“Time-to-Event Modeling to Uncover the True Effect on Standardized Testing on College Success”

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Abstract

The increase in the number of institutions providing test-optional admissions could be a form of strategic enrollment, to increase opportunities for prospective students or institutional outcomes. Alternatively, institutions could have participated in test-optional admissions simply because they have less faith that standardized tests are a reliable measure of college success. This study aims to uncover the true validity of standardized testing on a student's ability to graduate college on time, as well as investigate other determinants that could affect college success. Standard regression modeling indicates that standardized tests do significantly impact the probability of a student completing their degree on time. However, an increase in graduation probabilities by 1.5% to 2.7% for a one standard deviation increase in test scores suggests there is some evidence of economic insignificance. Hazard models produced in this study provides us with mixed results, where test scores were significant in determining college success in four years but not in six. Results from this study should encourage students to carefully allocate their time and resources to maximize their ability to achieve college success, since other determinants are impactful. In addition, institutions- especially higher selective institutions- should provide test-optional admissions. Through test-optional admissions, institutions can increase educational opportunities and outcomes to low-scoring and high-achieving underrepresented students, without having to incur high costs.

Introduction

Within higher education, there continues to be a growing movement for questioning the true validity of standardized tests in estimating college success. This trend has escalated to the degree where institutions from all corners of the country are questioning whether standardized tests still hold valuable information that could be used in their admissions recruitment process. Back in September 2013, more than 800 accredited colleges and universities did not require prospective students to submit test score results (FairTest, 2013). However, as of February 2021, more than 1,300 four-year universities and colleges have now pledged to include test-optional applications for Fall 2022 applicants (FairTest, 2021). The persistent increase for providing test-optional applications could derive from an assortment or combination of outreach, strategic enrollment, or outcome-based decisions made by participating institutions. One other reason for this shift could be that participating institutions have less faith in college entrance exams as a reliable predictor of college success.

The purpose of this study is to uncover the true validity of standardized testing in determining college success. Standard OLS and probit regressions will be used in this study to estimate the marginal effect of standardized test scores on college success. In addition, *hazard (“time-to-event”)* modeling will be utilized to assess if standardized tests affect the rate at which students achieve college success. If I am able to uncover that standardized test scores do not affect the probability or rate students achieve college success, then results produced by this study could incentivize more institutions to offer test-optional admissions. This policy could increase college accessibility and outcomes for high-achieving, low-scoring, students.

Previous Literature

Growing evidence from the literature, suggesting that standardized tests may not be effective at estimating college success as initially perceived, could have persuaded participating institutions to adopt a test-optional model. This section of the paper will discuss previous studies that have uncovered the relationship between test scores and achieving college success. We will also explore other determinants that could affect college success and previous time-to-event studies within education economics.

Determinants of College Success

One of the most widely used arguments for diminishing the influence of standardized tests in college applications stems from how much test performance and student demographics correlate with each other. When investigating test performance on financial resources, there does seem to be a moderate association between income, socioeconomic status, and scores. Sackett et al. (2009) uncovered a correlation equaling to .42. Furthermore, there is evidence of academic disparity for students from minority groups. Using data from The College Board, Dixon-Román et al. found that differences in SAT scores were substantial between black and white high school students (Dixon-Román, Everson, & McArdle, 2013). The bias that exists from standardized tests may have created significant barriers for low-income and racial minority students who want to pursue an undergraduate career. Specifically, students from low-income and racial minority backgrounds tend to have lower outcomes on standardized tests (Ragan, Li, & Matos-Diaz, 2011; Sackett et al., 2009). These barriers have the potential of discouraging high-achieving students from applying and enrolling into higher selective institutions or from college completely (Sackett, et al., 2012).

Another argument that has been used to de-emphasize the significance of standardized test scores regards its predictive power when estimating college success. Although there has been evidence from the College Board indicating that standardized test scores do predict first-year college GPA (FYGPA) as effectively as high school GPA when utilizing logistic regressions (Kobrin & Michel, 2006), many other researchers have uncovered that high school GPA (HSGPA) is a stronger predictor of college success over SAT scores (Kobrin & Michel, 2006). Using students from the University of California system, Rothstein found that SAT scores play a smaller contribution in determining FYGPA than originally anticipated, about 20% less (Rothstein, 2004). In terms of other measurements of college success, using a similar demographic from Rothstein's study, Geiser and Santelices uncovered that HSGPA was a better predictor at determining longer-term academic outcomes-i.e., graduating college on time (Geiser & Santelices, 2007). Especially for students from racial backgrounds, standardized test scores may not be the most effective parameter to use in estimating college success. Utilizing HSGPA has also been shown to have a stronger predictive ability in estimating academic achievement for minority students (Hoffman & Lowitzki, 2005; Ragan, Li, & Matos-Diaz, 2011).

Although HSGPA and SAT scores are the two main measures that can determine admissions decisions, it is important to acknowledge the other determinants that can influence student's abilities to achieve college success. Factors such as income, parental education, and where you go to school can significantly determine who will continue and complete their four-year degree. Using non-linear regression analysis, Ishitani and Terry used the Beginning Postsecondary Student Longitudinal survey (BPS) of '90 and '94 to estimate which variables could affect student retention. From their findings, they uncovered that lower-income students pre-maturely exit college at higher rates than more affluent students. In addition, students whose mothers graduated with a four-year degree are less likely to drop out of school (Ishitani & DesJardins, 2002).

Where you attend school can also significantly determine how likely a prospective student is to have a successful academic career. Although students from Ball State University who attended religious high schools perform better in college compared to their public and non-religious private school counterparts, Horowitz and Spector uncovered that there was no statistical difference in college GPAs between students that have attended a public and non-religious private high school (Hoeowitz & Spector, 2005). Interestingly, for students that are conflicted about the type of institution they would like to begin their schooling at, choosing the right college level has been shown to significantly impact college success rates. One study, which utilized three different education survey datasets[1], showed that starting at a two-year school can reduce the marginal probability of graduating between 20 to 41.4 percentage points (Sandy, Gonzalez, & Hilmer, 2006).

Another important determinant that can influence a student's decision of attending college is how to pay for their post-secondary education. In most cases, students may need to undergo debt through loans to support their education and reduce the up-front, out-of-pocket, expenses of college. Even though they can put some students in long-term financial burdens, these loans can potentially help students increase the likelihood of college success. For students who began their post-secondary careers at a two-year institution, these non-traditional students tend to have lower dropout rates when offered federal subsidized and unsubsidized student loans

[1] Sandy, Gonzalez, & Hilmer utilized data from the National Longitudinal Survey of 1972 (NLS72), High School and Beyond, and the Beginning Postseconday Student Longitudinal survey (BPS). These authors uncovered that all three surveys gave negative coefficients for their *started at a 2-year school* variable. Found on page 463, the regression coefficients of this variable for the NLS72, HSB, and BPS were -.2-, -.193, and-.414, respectfully. All coefficients were significant at the 5% level (Sandy, Gonzalez, & Hilmer, 2006).

(Chen & Hossler, 2017). Some eligible parents may choose to obtain debt themselves to support their student's academic career, through the Parent PLUS Loan program. Although in some cases undergoing this debt may be burdensome, there is evidence that these loans do increase the likelihood of students completing their four-year degree. Using propensity score analysis, Woo and Lew uncovered that students whose parents obtain a PLUS Loan can expect their likelihood of obtaining a four-year degree to increase by 43% (Woo & Lew, 2020).

In addition to loans, a student can also expand their financial resources to support their college education through grants. Similar to loans, grants can also increase college success. Using data from the National Longitudinal Survey to study the effects created by the termination of the Social Security Benefits program, Dynarski was able to find that grant aid increased college attainment by .16 percent and the probability of college success by four percent (Dynarski, 2003). This same relationship can be shown for more specific student demographics. Utilizing a regression discontinuity design on Florida students, Castleman and Long were able to find that students just above the Florida Student Access Grant (FSAG) cut-off had a 22% increase chance in graduating within six years, compared to students just below the cut-off (Castleman & Long, 2006). Grants and financial aid have the ability to help students achieve academic success. Especially for students who are from low-income groups, the effect of obtaining more aid can have both short- and long-term benefits, by increasing the likelihood of college attainment and completion (Denning, Marx, & Turner, 2019).

The Case for Test-Optional

Some institutions may still be hesitant on whether to adopt a test-optional model for their admissions process. Individuals who are against test-optional models may argue it decreases institutional quality. However, institutions that provide test-optional admissions have not seen significant decreases in student quality. In fact, compared to institutions that have not adopted such models, test-optional institutions experienced increases in their perceived selectivity (Saboe & Terrizzi, 2019; Belasco, Rosinger, & Hearn, 2015). Furthermore, institutional outcomes, such as graduation rates, do not seem to be affected when adopting a test-optional admissions model. When using data from over 30 public and private universities that had test-optional admissions, Hiss and Franks found there was no difference in GPA or graduation rates between students that have and have not reported standardized test scores to their college (Franks & Hiss, 2014).

Survival Models within Education Economics

Survival analysis is applied mostly within the medical, epidemiology, and clinical trial literature. Of all the available models, the most commonly used time-to-event model is the Cox Proportional Hazard Model, which can produce hazard ratios (Spruance, Reid, Grace, & Samore, 2004). Hazard models can help uncover research questions involving time-to-event by calculating the instantaneous rate a certain event will occur between two groups [2] (Sashegyi & Ferry, 2017). Although this specific type of model houses within the medical and labor economics fields, survival analysis has been shown to answer research questions within the field of education economics.

In one study, DesJardins et. al. utilized survival analysis to estimate the risk of stopout, dropout, re-enrollment, and graduation rates based on certain demographics among first-time freshman students at the University of Minnesota. From their study, these authors found that higher performance in high school is associated with graduating at higher rates, along with lower

[2] Additional explanation of Hazard Ratios and the Cox Proportional Hazard Model can be found in the *Methodology* section of this paper.

rates of stopout[3]. Interestingly, students who performed high on the ACT stopout at higher rates, compared to students with lower scores (DesJardins, Ahlburg, & McCall, 2006). In a similar study done by the same researchers, the authors utilized hazard models to study the effects of changes in financial aid packages on student's ability to persist in college. From their finding, the authors found that increases in financial aid offered does decrease the risk of students stopping out of their university (DesJardins, Dennis A. Ahlburg, & Brian P. McCall, 2002). Another example of survival analysis within higher education economics involves a study conducted by Ahlburg, McCall, and Na. Using the National Longitudinal Survey of Youth survey to study the effects of postponing college matriculation, these authors used discrete hazard modeling to find that students who wait longer to matriculate into college are at higher risk of not completing their four-year degree (Ahlburg, McCall, & Na, 2002).

Evidence from the previous literature shows that student outcomes may not solely and significantly affected by standardized testing. Additionally, institutions do not have to undergo high opportunity costs to provide test-optional admissions. As well as expanding the higher education economics literature with methodologies not commonly used within the field, the purpose of this study is to evaluate the role of standardized testing in predicting college success. If standardized tests do not play a significant role in determining four- or six-year graduation probabilities and rates, this may encourage students to focus their attention on other determinants that can maximize their chance of achieving college success. If standardized test scores do not significantly predict college success, colleges may wish to weigh standardized test scores less in

[3] "Stopout" refers to a discontinuity, non-continuous, or interruption in college enrollment from semester to semester. More information on stopout can be found in (DesJardins, Ahlburg, & McCall, The effects of interrupted enrollment on graduation from college: Racial, income, and ability differences, 2006).

their admissions process or provide test-optional admissions to increase academic outcomes for underrepresented students.

Data

This next section of the paper will describe the data that will aid us in uncovering the true validity of standardized tests. Not only will this section describe in detail the data that our models will be applied to, but it will describe the standardized test score utilized, data restrictions, and the variables that the models will use. Additional information about the variables can be found in the appendix.

ELS description

The data that will be utilized to answer our research question will be the unrestricted version of the Educational Longitudinal Study (ELS) of 2002 survey. The purpose of this survey was to obtain a nationally representative dataset of 10^{th}-grade students within the US, to track their educational and workforce progress and achievements after they have graduated from high school. What makes this dataset unique and useful for this study is that the ELS surveyed, tracked, and followed up with participants for up to 10 years after being originally surveyed. Known as the *Base Year*, the original survey was conducted in 2002, when all the student participants were in 10^{th}-grade of high school. Follow-ups were then conducted with the same cohort of students in 2004 (i.e., *First Follow-up*), 2006 (i.e., *Second Follow-up*), and 2012 (i.e., *Third Follow-up*) (Sciences, Lauff, & Ingels, 2014).

The Base-Year and First Follow-up surveys contain mainly demographic variables. [4] Additionally, the Second and Third Follow-ups[5] of the ELS survey holds information on how students progressed academically and/or professionally. In more detail, the last two follow-ups contain information on when and where students attend college, as well as when they disassociated from college. Most of the survey data that will be utilized in this study will come from the Third Follow-up. However, information from previous follow-ups will be utilized in our models.

Another advantage of utilizing the ELS survey is that it offers student transcript information. In addition to information that could be found in high school transcripts, this survey does contain transcript information from the postsecondary institutions that students have enrolled at. Since self-reported information from the ELS has the potential of creating noise within the regression coefficients we will produce, student transcript information will be utilized to help control for this. High school transcript data were collected in 2004, while postsecondary education transcripts were collected one year after the end of the Third Follow-up, 2013. The ELS survey, partnered with the U.S. Department of Education, also incorporates college entrance exam[6] and financial aid data (Sciences, Lauff, & Ingels, 2014).

There are a wide variety of datasets that could have been used for this study. Overall, this study could have used the National Longitudinal Study of the High School Class of 1972 (NLS

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[4] The Base-Year and First Follow-up of the survey contained questions on high school/student life experiences, their perception of the high school currently attending, and future plans after high school. In addition, the Base-Year and First Follow-up of the survey contained test-scores data conducted by the ELS. More information about the test score variable that will be utilized in this study can be found in the *Test Score Measure* Section of this paper.

[5] Most students who participated in the Second Follow-up were interviewed two years after they have graduated from high school. Participating students in the Third Follow-up were interviewed roughly eight years after graduating high school.

[6] College entrance exam data, such as the SAT/ACT, was only available through the restricted version of the ELS 2002 survey. The ELS was able to provide standardized test scores though a self-developed *Cognitive Test Battery,* which will be discussed in the *Test Score Measure* Section of this paper.

‘79), High School and Beyond, or the National Education Longitudinal Study of 1988 (NELS ‘88). The ELS 2002 survey was the preferred survey because of the following. To begin, the ELS dataset contains student data that is more representative of the current national student body at the time this paper was written (2021), compared to other surveys provided by the National Center for Education Statistics (NCES). Since the magnitude of students enrolling into postsecondary institutions is higher for the class of 2004 compared to the class of 1992 (U.S. Department of Education, 2016), using later surveys provided by the NCES can help further control for potential differences in national representation that could bias our results. More importantly, produced results from this paper can be more generalizable, representative, and applicable to more recent student cohorts pursuing a college education.

Test Score Measure

One of the disadvantages of the unrestricted version of the ELS survey is that there are limits to the amount of information that could be given and analyzed. Specifically, the unrestricted version of the ELS survey suppresses student’s college entrance exams. Due to this issue, we cannot conduct the intended analysis of this paper utilizing reported SAT or ACT scores. The NCES suppressed this information in the unrestricted version of the ELS. There is a solution to this, however. The ELS requires student respondents to complete the *ELS Cognitive Assessment Battery*[7] in the Base-Year of the survey. Instead of using SAT/ACT scores that are not provided by the unrestricted ELS survey, we can use student’s test scores from the Assessment Battery to help answer our research question. Another advantage of this Assessment

[7] More information about the ELS Assessment Battery structure, design, and format can be found in (National Center for Education Statistics, 2008) or https://nces.ed.gov/pubs2008/els_hsmath/app_a5.asp.

Battery is every student has a score, since it is possible for students to not have an entrance exam score.

