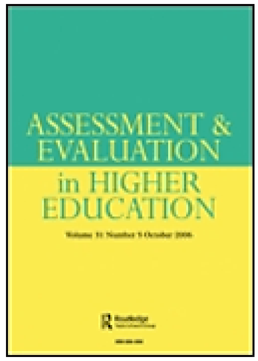

Early Indicators of Student Success: A Multi-State Analysis

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Abstract

This paper reports the results of a four-state collaboration that uses Student Unit Record Database Systems that track students from high school into college. The goal is to determine whether it is possible to accurately predict which students will not graduate using very early indicators – variables available at college entry or during the first semester. Using similar statistical models across four state university systems, we are able to identify students at greatest risk of non-completion quite accurately at early stages, allowing college staff to prioritize interventions and supports aimed at improving completion for those at greatest risk. Our models do not use gender, race or ethnicity in determining probability of non-completion.

Keywords: undergraduates, graduation, dropout, prediction, early indicators

Introduction

In recent years, several states have compiled databases that track multiple cohorts of students from high school into college and later into the labor force. These Student Unit Record Database Systems (SURDS)[i] typically compile socio-demographic information for hundreds of thousands of high school students along with measures of academic performance, such as scores on state tests and high school GPA. For students who attend college, SURDS compile information on colleges attended and transcript details of grades, credits, and major field of study. They track undergraduates who transfer from one college to another and record degrees conferred from all institutions (New America Foundation 2017). Some states incorporate students' quarterly earnings before, during and after college, drawn from state departments of labor. These databases are purged of individual identifiers and access is restricted to researchers under controlled circumstances to ensure the security of the data.

Administrative data are usually more reliable than self-reported survey data, and incorporate many more students than typical longitudinal surveys, allowing previously unnoticeable patters to emerge. Researchers can zoom in on particular subpopulations of students, whether defined in terms of student characteristics (such as low-income or high-performing students) or defined institutionally (those attending flagship versus secondary campuses of public universities, or two-year versus four-year college students). Databases that document each individual's education over a long period allow scholars to identify different patterns or trajectories from high school through college and into the labor market. Using SURDS, scholars can identify points in the educational process where some students tend to fall behind, or evaluate the labor market consequences of taking different routes through college.

In short, educational research has now entered the era of Big Data. Dynarski and Berends (2015) argue that SURDS are a game changer for educational research. These databases, unfortunately, are collected by individual states in part because federal agencies such as the U.S. Department of Education are forbidden by law from using their administrative records to track student progress. Efforts are underway in Congress, however, to reverse this legal prohibition. If successful, this might open the way to a national Student Unit Record System (Kreighbaum 2017).

In this paper, we present collaborative research analyzing SURDS data from four different states – Texas, New York, Virginia and Illinois – to examine degree completion. By studying four state SURDS individually, each using data on past cohorts of students who had been tracked for sufficient years to graduate, we determine whether the same statistical model can predict graduation in different states, assessing the generalizability of findings.

Our central research question is whether it is possible to use SURDS data to predict accurately which undergraduates did not graduate. Nationwide, about three-quarters of high school graduates attend college at some point, nearly a third of whom fail to complete a degree.[ii]

A large body of research has identified factors that on average are associated with degree non-completion (Achieve 2004; Adelman 1997, 1999, 2006; Attewell, Heil, and Reisel 2011; Braxton 2000; Chen 2005; Complete College America 2011; Horn, Kojaku, and Carroll 2001; Tinto 1994, 2012). The use of SURDS in this paper has a different goal: to predict which individual students are most likely to complete the credential. If one can determine with a reasonable degree of accuracy from the first semester of college or even before entry to college which individuals are at high risk of non-completion, this information can be used to reach out to those particular students with counseling, support, or other interventions to increase graduation.

Finding generalizable, early indicators of undergraduate success could also play a role in assessing or evaluating institutional efforts at improvement. Many colleges have thrown themselves into a flurry of innovation and experimentation aimed at improving degree completion: trying new pedagogical approaches, different curricula, new counseling approaches, or pre-structured course pathways (Bailey, Jaggers, and Jenkins 2015; Tinto 2012). Evaluating experiments like these can be a lengthy process. If early leading indicators can accurately predict later academic achievement, evaluators may examine whether experiments or interventions move the needle on those early indicators, before degree completion or other longer-term outcomes are known. Thus, a second potential for finding early indicators of student success is to provide rapid feedback on organizational innovations and interventions.

Several commercial information systems sold to colleges (e.g., Starfish, EAB, Civitas) already provide early warnings or alerts that a particular student is at risk of dropping out or failing a course. These systems typically require faculty members to input information for their classes about students' weekly attendance and grades on midterms and assignments. Based on analyses of these data, the programs issue alerts that identify students at high risk of failure in that particular course, allowing college staff to intervene to support students in difficulty. By contrast, SURDS do not require special data collection efforts by faculty for their classes. They use data already known for each student at entry to college, along with information collected at registration on course-load and remedial course placements. Later models include additional measures of student performance in the first semester of college.

This paper finds that it is possible to accurately predict individuals' probability of graduating with such early SURDS indicators. This contrasts with most of the commercial alert systems that focus on predicting passage or failure of a particular course. Using SURDS data, we generate predictions using logistic regression models, finding that these yield accurate predictions of non-completion across four different states, especially for those students at highest risk of non-completion. Below, we outline these models, as well as discuss conceptual and methodological issues, and address certain ethical concerns about using early indicators of student success.

Prior literature

Tinto (1988, 1994, 2012) developed a theory emphasizing the importance of a student's academic and social integration for persistence in college, arguing that a lack of fit between a student and the college was a proximal cause of dropping out. Using national survey data, Clifford Adelman (1999, 2006) developed a theory of academic momentum, in which student progress in the first year of college, specifically completing 20 or more credits, was predictive of degree completion. Students who completed fewer credits were less likely to persist. Adelman (1999) identified academic preparation as central to sustaining momentum: students who did not take a rigorous curriculum during high school (most especially in mathematics) and consequently faced difficulties in college were at high risk of non-completion (cf. Chingos 2018). The idea that passing college mathematics courses, especially remedial math, constitute a major hurdle to degree completion has led to widespread efforts to reform that part of the curriculum (Bailey, Jeong, and Cho 2010; Chen and Simone 2016; Hayward and Willett 2014).

Other research emphasizes competing demands faced by many undergraduates who need to juggle academic studies with paid employment and family obligations, creating time binds that lower graduation rates (Stinebrickner and Stinebrickner 2003, 2004; Bozick 2007). St. John (2003), Goldrick-Rab (2016) and others highlight the role of finances, arguing that inadequate financial aid generates financial stresses leading some students to drop out because they cannot afford to continue. This literature has identified important factors associated with attrition and completion, and has estimated average effects of predictors across representative samples of students. It has not, however, focused on predicting completion outcomes for individual students, the goal of this paper.

