Promise 2016-2019 Academic Evaluation

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Summary of Results

This analysis looks at the impacts of Salt Lake Community College's (SLCC) Promise program on three primary student outcomes: term GPA, term Credits and Fall-to-Fall retention. The Promise program was designed to encourage Pell qualifying students to engage in behaviors that are associated with high academic success. To qualify for SLCC's Promise in addition to qualifying for Pell, a student needs to maintain a passing GPA, enroll in at least 12 credits in a term, and have a Degreeworks plan on file. Assessing the impacts of Promise on behavioral change vs self-selection is difficult because of Promise's requirements for both term GPA and term Credits (Promise's requirements automatically select students who are likely engaging in behaviors that are associated with high academic success).

Promise is a relatively small program in terms of student involvement with 3,071 total awards to 1775 total students since Fall 2016.

- Term credits earned impact: There appears to be positive Promise effect. A statistical model estimates Promise students took an additional 3-4 credits per term (consistent with prior Promise study results). There is a high likelihood of self-selection bias with this result that will be discussed later.
- Students taking more term credits are associated with higher Fall-to-Fall retention. A statistical model was used to estimate the indirect effect of Promise on Fall-to-Fall Retention via the increase in term credits to be a 5.7% increase in Fall-to-Fall retention. For Fall 2018 promise students (444) this estimated effect translates to 25 students retaining because of this indirect effect via increasing term credits ($14,714 of Promise funds distributed per student retained for Fall 2018).
- Term passing GPA impact: There appears to be a small positive Promise effect on GPA outcomes. A statistical model estimated a *maximum* impact of receiving Promise ranging between a 1.1% to 6.5% increase in the likelihood of reviving a passing term GPA (>2.0). It appears Promise students are students who engage in behaviors that are associated with high academic success. It is hard to attribute why their GPA is higher, it could be Promise prompted behavior change or it could that Promise students already had habits that qualified them for the program.
- Fall-to-Fall(F-F) retention impact: There appears to be **no direct** Promise effect on Fall-Fall retention (consistent with prior Promise study results). Promise tuition waivers alone do not seem to be an effective incentive for re-enrollment at SLCC in the subsequent Fall semester.
- Completion impact: Promise is still too new of a program to assess completion in a manner consistent with other SLCC studies (6-year completion time frame).

Promise students take more classes and they do well in them but it is very difficult to prove their success is the result of Promise alone and not other pre-existing habits. The changes in Fall-to-Fall retention when measured directly are too small to pass statistical significance. The indirect effects that were estimated and are presented in this paper fall short of *stong causal evidence* but do provide possible effect sizes and connect correlation in a useful manner. It is very difficult to separate effects since students who take around 9 credit hours and are not promise students retain at very similar rates anyways (suggesting strong self-selection issues). It is possible that Promise helped incentivize retention (changed student behavior) but it is also possible (in my opinion likely) that the Promise program's requirements limit the programs appeal to students who do not already possess strong academic habits to begin with.

Data Used for the Analysis

The data used for this analysis was pulled out of SLCC's data warehouse. The data pulled consisted of all enrolled Pell eligible students from Fall 2015 (one year prior to SLCC Promise) to Fall 2018. Since Pell eligibility is necessary to be considered for Promise funds, it is an important filter placed on our data from the beginning in order to make apples to apples comparisons to determine Promise's true effects.

The data was grouped in two different sets for the three statistical models used. The first grouping consisted of only Fall semesters ending in Fall 2017. The Fall semester subset (F-F data) was half the size of the other data set used as it only consisted of Fall semesters (excluding spring and summer) and was stopped in Fall 2017 since Fall 2018 students would not have had the opportunity to continue Fall-to-Fall until Fall 2019.

The other data set which was only limited to enrolled Pell eligible students was used to evaluate the percentage of students with passing term GPAs (> 2.0) and term credits earned.