The purpose of the ELS assessment was to test student's academic achievement and abilities in reading and mathematics. To test reading ability, the assessment required students to answer questions from reading passages of one paragraph to one page long. These passages contain literature on a wide range of topics, including natural and social science. The mathematics portion of the exam contains questions that test student's arithmetic, algebraic, geometry, and data/probability knowledge and skills. In addition, the mathematics test assessed for mathematical understanding, comprehension, and problem solving (National Center for Education Statistics, 2008).

Although the ELS Cognitive Assessment Battery is no perfect substitute, this assessment does share similar traits and testing standards with the nationally known SAT and ACT college entrance exams. Student respondents of the ELS are given a test score that can be compared to other students who took the same exam. Because of these similarities, utilizing test scores information from the assessment battery can be useful to uncover our research question.

Sample Restrictions

In total, 16,197 10th-grade students originally participated in the survey. Although the sample size in the original ELS dataset is sufficient to apply our empirical models too, it is important to note that not all participants of the survey had the experience of attempting to earn a four-year college degree. Some students from the ELS survey decided not to advance their academic careers to the postsecondary level. In addition, some students who attended a postsecondary institution could have decided not to pursue a four-year degree (i.e., students who attend a two-year institution and decide not to attend a four-year university). Because of the wide variety of academic and non-academic pathways students decided to undergo, it is crucial to have an appropriate sample of students that can best answer our research question.

To uncover the true effectiveness of standardized test scores on graduating from college by four or six years, our sample will need to contain students that have shown intent of pursuing a four-year degree. To account for this, I only included students who, or whose postsecondary transcripts have, indicated they have attended at least one four-year university by the Third Follow-up[8] of the survey. Another restriction that was made involves when students started their postsecondary education. Although most students in our sample do not experience a lag between when they exit high school and enter their first college, some students within our sample do start college at a much later date. More specifically, some students in this sample could have started their college careers close to the Third Follow-up of the ELS survey, in 2012. Since the ELS survey does not follow up with students again after 2012, we could have an issue where the ELS survey cannot assess if these students did or did not graduate from college. To control for this issue, I restricted the sample to only include students that have started their postsecondary careers by 2006. [9] This restriction allows us to more accurately identify students who graduated by our four- and six-year targets.

An additional restriction was applied regarding our key variable of interest. Since our variable of interest is the student's test score from the ELS Cognitive Assessment Battery, all students in the sample must have an assigned test score. Those who do not have a test score

[8] This exclusion led to 7,132 observations being dropped from the original sample. The survey question utilized to conduct this restriction was asked in the Third Follow-up.
[9] The survey question that was utilized to apply this restriction was asked in the Third Follow-up of the ELS survey. This restriction led to 1,109 students being excluded from the sample.

assigned were excluded from the sample[10]. After applying these restrictions, we have 7,879 students whose data we can utilize in this study.

There is one last restriction that must be considered, which involves the hazard model we will produce. One feature that the Cox Proportional Hazard model holds is that it is dependent on a time variable, so survival, duration rates, and hazard ratio regression coefficients can be produced (Boudreau & Lawless, 2006). Since the Hazard Cox model requires a time variable, we will utilize the enrollment year that a student either graduated or disassociated from college (*Yearsenroll*). The issue that arises with utilizing this variable is that the ELS was not able to obtain *Yearsenroll* for all student respondents from its survey, classifying them as missing. To adjust for this issue, I excluded individuals from the sample if the ELS was not able to obtain *Yearsenroll* for students. [11] Although that this restriction will potentially affect the OLS and probit regression coefficients, this restriction is important to have data consistency across all three models. After all restrictions are applied, we are left with 7,640 students in our sample.

Variables

The college success outcome we will focus our attention on in this study is if students were able to successfully obtain their college degree by our four- or six-year targets. For students whose transcripts indicated they were able to obtain a four-year degree by 48 and 72 months, then $Grad_4$ and $Grad_6$ will equal one, respectively. Students that did not complete their degree by 48 and 72 months, or prematurely disassociated from school, then $Grad_4$ and $Grad_6$ will equal zero, respectively. From the ELS data after restrictions were applied, 29.8% of all students

[10] Only a small portion of students in the sample did not have an assigned test score from the Base-Year ELS Cognitive Assessment Battery. 77 students were dropped from the sample due to this restriction.
[11] The *Yearsenroll* variable was created using data from student's postsecondary transcripts. 239 observations were dropped after applying this restriction- 3% of the 7,879 students from the first three restrictions applied. Note that enrollment years is not equal to calendar years.

Table 1: *Variables and Variable Description*

Variable	Type	Description	Categories
$Grad_4$	Binary	Graduated college by four years	
$Grad_6$	Binary	Graduated college by six years	
Testscore	Continuous	ELS Battery Assessment Test Score	
TestscoreST	Continuous	*Testscore* standardized	
Enrollyears	Continuous	Total number of college enrollment years	
Sex	Categorical	Student's sex reported	*Male*, Female*
Race	Categorical	Student's race reported	*Amer. Indian, Asian and Hawaii/Pac. Islander, Afr. Amer/ Black, Hispanic, White*, More than one Race,*
SSE	Categorical	Student socioeconomic status	*Low, Lower-Middle, Middle*, Upper-Middle, Upper*
MotherGrad	Binary	Mother Earned a bachelor’s degree	
FatherGrad	Binary	Father Earned a bachelor’s Degree	
Region	Categorical	The geographical region of student's high school	*Northeast*, Midwest, South, West*
HSCrt	Categorical	The control of high school students attended	*Public*, Catholic, Other Private*
HSGrade	Categorical	Overall high school Letter Grade	*A*, B, C, D, F*
Gapmonths	Continuous	Months between HS exit and college entrance	
UGapmonths	Binary	Missing *Gapmonths*	
FCLvl	Categorical	First college attended Level	*Four-year*, Two-year, Less than two-year*
FCCrt	Categorical	First College Attended Control	*Public*, Private for-profit, Private not-for-profit*
FCSel	Categorical	First College attended selectivity	Highly Selective four-year*, Moderately Selective four-year, Inclusive four-year, Unclassified four-year, Unclassified two-year, Unclassified less than two-years
Inoutstate	Categorical	First college in- or out-of state	In-state*, Out-of-State
FYGPA	Continuous	First-year college GPA	
UFYGPA	Binary	Unknown First-year college GPA	
Stopout	Categorical	Ever discontinued enrollment for 4+ months	Yes, No*, Missing
Loan	Binary	Ever received a Loan	

Note: *HSGrade, FCLvl, FCCrt, FCSel*, and *inoutstate* all contain an extra category to identify observations that have missing data. “*” represent variables that will serve as the base comparison group once models are applied. The *Yearsenroll* variable will not be included in out OLS or probit regressions. This variable will solely be included in our Hazard Proportional Cox regressions. Summary statistics for each variable and category can be found in table A of the appendix.

who pursued a four-year degree graduated by four years, while 56.8% of all students in our sample graduated by six years.

As mentioned, the testing data we will utilize to uncover the effect of standardized testing on college outcomes will be student's test scores from the ELS Assessment Battery, *Testscore*. [12] The regression models will use the standardization of *Testscore,* which will be called *TestscoreST.* The benefit of using *TestscoreST* over *Testscore* will be its ease with interpretation. The *TestscoreST* regression coefficient represents how a one standard deviation increase in test score increases the probability of students graduating (Wooldridge, 2016). For the probit regressions, the marginal effects are presented and they represent how a one standard deviation in test score affects the probability of graduation. As for our Hazard Cox model, standardized variables can be interpreted as the increase in the *hazard* associated with a one standard deviation increase in test score (Sashegyi & Ferry, 2017).

More information on hazards will be discussed in the methodology section of this paper. All other covariates that will be involved in this analysis can be found in table 1 above. Just to note, *Yearsenroll* will not be a covariate in the OLS and probit models. This variable will only be utilized in the Cox Proportional Hazard model, since this model heavily depends upon a time-to-event variable (Boudreau & Lawless, 2006). Additional information about variable summary statistics can be found in Appendix Table A.

Methodology

In summary, three econometric models will be utilized to uncover the effect of standardized tests on the probability students will graduate by our four- or six-year targets. OLS

[12] Figure A in the appendix contains the distribution of scores students earned.

and probit models will be applied to estimate the marginal effect of standardized test scores on the probability of graduating from college, while the Hazard Cox model will estimate the increase in the *hazard* that is associated with a one-unit increase in *TestScoreST*.

Standard Regression Modeling

Standard Ordinary Least Squares (OLS) and probit models will serve as our preliminary models to answer our research question. Since our outcome variable is binary, our OLS will be classified as a Linear Probability OLS Model. Using the data restrictions placed and the variables listed in table 1, our preliminary OLS model will be the following.

$$Grad_{i,t} = \beta_0 + TestscoreST_i \, \beta_1 + \sum X_i \, \beta + \epsilon_i, \qquad t \in \{4,6\}$$

Where $Grad_{i,t}$ is equal to one if student *i* graduated from college by *t* equals four or six years, $TestsoreST_i$ are student *i's* test scores from the ELS Assessment Battery, and X_i will be our control covariates from Table 1.

The benefit of using this Linear Probability Model is that we can estimate marginal probabilities from a one-unit increase in our independent variables. The effects of standardized test scores are captured in β_1, our coefficient of interest. To interpret this coefficient, a one-unit increase in *TestscoreST* would, on average, increase the probability of a student graduating college by β_1. However, if the coefficient of β_1 is not statistically different from zero, it would imply that a one standard deviation increase in *Test score* (i.e, a one-unit increase in *TestscoreST*) does not statistically affect the probability of a student graduating from college by our four- or six-year targets. If β_1 does turn out to be statistically insignificant, then there would be more evidence to question the validity of standardized test scores in determining college success.

Although a linear probability regression can provide estimates of marginal effects, it does have limitations. The biggest disadvantage that comes from linear probability models is that they can produce fitted values below zero and above one. To add on, the linear probability model results in heteroskedasticity (Wooldridge, 2016). Due to this issue, you should estimate a regression model with heteroskedasticity using robust standard errors. The probit regression estimates regression coefficients that necessarily only lead to predicted values between zero and one. For this study, we will also utilize probit regressions and calculate marginal effects for each of our independent variables.

$$P\left(Grad_{i,t} \middle| X_i\right) = G\left(\beta_0 + TestST_i\, \beta_1 + \sum X_i\, \beta\right) \in [0,1], \qquad t \in \{4,6\}$$

The equation above will be our desired probit model. To obtain the marginal effect of standardized test scores on the probability of graduating by our four- and six-year targets, we will need to obtain the partial effects by using the following equation. Once the following partial equation is calculated, the interpretation of this coefficient will be similar to our OLS equation, where the marginal probability of graduating for a one-unit increase in $TestscoreST$ will increase by β_1 (Wooldridge, 2016).

Time-to-Event Modeling

Time-to-event modeling is more often utilized in the field of epidemiology. The purpose of time-to-event modeling is to uncover the length of time it takes for an individual to experience a certain outcome, as well as measure the likelihood that a dichotomous outcome will happen. Such analysis to uncover the likelihood of an event occurring can be calculated using logistic regression. However, since time-to-event studies are heavily dependent on the time it takes for individuals to experience an outcome, it would be inappropriate to utilize logistic regressions-due to logistic regressions underperforming in studies that involve time (Schober & Vetter, 2018). One of the most popular types of time-to-event models is the Cox Proportional Hazard Survival model. This specific model utilizes *Hazard Ratios* to estimate the rate of an outcome occurring at a given point in time between two different groups (Cox, 1972). In a medical example, hazard ratios can be used to study the rate of an intervened treatment group experiencing an outcome (i.e, obtaining cancer or death) over a control group that has not been intervened. Applying to this paper, the hazard ratio can be used to estimate the rate of not graduating between students from two different groups at certain points in time. As an example, we could compare rates between students who attended different high schools, colleges, demographics, and more.

Hazards, Rates, and Ratios

Formally, a *hazard* is an instantaneous probability an individual will experience an event at a given point in time (Sashegyi & Ferry, 2017), such as death or obtaining cancer. More specifically, a *hazard* can be defined as the conditional probability that an individual will experience an event/outcome at time t, given that they have still survived by t (Guillory, 2008). This can mathematically be shown by Guillory/Cox's discrete-time hazard equation below.

$$h(t) = P(T = t | T \geq t)$$

Where $h(t)$ is the hazard probability, T is a non-negative random variable for the waiting time of an event to occur, and t is the time an individual experiencing the event/outcome conditional on having survived at that point (Guillory, 2008). For this paper, the hazard will refer to is the probability that a given student did not graduate by our targets at a given point in time, conditional on if they are still in school by time t.

Calculating hazard rates involves understanding the proportion of individuals who have survived and failed to survive to time t, conditional on everyone having survived to t. One can denote the hazard rate, $\lambda(t)$, by the following.

$$\lambda(t) = \frac{f(t)}{S(t)}$$

Where $f(t)$[13] is the probability density of not graduating by time t, $S(t)$ is the proportion of students surviving by time t, and $\lambda(t)$ is the conditional failure rate (i.e., our hazard rate) for discrete-time (Charan, 2020).

Hazard Ratios (HR) can be defined as the ratio of hazards rates between two groups such that,

$$HR(t) = \frac{\lambda_1(t)}{\lambda_0(t)}$$

where $HR(t)$ is the hazard ratio between groups one and zero, $\lambda_1(t)$ is the hazard rate for group one, and $\lambda_0(t)$ is the hazard rate for our baseline group, group zero. Typically in epidemiology, hazard ratios are calculated by using the hazard rates between a treatment and control group. However, hazard ratios can be beneficial to use in this study, because they can measure the rate a group experiences a hazard at a given time t compared to another group, given that everyone in both groups has still survived by time t (Schober & Vetter, 2018). Interpretation of these types of ratios is intuitive.

[13] Where T is a non-negative random variable for the waiting time of an event to occur, probability distribution of the hazard rate at time t, $f(t)$, is derived from the discrete hazard proability such that, $P(T = t|T \geq t)$= $P(T = t)$. Please refer to (Guillory, 2008; Charan, 2020; Cox, 1973) for more information about survival functions.

- $HR(t)$ = *1* indicates no difference in hazard rates between the two groups, or no effect in the hazard.
- $HR(t)$ > *1* indicates group one has a higher hazard rate than the comparison group. In other words, there exists an increase in the hazard.
- $HR(t)$ < *1* indicates group one has a lower hazard rate than the comparison group or there exists a decrease/reduction in the hazard.

Alternatively, we can interpret hazard ratios as a percentage term. By simply taking $h = (HR(t) - 1) * 100$, we can get the increase/decrease percent in the hazard for a group, compared to a baseline comparison group. If the value of h is negative, then group one experiences a reduction in the hazard rate by h%, vice versa (Sashegyi & Ferry, 2017). To apply this concept to answer our research question, we can compare hazard rates between students from different groups- such as student gender, socioeconomic status, the types of school they attended, and so on. More importantly, we can uncover the hazard ratio of a one standard deviation increase in a student's test score. If our hazard ratio for a one-unit increase in $TestscoreST$ turns out to be no different than one, we could be able to conclude that standardized test scores do not affect the hazard. That is, there is no significant effect on the rate at which students fail to graduate college on time from a one-unit increase in $TestScoreST$.

Cox Proportional Hazard Model

The Cox Proportional Hazard model is a commonly used survival model that can produce hazard ratios, while controlling for covariates that can potentially affect an outcome. Traditionally, the Cox Proportional Hazard model is taken in the following form,

$$\lambda(t) = \lambda_0(t) \exp[\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k],$$

where $\lambda(t)$ is the hazard function, $\lambda_0(t)$ is the baseline hazard, and $\beta_1 x_1, \ldots, \beta_k x_k$ represents the covariates we will include in the regression. There are some benefits when utilizing this equation. To begin, the baseline hazard function is estimated non-parametrically, indicating that survival functions are not assumed to have any underlining distribution or shape to them (Guillory, 2008). Additionally, the exponent of a regression coefficient, $\exp(\beta_i)$, is the equation's estimate of the hazard ratio for covariate x_i (Bradburn, Clark, Love, & Altman, 2003). To uncover an answer to our research question, we can use the following Cox Proportional Hazard regression equation.

$$\lambda(t) = \lambda_0(t) \exp[TestscoreST_i x_1 + \sum X_i \beta]$$

Where $TestscoreST_i$ are student test scores from the ELS Assessment Battery and X_i are our control variables, as before. Using our knowledge on hazard ratios, if the model above estimates that $\exp(TestscoreST)$ is not statistically different from one, then we will have enough evidence to show that standardized test scores do not influence the rate at which students fail to graduate from college by four or six years, i.e. there is no effect in the hazard.