Methods

Data

Researchers in each state had access to and analyzed their own state's SURDS database based on entering cohorts from Fall 1999 through Spring 2010, and their graduation and academic data through 2016. In three states, data were analyzed separately for public four-year colleges and for two-year community colleges. For one state (Illinois) only data on community colleges were available. Although data on private college enrollments were available in some SURDS, private colleges did not usually report transcript information, so were excluded from the analyses for this paper. The SURDS data were longitudinal, following each student from entry into college for at least ten years, at which time the SURDS indicated whether that individual had graduated. Sample sizes ranged from 48,783 BA students in Texas, to 357,836 for AA students in New York.

Variables

Graduation was constructed as a binary outcome variable. For students initially entering a four-year college, we defined our milestone as completion of the bachelor's degree within 12 semesters of entry. The equivalent milestone for undergraduates who started at community colleges is more complicated. Many students who begin at community college say they intend to earn their baccalaureate, and commonly transfer to a four-year college without first completing their associate's degree (Long and Kurlaender 2009). Thus, simply counting whether or not a student received an associate's would be misleading as a measure of student success for those who start higher education in a community college. Instead, we count as having reached an important milestone community college matriculants who either obtain the associate's degree or a baccalaureate, or who accumulate 60 or more credits, which are the minimum required at most community colleges to receive an associate's degree.

After exploratory modeling, we settled on the following independent variables available to college staff at the beginning of each student's freshman year: age at college entry, parental adjusted gross income ("AGI"), high school GPA, SAT, ACT, or TAKS score, remedial requirements (math, reading, writing), workload in semester 1 (total number of credits counting both remedial and non-remedial courses), and whether a major was declared at college entry (a dichotomous variable). Another set of variables contains measures of student performance during the first semester of college: GPA in first semester; credits earned in first semester; whether remedial math was taken in the first semester (if required), and if so whether it was passed; and equivalent measures for taking or passing remedial reading or remedial writing in the first semester. All continuous variables were converted into categorical predictors, allowing the addition of a "missing" category for each variable.

Appendix A reports details for each variable. There were some differences in data availability between states. For example, Texas used a statewide assessment of math and English skills that is mandatory for high school seniors, transforming this into a percentile score; whereas the New York data used SAT scores. Different state SURDS also had somewhat different measures of low income. Some used eligibility for free or subsidized school lunches in high school, while others used Pell eligibility or adjusted parental income. Consequently, the variables in models are not identical across the states, though are quite similar.

We also examined whether adding later measures of student performance describing performance after the first year of college improved the accuracy of models predicting graduation. We found that later academic performance measures did not substantially improve prediction. Simply knowing how well a student performed during their first semester of college was sufficient.

Readers should note that we deliberately avoided using gender, race or ethnicity as predictors of retention and graduation in statistical models. Despite being aware that these demographic characteristics are associated on average with higher or lower completion rates, we avoided building models predicting individual progress that relied on group characteristics of this type. To do so might reify stereotypes and lead to what economists term "statistical discrimination" – assessing individuals' promise by their group membership (Arrow 1973). After completing our analyses without such attributes, we checked (separately for each state SURDS) to see whether the inclusion of gender and race/ethnicity would have improved predictive accuracy. Adding those variables made very little if any improvement in predictive accuracy, given the behavioral measures already in the model. There were two exceptions: a student's age at college entry and a family income measure were both associated with later academic progress such that omitting those particular predictors would impair predictive power. We judged that incorporating those two particular variables into the models would be less problematic than building predictive models in which gender, race, or ethnicity played a substantial role.

Statistical Models

We followed a multi-stage strategy for creating and evaluating predictive models. The first step estimated preliminary logistic regression models predicting graduation, as defined above. These yielded an initial predicted probability of reaching that milestone for each individual student. The original data, however, was first split into two different parts using random assignment. This functions as a type of replication, ensuring that patterns identified in a particular analysis or model are also found in other out-of-sample data (Rogers and Girolami 2012). Our training data, consisting of 70% randomly selected cases out of the full sample, was used to construct our predictive model. The remaining 30% of the full sample, our test data, was withheld from the logistic regression.

After a logistic regression model was built from the training data, the prediction equation from that analysis was used to "score" the cases in the test sample, providing a predicted probability (or p-hat) of reaching each milestone for each test individual. We standardized the distribution of p-hats into decile groups of equal size. For the purpose of evaluating the model's accuracy in its tails, we also look at the bottom 5% and the bottom 1% of this distribution: the cases for which our best model indicates a very low chance of graduation. The predicted probabilities from our training data were then cross-tabulated with the actual measured milestone outcomes for the test-sample individuals, yielding statistics that measured the accuracy of our predictions.

Cross-validation assesses whether a model developed from a training sample generalizes to out-of-sample data, reflecting the overall population, and therefore can be considered reproducible. Cross-validation is a protection from what data miners term “overfitting” – the possibility that a strongly predictive model partly reflects random noise, or finds relationships in a dataset that would not apply to data drawn from other samples (Rogers and Girolami 2012). In all our tables presented below, the reported accuracy statistics are always for the held-back test data, which is the equivalent of applying a predictive model to new data.

Findings

Online appendices (B1-B4) report the logistic regression models for each state, including their coefficients and standard errors. Generally, the most powerful predictors for graduation were consistent with the academic momentum perspective: credits earned in the first semester and first semester GPA were the strongest predictors. Among community college entrants, the next most powerful predictor was each student’s status regarding remedial math – whether the student was required to take remedial math, and if so whether the student passed or withdrew/failed, or whether the student avoided taking the remedial course in the first semester. For students entering four-year colleges, the strongest predictors were again academic momentum in the first semester. However, high school GPA, adjusted parental income, and age at entry were also important factors associated with graduation.

Table 1 reports these predicted probability statistics for each state's two-year entrants, with Model A including only variables known at entry, and Model B including first-semester variables. The resulting pattern is in every case curvilinear. The predictive accuracy of the model is very high for students least likely to graduate. For students in the highest 1% group of risk scores at entry to community college, non-graduation rates ranged from 85% for Virginia, to 94% for Texas in Model A, and above 97% for all four states in Model B. Even for students with the highest 20% risk scores, non-graduation rates ranged from 79% for New York, to 88% for Virginia in Model A, and above 91% for all four states in Model B. At the other end of the spectrum, the students with the lowest decile of risk scores – those most likely to graduate – did not graduate at a range of 15% in Texas, to 44% in Virginia in Model A. With data after the first-semester in Model B, non-graduation rates ranged from 10% in Texas, to 29% in Virginia for students in the lowest decile of risk scores. For students with predicted probabilities in the mid-range, the accuracy of the model is much lower. Students in most middle deciles, for example, have close to average graduation rates.