Study Results

The table below presents the size of the Promise program through Summer 2019

Terms	Total Term Awards	Total Funds Disbursed
Fall 2016	529	$403,154.75
Spring 2017	540	$415,587.00
Fall 2017	538	$401,203.75
Spring 2018	438	$323,842.75
Summer 2018	212	$117,792.00
Fall 2018	444	$367,842.88
Spring 2019	395	$316,414.50
Summer 2019	208	$127,597.49

Results Fall-to-Fall Retention

The heat map below (Figure 1) visualizes the correlation between all the variables in the data set. For Fall-to-Fall Retention (F_F column second from the right) we can see the strongest correlation (darkest color) for the whole Fall-to-Fall data set (approximately 40,000 student records) is TERM_UG_CREDITS (undergraduate credits earned) and CREDITS_ATTEMPTED (term credits attempted). The correlation between TERM_UG_CREDITS and F_F is blue indicating the correlation is positive, i.e. students with higher term credits are more likely to retain. This correlation does not establish any causal relation, but if we are going to evaluate Promise's effects on Fall-to-Fall retention we need to consider the fact that a student taking a high credit load (more than 11 say) would simultaneously qualify for Promise and be more likely to retain than a student taking a low or moderate credit load (in the range of 3-9). This presents a challenge to truly identifying the causal relationship between Promise and Fall-to-Fall retention. If Promise increases a students term credits taken, adjusting for term credits in a statistical model will eliminate any indirect effect of Promise on Fall-to-Fall retention and focus solely on the direct effect of Promise on retention (Promise as a financial incentive to return next year). However without controlling for term credits it is hard to develop a control group to make the kinds of comparisons needed to determine if Promise changed student behavior.

Simple direct and indirect effects of Promise on Fall-to-Fallretention.

Figure 2 below highlights the direct and possible indirect effects of Promise on Fall-to-Fall retention. The arrow from Promise (PRM) to Fall-to-Fall Retention (FF) indicates the direct effect, *Promise as a financial incentive to return to SLCC*. This is fairly simple effect to understand, students see that they won't have a

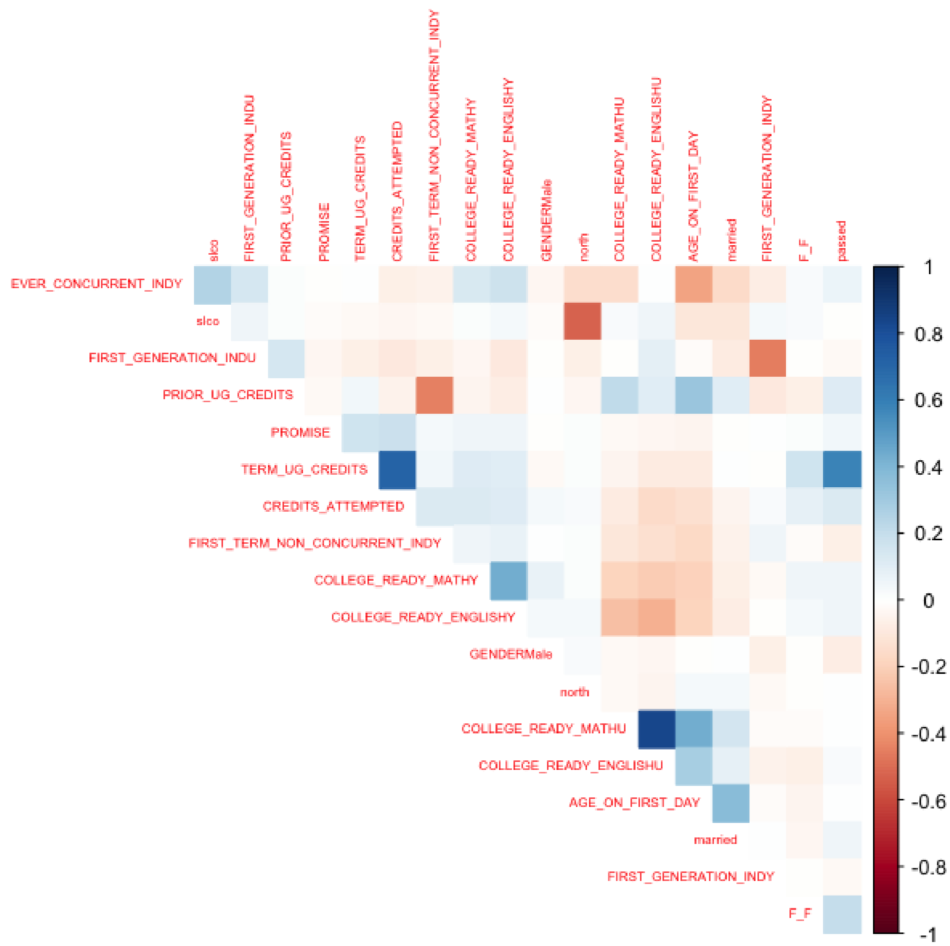


Figure 1: Correlation heat map: This plot visually displays how correlated any two variables are to each other for the data set used to evaluate Promise's impacts. The more intense the color the more correlated the two variables are. Blue indicates a positive coreelation. Red indicates a negative correlation. The Passed variable references the metric used to asses Promise student's ability to maintain a passing GPA (>2.0). North and slco refer to the geographic locations along the Wasatch front with Utah county being held out to avoid multicolinearity.

