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POLICY BRIEF

Early Leading Indicators of Student Success: A Multi-State Analysis

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What We Studied

Despite considerable advances made in broadening access to higher education, some evidence suggests that college completion rates have actually declined over time, and attainment gaps stemming from race/ethnicity and socioeconomic background have remained stubbornly persistent (Bound, Lovenheim, & Turner, 2010; National Center for Education Statistics, 2019). Colleges and universities are searching for ways to better identify students with lower odds of postsecondary success and develop programs to support their persistence and completion. A number of for-profit companies have developed proprietary software, such as "early warning systems," that analyze student and institutional data to make those predictions. However, this software is not accessible to all institutions, and rarely do these companies disclose the nature, validity, or reliability of their algorithms.

In this paper, we present collaborative research from four different states – Texas, New York, Virginia and Illinois – examining the feasibility and accuracy of models that predict students' likelihood of degree completion using only administrative data on students' pre-college characteristics and early college experiences. We employ fairly simple statistical methods on statewide longitudinal data systems (also known as student unit records systems or "SURDS") to predict degree completion for undergraduate students. Importantly, our focus is on the overall predictive validity of these models, which is often neglected in educational research that focuses on relationships between student characteristics and degree completion (American Diploma Project, 2004; Adelman, 1997, 1999, 2006; Attewell, Heil & Reisel, 2011; Braxton, 2000; Chen & Carroll, 2005; Complete College America, 2011; Horn, Kojaku & Carroll, 2001; Tinto, 1994, 2012).

Our results show that we can accurately predict students' probability of graduating with such early SURDS indicators. This suggests that state agencies and organizations that house this longitudinal data could use it to make these types of predictive systems more accessible to colleges and universities, particularly those that do not have the in-house capacity to conduct these types of analyses. These systems could be used to help prioritize student supports and evaluate the efficacy of those interventions. The remainder of this brief more deeply discusses the data and methods used in this study, our results, and the significance of this work.

How We Analyzed the Data

Researchers in each state had access to and analyzed their own state's SURDS database. In Texas, the Texas Education Research Center was used to integrate data from the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and the Texas Workforce Commission (TWC). While researchers in other states used data on entering cohorts stretching as far back as Fall 1999, we used data on beginning college students in Texas in 2010-11 due to the lack of availability of college course enrollment data before this point. While the sample includes students from different high school graduate cohorts, it is restricted to students who graduated from a Texas public

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high school. The sample includes n = 108,028 students who began at a public two-year institution and n = 48,541 students who began at a public four-year institution.

Variables

We have two primary outcome variables: persistence and attainment. Persistence is defined as whether students were enrolled in any postsecondary institution in the third long semester (Fall or Spring) after beginning college. Attainment is defined slightly differently depending on whether students began at a two-year or a four-year. For four-year students, attainment is a dichotomous indicator of whether students earned a bachelor's degree within six years of first enrollment. 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 & 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 or class rank (for Texas), a measure of standardized achievement (SAT, ACT, or TAKS score), remedial requirements (math, reading, writing), credit load 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; and whether remedial courses were taken in the first semester (if required), and if so whether they were passed. All continuous variables were converted into categorical predictors, allowing the addition of a "missing" category for each variable. This list of variables and their possible values is included in Table A1 in the Appendix.

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 often associated with college outcomes, 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.

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 & 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 & 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.

What We Discovered

Table A2 in the Appendix provides the statistical models used to estimate students' likelihood of predicting their college outcomes. Generally, the most powerful predictors for graduation in the regression analyses underlying our models 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.

We focus our discussion on the models predicting graduation in the remainder of the paper. Table 1 reports predicted graduation 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.

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.

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.

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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 accuracy 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

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.

Discussion/Policy Recommendations

We have demonstrated that 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. Of course, platforms that integrate additional data sources from students – surveys administered to them, online course engagement, and use of institutional services – would likely have even greater predictive accuracy. But platforms with these capabilities are both costly to acquire and complex to administer and keep up-to-date.