[Table 1 about here]

A similar pattern emerges among four-year college entrants (Table 2), albeit with higher graduation rates typical for these students. For students in the highest 1% group of risk scores at entry to a four-year college, non-graduation rates were 76% for Virginia, 87% for New York, and 92% for Texas in Model A. With the addition of first-semester variables (Model B), the non-graduation rates for the highest-risk students rose to 95% and above. For students in the lowest decile of risk, only 7% did not graduate in Virginia, 14% did not graduate in Texas, and 21% did not graduate in New York for Model A. These predictions were more accurate after the first semester's data was added in Model B, with non-graduation rates ranging from 4.5% for

Virginia's lowest decile of risk, to 16% for New York. Like with the two-year entrants, the students with middle-decile risk scores were more of a 50:50 proposition.

[Table 2 about here]

If the goal were accurate prediction for every student across the distribution, this curvilinear distribution would be a serious drawback. If the goal, however, is to provide actionable information identifying those students at highest risk of not graduating, the model successfully identifies those students.

Discussion and Conclusion

We have demonstrated it is possible to predict with considerable accuracy an individual student's likelihood of graduating. Our models use a modest number of variables that all four states collect as part of their SURDS, without the arduous data entry burden of commercial early alert systems.

Several commercial products exist to improve student success, for example Starfish Retention Solutions' EARLY ALERT product and Educational Advisory Board's (EAB) offerings. Some of these commercial products have a much broader span than the predictive models presented in this paper, including addressing issues such as student admissions and yield, financial aid, and by providing early warnings via email to students or to counselors. These software products have clear strengths, but differ from our SURDS-based analytical models in this respect: several of the commercial student-tracking and alert systems use "real time" behavioral measures such as class attendance or performance to identify which students are having difficulty.

These early alert systems are certainly powerful indicators of student progress, but require regular updates from faculty regarding student attendance and grades. That level of effort may well pay off. However, those indicators used by such commercial systems are very different from the information available in SURDS on which this paper has been based. Our models use information that is routinely collected by colleges (or state SURDS systems) such as GPA, credits attempted and earned, status of remedial coursework, and so on. They do not require data from real-time monitoring of student progress throughout the course of the semester. In that sense, our models are more limited than the commercial products, but nevertheless attain a high level of predictive accuracy.

The predictive accuracy of our model has a curvilinear shape for all four state SURDS. The highest predictive accuracy – usually exceeding 95 percent – occurs for students at highest risk of non-graduation. Prediction in the middle of the distribution is much less accurate. In this "murky middle" exists a large swath of students who have roughly similar chances of graduating or not graduating. These early indicators are not effective in distinguishing among those in the middle. The existence of a murky middle does not lessen the value of the early indicator models summarized above. If the purpose of intervening is to enhance graduation rates, college administrators should find it useful to know which among their students are most and least likely to graduate. That knowledge, provided in a timely fashion by our early indicator models in the form of risk scores, would allow college staff to prioritize outreach to students and target support services to those at greatest need. In our view, prioritization of interventions and support services is the most immediate and practical use of our early indictor models of student success.

It is possible that some institutions might use predictive scores to separate matriculants at highest risk of non-completion from other students at less risk, and tailor a special program for the former. One analogous situation is the City University of New York's pre-matriculation program, CUNY Start. This voluntary program identifies applicants to community college who have multiple remediation needs, based on their placement test scores in math, reading, and writing, taken just before they intend to start college. (This is a less elaborate method for assessing risk than the multivariate predictive models discussed in this paper, but the analogy is instructive). Those identified students at CUNY are invited to defer immediate enrollment in a community college program, and instead are offered the option of taking one or two twelve-week courses, at very low tuition, which focus on remedial coursework, taught by teachers especially skilled at adult education. The goal is to raise those students' skills to such a level that they can pass the skills tests and then begin their community college program without further remedial coursework.

Initial evaluations of the CUNY Start program report that significantly larger proportions of Start students pass the skills tests needed to exit remediation than a comparison group of community college students who take remedial coursework alongside non-remedial classes, during their early semesters at community college (Scrivener and Logue 2016). Some students who do not pass their courses in this special track may decide not to enter community college – we don't have data on how many – and if so would have paid far less tuition than they would had done had they started community college and taken remedial coursework there. One should recall that Adelman (2006) found that about 13% of entering students in a national sample drop out before completing ten credits.

A second policy option would use risk scores to identify high-risk students in order to offer those students additional academic or social supports (cf. Tinto 2012). Another analogue can be found in the City University of New York's Accelerated Study in Associate Program (ASAP), which identifies potential participants based on low placement-test scores that cause them to take one or two remedial courses. (Again, using a less elaborate metric than the risk score approach described by this paper.) ASAP offers selected participants a range of extra supports, such as individual advisors or counsellors whom they meet on a regular basis. Participants are "block scheduled" so they take courses with other like-situated students. They also receive certain material benefits, in terms of free textbooks and a free transport pass. CUNY's ASAP program is a complex intervention, initially targeted at high risk community college students. Random assignment evaluations have documented near-doubling of graduation rates for ASAP students compared to control groups (Gupta 2017).

In 2015, Ohio began replicating this ASAP program in three of its community colleges (Miller et al. 2020). Student volunteers were randomly assigned treatment of academic services similar to CUNY's, as well as financial assistance in the form of tuition and textbook waivers, and career advisement (Miller et al. 2020). Ohio's ASAP program doubled the graduation rate for students with developmental requirements, and significantly boosted graduation rates for those without (Miller et al. 2020, 50). This program cost the colleges an additional 42% per student, but cost 22% less per degree conferred compared with the control group (Miller et al. 2020, 53). These two programs illustrate two types of policies where participants are selected using early or leading indicators of student success. But we stress that these two real-world examples did not use the multivariate indicators discussed earlier in this paper. Instead they selected participants, on a voluntary basis, based on the placement test scores of incoming undergraduates.

This brings us to the important issue of how error in prediction might affect such policies regarding interventions. The first thing to note is that the current indicators of risk being used in many colleges, specifically skills or placement test scores from commercially available ACCUPLACER or COMPASS tests, have been criticized for being quite inaccurate (Scott-

Clayton 2012; Rodriguez et al. 2014). The status quo approach to identifying at-risk students and directing them into special classes is already error laden.