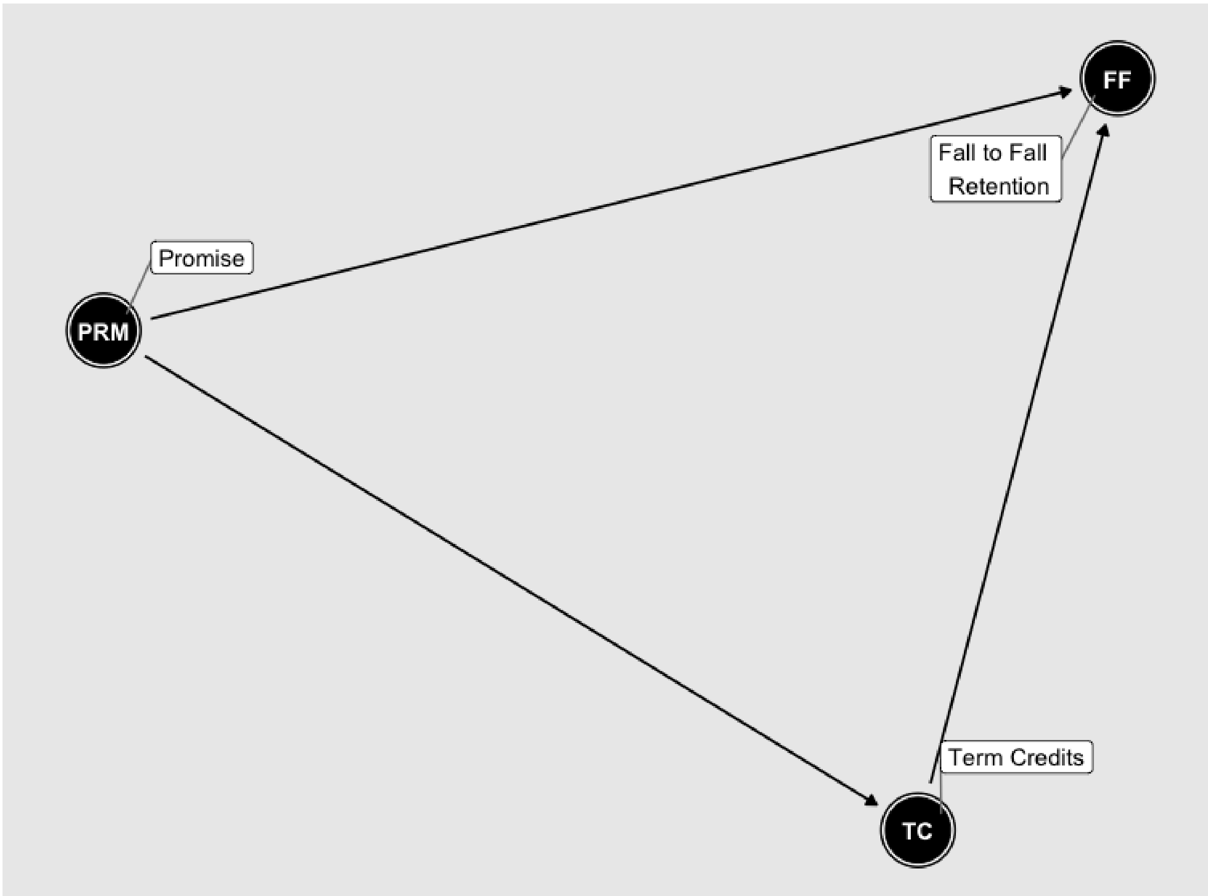


Figure 2: Simple Directed Acyclic Graph (DAG): Direct and indirect effects of Promise. This graph shows the pathways Promise is suspected of impacting Fall-to-Fallretention. Statistical testing found no evidence of a relationship between PRM -> FF (or the direct financial incentive theory) and there is some evidence of a potential indirect relationship of PRM -> TC -> FF (or the increasing student credits leads to a higher likelihood of retention theory).

Pell gap at SLCC where they might at other institutions and that entices them to stay at SLCC until they complete. This effect has been statistically modeled with several methods and none of the results show an effect. In other words, there appears to be no direct effect of Promise as a financial incentive for retention.