Assumptions of Cox Model

The Cox Hazard model does require some assumptions to have valid and reasonable results. Before introducing these assumptions, it is important to note that the hazard function above and survival curves that will be produced do not require any specific form or shape. That is, there is no assumption on the underlining shape or distribution that survival curves must follow (Guillory, 2008; Schober & Vetter, 2018; Cox, 1973). The most important assumption that the Cox Proportional Hazard Model must hold on to is the Proportional Hazards Assumption, where hazard ratios must remain constant over time (Spruance, Reid, Grace, &

Samore, 2004; Guillory, 2008; Cox 1973). In other words, each covariate must have a multiplicative relationship in hazard ratios across all time (Xue, et al., 2013). If hazard ratios happen to not be proportional across all time, then it would indicate that the hazard ratio for that specific covariate is dependent on time. Meaning, a hazard ratio between two groups at a specific point in time is different from a hazard ratio at another given point in time. If covariates that are dependent on time are not accounted or adjusted for, misleading results will occur and we will have less causal abilities (Bellera, et al., 2010; Vatcheva, McCormick, & Rahbar, 2015).

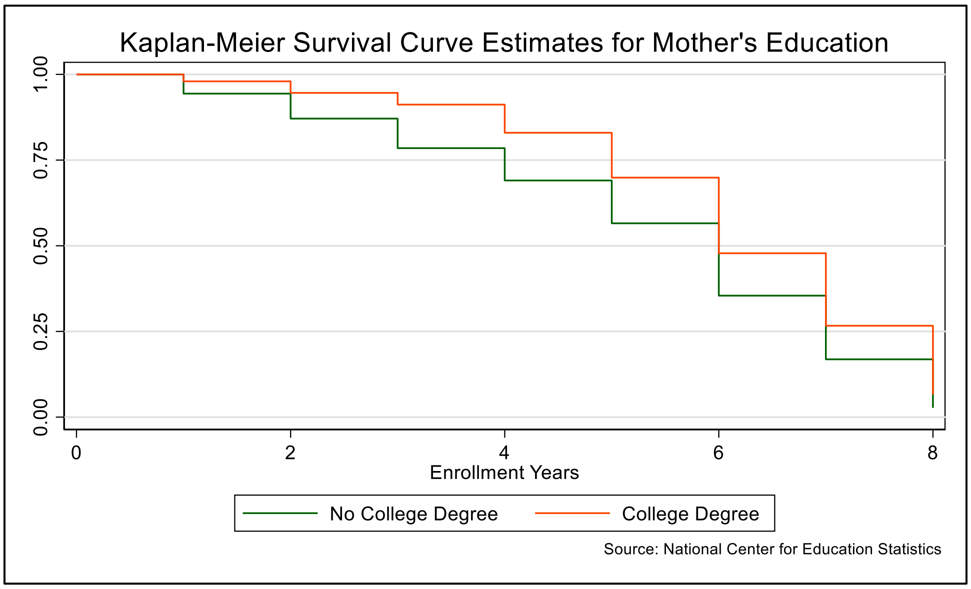

Figure 1: Example of a Kaplan-Meier survival function for estimated survival rates between students whose mothers did or did not obtain a college degree. Data was produced after estimating model 8 from Appendix table D.

There are multiple ways to test for proportional hazards. A way to visually assess if proportional hazards are held across time for covariates is to transform Kaplan-Meier survival curves into a *log(-log(S(T)))* form along time, where *S(t)* is the survival function. Figure 1 provides an example of survival curves. To confirm that the proportional hazard assumption does hold, we can visually inspect that all transformed survival functions for each category in a covariate are parallel to its perspective baseline/comparison group. For lines that do not look parallel to one

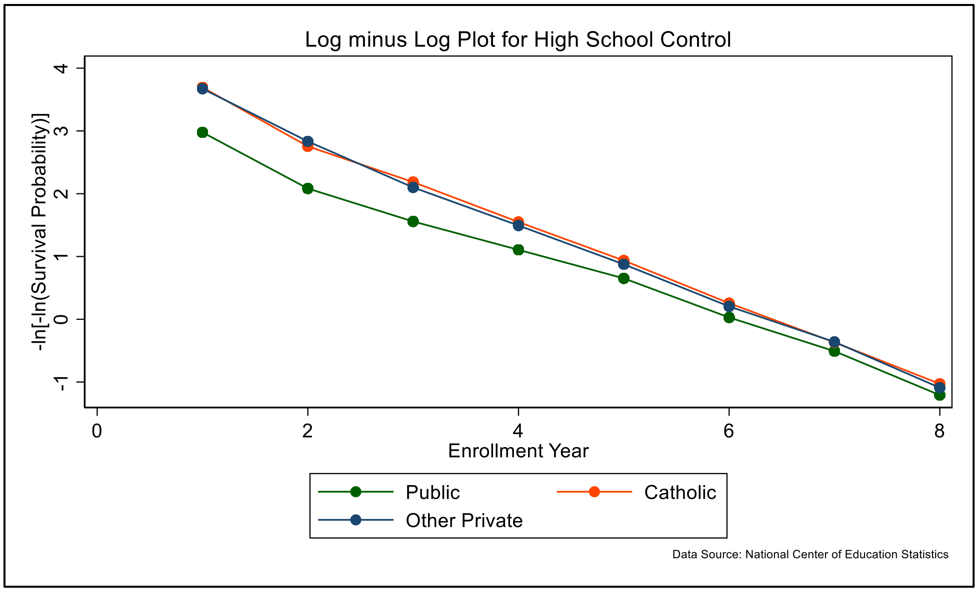

Figure 2: Example of covariate passing the proportional hazards assumption by visual inspections, using the log negative log of the Kaplan-Meier survival for the *HSCrt* variable. The baseline group was students who attended a public high school. Data was produced after estimating model 8 from Appendix table D.

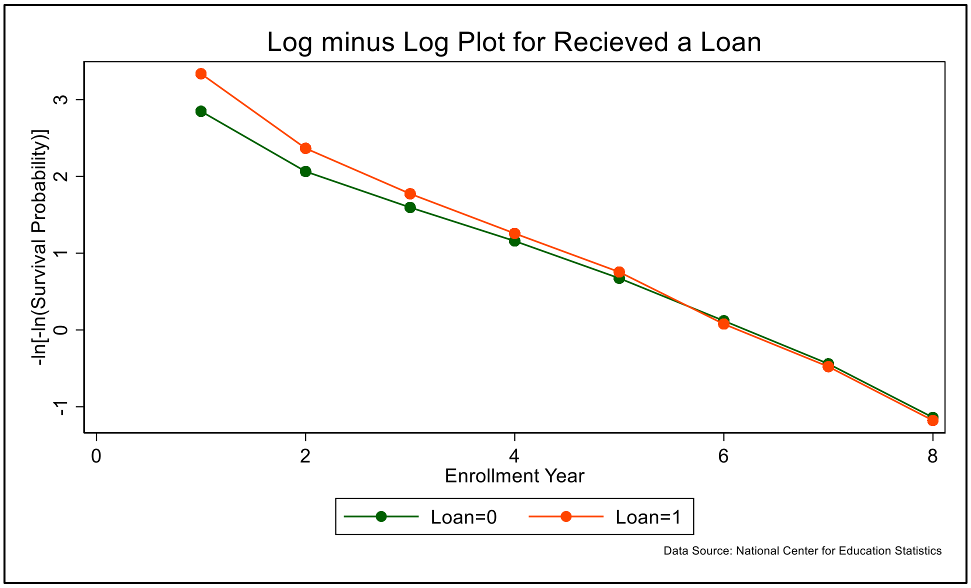

Figure 3: Example of covariate violating the proportional hazards assumption by visual inspections, using the log negative log of the Kaplan-Meier survival for the *Loan* variable. Data was produced after estimating model 8 from Appendix table D.

another, this will suggest that the assumption has not been held (Bellera, et al., 2010). Figure 2 above represents an example of parallel trends. Since our baseline group for the control of high school students attended (*HSCrt*) was *Public* School, and the *Catholic* and *Other Private* lines do look fairly parallel with its baseline group, there is some evidence that the assumption holds for the *HSCrt* variable. Figure 3 represents an example of a log minus log graph for a variable that has non-parallel lines, thus violating the assumption.

The visual inspection method should be taken with caution because it may not be the most effective way to test the proportional hazards assumption (Li, Han, Hou, & Chen, 2015). [14] A more effective way to test for proportional hazards is by using Schoenfeld residuals, where it mathematically assesses if the residuals of each covariate, against time, have an underlining pattern to them. If the residuals of a given covariate are statistically centered around zero, then the covariate is said to have no pattern with time in its residuals, thus there exists proportional hazard across time and the assumption is held (Xue, et al., 2013).

If some of our covariates are dependent on time, there is a solution that is appropriate for this study. Interacting time-dependent variables with time can help control this issue. However, there will be extra interpretation needed on these variables, which will be different compared to variables that do pass the assumption (Jin & Boehmke, 2017). If time-dependent covariates are found in our preliminary Hazard Cox regression outputs, we will need to adjust our original Hazard model above to the following equation.

$$\lambda(t) = \lambda_0(t)\exp[TestscoreST_i x_1 + \sum X_i\,\beta + \sum \gamma(\,X_i \cdot f(t))]$$

[14] *Log(-Log(S(t)))* graphs that have multiple categories may make it harder to identify if the assumption is met, since there are multiple lines on one graph.

Where γ is our coefficient for the interaction between a given covariate X_i and our desired time function t $(f(t) = t, t^2,$ ln $(t), \ldots)$ (Bellera, et al.,2010; Cox,1972). Interpretation for non-time-dependent variables will be the same as before, where the hazard ratio for covariate X_i will be its respective β. Alternatively, $(\beta - 1) * 100$ will be the percent increase or reduction in the hazard. However, those variables that are time-dependent will be interpreted differently. If X_i is a time-dependent variable, its hazard ratio can be interpreted mathematically by $\beta_i + \gamma \cdot X_i \cdot f(t)$. Where β is the hazard ratio at time zero, and γ is the increase in the hazard for an additional unit of time. If γ>1, then it is said that the hazard ratio for X_i increases over time, vice versa (Bellera, et al., 2010). Alternatively, $(\gamma - 1) * 100$ can be interpreted as the percent increase in the hazard from a one-unit increase in time, for covariate X_i $(\text{STATALIST}, 2015)$.

Results

This section will go over all the models we applied the ELS data to- OLS, probit, and Hazard Cox. All regression tables listed in this section will only show selected variables to highlight key findings. Regression tables containing all the covariates listed in table 1 can be found in the appendix. The models that we will most focus our attention on from each table will be models (4) and (8), which control for the most confounding factors.

OLS

Table 2 below contains our estimated coefficients for determining how much a one-unit increase in our variables affects the probability of a student graduating from college by our targets using OLS, certis peribus. From the OLS table, we can see that the type of high school students attend does affect the probability that a student will graduate by our targets. For students that attended a *Catholic* school, compared to students who attended *Public* school, we can expect

Table 2: OLS Regression Results for Impact of Standardized Test Scores on College Success

	Dependent Variable (Graduated)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized Test Score	0.134***	0.112***	0.061***	0.027***	0.152***	0.117***	0.049***	0.016**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
High School Control (HCCrt)								
Catholic			-0.008	-0.050***			0.084***	0.042***
			(0.013)	(0.013)			(0.014)	(0.013)
Other private			0.024	-0.034*			0.071***	0.034*
			(0.016)	(0.015)			(0.016)	(0.015)
Months between HS and College				-0.001				-0.003***
				(0.001)				(0.001)
First College Level (FCLvl)								
Two-year institution				-0.041				-0.012
				(0.021)				(0.024)
Less-than-two-year institution				-0.037				-0.219***
				(0.042)				(0.058)
First College Control (FCCrt)								
Private for-profit				0.001				-0.103***
				(0.024)				(0.026)
Private not-for-profit				0.091***				0.012
				(0.013)				(0.012)
inoutstate								
In-State				-0.039**				-0.002
				(0.013)				(0.012)
First Institution Selectivity (FCSel)								
Inclusive 4-year				-0.167***				-0.137***
				(0.017)				(0.018)
Moderately selective 4-year				-0.107***				-0.058***
				(0.014)				(0.013)
Unclassified 4-year				-0.168***				-0.210***
				(0.019)				(0.021)
First-Year College GPA (FYGPA)				0.100***				0.127***
				(0.005)				(0.006)
Stopout								
Yes				-0.199***				-0.327***
				(0.010)				(0.012)
Loan								
Yes				-0.017				0.020
				(0.010)				(0.010)
Demographic	No	Yes	Yes	Yes	No	Yes	Yes	Yes
High school GPA	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.085	0.122	0.172	0.278	0.093	0.127	0.201	0.350
Adjusted R-squared	0.085	0.120	0.169	0.274	0.093	0.126	0.199	0.346
F-Statistic	830.346	76.327	89.624	85.829	911.478	82.996	156.932	148.952
Joint Significance Statistic	-	22.10	31.66	76.98	-	20.42	48.56	120.19
rmse	0.438	0.429	0.417	0.390	0.473	0.464	0.445	0.402
Out-of-Sample Predictions	2.02%	3.14%	4.43%	11.66%	0.03%	0.21%	1.30%	7.25%

*Note:*Ugapmonths and UFYGPA were included in models (4) and (8). Missing categories from the FCLvl, FCCrl, inoutstate, and stopout variables were all included in regression models (4) and (8) but have been excluded from this table. The Unclassified two-year, Unclassified less than two-year, and Unknown categories from the FCSel variable were included in models (4) and (8) but have been excluded from this table. Demographic variables include Student Sex, Race, SSE, Mothergrad, Fathergrad, and Region. N=7640 for all models. Coefficients from all variables can be found in Appendix Table B.

Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

their probability of graduating to decrease by 5% on average in the four-year model. However, this finding changes in the six-year model, where the probability for *Catholic* school students increases by 4.2%, on average, compared to *Public* school students. A similar story can be seen between students who attended *Other Private* schools, compared to *Public* school students. From the four-year model, *Other Private* school students have a decreasing probability of graduating by 3.4%, while having an increase in the probability of graduating college by 3.4% in the six-year model.

The regression also offers mixed results for the level of institution students start their postsecondary careers at. On average, students who started their college careers at a *Two-year* institution can expect their probability of graduating by four years to decrease by 4.1%, compared to students who started at a *Four-year* school. This effect does persist in the six-year model, where the coefficient is -.012. However, these variables are insignificant. For students who started college at a *Less-than-two-year* school, there is no significant difference in the probability students will graduate in four years, compared to students who started at a *Four-year* school. The same cannot be said in the six-year model, where the probability of graduating decreases by over 21.9% when starting at a *Less-than-two-year* school, compared to a *four-year* school.

Mixed results are also shown for the *Control* of student's first postsecondary institutions were classified as. Students who attend a *Private for-profit* institutions do not experience a significant decline in four-year graduation probability, compared to those students who attended a *Public* institution. However, this probability declines in the six-year model, by on average 10.3%. As for students that started college at a *Private not-for-profit,* we can expect the marginal probability of graduating by our four-year target to increase by 9.1%. This effect disappears in the six-year model, however, where the probability is 1.2% and is statistically insignificant. *In-State* students experience a reduction in the probability of graduating in four-year by 3.9%, but this effect is insignificant in the six-year model.