As state agencies continue to invest in modernizing data infrastructure, we believe it is both feasible and extremely useful to develop systems using approaches such as those described in this paper to provide institutions greater information about students' academic needs. Doing so would allow institutions to better tailor interventions and supports to specific groups of students. Additionally, students' predicted success rates themselves can be used as a meaningful outcome rather than waiting as many as six years to determine if interventions moved the needle on student success.

While the benefits of this approach are promising, we conclude with two cautionary points. First, institutions could use these types of methods to identify students with lower likelihood of graduating and deny them admissions as a result. We would strongly advise against approach, as it could have a disparate impact on students of color and low-income students. Second, there are various other methodologies that could be used for this purpose, some with greater accuracy than logistic regression. There is an important tradeoff between the predictive accuracy of the model and the interpretability of the results. While we erred on the side of well-known methods that are easier to interpret, additional research should investigate potential improvements to the models and the tradeoffs with interpretability.

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Appendix

Table A1

Variables Description (New York)

Dependent variable

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

Independent variables

Age at entry

- 18 or younger
- 19
- 20
- 21
- 22
- 23
- 24
- 25 or older

SAT score

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

Major in semester 1

- Declared
- Not declared
- Unclassified (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

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

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

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

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

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

Table A2:

Logistic Regression Models of Persistence and Attainment

	Two-Year Institution Models			Four-Year Institution Models		
	Model 1 (Persist)	Model 2a (Attain)	Model 2b (Attain)	Model 1 (Persist)	Model 2a (Attain)	Model 2b (Attain)
Age at Enrollment (19)						
<19	1.300***	1.171***	1.147***	1.313***	1.171***	1.153***
	(0.0281)	(0.0280)	(0.0290)	(0.0640)	(0.0434)	(0.0470)
20	0.851***	0.944	0.960	0.599***	0.601***	0.648**
	(0.0293)	(0.0377)	(0.0404)	(0.0718)	(0.0758)	(0.0904)
21	0.858***	0.960	0.948	0.719*	0.672*	0.716
	(0.0352)	(0.0454)	(0.0473)	(0.111)	(0.115)	(0.134)
22	0.861***	1.061	0.991	0.595**	1.140	1.053
	(0.0382)	(0.0533)	(0.0524)	(0.116)	(0.218)	(0.222)
23	0.917	1.082	0.996	0.927	1.151	0.961
	(0.0445)	(0.0595)	(0.0577)	(0.205)	(0.237)	(0.219)
24	0.875**	1.046	0.909	0.817	1.512	1.214
	(0.0436)	(0.0595)	(0.0547)	(0.211)	(0.355)	(0.324)
25+	1.018	1.200***	0.974	0.758*	1.018	0.813
	(0.0284)	(0.0373)	(0.0322)	(0.0862)	(0.115)	(0.101)
Income Quartile (Bottom 25%)						
25-50%	1.057*	1.177***	1.077**	1.102	1.179***	1.163***
	(0.0245)	(0.0295)	(0.0287)	(0.0557)	(0.0467)	(0.0505)
50-75%	1.071**	1.294***	1.099***	1.265***	1.354***	1.292***
	(0.0262)	(0.0336)	(0.0302)	(0.0622)	(0.0506)	(0.0529)
Top 25%	1.148***	1.488***	1.204***	1.657***	2.085***	1.853***
	(0.0327)	(0.0426)	(0.0363)	(0.0778)	(0.0718)	(0.0699)
no record	1.006	1.138***	0.985	0.716***	1.301***	0.966
	(0.0207)	(0.0262)	(0.0240)	(0.0462)	(0.0694)	(0.0558)
HS Class Rank (26-100%)						
Top 10%	0.961	1.070	0.813**	2.013***	3.200***	2.345***
	(0.0786)	(0.0776)	(0.0608)	(0.0972)	(0.0879)	(0.0706)
11-25%	1.016	0.817***	0.687***	1.409***	1.922***	1.568***
	(0.0672)	(0.0444)	(0.0390)	(0.0553)	(0.0473)	(0.0421)
Missing	0.333***	0.113***	0.125***	0.801**	0.790**	0.846*
	(0.0070)	(0.0022)	(0.0026)	(0.0622)	(0.0612)	(0.0720)
SAT Score Quintile (1st)						
2nd				1.014	1.368***	1.198***
				(0.0525)	(0.0531)	(0.0513)
3rd				1.045	1.646***	1.252***
				(0.0598)	(0.0665)	(0.0569)
4th				1.056	1.863***	1.284***
				(0.0619)	(0.0746)	(0.0586)
5th				1.106	2.408***	1.382***
				(0.0732)	(0.103)	(0.0675)
No Record				0.741***	0.902*	0.689***
				(0.0448)	(0.0454)	(0.0387)
TAKS Reading Quintile (3rd)						
1st	0.961	0.858***	0.902**			
	(0.0322)	(0.0298)	(0.0332)			
2nd	0.990	0.950	0.968			
	(0.0317)	(0.0309)	(0.0331)			
4th	1.004	1.089*	1.048			
	(0.0373)	(0.0399)	(0.0405)			
5th	1.021	1.158***	1.067			
	(0.0446)	(0.0492)	(0.0477)			
No Record	0.931	0.927	0.849*			
	(0.0613)	(0.0704)	(0.0700)			
TAKS Math Quintile (3rd)						
1st	0.937*	0.706***	0.807***			