We do know (and will discuss later) that Promise students are associated with a 3-4 credit higher term credit load than non-Promise students. This potentially provides an indirect pathway for Promise to impact Fall-to-Fall retention since term credits and Fall-to-Fall retention are correlated. This indirect effect is shown in Figure 2 by following the arrows from PRM to TC to FF and the theory goes like this; Promise students take more credits and taking more credits is correlated with an increased likelihood of Fall-to-Fall retention. Using a mediation model (Lara Pantlin's suggestion) on a Propensity Score match treatment and control group sample we are able to get an idea of what this indirect effect might be while attempting to adjust for as many self selection issues as possible. A mediation model is a simple method apparently used widely in Psychology research to estimate effects that are moderated or mediated through other variables. In this case term credits potentially mediates Promise's effect on Fall-to-Fall retention. This method uses regression interaction techniques to determine conditional effects of the variables in the model on each other.[1]

The table below displays the estimated values for both the direct and indirect effects of Promise on Fall-to-Fall

[1]DSA's Lara Pantlin used this technique extensively in her dissertation. We are lucky to have her on our team.

retention. The statistical modeling using a mediation model on a propensity score matched sample and several other models (including the regression output displayed below) find the direct effect (*PRM -> FF*) to be zero and not statistically significant. The correlation between Promise students and more term credits in the mediation model is estimated to be 3.8 credits (*PRM -> TC*). This value is slightly higher than the MLM regression model below estimated but it is very close to that estimate and also in agreement with the Fall 2016 evaluation of Promise. According to the mediation model Promise students take 3.8 more credits than their PS matched control group counterparts. Term credits are correlated with higher Fall-to-Fall retention rates. The mediation model estimates that there is a 1.5% increase in Fall-to-Fall retention associated with every term credit taken (*TC -> FF*). If we multiply the estimated *PRM -> TC* value with the *TC -> FF* value we will arrive at the indirect effect of Promise on Fall-to-Fall retention (via Promise's impact on Term Credits). According to the mediation model this is a 5.7% increase in Fall-to-Fall retention. To see the number of students this translates to you just need to multiple the number of students in a Fall semester who accepted Promise funds by 5.7%.

	Estimated Effects
Direct Effect (PRM -> FF)	0.3%: Not Significant
PRM -> TC	3.8 Credits: Significant
TC -> FF	1.5%: Significant
Indirect Effect	5.7%

Since I am fairly confident in the relationship between *PRM -> TC* established with the mediation model and several other methods, I believe this 5.7% indirect effect of Promise on Fall-to-Fall retention is the closest we can get to understanding the impacts of Promise on retention.[2] The relationship between *TC -> FF* seems reasonable. There is still a lot of uncontrollable self selection bias inherent in this analysis so take the 5.7% indirect effect estimate as a good upper bound on the impacts of Promise on retention.

Complications with self-selection

Figure 3 below outlines the complications of self selection and limits of causal statements that can be made for Promise's role in Fall-to-Fall retention. Briefly, their is multi-directional effects between Promise and term credits (*TC <-> PRM*). A student needs to have a certain level of credits to be eligible for the program to begin with and it appears Promise potentially increases some students credit loads. Since term credits is the most correlated variable with retention in our data set this creates a *chicken or the egg scenario*. It is my understanding from a conversation with staff in Financial Aid that they do not contact students who are far from meeting Promise's requirements (i.e. below a credit hour threshold and/or missing other requirements) since if the student drops their classes they lose their tuition waiver and are faced with a bill.[3]

Further complicating this is the fact that there are many other factors that are unaccountable for that could easily be driving both variables, Promise and term credits. Noncognitive student attributes (*NC*) such as; ability, intention, motivation, a flexible work schedule, and goals could easily be causing a student to take a high course load with intention and this would mean they are eligible for Promise just as a lucky coincidence or icing on the cake. The student already had the drive and ability to achieve their academic goals and this enabled them to easily qualify for Promise. In this example it is hard to say that Promise caused anything other than reducing a financial burden (a very significant impact to be sure). We can't measure if the connections between *TC* and *PRM* to *NC* are multi-directional, meaning that Promise and taking more term credits would impact these noncognitive attributes (I suspect that they should as student often experience personal growth while in school). These confounding effects remain outside our ability to control for them adequately and can cast doubt on causal statements.

[2] Without abusing statistical methodology, making heroic assumptions or producing a new instrument for an IV analysis.
[3] Financial Aid tries to avoid this for students.