The *Selectivity* of an institution seems to matter a great deal in determining who will graduate on time. Compared to students from *Highly Selective* institutions, students from *Inclusive, Moderate*, and *Unclassified four-year* institutions can expect the probability of graduating to decline heavily by 16.7%, 10.7%, and 16.8%, respectively. This negative effect does persist in the six-year model, where probabilities decline by 13.7%, 5.8%, and 21%, respectively. The GPA students earn in their first year of college can truly affect how likely they are to finish school on time. From the *FYGPA* variable, for every one-point increase in first-year college GPA, we can expect the probability of graduating in four years to increase by 10%, on average. As for the six-year model, a one-point increase in *FYGPA* can increase a student's probability of graduating by 12.7%.

Oddly, obtaining a loan during school can decrease the probability of graduating in four years by 1.7%. However, this variable is insignificant in the four-year, as well as in the six-year model. Although not shown in the table above, high school GPA was included in the model. In summary, for students whose average *HSGPA* did not average to be an *A*, they can expect a penalty in their probability of graduating by four- and six years. *Stopout* also drastically affects how likely students will be able to graduate on time. From the -.199 and -.327 coefficients presented, we can that discontinuing enrollment decreases graduation likelihood by 19.9% and 32.7% in the four- and six-year models, respectively.

As for our main coefficient of interest, *TestscoreST* this coefficient turned out to be .027 in the four-year model and significant at all alpha levels. To interpret this coefficient, a one-unit increase in *TestscoreST* (i.e. a one standard deviation increase in *Testscore*) increases the probability of graduating college in four years by 2.7%. The six-year model also supports a positive, and significant, relationship between stardardized test scores and college success. From the .016 coefficient shown in model 8 indicates that a one standard deviation increase in standardized test increases graduation probability by 1.6%. From these results, we can support that standardized tests does significantly affect the probability of a student completing school on time. Coefficients for variables not shown in table 2 can be found in Appendix Table B.

Non-Linear Probit

As discussed, one of the most consequential drawbacks of utilizing a linear probability model is that it can produce predictions outside a [0,1] range (Wooldridge, 2016). To control for this, table 3 below will contain marginal probabilities created from our probit model, which will obtain slightly more precise estimates. From the model, we can see that compared to students who attended a *Public* school, *Catholic* high school students can expect to have a 4.3% decrease in four-year graduation probability. However, this coefficient changes in the six-year model, where graduation probability increases by 3.7%, on average. As for students who attended *Other private* high schools, there is a statistical difference in the marginal probability of graduating by four years, compared to *Public* high school students, where probabilities decline by 2.9%, but statistically insignificant in the six-year model.

Our margins probit model also shows some mixed results for the type of institution students start their college careers at. When it comes to the student's first college level, attending a *Two-year* school decreases the marginal probability of graduating in four years by 7.2%, compared to students that started their college careers at a *Four-year* school. However, this coefficient turns out to be insignificant in the six-year model. There seems to be a large penalty

Table 3: Probit Marginal Effects

	Dependent Variable (Graduated)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized Test Score	0.138***	0.114***	0.063***	0.021***	0.150***	0.116***	0.049***	0.015*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
High School Control (HCCrt)								
Catholic			-0.003	-0.043***			0.082***	0.037**
			(0.013)	(0.012)			(0.014)	(0.013)
Other private			0.024	-0.029*			0.069***	0.029
			(0.015)	(0.014)			(0.017)	(0.015)
				-0.001				-0.003**
Months between HS and College				(0.001)				(0.001)
				-0.033				0.037
First College Level (FCLvl)				(0.066)				(0.050)
Two-year institution								
				-0.072**				-0.003
				(0.023)				(0.023)
Less-than-two-year institution								
				omitted				-0.301**
								(0.102)
First College Control (FCCrt)								
Private for-profit				-0.004				-0.115***
				(0.034)				(0.031)
Private not-for-profit				0.071***				0.011
				(0.012)				(0.012)
inoutstate								
In-State				-0.031**				-0.003
				(0.012)				(0.013)
First Institution Selectivity (FCSel)								
Inclusive 4-year				-0.136***				-0.127***
				(0.017)				(0.019)
Moderately selective 4-year				-0.073***				-0.058***
				(0.012)				(0.013)
Unclassified 4-year				-0.144***				-0.205***
				(0.021)				(0.023)
First-Year College GPA (FYGPA)								
				0.135***				0.126***
				(0.008)				(0.007)
Stopout								
Yes				-0.220***				-0.322***
				(0.011)				(0.012)
Loan				-0.016				0.019
Yes				(0.010)				(0.010)
Demographic	No	Yes	Yes	Yes	No	Yes	Yes	Yes
High school GPA	No	No	Yes	Yes	No	No	Yes	Yes
Observations	7640	7640	7628	7583	7640	7640	7628	7610
Log Pseudo Max Liklihood Estimation	-4307.010	-4154.986	-3943.774	-3377.451	-4872.848	-4730.365	-4408.327	-3688.374
Likelihood Ratio Statistic	-	304.048	422.425	1132.646	-	284.967	644.076	1439.905
Psudo R-squared (prior to margins)	0.075	0.108	0.152	0.272	0.071	0.098	0.158	0.293

Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

Note: Ugapmonths and *UFYGPA* were included in models (4) and (8). *Missing* categories from the *FCLvl*, *FCCrl,inoutstate,* and *stopout* variables were all included in regression models (4) and (8) but have been excluded from this table. The *Unclassified two-year*, *Unclassified less than two-year*, and *Unknown* categories from the *FCSel* variable were included in models (4) and (8) but have been excluded from this table. Demographic variables include Student *Sex, Race, SSE, Mothergrad, Fathergrad,* and *Region*. The *less-than-two-year* variable for model (4) was omitted due to predicting failure perfectly. Coefficients from all variables can be found in Appendix Table C.

in the probability of graduating by six years for students that start college at a *Less-than-two-year* college compared to those that started at a *Four-year* school, where the penalty is 30.1%.

The coefficients regarding the *Control* of student's first postsecondary institutions also provide us with some mixed results. Compared to students who started college at a *Public* institution, students who attend a *Private for-profit* college do not see a significant difference in the marginal probability of graduating by four years. However, the six-year model indicates these students are less likely to graduate on time, where the graduation probability decreases by 11.5%. As for students who started college at a *Private not-for-profit* school, compared to *Public* school college students, their probability of graduating increases by 7.1% in the four-year model, but this effect is insignificant in the six-year model. *In-state* students can expect a decline of 3.1% in the probability they will graduate by four years, compared to *Out-of-State* students, but this effect is insignificant in the six-year model.

Similar to OLS, the probit model can also support that the *Selectivity* of a student's first college does greatly affect the probability of students graduating from our targets. Compared to students from *Highly Selective* institutions, students from *Inclusive, Moderate*, and *Unclassified four-year* institutions can expect the probability of graduating to decline heavily by 13.6%, 7.3%, and 12.6%, respectively. This negative effect does persist in the six-year model as well, where probabilities decline by 12.7%, 5.8%, and 20.5%, respectively. *FYGPA* can significantly determine the probability that a student will graduate by our targets. The model suggests that, on average, four- and six, year graduation probabilities increase by 13.5% and 12.6%, respectively, for a one-point increase in first-year GPA. In terms of financial resources, the probit model was not able to support that obtaining a loan affects the probabilities that students will graduate by four or six years. Both model shows that students undergo a large penalty when they choose to stopout of school. From the -.22 and -.322 coefficients presented, we can that discontinuing enrollment decreases graduation likelihood by 22% and 32.2% in the four- and six-year models, respectively.

As for our variable of interest, *TestscoreST*, the model suggests that higher test scores do positively impact the probability of graduating by four and six years. For a one standard deviation increase in *Testscore*, students can expect the probability of graduating in four years to increase by 2.1%. In the six-year model, a one standard deviation increase in test scores increases the probability of graduating by 1.5%, Both OLS and probit show similar results in how test scores influence college success, where test scores play a significant role in both four- and six-year models. To view all coefficients produced by the probit model, appendix table C contains this information. Table 6 compares the coefficients produced by OLS and probit models.

Cox Proportional Hazard Model

Table 4 below contains our preliminary results for the true effect of standardized testing on student's ability to graduate college on time. Focusing our attention on models (4) and (8) we can see that there is no significant difference in the hazard rates between students who attended a *Catholic* versus a *Public* high school in the four-year model. However, *Catholic* high school students experience a significant decrease in their rate of dropping out of school in the six-year model, compared to *Public* school students. As for students who attended *Other Private* high schools, there seems to be a significant increase in the hazard in the four-year model, but this effect does not persist in the six-year model. From the *Gapmonths* coefficient, we can see that delaying postsecondary entry by one month increases the rate at which students not graduating on time in both the four- and six-year models by on average 3.2% and 3.1%, respectively. Interestingly, there is no significant effect in graduation rates for students that attended a *Two-*

Appendix Table 4: *Hazard Cox Results (no time-dependent covariate adjustments)*

	Dependent Variable (Graduated), Time factor (Number of Enrollment Years)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized Test Score	0.887***	0.906***	0.950***	0.981	0.759***	0.809***	0.920***	0.963
	(0.011)	(0.012)	(0.014)	(0.015)	(0.013)	(0.015)	(0.018)	(0.020)
High School Control (HCCrt)								
Catholic			1.019	1.017			0.815***	0.846***
			(0.031)	(0.033)			(0.037)	(0.040)
Other private			1.079*	1.091*			0.924	0.931
			(0.039)	(0.043)			(0.051)	(0.055)
Months between HS and College (Gapmonths)				1.032***				1.031***
				(0.002)				(0.002)
First College Level (FCLvl)								
Two-year institution				0.960				0.923
				(0.054)				(0.069)
Less-than-two-year institution				0.752				1.061
				(0.160)				(0.201)
First College Control (FCCrt)								
Private for-profit				1.511***				1.633***
				(0.143)				(0.154)
Private not-for-profit				1.088*				1.155**
				(0.037)				(0.055)
inoutstate								
In-State				0.989				0.948
				(0.035)				(0.045)
First Institution Selectivity (FCSel)								
Inclusive 4-year				1.300***				1.600***
				(0.060)				(0.104)
Moderately selective 4-year				1.144***				1.302***
				(0.037)				(0.069)
Unclassified 4-year				1.308***				1.833***
				(0.074)				(0.130)
First-Year College GPA (FYGPA)				0.760***				0.671***
				(0.014)				(0.016)
Stopout								
Yes				0.942*				1.470***
				(0.030)				(0.026)
Loan								
Yes				0.884***				0.826***
				(0.025)				(0.032)
Demographic	No	Yes	Yes	Yes	No	Yes	Yes	Yes
High school GPA	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Ugapmonths and *UFYGPA* were included in models (4) and (8). *Missing* categories from the *FCLvl*, *FCCrl*, and *inoutstate* variables were all included in regression models (4) and (8) but have been excluded from this table. The *Unclassified two-year*, *Unclassified less than two-year*, and *Unknown* categories from the *FCSel* variable were included in models (4) and (8) but have been excluded from this table. Demographic variables include Student *Sex, Race, SSE, Mothergrad, Fathergrad*, and *Region*. N=7640 for all models. Coefficients from all variables can be found in Appendix Table D.

Standard errors in parentheses
*p<0.05, **p<.01, ***p<.001

year or *Less-than-two-year* school in both the four- and six-year models, compared to students that started college at a four-year school.

As for the type of school institution students attend, students who attended a *Private for-profit* institution have higher hazard rates in both four- and six-year models by 51.1% and 63.3% respectively, compared to their *Public* student counterparts. This same effect can also be shown for students that decided to attend a *Private not-for-profit* institution, where the hazard increases by 8.8% in the four-year model and 15.5% in the six-year model. From the *in-state* variable, we can see there was no difference in the hazard rates between students whose first institution was in-state and out-of-state.

There seem to be wide differences in the rates at which students graduate from college, depending upon the institutional selectivity. Compared to students who attended a *Highly Selective* institution, students who attend an *inclusive four-year, moderately selective four-year*, and *unclassified four-year* institutions had increases in hazards in the four-year model by 30%, 14.4%, and 30.8%, respectively. These increases in the hazard do persist in the six-year model, where the hazard rates increase for *inclusive four-year, moderately selective four-year,* and *unclassified four-year* by 60%, 30.2%, and 83.3%, respectively. Student's first-year college GPA does significantly affect the rates at which students do not complete their four-year degree. From the *FYGPA* coefficient, we can see that an increase in one-unit in GPA decreases the hazard by 24% in the four-year model and 45.5% in the six-year model. *Stopout* is a very interesting varaible. In model four, we can see that the rate at which students fail to graduate is lower when students stopout of school. However, in the six-year model, the hazard increases by 47% and statistically significant at all levels. As for the effect in the hazard from obtaining student loans, students who were able to obtain a loan can expect a significant decrease in not graduating on time in both the four- and six-year model, compared to students who were not able to obtain a loan.

As for our variable of interest, *TestscoreST*, the model does suggest that there is a decrease in the rate at which students fail to complete their degree on time for a one standard deviation increase in test score, where the reduction in the hazard is 1.9% in the four-year model and 3.7% in the six-year model. Although there is a reduction in the hazard for a one-unit increase in standardized test scores, both four- and six-year models suggest that the hazard ratio is not statistically different from one at any alpha level. Since there no statistical evidence to suggest that obtaining higher standardized test scores can increase or decrease the rate students graduate from college on time, we have more evidence to support that standardized tests may not be an effective determinant of college success. All coefficients produced by the preliminary hazard cox models can be found in appendix table D.

Time-dependent adjustments

Although table 4 provides interesting preliminary results for the increase/decrease rate at which students fail to obtain a college degree based on different student characteristics, these results are misleading and do not accurately represent the true effect of test scores on college success. This is due to the issue that arises with some of the covariates the model was implemented with, where they violate the important proportional hazards assumption. Since this assumption is key to obtain reasonable, accurate, and reliable results, we will need to adjust the functional form of coefficients that fail the assumption. As stated, there are different ways to identify and adjust for non-proportional hazards. For this study, we will use the Schoenfeld Residual to identify which coefficients are not proportional across time. From Appendix Table E, we can see that *Asian and Hawaii/Pac.*, *Low* income, *Dadcoll*, *Midwest*, *Catholic*, *HSGrade D*, *Two-year, Gapmonths,UGapmonths, All FCCrt variables, Private for-profit,* all *FCSel* variables except for *Unclass two-year,CollGPA, FYGPA, Stopout Yes,*and *Loan* from model 4 all violate the proportional assumption. As for model 6, *Asian and Hawaii/Pac., Low, Upper, Momcoll, Dadcoll, Caholic, HSGrade D, Gapmonths, UGapmonths, Private not-for-profit, Inclusive, Moderately selective, Unclassified four-year, Unclass less than two-years, FYGPA, Unknown FYGPA*, missing *FYGPA, Stopout Yes*, and *Loan* all violated the assumption[15].

After all the variables that violate the assumption are uncovered, it is appropriate to interact these variables with time to control for the non-proportionality that exists within them. As expressed before, interacting with time can be another reliable method to uncover non-proportional hazards. If the time-interacted variable is statistically significant, then there is evidence of that covariate being dependent on time, thus violating the assumption (Bellera, et al., 2010; Cox, 1972). From the list of variables we have created above, not only did I interacted with these with time, but I also assessed for non-proportional hazards again and checking if these time-interacted covariates were statistically significant. If the regression outputs stated a time-interacted covariate was statistically insignificant, I reduced their functional form to not include them as time-interacted. After testing for non-proportional hazards for a second time, by checking the significance of the time-interacted coefficient, *Amer. Indian/Alaska Native, Low, Dadcoll, Catholic, Gapmonths, Private for-profit, Inclusive 4-year, FYGPA, Unknown FYGPA, Stopout,* and *Loan* all violated the assumption from model four and will keep their time-

[15] The Schoenfeld Residuals assesses the residuals of each covariate that is represented in the model, so see if there are any patterns within these residuals. If there is evidence of a given covariate having a functional form that is related to time, then the Schoenfeld Residuals will give a statistically significant value to them. By achieving statistical significant, it is said that the given covariate is dependent on time, thus failing the proportional hazards assumption. Ideally, we would like our covariates to fail to reject the null, to mathematically show that they are not dependent on time. More information about Schoenfeld Residuals can be found from the following (Bellera, et al., 2010; Cox, 1972; Xue, et al., 2013).

interacted variables. As for the six-year model, *Amer. Indian/Alaska Native, Low, Upper, Momcoll Dadcoll, Private not-for-profit, Inclusive 4-year, Moderatly Selective four-year, Unclassified 4-year, FYGPA, Unknown FYGPA, Stopout,* and *Loan* violate the hazard assumption and will keep their time-interacted functional form.