	(0.0303)	(0.0239)	(0.0288)			
2nd	0.954	0.901**	0.945			
	(0.0300)	(0.0286)	(0.0316)			
4th	1.100**	1.186***	1.107**			
	(0.0402)	(0.0419)	(0.0413)			
5th	1.027	1.349***	1.153**			
	(0.0480)	(0.0602)	(0.0543)			
No Record	0.924	0.967	0.969			
	(0.0609)	(0.0735)	(0.0799)			
Remedial Requirement (None)						
Math	0.999	0.737***	0.915**	0.999	0.662***	0.818**
	(0.0258)	(0.0153)	(0.0260)	(0.0740)	(0.0346)	(0.0554)
Reading	1.032	0.962	1.143*	1.022	0.761**	0.801
	(0.0542)	(0.0448)	(0.0648)	(0.148)	(0.0720)	(0.106)
Two or more	0.858***	0.496***	0.796***	0.890	0.536***	0.598***
	(0.0300)	(0.00971)	(0.0317)	(0.0997)	(0.0239)	(0.0726)
Writing	1.105	0.859**	1.015	0.885	0.642***	0.687**
	(0.0631)	(0.0461)	(0.0634)	(0.124)	(0.0629)	(0.0921)
Credits Attempted Sem 1 (12-13)						
<8	0.966	0.558***	0.954	1.970***	0.790***	1.281**
	(0.0220)	(0.0114)	(0.0272)	(0.172)	(0.0453)	(0.105)
8-11	0.963	0.787***	0.952*	1.003	0.575***	0.766***
	(0.0203)	(0.0171)	(0.0232)	(0.0766)	(0.0390)	(0.0603)
14-15	0.982	1.228***	0.941	0.892**	1.307***	0.977
	(0.0307)	(0.0347)	(0.0314)	(0.0395)	(0.0303)	(0.0360)
16-17	0.879**	1.535***	0.944	0.911	1.437***	0.852**
	(0.0398)	(0.0588)	(0.0442)	(0.0605)	(0.0442)	(0.0438)
18-19	1.459***	1.618***	0.936	0.713*	1.607***	0.790
	(0.0802)	(0.0751)	(0.0520)	(0.115)	(0.148)	(0.105)
20+	1.770***	2.139***	1.015	1.455	2.054***	0.781
	(0.0977)	(0.0794)	(0.0572)	(0.377)	(0.240)	(0.161)
Major Undeclared	1.057***	0.934***	0.961*	1.057	0.809***	0.865***
	(0.0149)	(0.0142)	(0.0154)	(0.0346)	(0.0182)	(0.0212)
Remedial Math Outcome (Not Required)						
Failed/Withdrew One or More	0.865***		0.694***	0.904		0.669***
	(0.0233)		(0.0229)	(0.0513)		(0.0421)
Passed All	1.678***		1.297***	1.374***		1.108*
	(0.0404)		(0.0332)	(0.0803)		(0.0499)
Required, Not Taken	1.018		0.825***	0.892		0.932
	(0.0289)		(0.0269)	(0.0725)		(0.0723)
Remedial Reading Outcome (Not Required)						
Failed/Withdrew One or More	0.742***		0.602***	1.048		0.584**
	(0.0285)		(0.0344)	(0.121)		(0.102)
Passed All	1.556***		1.218***	1.690***		1.175
	(0.0444)		(0.0398)	(0.166)		(0.106)
Required, Not Taken	0.951		0.915*	1.013		1.105
	(0.0306)		(0.0360)	(0.112)		(0.128)
Remedial Writing Outcome (Not Required)						
Failed/Withdrew One or More	0.813***		0.691***	0.744**		0.780
	(0.0294)		(0.0368)	(0.0798)		(0.118)
Passed All	1.732***		1.362***	1.484***		1.288**
	(0.0468)		(0.0411)	(0.143)		(0.112)
Required, Not Taken	1.026		0.939	1.074		1.104
	(0.0302)		(0.0343)	(0.115)		(0.124)
Credits Earned Sem 1 (4-7)						
0	2.005***		1.954***	1.501***		2.174***
	(0.0573)		(0.0788)	(0.139)		(0.387)
1-3	0.799***		0.645***	0.680***		0.515***
	(0.0184)		(0.0176)	(0.0597)		(0.0537)
8-11	1.289***		1.496***	1.589***		1.842***
	(0.0306)		(0.0393)	(0.0945)		(0.119)
12-13	1.655***		2.083***	2.170***		2.802***