For the higher-risk end of the spectrum, most predictions of non-graduation in the models we developed were 95% accurate or better, meaning that at most five in a hundred identified as being at risk of non-completion would in fact have completed their degree. One ethical issue is whether individuals (or colleges) would be harmed if these 5% were erroneously classified as high-risk. If risk scores are used to prioritize provision of extra academic and counselling support, it seems unlikely that a misclassified student would be harmed by being encouraged to make use of such targeted support, especially since students may decide to spurn those supports if they so choose. From the institution's perspective, if they identify students for extra support, 95% of whom would not be likely to complete their degree and (due to inaccurate prediction) 5% would graduate anyway, then perhaps 5% of the extra supports are "wasted" in the sense that they would better be targeted elsewhere. In our judgement, this is a relatively small misallocation of resources, with little risk of harm to students who were misclassified as needing those supports. More serious harm would occur if risk scores were used to discourage students deemed at-risk from attempting a degree program, since for about 5% of those identified persons would have completed a degree. We would argue against that type of use for early indicators.

This research collaboration has shown that it is possible to develop early indicators of student success. As more states provide access to SURDS data, we expect to see wider use of early indicators of student success as a way of targeting support services and for assessing institutional interventions aimed at improving student success.

Statement of Research Ethics

Each of the state SURDS datasets are maintained in secure facilities. Analyses were undertaken using protocols that were approved by the Institutional Review Boards for each state entity.

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[i] Also known as Student Unit Record Systems (SURS), or as State Longitudinal Data Systems (SLDSs). The abbreviation SURDS will be used for this paper.

[ii] These figures were calculated by the authors using nationally-representative data for people aged 25 to 35 in the public use microsample of the 2015 American Community Survey (ACS). The ACS education variable does not identify people who received only a certificate while in college, so those individuals are counted among the college-going group who did not complete a degree.

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Table 1. AA students' predicted probability distribution of graduation by actual % of students that did not graduate

Probability group by model prediction on test data	**New York** (*N*=107,351)		**Texas** (*N*=46,244)		**Virginia** (*N*=60,085)		**Illinois** (*N*=34,828)	
	Model A[a]	Model B[b]	Model A	Model B	Model A	Model B	Model A	Model B
bottom 1% (least likely to graduate)	86.90	97.95	94.34	98.49	85.00	99.18	93.14	97.44
bottom 5%	84.45	96.52	91.75	96.20	87.41	97.63	86.94	97.36
bottom 10%	83.29	95.46	90.64	95.63	87.77	96.98	85.79	97.50
2nd decile	79.27	90.90	87.55	92.69	87.91	94.40	81.07	95.64
3rd decile	74.67	85.10	84.01	88.95	83.83	91.97	76.22	89.58
4th decile	72.13	78.32	82.64	83.95	82.88	86.74	70.87	82.03
5th decile	69.65	71.36	78.06	78.14	78.21	83.08	68.08	71.11
6th decile	64.73	63.13	73.01	71.96	76.85	76.62	63.04	63.16
7th decile	59.87	55.64	65.36	59.45	69.92	69.57	58.61	51.94
8th decile	55.67	46.22	47.04	45.21	64.10	60.35	53.19	41.99
9th decile	48.25	35.58	26.71	24.72	57.03	47.12	45.16	30.20
10th decile (most likely to graduate)	35.92	21.80	15.23	10.08	44.41	28.87	34.28	15.42
% did not graduate overall	**64.35**	**64.35**	**65.08**	**65.08**	**73.58**	**73.58**	**63.86**	**63.86**

Note: [a] Model A = Variables at college entry. [b] Model B = Variables at college entry + 1st semester variables.

Table 2. BA students' predicted probability distribution of graduation by actual % of students that did not graduate

Probability group by model prediction on test data	**New York** (N=47,045)		**Texas** (N=20,736)		**Virginia** (N=63,773)	
	Model A[a]	Model B[b]	Model A	Model B	Model A	Model B
bottom 1% (least likely to graduate)	87.42	96.96	91.83	98.56	76.18	94.98
bottom 5%	81.42	95.66	87.15	96.53	65.07	86.58
bottom 10%	76.22	92.90	82.74	94.17	60.33	78.07
2nd decile	67.12	80.22	68.38	81.73	48.74	52.96
3rd decile	61.29	67.59	60.42	66.57	38.47	38.92
4th decile	58.12	59.54	53.24	54.58	30.25	27.94
5th decile	52.61	50.56	47.58	45.24	24.89	20.57
6th decile	49.52	44.62	41.91	35.47	18.82	15.56
7th decile	46.84	38.83	34.00	28.96	16.78	12.06
8th decile	41.79	34.09	26.20	20.09	13.42	10.12
9th decile	35.06	26.20	21.52	15.25	9.14	7.39
10th decile (most likely to graduate)	21.47	15.90	13.66	10.44	7.04	4.50
% did not graduate overall	**51.05**	**51.05**	**45.25**	**45.25**	**26.81**	**26.81**

Note: [a] Model A = Variables at college entry. [b] Model B = Variables at college entry + 1st semester variables.

Appendix A. Variables descriptions (New York)

Dependent variable
Graduation (AA, BA, or 60 credits for AA entrants)

Race
White
Black
Hispanic
Asian
Native American

High school GPA
A-/A: 3.67-4.00
B+: 3.33-3.67
B: 3.00-3.33
B-: 2.67-3.00
C+: 2.33-2.67
No HS GPA record

SAT score
1st quintile
2nd quintile
3rd quintile
4th quintile
5th quintile
No SAT score

Age at entry
18 or younger
19
20
21
22
23
24
25 or older

Parental adjusted gross income

1st quartile (highest)
2nd quartile
3rd quartile
4th quartile
Parent AGI missing
Parent AGI missing for cohort

Major in semester 1

Declared
Not declared
Unclassified (unknown)

Remedial requirements at entry

No remedial requirement
Remedial math required only
Remedial reading required only
Remedial writing required only
Two or more remedial requirements
Remedial requirement unknown

Remedial math semester 1

Not required, not taken
Required, not taken
Passed all
Failed/withdrew one or more

Remedial reading semester 1

Not required, not taken
Required, not taken
Passed all
Failed/withdrew one or more