After double-checking for time-dependent covariates, I tested the *TestScoreST* variable for non-proportional hazards, by utilizing the time-interaction method. From this step in the analysis, I uncovered that *TestScoreST* does fail the assumption in the four-year model, while the variable passes the assumption in the six-year model. Due to *TestScoreST* failing the proportional hazards assumption in the four-year model, we will need to include a time-interacted variable to control for this issue.

Table 5 below contains the hazard ratios produced from the Cox Hazard Proportional model, while adjusting for time-dependent covariates. From models (4) and (8), *Catholic*, which is time-dependent, has a hazard ratio of .84 at time zero and the hazard increases by 4.2% for every additional year students are in college in the four-year model, but the hazard ratio at time zero is insignificant. In the six-year model, there is a 15.7% reduction in the hazard, compared to students who attended a *Public* high school. *Other Private,* which is not time-dependent, has a coefficient of 1.087 in the four-year model and .930 in the six-year model. These results indicate students who attended *Other Private* high schools had an increase in the hazard of not graduating by four-year by 8.7%, compared to those students that attended a *Public* high school. Since the *Other Private* coefficient is statistically insignificant in the six-year model, this indicates that there is no effect on the hazard when compared to students from *Public* high schools. To add on, the number of months students delay their school does affect the rate at which students graduate.

Table 5: Hazard Cox with Time-dependent Adjustments

	Dependent Variable (Graduated), Time factor(Number of Enrollment Years)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Regression								
Standardized Test Score	0.559***	0.632***	0.810***	0.886**	0.513***	0.597***	0.806***	0.966
	(0.019)	(0.024)	(0.034)	(0.035)	(0.018)	(0.024)	(0.036)	(0.019)
High School Control (HCCrt)								
Catholic			0.718***	0.840			0.561***	0.843***
			(0.069)	(0.078)			(0.065)	(0.038)
Other private			0.875	1.087*			0.696**	0.930
			(0.099)	(0.042)			(0.096)	(0.054)
Months between HS and College (Gapmonths)				1.032***				1.026***
				(0.004)				(0.002)
First College Level (FCLvl)								
Two-year institution				0.992				0.983
				(0.052)				(0.070)
Less-than-two-year institution				0.888				1.085
				(0.155)				(0.218)
First College Control (FCCrt)								
Private for-profit				2.638***				1.546***
				(0.369)				(0.127)
Private not-for-profit				1.107**				1.158**
				(0.037)				(0.053)
inoutstate								
In-State				0.977				0.940
				(0.034)				(0.043)
First Institution Selectivity (FCSel)								
Inclusive 4-year				1.814***				2.645***
				(0.176)				(0.303)
Moderately selective 4-year				1.117***				1.638***
				(0.037)				(0.160)
Unclassified 4-year				1.249***				3.022***
				(0.066)				(0.364)
First-Year College GPA (FYGPA)				0.360***				0.375***
				(0.015)				(0.016)
Stopout								
Yes				0.739***				0.631***
				(0.055)				(0.056)
Ever Received a Loan								
Yes				0.650***				0.564***
				(0.049)				(0.047)

Time Varying Covariates								
Standardized Test Score	1.111***	1.087***	1.038***	1.024**	1.099***	1.077***	1.034***	
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	
High School Control								
Catholic			1.082***	1.042*			1.093***	
			(0.021)	(0.019)			(0.025)	
Other private			1.050*				1.070*	
			(0.024)				(0.030)	
Months between HS and College				0.998*				
				(0.001)				
First College Control								
Private for-profit				0.840***				
				(0.025)				
First College Selectivity								
Inclusive 4-year				0.915***				0.876***
				(0.017)				(0.021)
Moderately selective 4-year								0.943**
								(0.018)
Unclassified 4-year								0.867***
								(0.020)
First-Year College GPA				1.191***				1.155***
				(0.010)				(0.010)
Stopout								
Yes				1.047***				1.253***
				(0.013)				(0.015)
Ever Received a Loan								
Yes				1.070***				1.097***
				(0.016)				(0.019)

Notes: Ugapmonths and UFYGPA were included in models (4) and (8). Missing categories from the FCLvl, FCCrl, and inoutstate variables were all included in regression models (4) and (8) but have been excluded from this table. The Unclassified two-year, Unclassified less than two-year, and Unknown categories from the FCSel variable were included in models (4) and (8) but have been excluded from this table. Demographic variables include Student Sex, Race, SSE, Mothergrad, Fathergrad, and Region. N=7640 for all models. Coefficients from all variables can be found in Appendix Table F.

Robust Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

From the *Gapmonths* coefficient, which is time-dependent, it indicates that the baseline hazard is 1.032 at year zero and decreases by .2% each enrollment year.

As for the type of school students attend, the model suggests that students who started college at a *Two-year* or *Less-than-two-year* do experience decreases in the hazard. However, the model suggests that these effects are insignificant, so there is no statistical effect on the hazard for these covariates. The *Control* of student's first institution they attended seems to influence the rate at which students graduate. For students whose first institution was a *Private For-profit* school, compared to students who attended a *Public* institution, we see the hazard ratio has a value of 2.638 at time zero and decreases by 16% every year in the four-year model. However, in the six-year model, *For-profit* school students experience an increase of 54.6% in the hazard, compared to *Public* school students. Surprisingly, *Private not-for-profit* students experience a higher rate of not graduating on time, compared to their *Public* school counterparts. From the *Private not-for-profit* hazard coefficient, students who attended a not-for-profit school over a *Public* school experience increases in the hazard by 10.7% and 15.8% in the four- and six-year models, respectively. From the *Instate* variable, the model suggests that there is no effect on the hazard between students who attended an in-state versus out-of-state school in both four- and six-year models.

The selectivity of student's first colleges seems to affect the rates at which students graduate on time. From the four-year model, the *Inclusive four-year* variable is time-dependent, where the hazard ratio at time zero is 1.814% and this ratio decreases by 8.5% every year. In the six-year model, this hazard ratio at time zero was 2.645 and decreases by 12.4% for every additional year. The *Moderately Selective four-year* variable was time-dependent in the six-year model, but it was not time-dependent in the four-year model. In the six-year model, this variable had a hazard ratio of 1.638 at time zero and decreases by 5.7% for a one-unit increase in time. In the four-year model, students who attended a moderately selective school, on average, had an increase in the rate students did not make it to graduation on time by 17.7%, compared to those that attended a highly selective school. The hazard ratio for *Unclassified four-year* students was 29.4% in the four-year model. In the six-year model, this variable's hazard ratio was 3.022 at time zero and decreases by 13.3% for every additional year.

FYGPA is time-dependent in both four-year and six-year models. From the coefficient values provided from the model, a one-unit increase in *FYGPA* reduces the rate students do not graduate on time by 64% at time zero, but this hazard increases by 19.1% for an additional unit of time in the four-year model. A similar result can be shown in the six-year model, where a one-unit increase in *FYGPA* reduces the hazard by 62.5% at time zero and increases by 15.5% each year. The *Stopout* variable in both models indicates that stopping out of school does decreases the rate at which students fail to graduate at time zero. Interestingly, the hazard ratios for both models do increase over time. In the four-year model, the stopout at time zero was .739 and increases by 4.7% every year. Additionally, the hazard ratio at time zero for stopping out of school was .659 and increases by 25.3% for each additional enrollment year. The *Loan* variable is also time-dependent for both four- and six-year models. From the *Loan* coefficient in the four-year model, students who were able to obtain a loan experience a 35% reduction in the hazard at time zero and increases by 7% every year. In the six-year model, obtaining a loan reduces the hazard by 43.6% at time zero and increases by 9.7% every year.

As for our variable of interest, *TestScoreST* was time-dependent in the four-year model, but it was not time-dependent in the six-year model. From the four-year model, an increase in one standard deviation in test score significantly reduces the hazard at time zero by 11.4%, and this hazard increases by 2.4% for each additional unit of time. Since our *TestScoreST* variable did pass the proportional assumption, we can interpret the hazard ratio for this coefficient normally. The hazard ratio of 0.966 indicates that a one standard deviation increase in student test scores reduces the hazard by 3.4%. However, this coefficient is not statistically significant, so there is no significant effect in the hazard from a one-unit increase in *TestScoreST*. From these results, we do not have enough evidence to say that standardized test score does not have affect four-year college completion. However, from the six-year model, there is some evidence to suggest that standardized testing may not have a significant effect in determining college success. All regression coefficients produced from table 5 can be found in Appendix Table E.

Discussion

Although some of my results do not, the majority of the results presented in this study do support the previous literature. When considering high school grades, there are large penalties in graduation probabilities and the rates at which students fail to graduate on time for students that do not earn an A in high school, which can be supported by (Cohn, Cohn, Balch, & Bradley, 2004; Geiser & Santelices, 2007). Along with high school GPA, the type of high school students attend can affect the likelihood or the rates at which students achieve college success. From the six-year model, we can see that the probability and rates of college success are not statistically different between public school and private school students. However, religious high school students seem to achieve higher rates and probabilities of achieving college success, which can be supported by Horowitz & Spector, 2005. Although there is some evidence of insignificance from the probit model, the OLS and hazard does support the literature that lagging your enrollment start data can decrease the probability and increase the rates at which students fail to graduate school in the six-year model (Ahlburg, McCall, & Na, 2002). The results from this paper also support the college GPA is very important in determining college success, where an increase in GPA increases the probability of graduating on time and decreases the hazard (Geiser & Santelices, 2007). Another observation involves financial aid. Although OLS disagrees that obtaining a loan can increase the probability of graduating on time, the probit and hazard model produced supports the literature that loans can positively influence college success (Chen & Hossler, 2017; Woo & Lew, 2020). One interesting disagreement across all models has to do with where students start their college careers at. Although there are mixed results from OLS and probit models, the Cox model suggests there is no effect on the hazard when students start at a two-year school, compared to a four-year school. This contradicts the literature that supports two-year students have, on average, lower probabilities of college success found from Sandy, Gonzalez, & Hilmer (2006).

One interesting finding that all models produced by this paper supports is that attending a highly selective institution can increase a student's ability of achieving college success. Since the models in this study support a positive association between institutional selectivity and college success, these results should influence more students to apply to higher selective colleges. Although this action may help students increase their likelihood of college success, many students seem to be discouraged by this idea. Especially among the lower-income population, students from this socioeconomic background tend to have lower test scores and are more underrepresented in the highly selective school applicant pool (Sackett, et al., 2012). This anomaly, known as "College Unmatching", tends to give more opportunities and benefits to higher-income students, while continues to leave marginalized students behind. One potential solution to help match students to the right colleges is to take offer an income-neutral approach in the application process, where family income holds less weight in the admissions process for higher selectivity institutions. This approach has the potential to increase educational outcomes for low- and middle-income students through increased wages after graduation (Chetty, Friedman, Saez, Turner, & Yagan, 2020). Applying an income-neutral admissions approach, with the intent of increasing low-income student admission into highly selective colleges, has been shown to increase educational outcomes for lower-income students. QuestBridge, a program that recruits highly talented low-income students to highly selective institutions, has been shown to increase educational outcomes for underrepresented students. This program has been very successful at recruiting low-income, high-achieving, students to where over 89% passed their Hardvard level course[16], while 63% of these students earned an A or B (Green, 2021).

Although all models, except the hazard six-year model, supports a statistical relationship between test scores and college success, there is some evidence of economic insignificance. The OLS and probit model suggest that a one standard deviation increase in test score increases the probability of a student graduating on time does increase by 2.1% and 2.7% in the four-year model, respectively. In addition, this relationship persists by around 1.5% to 1.6% in the six-year models. Even though the model does suggest statistical significance, a one standard deviation increase in test score from the ELS Assessment Battery is about an 8.5 point increase. When translating this result with the other college entrance exams, a one standard deviation increase in SAT scores is around a 200 point increase (National Center for Education Statistics, 2017). To add on, although retaking the SAT has been shown to increase scores, this increase is only about a .3 standard deviation increase (Goodman, Gurantz, & Smith, 2020).[17] With the high monetary cost of retaking the SAT that is present for some students, the college success benefits of gaining a one standard deviation increase in test score may not be worth it.

The Cox Proportional Hazard Model suggests a slightly different story for the true validity of standardized testing on college success. In the four-year model, the hazard is lowered when students can earn a one standard deviation increase in test scores, where this hazard

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[16] Over 300 11th and 12th grade students across high-poverty level high schools in 11 U.S. cities enrolled and attended the Hardvard course, “Poetry in America: The City From Whitman to Hip-Hop”. Students attending this class had the same expectations and course standards as those students who were fully admitted into Hardvard University.
[17] This figure was calculated using the SAT scores when the maximum score was 2400 (Goodman, Gurantz, & Smith, 2020).

increases over time. However, the six-year model found that there was no significant reduction in the rates at which students fail to graduate. Along with the evidence of economic insignificant present from OLS and probit, there is more evidence from the model to suggest that standardized test may not be the most influential determinant in uncovering six-year college success.

Policy Implementation

There will be two perspectives taken into consideration in terms of policy implementation. The first being from the student perspective, evidence from this study shows that standardized testing should not be the only factor that should be taken into consideration. As we have seen in this study, other determinants can significantly affect a student's ability to achieve college success. To begin, the grades that students earn in high school and their first year of college can significantly affect the probability and the rates at which students complete their college careers. In addition, discontinuing your postsecondary education and choosing the wrong type of institution can negatively affect a student's ability to complete their education on time. As shown from the model, attending a private for-profit school can diminish achieving college success. However, attending a two-year school has been shown to not affect the rates at which students fail to complete their degree. More education on this information for students will help students make the right decisions on how they want to allocate their time and resources, to maximize their likelihood of achieving college success.

From an institutional perspective, standardized testing should not hold a majority of the weight in the admissions process, since a vast number of determinants can influence college success- as shown in this study. More importantly, institutions, especially highly selective institutions, should consider allowing lower-scoring, high achieving, students to enroll at their university through test-optional admissions. Since lower-scoring students tend to be from underrepresented backgrounds and apply to higher selective institutions less frequently (Dixon-Román, Everson, & McArdle, 2013; Sackett, et al., 2012; Batedo & Bowman, 2017), allowing admissions for these students help increase student outcomes- as shown from the QuestBridge and Harvard program (Green, 2021) and this study. Institutions do not have to incur high costs when allowing underrepresented students to attend their university, where perceived selectivity and GPA outcomes are not significantly affected (Saboe & Terrizzi, 2019; Belasco, Rosinger, & Hearn, 2015).

Limitations

There are many limitations to this study that could have significantly affected the results produced by this paper. To begin, our data restrictions could have affected the results of this study. Although it would be interesting to include all students from the ELS survey in this study, as mentioned, we only kept students who started their postsecondary careers by 2006. Originally, this restriction was supposed to control for the inability to capture four- and six-year graduation rates from students starting school closer to the end of the survey, 2012. However, this comes at a trade-off of decreasing our sample size. Due to this loss of sample size from this restriction, results produced by this study could have biased our regression results. One other restriction involved our *Yearsenroll* variable, which is the year in student's academic careers they experience an outcome. Since the Proportional Hazard Model requires a time-to-event variable to appropriately calculate hazard rates, evey student must have this information. Unfortunately, not all students in our sample had this information, and these students were dropped from the sample. Because of this exclusion, our sample size did decrease, and results could have been different if every student had information on when they experienced graduating or dropped out of school.