	(0.0509)		(0.0695)	(0.133)		(0.185)
14-15	1.581***		2.366***	2.717***		3.404***
	(0.0804)		(0.125)	(0.205)		(0.253)
16-17	1.753***		2.695***	2.861***		3.889***
	(0.125)		(0.190)	(0.297)		(0.346)
18-19	1.400***		3.213***	5.526***		4.469***
	(0.120)		(0.269)	(1.482)		(0.839)
20+	1.192*		3.232***	3.015**		5.381***
	(0.0927)		(0.254)	(1.033)		(1.352)
GPA Sem 1 (D-/F)						
A+/A	5.200***		6.714***	10.24***		25.31***
	(0.149)		(0.245)	(0.684)		(1.760)
B	4.575***		5.226***	9.674***		16.92***
	(0.126)		(0.185)	(0.561)		(1.112)
B+	5.425***		6.485***	11.97***		21.73***
	(0.184)		(0.253)	(0.815)		(1.476)
B-	4.701***		5.752***	10.50***		12.65***
	(0.236)		(0.298)	(0.758)		(0.864)
C	3.344***		3.484***	6.394***		7.175***
	(0.0978)		(0.133)	(0.357)		(0.481)
C+	4.379***		4.286***	8.562***		10.18***
	(0.146)		(0.168)	(0.510)		(0.675)
C-	2.573***		2.793***	3.919***		4.892***
	(0.140)		(0.172)	(0.262)		(0.364)
D	1.705***		1.843***	2.350***		2.647***
	(0.0607)		(0.0897)	(0.144)		(0.220)
D+	2.106***		2.282***	3.106***		3.764***
	(0.0776)		(0.106)	(0.183)		(0.281)
N	108028	108028	108028	48541	48541	48541

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