Remedial writing semester 1

Not required, not taken
Required, not taken
Passed all

Failed/withdrew one or more	
Workload semester 1	
< 8 credits	
≥ 8 credits & < 12 credits	
≥ 12 credits & < 14 credits	
≥ 14 credits & < 16 credits	
≥ 16 credits & < 18 credits	
≥ 18 credits & < 20 credits	
> 20 credits	
Credits earned semester 1	
0 credits (but enrolled)	
> 0 credits & < 4 credits	
≥ 4 credits & < 8 credits	
≥ 8 credits & < 12 credits	
≥ 12 credits & < 14 credits	
≥ 14 credits & < 16 credits	
≥ 16 credits & < 18 credits	
≥ 18 credits & < 20 credits	
20 credits or more	
GPA semester 1 (non-remedial)	
A-/A: 3.67-4.00	
B+: 3.33-3.67	
B: 3.00-3.33	
B-: 2.67-3.00	
C+: 2.33-2.67	
C: 2.00-2.33	
C-: 1.67-2.00	
D+: 1.33-1.67	
D: 1.00-1.33	
D-/F: <1.00	
Enrolled, no GPA record	

Appendix B1. Predicting graduation with variables at entry and first semester (New York)

Variables	AA at entry Coefficients (SE)		BA at entry Coefficients (SE)	
	Entry variables	**Entry + semester 1 variables**	**Entry variables**	**Entry + semester 1 variables**
SAT quintiles (ref. = 3rd quintile)				
1st quintile (lowest)	-0.36***	0.052**	-0.16***	-0.018
	(0.016)	(0.018)	(0.027)	(0.029)
2nd quintile	-0.11***	0.071***	-0.032	0.031
	(0.016)	(0.018)	(0.021)	(0.023)
4th quintile	0.019	-0.12***	0.028	0.0064
	(0.022)	(0.024)	(0.017)	(0.018)
5th quintile (highest)	-0.074*	-0.33***	0.15***	-0.0039
	(0.033)	(0.037)	(0.017)	(0.018)
No SAT score	-0.62***	-0.27***	-0.20***	-0.12***
	(0.014)	(0.016)	(0.028)	(0.030)
Workload semester 1 (ref. 12 to 13 credits)				
Less than 8 credits	-0.63***	-0.24***	-1.10***	-0.30***
	(0.019)	(0.021)	(0.047)	(0.054)
8 to 11 credits	-0.38***	-0.14***	-0.57***	-0.20***
	(0.016)	(0.017)	(0.042)	(0.045)
14 to 15 credits	0.16***	0.10***	0.23***	-0.0065
	(0.0093)	(0.011)	(0.012)	(0.017)
16 to 17 credits	0.26***	0.088***	0.33***	-0.0042
	(0.012)	(0.014)	(0.016)	(0.022)
18 to 19 credits	0.39***	0.12***	0.22***	-0.10
	(0.015)	(0.017)	(0.049)	(0.059)
20 or more credits	0.73***	0.29***	0.071	0.059
	(0.016)	(0.018)	(0.095)	(0.10)
Major selection at entry (ref. = declared major)				
Did not declare major	0.11**	0.27***	0.032**	0.011
	(0.039)	(0.044)	(0.012)	(0.013)
Unclassified	0.032	-0.10***	0.33	0.23
	(0.017)	(0.019)	(0.17)	(0.18)
HS GPA (ref. = C+ or less: 0-2.66)				
B-: 2.67-2.99	0.48***	0.22***	0.50***	0.38***
	(0.0098)	(0.011)	(0.026)	(0.028)
B: 3.00-3.32	0.91***	0.45***	1.01***	0.72***
	(0.012)	(0.014)	(0.025)	(0.027)
B+: 3.33 - 3.66	1.30***	0.69***	1.64***	1.04***
	(0.021)	(0.023)	(0.027)	(0.029)

A-/A: 3.67-4.00	1.64***	0.91***	2.11***	1.24***
	(0.046)	(0.051)	(0.037)	(0.040)
No HS GPA record	0.21***	0.11***	0.88***	0.48***
	(0.010)	(0.011)	(0.037)	(0.040)
Age at entry (ref. = 19)				
18 or younger	0.21***	0.16***	0.10***	0.081***
	(0.012)	(0.013)	(0.013)	(0.014)
20	-0.29***	-0.26***	-0.27***	-0.24***
	(0.011)	(0.012)	(0.019)	(0.021)
21	-0.42***	-0.42***	-0.40***	-0.34***
	(0.014)	(0.016)	(0.033)	(0.035)
22	-0.34***	-0.40***	-0.42***	-0.40***
	(0.018)	(0.020)	(0.045)	(0.048)
23	-0.24***	-0.40***	-0.39***	-0.58***
	(0.017)	(0.019)	(0.048)	(0.051)
24 or older	-0.021	-0.35***	-0.30***	-0.64***
	(0.013)	(0.014)	(0.039)	(0.042)
Entry age missing	-2.84**	-2.61*	-1.39	-1.50
	(1.02)	(1.04)	(0.88)	(0.98)
Parental adjusted gross income (ref. = bottom quartile)				
Parent AGI missing	-0.11***	-0.20***	-0.21***	-0.24***
	(0.014)	(0.016)	(0.023)	(0.025)
2nd quartile	-0.015	-0.024	0.023	-0.011
	(0.017)	(0.019)	(0.025)	(0.026)
3rd quartile	-0.16***	-0.20***	-0.030	-0.091***
	(0.017)	(0.019)	(0.025)	(0.027)
Top quartile	-0.091***	-0.22***	0.11***	-0.0030
	(0.018)	(0.020)	(0.023)	(0.025)
Parental AGI missing for cohort	-0.047***	-0.14***	0.21***	0.32***
	(0.013)	(0.015)	(0.020)	(0.021)
Remedial requirement at entry (ref. = no remedial requirement)				
Remedial math required only	-0.073***			
	(0.011)			
Remedial reading required only	0.49***			
	(0.033)			
Remedial writing required only	0.28***			
	(0.013)			
2 or more remedial requirements	-0.21***			
	(0.0100)			
Remedial requirement unknown	0.028*			
	(0.013)			
GPA semester 1 (ref. = D-/F: <1.00)				

D: 1.00-1.32	0.28***	0.28***
	(0.030)	(0.077)
D+: 1.33-1.66	0.31***	0.53***
	(0.029)	(0.070)
C-: 1.67-1.99	0.47***	0.77***
	(0.029)	(0.068)
C: 2.00-2.32	0.70***	0.96***
	(0.026)	(0.066)
C+: 2.33-2.66	0.86***	1.20***
	(0.027)	(0.066)
B-: 2.67-2.99	1.03***	1.39***
	(0.026)	(0.066)
B: 3.00-3.32	1.25***	1.63***
	(0.025)	(0.065)
B+: 3.33 - 3.66	1.53***	1.92***
	(0.028)	(0.066)
A-/A: 3.67-4.00	1.71***	2.20***
	(0.026)	(0.066)
No GPA record	0.99***	1.08***
	(0.024)	(0.085)
Credits earned semester 1 (ref. = 12 to 13 credits)		
0 credits	-1.79***	-1.66***
	(0.034)	(0.090)
1 to 3 credits	-1.31***	-1.27***
	(0.019)	(0.053)
4 to 7 credits	-0.83***	-0.83***
	(0.016)	(0.027)
8 to 11 credits	-0.38***	-0.38***
	(0.015)	(0.017)
14 to 15 credits	0.24***	0.31***
	(0.024)	(0.020)
16 to 17 credits	0.45***	0.52***
	(0.039)	(0.029)
18 to 19 credits	0.72***	0.39**
	(0.061)	(0.12)
20 or more credits	0.85***	0.69
	(0.089)	(0.54)
Remedial math semester 1 (ref. = not required, not taken)		
Required, not taken	-0.44***	
	(0.016)	
Passed all	0.029**	
	(0.010)	
Failed/withdrew one or more	-0.54***	

