3.19	***	1.34	***	1.19	***
	(0.52)		(0.03)		(0.03)	

[a] Theta, the estimated variance of frailty, equals 0.0000007.

Robust standard errors in parentheses

Appendix A

Hazard-Ratio Estimates on Control Variables, Models with Time-Varying Coefficients

	Cox, shared gamma frailty		Weibull, unshared frailty	
sat equivalent	1.00	***	1.00	**
	(0.00)		(0.00)	
in top 25% in class rank	0.99		1.00	
	(0.02)		(0.02)	
hs gpa: A	1.10	**	1.18	**
(relative to below a high B)	(0.05)		(0.10)	
hs gpa: High B	1.11	**	1.16	**
(relative to below a high B)	(0.05)		(0.07)	
class rank missing	0.90	**	0.88	***
	(0.04)		(0.03)	
high school GPA missing	1.05		1.09	
	(0.07)		(0.08)	
inc_miss: not a dependent	0.84		0.82	
(relative to no FAFSA filed)	(0.11)		(0.14)	
low income on FAFSA	0.92	**	0.88	**
(relative to no FAFSA filed)	(0.03)		(0.05)	
middle income on FAFSA	0.93	***	0.95	*
(relative to no FAFSA filed)	(0.02)		(0.03)	
high income on FAFSA	0.97		1.01	
(relative to no FAFSA filed)	(0.03)		(0.05)	
rural	0.99		1.02	
	(0.02)		(0.04)	
free or reduced lunch	0.93	**	0.88	***
	(0.03)		(0.03)	
special ed participant	0.84	**	0.78	***
	(0.06)		(0.04)	
Limited English Proficient	0.98		0.88	
	(0.06)		(0.07)	
Undeclared major	0.56	***	0.49	***
	(0.05)		(0.09)	
number major changes	0.93	***	0.93	**
	(0.01)		(0.03)	
theta, variance of frailty	0.09		0.00	
	(0.03)		(0.00)	
p, shape parameter	-		26.10	
			(0.72)	

Standard errors in parentheses. Shared frailty (Cox) and variance clustered (Weibull) on universityattended.