Another limitation involves the sample of students this analysis used. Since the focus of this study was to estimate college success using students that shown intent of pursuing a four-year degree, we only used students who did go to at least one four-year school. Because of this restriction, we may be underrepresenting students who would have liked to advance their academic careers to the four-year level. As an example, students who went to a two-year school and did not go to a four-year school were left out of this analysis. Due to this restriction, there could be evidence of an upward bias in our model. In addition to sample selection, there are also limitations to variable selection and functional form. There were some variables in the survey that would be ideal to use if they had a continuous functional form. As an example, it would have been ideal to have our high school letter grade and family income variables as continuous variables, instead of discrete. Since the ELS suppresses the continuous forms of these variables and only provides high school GPA and family income in categories, we could not use the continuous forms of these variables. Interpretation for these two variables could have been more intuitive if their functional form was continuous. Instead of comparing the increased probability of hazard between *A* high school students, a continuous functional form could have allowed us to capture differences in graduation probabilities or hazards for a one-unit increase in high school GPA. Alternatively, we could have captured the marginal effect of college success probabilities or hazards for a one-unit increase in family income, given that our family income variable was continuous. Because of the restrictions in the ELS survey, categorical functional forms must be utilized.

Although the four- and six-year model does a solid job at explaining the variation in college success based upon the independent variables we added into the model (from our Adjusted and pseudo-R-squares), it is still possible that the model is suffering from omitted variable bias. One source of omitted variable bias could be high school rank. Since student's high school rank was a variable that has been shown in the literature to influence college success (Cohn, Cohn, Balch, & Bradley, 2004), this variable should have been included in the model to adjust for differences in GPA bias in schools, while also capturing the effect of performing academically higher compared to the student's classmates. Unfortunately, the ELS does suppress this information and restricts us from using this data. Due to this restriction, there may exist positive bias in our *TestscoreST* coefficients produces in all the models presented in this paper. This upward bias stems from the positive association between test scores and college success from this study and the association being shown from Cohn et. al study with high school rank.

The literature did show that earning a grant/scholarship can help increase college success (Castleman & Long, 2006; Dynarski, 2003), so there should have been a variable in our regression to capture this effect. Unfortunately, the ELS survey did not have a sufficient variable that indicated if students ever received a loan while in school. Due to the exclusion of this variable in the models, there could have also been an upward bias on the *TestscoreST* variable, since there is a positive association in scholarships/grants on college success.

The last example of an omitted variable stems from the major that students choose to pursue. The unrestricted version of the survey did have this information but to only student that completed their degree. Since the survey did not include majors for students who did not complete their degree, we could not add this information to the models. What would be interesting to include, given that majors for all students were available, would be to include an indicator for students that majored within the STEM (Science, Technology, Engineering, and Mathematics) fields. Since there is evidence from the literature to suggest that students who started as STEM majors are less likely to graduate by six years (Whalen & Shelley, 2010), there could be some negative bias non accounted for within our *TestscoreST* variable.

The last limitation that will be discussed is regarding how non-proportional hazards were treated. As seen, there are three different ways to adjust for proportional hazards. In this study, time interaction terms between time-dependent covariates and time helped control for non-proportionality. Although this technique, is very useful, it is possible that time-dependent variables could have a more appropriate functional form than time. From the *Assumptions of Cox Models* section of this paper, we learned that time can take a functional form of $(f(t) = t, t^2, \ln(t), \dots)$. It is possible to include non-proportional hazard covariates with any combination of the function of time ($t, t^2, \ln(t)$, and so on), but this study did not go beyond this scope. Due to this, the hazard cox model this study implemented could have failed to appropriately account for and apply the correct functional forms to the data, thus leading to more imprecise hazard coefficients. As an example, there could be a quadratic relationship between the number of months students delay starting college and the rate at which they fail to graduate school. If such a relationship existed, this would need to be accounted for in the hazard models. More advanced functional forms were not implemented into the model, due to its complexity with interpretation. Due to this limitation, the correct time-dependent adjustments on time-interacted covariates could not appropriately fit the data optimally.

Conclusion

The rise in college campuses providing test-optional admissions could have originated institutions wanting to increase college accessibility and opportunity for prospective students. More specifically, some institutions could have chosen to offer test-optional admission simply because they have less faith in having standardized testing be a reliable predictor of college success. The purpose of this study was to estimate the true validity of standardized testing at predicting college success. From OLS and probit models, standardized tests seem to have a significant impact on a student's ability to complete college by four and six years. Although statistically significant, there is some evidence of economic insignificant, due to OLS and probit indicating a one standard deviation in test scores increases the probability of graduating on time by around 1.5% to 2.7% in both four- and six-year models. Survival analysis provides us with mixed conclusions. In the four-year, the Proportional Hazard Cox model suggests standardized tests affect the rate at which students fail to graduate on time- i.e the *hazard*. However, the Cox model indicates there is no effect on the hazard for a one standard deviation increase in student test scores.

Although results are mixed, evidence from the results does support that standardized testing is not the only significant factor that can determine college success. Obtaining loans to support student's education, having a strong academic start in college, and attending higher selective schools can positively influence the probability of graduating from college on time and decrease the rate at which students fail to graduate on time. Interestingly, survival analysis suggests that the hazard rates between students who did and did not start their postsecondary careers at the four-year level are statistically the same, contradicting OLS, probit, and findings from previous studies (Sandy, Gonzalez, & Hilmer, 2006). In terms of policy implementation, students should not solely focus on maximizing their standardized test scores to maximize their probability of achieving college success. A one standard deviation in standardized test score from the ELS assessment battery is about an 8.5 point increase. When translating these results using SAT scores, a one standard deviation increase in SAT scores is almost a 200 point increase

(National Center for Education Statistics, 2017)[18], which may be unobtainable for some students (Goodman, Gurantz, & Smith, 2020). From an institutional perspective, universities- especially higher selective universities- should allow more lower-scoring, high-achieving, underrepresented students through test-optional admission. With the high benefit that underrepresented students can receive, as shown from the QuestBridge Program (Chetty, Friedman, Saez, Turner, & Yagan, 2020; Green, 2021), academic opportunity and achievement can be obtained under test-optional admission.

[18] This standard deviation was calculated using SAT scores with students from the graduating class of 2017. Additional information on distribution can be found here: https://nces.ed.gov/programs/digest/d17/tables/dt17_226.40.asp

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Appendix

Summary Statistics

Appendix Table A: *Variable Summary Statistics*

Variable		Description	Mean	Std. Dev.	Min	Max
$Grad_4$		*=1 if graduated from college by four years*	0.298	0.458	0	1
$Grad_6$		*=1 if graduated from college by six years*	0.558	0.497	0	1
Testscore		*ELS Assessment Battery test score*	55.394	8.506	20.910	81.040
TestscoreST		*Testscore standardized*	0.000	1.000	-4.054	3.015
Enrollyears		*Total enrollment years enrolled in college*	4.31	1.509	1	8
Sex						
	Male	*=1 if Male*	0.444	0.497	0	1
	Female	*=1 if Female*	0.556	0.497	0	1
Race						
	Amer. Indian	*=1 if American Indian/Alaskan Native*	0.005	0.069	0	1
	Asian/Hawaii/Pac. Islander	*=1 if Asian/Hawaii/Pac. Islander*	0.120	0.324	0	1
	Afr. Amer/ Black	*=1 if African American or Black*	0.110	0.313	0	1
	Hispanic	*=1 if Hispanic*	0.096	0.294	0	1
	More than one Race	*=1 if classified having more than one race*	0.044	0.205	0	1
	White	*=1 if White*	0.623	0.484	0	1
SSE						
	Low	*=1 if family income ≤ $35,00 a year*	0.221	0.415	0	1
	Lower-Middle	*=1 if 35,000<family income ≤ $50,000*	0.163	0.369	0	1
	Middle	*=1 if 50,000<family income ≤ $75,000*	0.220	0.414	0	1
	Upper-Middle	*=1 if 75,000<family income ≤ $100,000*	0.172	0.378	0	1
	Upper	*=1 if family income ≥ $100,000 a year*	0.224	0.417	0	1
MotherGrad		*=1 if mother earned a bachelor's degree*	0.395	0.489	0	1
FatherGrad		*=1 if father earned a bachelor's degree*	0.457	0.498	0	1
Region						
	Northeast	*=1 if student HS resides in U.S. northeast*	0.197	0.398	0	1
	Midwest	*=1 if student HS resides in U.S. midwest*	0.260	0.439	0	1
	South	*=1 if student HS resides in southern U.S.*	0.360	0.480	0	1
	West	*=1 if student HS resides in western U.S.*	0.184	0.387	0	1
HSCrt						
	Public	*=1 if student attended a public HS*	0.688	0.463	0	1
	Catholic	*=1 if student attended a catholic HS*	0.187	0.390	0	1
	Other Private	*=1 if student attended another private HS*	0.125	0.331	0	1
HSGrade						
	A	*=1 if HS GPA >3.50*	0.286	0.452	0	1
	B	*=1 if 3.00<HS GPA≤ 3.50*	0.286	0.452	0	1
	C	*=1 if 2.00<HS GPA≤ 3.00*	0.311	0.463	0	1
	D	*=1 if 1.00<HS GPA≤ 2.00*	0.044	0.205	0	1
	F	*=1 if HS GPA<1.00*	0.002	0.040	0	1
	Missing	*=1 if HS GPA was missing*	0.071	0.257	0	1

Appendix Table A: Variable Summary Statistics Cont.					
Variable	Description	Mean	Std. Dev.	Min	Max
Gapmonths	*Months between HS exit and college entrance*	3.261	5.265	-1	96
Ugapmonths	*=1 if Gapmonths is Unknown*	0.007	0.081	0	1
FCLvl					
Four-year	*=1 if First College was four-year*	0.813	0.390	0	1
Two-year	*=1 if First College was two-year*	0.180	0.385	0	1
Less than two-year	*=1 if first college was less than two-year*	0.006	0.076	0	1
Missing	*=1 if First College Level is Missing*	0.001	0.026	0	1
FCCrt					
Private for-profit	*=1 if First College was Private for-profit*	0.029	0.169	0	1
Private not-for-profit	*=1 if First College was Private not-for-profit*	0.262	0.440	0	1
Public	*=1 if First College was Public*	0.707	0.455	0	1
Missing	*=1 if First College Control is Missing*	0.001	0.038	0	1
FCSel					
Highly Selective four-year	*=1 if First College was ranked in the top one-fifth of all baccalaureate postsecondary institutions*	0.279	0.449	0	1
Moderately Selective four-year	*=1 if First College was ranked in the middle two-fifths of all baccalaureate postsecondary institutions*	0.315	0.465	0	1
Inclusive four-year	*=1 if First College do not require or report college entrance exam scores*	0.110	0.313	0	1
Unclassified four-year	*=1 if First College rank was unclassified, given being a four-year institution*	0.078	0.268	0	1
Unclassified two-year	*=1 if First College rank was unclassified, given being a two-year institution*	0.210	0.407	0	1
Unclassified less than two-year	*=1 if First College rank was unclassified, given being a less than two-year institution*	0.002	0.048	0	1
Missing	*=1 if First College Selectivity was Missing*	0.005	0.071	0	1
Inoutstate					
In-State	*=1 If First College attended was In-State*	0.768	0.422	0	1
Out-of-State	*=1 If First College attended was Out-of-State*	0.226	0.418	0	1
Missing	*=1 if First College in- or- out-of-state indictor was missing*	0.006	0.077	0	1
FYGPA	*First-year college GPA*	2.550	1.276	-1	4
UFYGPA	*Unknown first-year college GPA*	0.070	0.255	0	1
Stopout					
Yes	*=1 if ever discontinued enrollment 4+ months*	.539	.498	0	1
No	*=1 if never discontinued enrollment 4+ months*	.287	.452	0	1
Missing	*=if stopout data was unavailable*	.174	.325	0	1
Loan					
No	*=1 if student has never received a loan*	0.325	0.469	0	1
Yes	*=1 if student has ever received a loan*	0.675	0.469	0	1

Note: Missing data from the *FYGPA* and *Gapmonths* variables were coded as -1. To control for this missing data for these two variables, I included binary, dummy, variables. Although it is possible to drop these missing observations through deletion (Curley, Krause, Feiock, & Hawkins, 2019), I decided to flag these observations to increase sample size.

Regressions and Regression Supplements

OLS

Preliminary OLS regression Results for Impact of Standardized Test Scores on College Success

	Dependent Variable (Graduated)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized Test Score	0.134***	0.112***	0.061***	0.027***	0.152***	0.117***	0.049***	0.016**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Female		0.090***	0.051***	0.046***		0.064***	0.014	0.006
		(0.010)	(0.010)	(0.009)		(0.011)	(0.010)	(0.010)
Race								
Amer. Indian/Alaska Native		-0.044	-0.015	-0.016		-0.136	-0.081	-0.058
		(0.056)	(0.051)	(0.049)		(0.073)	(0.070)	(0.067)
Asian and Hawaii/Pac. Islander		0.052**	0.041*	0.030		0.030	0.031	0.020
		(0.017)	(0.017)	(0.016)		(0.018)	(0.018)	(0.017)
Black or African American		-0.014	0.027	0.024		-0.071***	-0.004	0.005
		(0.015)	(0.015)	(0.015)		(0.019)	(0.018)	(0.017)
Hispanic		0.001	0.019	0.028		-0.039*	-0.014	0.009
		(0.017)	(0.016)	(0.015)		(0.020)	(0.018)	(0.017)
More than one race		-0.034	-0.010	-0.002		-0.058*	-0.025	-0.007
		(0.024)	(0.023)	(0.021)		(0.027)	(0.025)	(0.022)
Socioeconomic Status								
Low		-0.009	-0.013	-0.007		-0.030	-0.029	-0.017
		(0.015)	(0.014)	(0.013)		(0.017)	(0.016)	(0.015)
Lower-Middle		0.013	0.006	0.016		0.005	-0.000	0.011
		(0.016)	(0.015)	(0.015)		(0.018)	(0.017)	(0.015)
Upper		0.063***	0.074***	0.037*		0.071***	0.072***	0.046**
		(0.016)	(0.016)	(0.015)		(0.017)	(0.016)	(0.015)
Upper-Middle		0.006	0.017	0.005		0.045*	0.049**	0.036*
		(0.016)	(0.016)	(0.015)		(0.017)	(0.017)	(0.015)
Mother Graduated College		0.066***	0.061***	0.040***		0.051***	0.043***	0.027*

	(0.012)	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)
Father Graduated College	0.053***	0.043***	0.021*	0.079***	0.061***	0.044***
	(0.012)	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)
High School Region						
Midwest	-0.073***	-0.105***	-0.059***	-0.051**	-0.092***	-0.044**
	(0.016)	(0.015)	(0.014)	(0.016)	(0.015)	(0.014)
South	-0.113***	-0.138***	-0.079***	-0.070***	-0.096***	-0.035**
	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)	(0.014)
West	-0.112***	-0.158***	-0.091***	-0.083***	-0.141***	-0.072***
	(0.017)	(0.017)	(0.016)	(0.018)	(0.017)	(0.016)
High School Control						
Catholic		-0.008	-0.050***		0.084***	0.042***
		(0.013)	(0.013)		(0.014)	(0.013)
Other private		0.024	-0.034*		0.071***	0.034*
		(0.016)	(0.015)		(0.016)	(0.015)
High School Letter Grade						
B		-0.170***	-0.088***		-0.149***	-0.055***
		(0.015)	(0.014)		(0.014)	(0.013)
C		-0.290***	-0.115***		-0.353***	-0.142***
		(0.014)	(0.015)		(0.015)	(0.016)
D		-0.336***	-0.091***		-0.516***	-0.197***
		(0.019)	(0.021)		(0.024)	(0.024)
F		-0.351***	-0.067		-0.601***	-0.195**
		(0.023)	(0.054)		(0.024)	(0.075)
missing		-0.194***	-0.077***		-0.219***	-0.072***
		(0.022)	(0.021)		(0.023)	(0.021)
Months between HS and College			-0.001			-0.003***
			(0.001)			(0.001)
Uknown gap months			-0.031			0.032
			(0.050)			(0.051)
First College Level						
Two-year institution			-0.041			-0.012
			(0.021)			(0.024)