		(0.013)		
Remedial reading semester 1 (ref. = not required, not taken)				
Required, not taken		0.13***		
		(0.022)		
Passed all		0.27***		
		(0.013)		
Failed/withdrew one or more		-0.30***		
		(0.023)		
Remedial writing semester 1 (ref. = not required, not taken)				
Required, not taken		0.17***		
		(0.014)		
Passed all		0.14***		
		(0.011)		
Failed/withdrew one or more		-0.26***		
		(0.015)		
Constant	-0.36***	-0.33***	-1.25***	-2.01***
	(0.019)	(0.033)	(0.033)	(0.073)
Observations	357,836	357,836	153,795	153,795

*** p<0.001, ** p<0.01, * p<0.05

Appendix B2. Predicting graduation with variables at entry and first semester (Texas)

	AA at entry Odds Ratios (SE)		**BA at entry** Odds Ratios (SE)	
Variables	**Entry variables**	**Entry + semester 1 variables**	**Entry variables**	**Entry + semester 1 variables**
TAKS-reading quintiles (ref. = 3rd quintile)				
1st quintile	0.858***	0.902**		
	(0.030)	(0.033)		
2nd quintile	0.950	0.968		
	(0.031)	(0.033)		
4th quintile	1.089*	1.048		
	(0.040)	(0.041)		
5th quintile (highest)	1.158***	1.067		
	(0.049)	(0.048)		
No TAKS-reading score	0.927	0.849*		
	(0.070)	(0.070)		
TAKS-math quintiles (ref. = 1st quintile)				
1st quintile	0.706***	0.807***		
	(0.024)	(0.029)		
2nd quintile	0.901*	0.945		
	(0.029)	(0.032)		
4th quintile	1.186***	1.107**		
	(0.042)	(0.041)		
5th quintile (highest)	1.349***	1.153**		
	(0.060)	(0.054)		
No TAKS-math score	0.967	0.969		
	(0.074)	(0.080)		
SAT quintiles (ref. = 1st quintile)				
2nd quintile			1.368***	1.198***
			(0.053)	(0.051)
3rd quintile			1.646***	1.252***
			(0.066)	(0.057)
4th quintile			1.863***	1.284***
			(0.075)	(0.059)
5th quintile (highest)			2.408***	1.382***
			(0.103)	(0.067)
No SAT score			0.902*	0.689***
			(0.045)	(0.039)
Workload semester 1 (ref. 12 to 13 credits)				
Less than 8 credits	0.631***	0.951	0.790***	1.281**

	(0.013)	(0.028)	(0.045)	(0.105)
8 to 11 credits	0.871***	1.008	0.575***	0.766***
	(0.019)	(0.024)	(0.039)	(0.060)
14 to 15 credits	1.121***	0.984	1.307***	0.977
	(0.031)	(0.032)	(0.030)	(0.036)
16 to 17 credits	1.138***	0.925	1.436***	0.852**
	(0.043)	(0.042)	(0.044)	(0.044)
18 to 19 credits	1.279***	1.015	1.607***	0.790
	(0.058)	(0.054)	(0.148)	(0.105)
20 or more credits	1.317***	1.052	2.054***	0.781
	(0.049)	(0.057)	(0.240)	(0.161)
Major selection at entry (ref. = Declared major)				
Did not declare major	1.052***	1.077***	0.809***	0.865***
	(0.016)	(0.017)	(0.018)	(0.021)
HS class rank by quartile (ref. = 3rd quartile)				
1st quartile (highest)	0.606***	0.562***	3.200***	2.345***
	(0.041)	(0.038)	(0.088)	(0.071)
2nd quartile	0.777***	0.746***	1.922***	1.568***
	(0.041)	(0.039)	(0.047)	(0.042)
4th quartile (lowest)	0.608***	0.742***	0.790**	0.846*
	(0.012)	(0.015)	(0.061)	(0.072)
Age at entry (ref. = 19)				
18 or younger	1.154***	1.126***	1.171***	1.153***
	(0.028)	(0.028)	(0.043)	(0.047)
20	0.956	0.977	0.601***	0.648**
	(0.040)	(0.041)	(0.076)	(0.090)
21	0.920	0.917	0.672*	0.716
	(0.046)	(0.047)	(0.115)	(0.134)
22	1.078	1.044	1.140	1.053
	(0.057)	(0.056)	(0.218)	(0.222)
23	1.075	1.013	1.151	0.961
	(0.062)	(0.060)	(0.237)	(0.219)
24	1.051	0.974	1.512	1.214
	(0.063)	(0.059)	(0.355)	(0.324)
25 or older	1.290***	1.148***	1.018	0.813
	(0.041)	(0.038)	(0.115)	(0.101)
Parental adjusted gross income (ref. = bottom quartile)				
Parent AGI missing	1.024	0.944*	1.301***	0.966
	(0.024)	(0.023)	(0.069)	(0.056)
2nd quartile	1.116***	1.051	1.179***	1.163***
	(0.028)	(0.027)	(0.047)	(0.051)
3rd quartile	1.177***	1.056*	1.354***	1.292***