Less-than-two-year institution	-0.037	-0.219***
	(0.042)	(0.058)
Missing	0.209	-0.222
	(0.208)	(0.233)
First College Control		
Missing	0.092	0.103
	(0.126)	(0.175)
Private for-profit	0.001	-0.103***
	(0.024)	(0.026)
Private not-for-profit	0.091***	0.012
	(0.013)	(0.012)
First College in- or out-of-state		
In-State	-0.039**	-0.002
	(0.013)	(0.012)
Uknown	-0.133**	-0.002
	(0.046)	(0.068)
First Institution Selectivity		
Inclusive 4-year	-0.167***	-0.137***
	(0.017)	(0.018)
Moderately selective 4-year	-0.107***	-0.058***
	(0.014)	(0.013)
Uknown	-0.278***	-0.127
	(0.048)	(0.072)
Unclassified 2-year	-0.152***	-0.147***
	(0.024)	(0.024)
Unclassified 4-year	-0.168***	-0.210***
	(0.019)	(0.021)
Unclassified less than 2-year	-0.182***	-0.109
	(0.053)	(0.070)
First-Year College GPA	0.100***	0.127***
	(0.005)	(0.006)
Uknown First-Year College GPA	0.315***	0.382***
	(0.024)	(0.030)

Stopout								
Missing				-0.087***				-.112***
				(0.013)				(0.015)
Yes				-0.199***				-0.327***
				(0.010)				(0.012)
Ever Receieved a Loan								
Yes				-0.017				0.020
				(0.010)				(0.010)
Constant	0.298***	0.260***	0.473***	0.297**	0.558***	0.514***	0.738***	0.454***
	(0.005)	(0.017)	(0.020)	(0.031)	(0.005)	(0.018)	(0.021)	(0.032)
R-squared	0.085	0.122	0.172	0.278	0.093	0.127	0.201	0.350
Adjusted R-squared	0.085	0.120	0.169	0.274	0.093	0.126	0.199	0.346
F-Statistic	830.346	76.327	89.624	85.829	911.478	82.996	156.932	148.952
Joint Significance Statistic	-	22.10	31.66	76.98	-	20.42	48.56	120.19
rmse	0.438	0.429	0.417	0.390	0.473	0.464	0.445	0.402
Out-of-Sample Predictions	2.02%	3.14%	4.43%	11.66%	0.03%	0.21%	1.30%	7.25%

Notes: Student races listed in the outputs above are compared to a student who classified themselves as white. Middle-income students were utilized as the comparison group for the *Race* variable. The comparison group for *HSCrt* was students who attended public high school. *HSGrade* coefficients from the outputs above are compared with students who have earned an *A* (cumulative *HSGPA*>3.50) in all the high school classes taken. The comparison group for *FCLvl* was students who have begun their college careers at a four-year university. Students who started their postsecondary careers are a public university/college were the comparison group for the *FCCrt* variable. The *inoutstate* base group were students who attended an out-of-state institution. Students who attended a highly selective four-year institution were assigned as the comparison group for the *FCSel* variable. The comparison group for the *Stopout* variable was students who did not stopout of school The comparison group for the *Loan* variable were students that have ever received a loan at the time they were pursuing their bachelor's degree. Coefficients from this table should be interpreted as the certis peribus increase or decrease in the probability of graduating by four or six years for a one-unit increase in covariates. Out-of-Sample predictions indicate the percent of students the model predicted to have graduation probabilities below zero and above one. *N=7640* for all models

Robust Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

Probit

Appendix Table C: Full Non-Linear Probit Regression Results for Impact of Standardized Test Scores on College Success

	Dependent Variable (Graduated)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized Test Score	0.138***	0.114***	0.063***	0.021***	0.150***	0.116***	0.049***	0.015*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Female		0.089***	0.049***	0.035***		0.064***	0.015	0.004
		(0.010)	(0.010)	(0.009)		(0.011)	(0.011)	(0.010)
Race								
Amer. Indian/Alaska Native		-0.063	-0.036	-0.032		-0.139	-0.082	-0.056
		(0.067)	(0.067)	(0.065)		(0.077)	(0.075)	(0.073)
Asian and Hawaii/Pac. Islander		0.051**	0.041*	0.032*		0.031	0.031	0.018
		(0.017)	(0.016)	(0.015)		(0.018)	(0.017)	(0.016)
Black or African American		-0.031	0.016	0.019		-0.069***	-0.001	0.005
		(0.018)	(0.019)	(0.018)		(0.019)	(0.018)	(0.016)
Hispanic		-0.004	0.012	0.026		-0.035	-0.012	0.010
		(0.019)	(0.018)	(0.017)		(0.019)	(0.018)	(0.017)
More than one race		-0.032	-0.012	-0.011		-0.057*	-0.024	-0.011
		(0.024)	(0.024)	(0.022)		(0.027)	(0.025)	(0.022)
Socioeconomic Status								
Low		-0.017	-0.020	-0.014		-0.029	-0.030	-0.016
		(0.016)	(0.015)	(0.014)		(0.017)	(0.016)	(0.015)
Lower-Middle		0.010	0.004	0.016		0.004	-0.002	0.009
		(0.016)	(0.015)	(0.015)		(0.018)	(0.017)	(0.015)
Upper		0.055***	0.066***	0.034*		0.071***	0.069***	0.043**
		(0.016)	(0.015)	(0.014)		(0.017)	(0.016)	(0.015)
Upper-Middle		0.007	0.016	0.006		0.043*	0.047**	0.032*
		(0.016)	(0.015)	(0.014)		(0.017)	(0.017)	(0.015)
Mother Graduated College		0.059***	0.053***	0.033***		0.051***	0.043***	0.027*
		(0.011)	(0.011)	(0.010)		(0.012)	(0.012)	(0.011)
Father Graduated College		0.051***	0.041***	0.018		0.076***	0.057***	0.040***
		(0.011)	(0.011)	(0.010)		(0.012)	(0.012)	(0.011)
High School Region								
Midwest		-0.072***	-0.107***	-0.060***		-0.050**	-0.089***	-0.043**
		(0.015)	(0.015)	(0.014)		(0.016)	(0.015)	(0.014)
South		-0.113***	-0.140***	-0.078***		-0.068***	-0.093***	-0.035**
		(0.014)	(0.014)	(0.013)		(0.015)	(0.014)	(0.013)
West		-0.111***	-0.157***	-0.087***		-0.083***	-0.139***	-0.072***

	(0.016)	(0.016)	(0.015)	(0.018)	(0.017)	(0.016)
High School Control						
Catholic		-0.003	-0.043***		0.082***	0.037**
		(0.013)	(0.012)		(0.014)	(0.013)
Other private		0.024	-0.029*		0.069***	0.029
		(0.015)	(0.014)		(0.017)	(0.015)
High School Letter Grade						
B		-0.156***	-0.042***		-0.152***	-0.050***
		(0.014)	(0.012)		(0.014)	(0.014)
C		-0.283***	-0.083***		-0.352***	-0.124***
		(0.015)	(0.015)		(0.015)	(0.016)
D		-0.369***	-0.115**		-0.542***	-0.218***
		(0.022)	(0.036)		(0.027)	(0.033)
F		*omitted*	*omitted*		*omitted*	*omitted*
missing		-0.180***	-0.043*		-0.222***	-0.069**
		(0.021)	(0.019)		(0.023)	(0.021)
Months between HS and College			-0.001			-0.003**
			(0.001)			(0.001)
Uknown gap months			-0.033			0.037
			(0.066)			(0.050)
First College Level						
Two-year institution			-0.072**			-0.003
			(0.023)			(0.023)
Less-than-two-year institution			*omitted*			-0.301**
						(0.102)
Missing			0.498**			-0.252
			(0.177)			(0.246)
First College Control						
Missing			0.036			0.135
			(0.199)			(0.200)
Private for-profit			-0.004			-0.115***
			(0.034)			(0.031)
Private not-for-profit			0.071***			0.011
			(0.012)			(0.012)
First College in- or out-of-state						
In-State			-0.031**			-0.003
			(0.012)			(0.013)
Uknown			-0.217***			0.006
			(0.061)			(0.074)
First Institution Selectivity						
Inclusive 4-year			-0.136***			-0.127***

				(0.017)				(0.019)
Moderately selective 4-year				-0.073***				-0.058***
				(0.012)				(0.013)
Uknown				-0.296***				-0.117
				(0.057)				(0.085)
Unclassified 2-year				-0.126***				-0.146***
				(0.024)				(0.025)
Unclassified 4-year				-0.144***				-0.205***
				(0.021)				(0.023)
Unclassified less than 2-year				*omitted*				*omitted*
First-Year College GPA				0.135***				0.126***
				(0.008)				(0.007)
Uknown First-Year College GPA				0.471***				0.399***
				(0.038)				(0.033)
Stopout								
Missing				-0.081***				-0.122***
				(0.013)				(0.016)
Yes				-0.220***				-0.322***
				(0.011)				(0.012)
Ever Receieved a Loan								
Yes				-0.016				0.019
				(0.010)				(0.010)
Observations	7640	7640	7628	7583	7640	7640	7628	7610
Log Pseudo Max Liklihood Estimation	-4307.010	-4154.986	-3943.774	-3377.451	-4872.848	-4730.365	-4408.327	-3688.374
Likelihood Ratio Statistic	-	304.048	422.425	1132.646	-	284.967	644.076	1439.905
Psudo R-squared (prior to margins)	0.075	0.108	0.152	0.272	0.071	0.098	0.158	0.293

Notes: Student races listed in the outputs above are compared to students who classified themselves as white. Middle-income students were utilized as the comparison group for the *Race* variable. The comparison group for *HSCrt* were students who attended public high school. *HSGrade* coefficients from the outputs above are compared with students who have earned an *A* (cumulative *HSGPA*>3.50) in all the high school classes taken. The comparison group for *FCLvl* were students who have begun their college careers at a four-year university. Students who started their postsecondary careers are a public university/college were the comparison group for the *FCCrt* variable. The *inoutstate* base group were students who attended an out-of-state institution. Students who attended a highly selective four-year institution were assigned as the comparison group for the *FCSel* variable. The comparison group for the *Loan* variable were students that have ever received a loan at the time they were pursuing their bachelor's degree. The *Unclassified less than two-year* variable from models (4) and (6), *less than two-year* from model (4), and *F* (from the *HSGrade* variable) from models (2)-(4) and (6)-(8) were omitted due to predicting failure perfectly. Coefficients from this table should be interpreted as the certis peribus increase or decrease in the probability of graduating by four or six years for a one-unit increase in covariates.

Robust Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

Proportional Hazard Cox

Appendix Table D: *Full Hazard Cox Regression Results for Impact of Standardized Test Scores on College Success(no time-dependent covariate adjustments)*

	Dependent Variable (Graduated), Time factor(Number of Enrollment Years)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized Test Score	0.887***	0.906***	0.950***	0.981	0.759***	0.809***	0.920***	0.963
	(0.011)	(0.012)	(0.014)	(0.015)	(0.013)	(0.015)	(0.018)	(0.020)
Female		0.874***	0.906***	0.926**		0.842***	0.915**	0.933*
		(0.020)	(0.021)	(0.023)		(0.027)	(0.030)	(0.032)
Race								
Amer. Indian/Alaska Native		0.918	0.908	0.952		1.046	0.998	1.014
		(0.170)	(0.163)	(0.152)		(0.246)	(0.221)	(0.192)
Asian and Hawaii/Pac. Islander		0.745***	0.756***	0.764***		0.739***	0.742***	0.752***
		(0.027)	(0.028)	(0.031)		(0.039)	(0.040)	(0.043)
Black or African American		1.022	0.976	0.939		1.118*	0.997	0.943
		(0.041)	(0.040)	(0.041)		(0.058)	(0.052)	(0.052)
Hispanic		0.862***	0.844***	0.838***		0.924	0.884*	0.862**
		(0.035)	(0.035)	(0.037)		(0.050)	(0.048)	(0.047)
More than one race		1.053	1.009	0.964		1.141	1.037	0.978
		(0.061)	(0.061)	(0.060)		(0.087)	(0.084)	(0.073)
Socioeconomic Status								
Low		1.074*	1.086*	1.093*		1.108*	1.126*	1.131**
		(0.039)	(0.039)	(0.040)		(0.053)	(0.054)	(0.054)
Lower-Middle		1.024	1.031	1.017		1.040	1.053	1.024
		(0.037)	(0.038)	(0.040)		(0.051)	(0.053)	(0.053)
Upper		0.913*	0.896**	0.900**		0.818***	0.818***	0.837**
		(0.032)	(0.033)	(0.035)		(0.043)	(0.044)	(0.047)
Upper-Middle		0.927*	0.924*	0.929		0.848**	0.849**	0.859**
		(0.032)	(0.033)	(0.035)		(0.043)	(0.043)	(0.047)
Mother Graduated College		0.851***	0.847***	0.863***		0.814***	0.819***	0.846***
		(0.022)	(0.022)	(0.024)		(0.031)	(0.031)	(0.033)
Father Graduated College		0.968	0.973	0.971		0.862***	0.892**	0.904**
		(0.025)	(0.026)	(0.027)		(0.032)	(0.034)	(0.035)
High School Region								
Midwest		0.969	1.009	1.023		1.000	1.103	1.064
		(0.034)	(0.036)	(0.039)		(0.050)	(0.056)	(0.055)
South		0.934*	0.974	0.936		0.954	1.032	0.919
		(0.031)	(0.033)	(0.034)		(0.045)	(0.049)	(0.045)
West		0.888**	0.940	0.906*		0.920	1.055	0.966

	(0.034)	(0.038)	(0.039)	(0.051)	(0.060)	(0.056)
High School Control						
Catholic		1.019	1.017		0.815***	0.846***
		(0.031)	(0.033)		(0.037)	(0.040)
Other private		1.079*	1.091*		0.924	0.931
		(0.039)	(0.043)		(0.051)	(0.055)
High School Letter Grade						
B		1.164***	1.052		1.494***	1.219***
		(0.036)	(0.035)		(0.078)	(0.066)
C		1.268***	1.004		2.088***	1.303***
		(0.042)	(0.038)		(0.109)	(0.074)
D		1.801***	1.229**		3.429***	1.673***
		(0.129)	(0.092)		(0.290)	(0.147)
F		1.855	1.278		3.592***	1.618
		(0.711)	(0.372)		(1.310)	(0.439)
missing		1.332***	1.093		1.969***	1.323***
		(0.066)	(0.059)		(0.142)	(0.103)
Months between HS and College			1.032***			1.031***
			(0.002)			(0.002)
Uknown gap months			1.072			0.992
			(0.210)			(0.212)
First College Level						
Two-year institution			0.960			0.923
			(0.054)			(0.069)
Less-than-two-year institution			0.752			1.061
			(0.160)			(0.201)
Missing			1.178			1.453
			(0.501)			(0.722)
First College Control						
Missing			1.955*			1.407
			(0.629)			(0.527)
Private for-profit			1.511***			1.633***
			(0.143)			(0.154)
Private not-for-profit			1.088*			1.155**
			(0.037)			(0.055)
First College in- or out-of-state						
In-State			0.989			0.948
			(0.035)			(0.045)
Uknown			1.050			1.034
			(0.180)			(0.191)
First Institution Selectivity						

Inclusive 4-year	1.300***	1.600***
	(0.060)	(0.104)
Moderately selective 4-year	1.144***	1.302***
	(0.037)	(0.069)
Uknown	1.199	1.433
	(0.208)	(0.280)
Unclassified 2-year	1.004	1.253**
	(0.059)	(0.104)
Unclassified 4-year	1.308***	1.833***
	(0.074)	(0.130)
Unclassified less than 2-year	1.532	1.309
	(0.602)	(0.491)
First-Year College GPA	0.760***	0.671***
	(0.014)	(0.016)
Uknown First-Year College GPA	0.841	0.546***
	(0.080)	(0.058)
Stopout		
Missing	1.011	1.251***
	(0.038)	(0.039)
Yes	0.942*	1.470***
	(0.030)	(0.026)
Ever Received a Loan		
Yes	0.884***	0.826***
	(0.025)	(0.032)

Notes: Student races listed in the outputs above are compared to students who classified themselves as white. Middle-income students were utilized as the comparison group for the Race variable. The comparison group for HSCrt were students who attended public high school. HSGrade coefficients from the outputs above are compared with students who have earned an A (cumulative HSGPA>3.50) in all the high school classes taken. The comparison group for FCLvl were students who have begun their college careers at a four-year university. Students who started their postsecondary careers are a public university/college were the comparison group for the FCCrt variable. The inoutstate base group were students who attended an out-of-state institution. Students who attended a highly selective four-year institution were assigned as the comparison group for the FCSel variable. The comparison group for the Loan variable were students that have ever received a loan at the time they were pursuing their bachelor's degree. Categorical coefficients should be interpreted as said in the Hazard Ratios (HR) Section of this paper (HR>1 is an increase in the hazard, HR=1 is no difference in the hazard, and HR<1 is a decrease in the hazard for categorical variables. For continuous variables, a one-unit increase in a variable increases the hazard by the coefficient of said variable). Alternatively, 1-HR is the percent increase/decrease in the hazard.

Robust Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

Appendix Table E: Schoenfeld Residual Analysis for Assessing Time-Dependent Variables

	Four-year model								Six-year Model							
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	rho	chi2	rho	chi2	rho	chi2	rho	chi2	rho	chi2	rho	chi2	rho	chi2	rho	chi2
Test Score Standardized	0.182	140.70*	0.138	77.81*	0.054	11.62*	0.017	1.260	0.187	110.71*	0.133	52.96*	0.044	6.1*	0.002	0.010
Female			0.062	14.3*	0.038	5.56*	0.022	1.920			0.069	13.73*	0.052	7.93*	0.025	2.030
Race																
Amer. Indian/Alaska Native			-0.028	4.340	-0.021	2.390	-0.007	0.190			-0.041	7.62*	-0.032	4.06*	-0.015	0.670
Asian and Hawaii/Pac. Islander			0.057	10.84*	0.073	18.18*	0.058	13.28*			0.074	14.86*	0.088	21.48*	0.065	12.82*
Black or African American			-0.032	4.53*	0.007	0.210	-0.005	0.140			-0.031	3.070	0.007	0.170	0.005	0.090
Hispanic			-0.001	0.000	0.014	0.800	0.007	0.200			-0.001	0.000	0.017	0.900	0.021	1.350
More than one race			-0.034	4.93*	-0.031	4.350	-0.011	0.6			-0.035	3.790	-0.035	4.16*	0.008	0.170
Socioeconomic Status																
Low			-0.044	11.06*	-0.062	15.89*	-0.051	11.24*			-0.059	10.7*	-0.060	11.51*	-0.035	3.92*
Lower-Middle			-0.017	0.140	-0.012	0.550	-0.016	1.050			-0.006	0.110	-0.006	0.110	0.003	0.040
Upper			0.022	1.480	0.021	1.550	0.023	1.980			0.037	3.640	0.037	3.830	0.038	4.40*
Upper-Middle			0.008	1.510	0.022	1.680	0.008	0.220			0.025	1.620	0.027	1.970	0.018	0.960
momcoll			0.033	5.07*	0.038	5.1*	0.027	2.720			0.053	7.35*	0.047	6.01*	0.039	4.37*
dadcoll			0.031	2.690	0.029	2.960	0.052	10.49*			0.030	2.460	0.028	2.220	0.060	10.42*
High School Region																
Midwest			-0.013	0.590	-0.043	7.02*	-0.036	5.35*			-0.020	1.170	-0.047	6.27*	-0.028	2.220
South			-0.020	0.530	-0.039	5.97*	-0.012	0.610			-0.025	1.760	-0.041	4.89*	-0.010	0.280
West			-0.002	0.000	-0.036	5.16*	-0.019	1.550			-0.008	0.200	-0.038	4.49*	-0.016	0.870
High School Control																
Catholic					0.055	10.58*	0.043	7.16*					0.061	10.03*	0.059	9.96*
Other Private					0.037	4.82*	0.019	1.430					0.042	4.82*	0.025	2.020
High School Letter Grade																
B					-0.050	8.13*	-0.007	0.160					-0.058	9.29*	-0.035	3.660
C					-0.124	54.60*	-0.018	1.320					-0.114	37.43*	-0.048	6.79*
D					-0.147	134.85*	-0.075	32.83*					-0.138	72.15*	-0.071	18.19*
F					-0.042	16.29*	-0.006	0.170					-0.040	8.4*	0.004	0.060
Missing					-0.064	14.31*	-0.018	1.400					-0.076	15.59*	-0.030	2.770
Months between HS and College							0.031	4.34*							0.051	6.60*
Uknown gap months							-0.031	7.9*							-0.033	4.40*
First College Level																
Two-year institution							0.000	0.000							0.008	0.180
Less-than-two-year institution							-0.014	1.010							-0.009	0.190
Missing							-0.007	0.180							-0.007	0.100
First College Control																
Missing							0.030	3.55*							0.029	2.040
Private for-profit							-0.052	20.15*							-0.018	1.340
Private not-for-profit							-0.039	6.34*							-0.037	4.19*
First College in- or out-of-state																
Instate							0.002	0.020							-0.007	0.130
Unknown							0.015	1.050							0.007	0.120
First Institution Selectivity																
Inclusive							-0.067	19.8*							-0.060	10.60*

Moderately selective							-0.040	5.32*							-0.042	4.67*
Uknown							0.031	3.97*							0.015	0.500
Unclass two year							-0.014	1.520							-0.021	1.330
Unclass four-year							-0.087	37.37*							-0.076	17.35*
unclass less than four year							-0.016	2.620							-0.029	5.44*
collgpa							0.206	268.75*							0.209	192.43*
misscollgpa							0.072	37.94*							0.107	52.31*
Stopout																
Missing							0.055	12.86*							- 0.126	48.20*
Yes							0.091	36.82*							0.193	124.500
Loan							0.088	35.10*							0.110	42.12*
global test		140.70*		227.97*		387.89*		819.28*		110.71*		208.9*		275.42*		555.39*

*Note: * indicates a variable as a p-value of 5% or more. P-values of 5% or more indicate that these variables fail the Proportional Hazards Assumption, thus are dependent on time. Time-dependent variables will be interacted with time.*

Appendix Table F: Hazard Cox Regression Results for Impact of Test Scores on College Success (with time-dependent adjustments)

	Dependent Variable (Graduated), Time factor(Number of Enrollment Years)							
	Four-Year Model				Six-Year Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Regression								
Standardized Test Score	0.559***	0.632***	0.810***	0.886**	0.513***	0.597***	0.806***	0.966
	(0.019)	(0.024)	(0.034)	(0.035)	(0.018)	(0.024)	(0.036)	(0.019)
Female		0.659***	0.771***	0.940**		0.640***	0.757***	0.947
		(0.046)	(0.054)	(0.021)		(0.049)	(0.058)	(0.030)
Race								
Amer. Indian/Alaska Native		0.960	0.927	0.923		1.114	1.018	0.952
		(0.158)	(0.148)	(0.132)		(0.227)	(0.201)	(0.170)
Asian and Hawaii/Pac. Islander		0.437***	0.453***	0.473***		0.393***	0.414***	0.447***
		(0.055)	(0.058)	(0.060)		(0.055)	(0.059)	(0.065)
Black or African American		1.262*	0.961	0.935		1.103*	0.980	0.939
		(0.131)	(0.036)	(0.035)		(0.054)	(0.047)	(0.047)
Hispanic		0.872***	0.851***	0.832***		0.937	0.889*	0.863**
		(0.034)	(0.033)	(0.032)		(0.047)	(0.045)	(0.043)
More than one race		1.483**	0.999	0.951		1.115	1.330	0.950
		(0.220)	(0.057)	(0.052)		(0.083)	(0.212)	(0.066)
Socioeconomic Status								
Low		1.546***	1.540***	1.426***		1.625***	1.554***	1.409***
		(0.134)	(0.132)	(0.118)		(0.150)	(0.141)	(0.125)
Lower-Middle		1.009	1.011	1.010		1.023	1.033	1.022
		(0.037)	(0.037)	(0.037)		(0.051)	(0.051)	(0.050)
Upper		0.907**	0.891**	0.886**		0.812***	0.808***	0.626***
		(0.034)	(0.033)	(0.034)		(0.044)	(0.044)	(0.079)
Upper-Middle		0.917*	0.910**	0.924*		0.838***	0.835***	0.865**
		(0.033)	(0.033)	(0.033)		(0.043)	(0.043)	(0.044)
Mother Graduated College		0.579***	0.606***	0.854***		0.531***	0.562***	0.664***
		(0.046)	(0.049)	(0.023)		(0.050)	(0.053)	(0.065)
Father Graduated College		0.974	0.973	0.714***		0.871***	0.896**	0.746**
		(0.025)	(0.025)	(0.054)		(0.032)	(0.033)	(0.069)
High School Region								

Midwest	0.956	1.093	0.994	0.983	1.080	1.054
	(0.034)	(0.090)	(0.036)	(0.048)	(0.053)	(0.052)
South	0.925*	0.955	0.919*	0.942	1.012	0.918
	(0.031)	(0.032)	(0.032)	(0.043)	(0.047)	(0.044)
West	0.890**	0.936	0.923*	0.921	1.056	1.000
	(0.034)	(0.037)	(0.038)	(0.050)	(0.058)	(0.056)
High School Control						
Catholic		0.718***	0.840		0.561***	0.843***
		(0.069)	(0.078)		(0.065)	(0.038)
Other private		0.875	1.087*		0.696**	0.930
		(0.099)	(0.042)		(0.096)	(0.054)
High School Letter Grade						
B		1.892***	1.054		2.445***	1.197***
		(0.205)	(0.036)		(0.346)	(0.064)
C		3.552***	1.039		5.023***	1.320***
		(0.385)	(0.038)		(0.681)	(0.073)
D		9.404***	1.230***		12.030***	1.627***
		(1.427)	(0.076)		(2.031)	(0.129)
F		15.930***	1.182		18.438***	1.615
		(9.501)	(0.295)		(10.815)	(0.416)
missing		3.420***	1.103		4.662***	1.341***
		(0.528)	(0.058)		(0.838)	(0.101)
Months between HS and College			1.032***			1.026***
			(0.004)			(0.002)
Uknown gap months			1.174			1.112
			(0.158)			(0.179)
First College Level						
Two-year institution			0.992			0.983
			(0.052)			(0.070)
Less-than-two-year institution			0.888			1.085
			(0.155)			(0.218)
Missing			0.945			1.347
			(0.351)			(0.625)
First College Control						
Missing			1.657			1.208
			(0.463)			(0.438)
Private for-profit			2.638***			1.546***

				(0.369)				(0.127)
Private not-for-profit				1.107**				1.158**
				(0.037)				(0.053)
First College in- or out-of-state								
In-State				0.977				0.940
				(0.034)				(0.043)
Uknown				1.081				1.065
				(0.165)				(0.194)
First Institution Selectivity								
Inclusive 4-year				1.814***				2.645***
				(0.176)				(0.303)
Moderately selective 4-year				1.117***				1.638***
				(0.037)				(0.160)
Uknown				1.103				1.408
				(0.168)				(0.281)
Unclassified 2-year				0.959				1.142
				(0.054)				(0.095)
Unclassified 4-year				1.249***				3.022***
				(0.066)				(0.364)
Unclassified less than 2-year				1.084				1.436
				(0.274)				(0.472)
First-Year College GPA				0.360***				0.375***
				(0.015)				(0.016)
Uknown First-Year College GPA				0.195***				0.191***
				(0.032)				(0.032)
Stopout								
Missing				0.975				0.659***
				(0.032)				(0.073)
Yes				1.047***				1.253***
				(0.014)				(0.049)
Ever Received a Loan								
Yes				0.650***				0.564***
				(0.049)				(0.047)
Time Varying Covariates								
Standardized Test Score	1.111***	1.087***	1.038***	1.024**	1.099***	1.077***	1.034***	
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	
Female		1.070***	1.041**			1.073***	1.050**	

	(0.014)	(0.014)		(0.016)	(0.016)	
Asian and Hawaii/Pac. Islander	1.120***	1.115***	1.108***	1.150***	1.133***	1.121***
	(0.025)	(0.026)	(0.025)	(0.029)	(0.029)	(0.029)
Black or African American	0.950**					
	(0.019)					
More than one race	0.922**				0.939*	
	(0.026)				(0.029)	
Socioeconomic Status						
Low	0.918***	0.919***	0.933***	0.910***	0.920***	0.940***
	(0.015)	(0.015)	(0.014)	(0.016)	(0.016)	(0.016)
Upper						1.064*
						(0.026)
Mother Graduated College	1.089***	1.077***		1.103***	1.091***	1.053**
	(0.016)	(0.017)		(0.019)	(0.019)	(0.020)
Father Graduated College			1.071***			1.045*
			(0.016)			(0.019)
Region						
Midwest		0.978				
		(0.016)				
High School Control						
Catholic		1.082***	1.042*		1.093***	
		(0.021)	(0.019)		(0.025)	
Other private		1.050*			1.070*	
		(0.024)			(0.030)	
High Letter Grade						
B		0.894***			0.887***	
		(0.020)			(0.025)	
C		0.793***			0.810***	
		(0.017)			(0.022)	
D		0.669***			0.724***	
		(0.020)			(0.025)	
F		0.586***			0.658***	
		(0.067)			(0.074)	
missing		0.803***			0.808***	
		(0.025)			(0.030)	
Months between HS and College			0.998*			
			(0.001)			

First College Control			
	Private for-profit	0.840***	
		(0.025)	
First College Selectivity			
	Inclusive 4-year	0.915***	0.876***
		(0.017)	(0.021)
	Moderately selective 4-year		0.943**
			(0.018)
	Unclassified 4-year		0.867***
			(0.020)
First-Year College GPA		1.191***	1.155***
		(0.010)	(0.010)
Uknown First-Year College GPA		1.329***	1.255***
		(0.044)	(0.049)
Stopout			
	Yes	0.950***	0.822***
		(0.013)	(0.015)
	Missing		0.957*
			(0.020)
Ever Received a Loan			
	Yes	1.070***	1.097***
		(0.016)	(0.019)

Notes: Student races listed in the outputs above are compared to students who classified themselves as white. Middle-income students were utilized as the comparison group for the *Race* variable. The comparison group for *HSCrt* were students who attended public high school. *HSGrade* coefficients from the outputs above are compared with students who have earned an *A* (cumulative *HSGPA*>3.50) in all the high school classes taken. The comparison group for *FCLvl* were students who have begun their college careers at a four-year university. Students who started their postsecondary careers are a public university/college were the comparison group for the *FCCrt* variable. The *inoutstate* base group were students who attended an out-of-state institution. Students who attended a highly selective four-year institution were assigned as the comparison group for the *FCSel* variable. The comparison group for the *Loan* variable were students that have ever received a loan at the time they were pursuing their bachelor's degree. Categorical coefficients that are not time-dependent should be interpreted as said in the *Hazard Ratios* (HR) Section of this paper (HR>1 is an increase in the hazard, HR=1 is no difference in the hazard, and HR<1 is a decrease in the hazard for categorical variables. For continuous variables, a one-unit increase in a variable increase the hazard by the coefficient of said variable). Alternatively, *1-HR* is the percent increase/decrease in the hazard. Variables that are time-dependent will have a different interpretation and will show up two times in the regression results. For time-dependent covariates, coefficients that are in the *Main* portion of the regression indicates the hazard at t=0. Coefficients are located in the *Time-Varying Covariates* section of the table, that is the increase/decrease in the hazard for an additional unit of time.

Robust Standard errors in parentheses
* p<0.05, **p<.01, ***p<.001

Visualizations