	(0.031)	(0.028)	(0.051)	(0.053)
Top quartile	0.987	0.866***	2.085***	1.853***
	(0.029)	(0.025)	(0.072)	(0.070)
Remedial requirement at entry (ref. = no remedial requirement)				
Remedial math required only	0.901***	0.993	0.662***	0.818**
	(0.019)	(0.028)	(0.035)	(0.055)
Remedial reading required only	1.046	1.109	0.761**	0.801
	(0.049)	(0.062)	(0.072)	(0.106)
Remedial writing required only	0.947	1.082	0.642***	0.687**
	(0.052)	(0.067)	(0.063)	(0.092)
2 or more remedial requirements	0.646***	0.903**	0.536***	0.598***
	(0.013)	(0.036)	(0.024)	(0.073)
GPA semester 1 (ref. = D-/F: <1.00)				
D: 1.00-1.32		1.640***		2.647***
		(0.080)		(0.220)
D+: 1.33-1.66		1.983***		3.764***
		(0.094)		(0.281)
C-: 1.67-1.99		2.429***		4.892***
		(0.149)		(0.364)
C: 2.00-2.32		2.407***		7.175***
		(0.092)		(0.481)
C+: 2.33-2.66		2.756***		10.175***
		(0.108)		(0.675)
B-: 2.67-2.99		2.945***		12.651***
		(0.146)		(0.864)
B: 3.00-3.32		2.880***		16.925***
		(0.102)		(1.112)
B+: 3.33 - 3.66		3.010***		21.728***
		(0.119)		(1.476)
A+/A: 3.67-4.00		3.133***		25.308***
		(0.114)		(1.760)
Credits earned semester 1 (ref. = 4 to 7 credits)				
0 credits		1.336***		2.174***
		(0.055)		(0.387)
1 to 3 credits		0.733***		0.515***
		(0.020)		(0.054)
8 to 11 credits		1.290***		1.842***
		(0.034)		(0.119)
12 to 13 credits		1.515***		2.802***
		(0.050)		(0.185)
14 to 15 credits		1.540***		3.404***
		(0.077)		(0.253)

16 to 17 credits		1.474***		3.889***
		(0.099)		(0.346)
18 to 19 credits		1.492***		4.469***
		(0.116)		(0.839)
20 or more credits		1.347***		5.381***
		(0.102)		(1.352)
Remedial math semester 1 (ref. = not required, not taken)				
Required, not taken		0.896***		0.931
		(0.029)		(0.072)
Passed all		1.297***		1.108*
		(0.032)		(0.050)
Failed/withdrew one or more		0.775***		0.669***
		(0.026)		(0.042)
Remedial reading semester 1 (ref. = not required, not taken)				
Required, not taken		0.960		1.105
		(0.038)		(0.128)
Passed all		1.250***		1.175
		(0.041)		(0.106)
Failed/withdrew one or more		0.612***		0.584**
		(0.036)		(0.102)
Remedial writing semester 1 (ref. = not required, not taken)				
Required, not taken		0.877***		1.104
		(0.032)		(0.124)
Passed all		1.230***		1.288**
		(0.037)		(0.112)
Failed/withdrew one or more		0.677***		0.780
		(0.037)		(0.118)
Constant	0.443***	0.141***	0.276***	0.021***
	(0.020)	(0.008)	(0.015)	(0.002)
Observations	107,983	107,983	48,783	48,783

*** p<0.001, ** p<0.01, * p<0.05

Appendix B3. Predicting graduation with variables at entry and first semester (Virginia)

Variables	Entry variables	Entry + semester 1 variables	Entry variables	Entry + semester 1 variables
SAT quintiles (ref. = 1st quintile)				
2nd quintile (2nd lowest)	0.866	0.915	1.121***	1.142***
	(0.112)	(0.131)	(0.017)	(0.019)
3rd quintile	0.733	0.791	1.252***	1.228***
	(0.127)	(0.152)	(0.020)	(0.021)
4th quintile	0.481**	0.506*	1.389***	1.280***
	(0.118)	(0.136)	(0.024)	(0.024)
5th quintile (highest)	1.506	1.681	1.947***	1.479***
	(0.690)	(0.874)	(0.039)	(0.031)
No SAT score	0.752***	0.564***	0.816***	0.829***
	(0.043)	(0.035)	(0.014)	(0.015)
Workload semester 1 (ref. = less than 8 credits)				
8 to 11 credits	1.864***	1.112***	1.535***	0.891
	(0.024)	(0.023)	(0.108)	(0.067)
12 to 13 credits	2.977***	1.296***	2.457	0.883
	(0.044)	(0.034)	(0.157)	(0.062)
14 to 15 credits	4.659***	1.583***	3.657***	0.947
	(0.085)	(0.051)	(0.233)	(0.066)
16 to 17 credits	5.803***	1.441***	3.965***	0.830**
	(0.139)	(0.063)	(0.253)	(0.059)
18 to 19 credits	1.127***	1.515***	3.617***	0.617***
	(0.094)	(0.129)	(0.257)	(0.053)
20 or more credits	6.769***	0.884	2.939***	0.781
Missing	(0.350)	(0.220)	(0.352)	(0.135)
	0.766***	0.517***	2.522***	2.316***
	(0.018)	(0.025)	(0.240)	(0.235)
Major selection at entry (ref. = declared major)				
Did not declare major	2.472***	2.834***	1.017	1.050***
	(0.350)	(0.428)	(0.010)	(0.011)
HS GPA (ref. = C+)				
B-	1.376***	1.182**	1.346***	1.191***
	(0.075)	(0.069)	(0.033)	(0.032)
B	1.987***	1.396***	2.127***	1.620***
	(0.112)	(0.085)	(0.049)	(0.041)
B+	2.965***	1.743***	3.394***	2.156***
	(0.200)	(0.127)	(0.080)	(0.055)
A/A+	4.389***	2.031***	6.810***	3.344***
	(0.380)	(0.188)	(0.163)	(0.088)

Missing	1.244***	1.147***	2.793***	1.748***
	(0.049)	(0.049)	(0.069)	(0.047)
Age at entry (ref. = 18 or younger)				
19	0.800***	0.804***	0.938***	0.933***
	(0.010)	(0.011)	(0.012)	(0.013)
20	0.663***	0.631***	0.593***	0.587***
	(0.014)	(0.015)	(0.026)	(0.028)
21	0.626***	0.546***	0.546***	0.521***
	(0.018)	(0.017)	(0.041)	(0.043)
22	0.655***	0.518***	0.415***	0.378***
	(0.021)	(0.018)	(0.040)	(0.039)
23	0.691***	0.525***	0.525***	0.453***
	(0.024)	(0.019)	(0.061)	(0.056)
24	0.667***	0.478***	0.447***	0.392***
	(0.024)	(0.018)	(0.058)	(0.055)
25 or older	0.721***	0.488*	0.523***	0.425***
	(0.011)	(0.008)	(0.037)	(0.032)
Parental adjusted gross income (ref. = bottom quartile)				
Parent AGI missing	1.389***	1.235***	1.879***	1.735***
	(0.019)	(0.018)	(0.034)	(0.034)
2nd quartile	1.432***	1.223***	1.164***	1.099***
	(0.023)	(0.021)	(0.023)	(0.024)
3rd quartile	1.793***	1.360***	1.406***	1.309***
	(0.031)	(0.026)	(0.026)	(0.026)
Top quartile	1.972***	1.498***	1.910***	1.727***
	(0.050)	(0.042)	(0.036)	(0.035)
Remedial courses taken at entry (ref. = none taken)				
Remedial math only	1.213***	0.869***	1.187*	1.615***
	(0.016)	(0.016)	(0.104)	(0.171)
Remedial English only	1.293***	0.882***	1.308	2.325***
	(0.020)	(0.019)	(0.198)	(0.450)
2 or more remedial classes	1.231***	0.880***	1.380	2.486**
	(0.019)	(0.019)	(0.420)	(0.842)
GPA semester 1 (ref. = D-/F: <1.00)				
D		1.086		1.617***
		(0.054)		(0.091)
D+		1.399***		1.902***
		(0.050)		(0.093)
C-		1.743***		2.509***
		(0.054)		(0.116)
C		1.989***		3.306***
		(0.071)		(0.153)

C+		2.421***		4.390***
		(0.076)		(0.201)
B-		3.025***		5.650***
		(0.089)		(0.258)
B		3.864***		7.542***
		(0.126)		(0.349)
B+		4.669***		8.751***
		(0.145)		(0.410)
A+/A		5.503***		10.421***
		(0.157)		(0.498)
No GPA record		2.479***		3.802***
		(0.097)		(0.274)
Credits earned semester 1 (ref. = 4 to 7 credits)				
0 credits		0.357***		0.866
		(0.014)		(0.064)
1 to 3 credits		0.515***		0.541***
		(0.009)		(0.033)
8 to 11 credits		1.659***		1.795***
		(0.034)		(0.058)
12 to 13 credits		2.536***		2.973***
		(0.070)		(0.097)
14 to 15 credits		3.249***		4.110***
		(0.118)		(0.140)
16 to 17 credits		4.279***		4.909***
		(0.224)		(0.183)
18 to 19 credits		4.262***		6.167***
		(0.484)		(0.471)
20 or more credits		2.955***		2.486***
		(0.841)		(0.544)
Remedial semester 1 (ref. = none taken)				
Failed/Withdrawn		0.751***		0.480***
		(0.019)		(0.076)
Passed		2.093**		0.890
		(0.037)		(0.091)
Constant	0.173***	0.155***	0.141***	0.057***
	(0.011)	(0.012)	(0.010)	(0.005)
Observations	263,857	263,857	277,915	277,915

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Appendix B4. Predicting graduation with variables at entry and first semester (Illinois)

	AA at entry Odds Ratios	
Variables	**Entry variables**	**Entry + semester 1 variables**
ACT score (ref. = 17-24)		
ACT score 1-8	0.709	1.208
	(0.337)	(0.623)
ACT score 9-16	0.764***	0.862***
	(0.028)	(0.038)
ACT score 25-30	0.792	0.711*
	(0.115)	(0.120)
ACT score 31-36	0.458***	0.610***
	(0.022)	(0.033)
Unknown	0.534***	0.594***
	(0.020)	(0.026)
Workload semester 1 (ref. 12 to 13 credits)		
Less than 8 credits	0.206***	1.015
	(0.031)	(0.167)
8 to 11 credits	0.397***	0.908
	(0.028)	(0.071)
14 to 15 credits	1.524***	1.084**
	(0.027)	(0.033)
16 to 17 credits	2.197***	1.133***
	(0.051)	(0.044)
18 to 19 credits	2.436***	0.935
	(0.100)	(0.067)
20 or more credits	2.689***	0.919
	(0.161)	(0.107)
Major selection at entry (ref. = liberal arts)		
General studies – AA		0.746***
		(0.021)

General studies – AS		1.042
		(0.025)
Others		0.860***
		(0.019)
HS GPA percentile (ref. = 0 percentile rank)		
25% or less		
	1.069	1.150**
	(0.046)	(0.058)
26-50%		
	1.298***	1.172***
	(0.052)	(0.053)
51-75%		
	1.375***	1.154**
	(0.056)	(0.053)
76-100%		
	1.271***	1.086
	(0.056)	(0.056)
Unknown		
	1.068	1.052
	(0.037)	(0.041)
Age at entry (ref. = 19)		
18 or younger		
	1.488***	1.293***
	(0.037)	(0.037)
20		
	0.858***	0.895*
	(0.040)	(0.047)
21		
	0.750***	0.710***
	(0.046)	(0.048)
22		
	0.860*	0.695***
	(0.059)	(0.053)
23		
	1.029	0.749***
	(0.072)	(0.059)
24	0.914	0.626***
	(0.072)	(0.055)
25 or older		
	1.164***	0.723***
	(0.043)	(0.030)
Economic disadvantage status (ref. = no)		
Yes	0.823***	0.851***
	(0.014)	(0.016)

Remedial requirement at entry (ref. = no remedial requirement)		
Remedial math required only	0.675***	
	(0.012)	
Remedial reading required only	0.529***	
	(0.029)	
Remedial writing required only	0.599***	
	(0.026)	
2 or more remedial requirements	0.379***	
	(0.009)	
GPA semester 1 (ref. = D-/F: <1.00)		
D: 1.00-1.32		1.325***
		(0.107)
D+: 1.33-1.66		1.717***
		(0.124)
C-: 1.67-1.99		3.489***
		(0.214)
C: 2.00-2.32		2.602***
		(0.176)
C+: 2.33-2.66		5.622***
		(0.342)
B-: 2.67-2.99		10.300***
		(0.620)
B: 3.00-3.32		8.629***
		(0.528)
B+: 3.33 - 3.66		15.318***
		(0.957)
A+/A: 3.67-4.00		18.125***
		(1.140)
Credits earned semester 1 (ref. = 12 to 13 credits)		
0 credits		0.338***

		(0.025)
1 to 3 credits		0.246***
		(0.018)
4 to 7 credits		0.390***
		(0.017)
8 to 11 credits		0.603***
		(0.017)
14 to 15 credits		1.294***
		(0.046)
16 to 17 credits		1.767***
		(0.083)
18 to 19 credits		2.101***
		(0.190)
20 or more credits		1.875***
		(0.264)
Remedial math semester 1 (ref. = not required, not taken)		
Required, not taken		1.003
		(0.022)
Passed all		1.432***
		(0.040)
Failed/withdrew one or more		1.444***
		(0.080)
Remedial English semester 1 (ref. = not required, not taken)		
Required, not taken		1.005
		(0.078)
Passed all		1.415***
		(0.029)
Failed/withdrew one or more		0.884**
		(0.041)
Constant	0.736***	0.124***

	(0.038)	(0.010)
Observations	81,600	81,600

*** p<0.001, ** p<0.01, * p<0.05