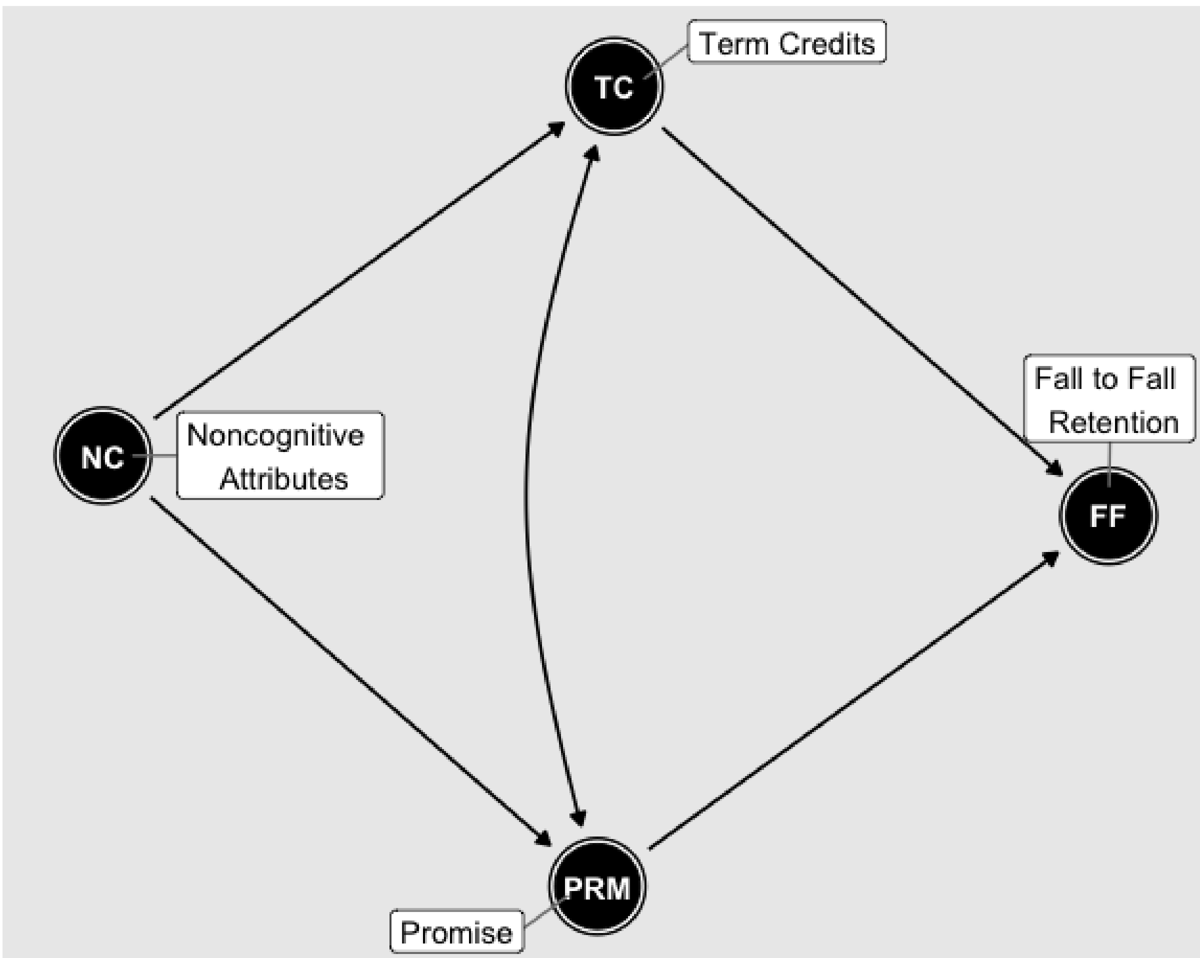


Figure 3: Full DAG: Modeling the potential self selection process and its complexities for Promise/Fall-to-Fallretetnion modeling.

Regression Model Results Details

Table 3 below outlines the primary models used to assess Promise. There were two derivatives of Multilevel regression Models (MLM) used to evaluate the impact of Promise (2 logitistic regression and 1 linear regression). The results for all three models are below with the estimated effects of Promise on the first line. The first two models from left to right are in Log-odds scale and are thus not directly interpretable without some calculations (however the appropriate interpretation for the estimated Promise effects were summarized in the Results Summary section on the first page). The third model from left to right is a linear model and is directly interpretable on a term credits level. GPA scores for both High School and Prior Undergrad GPA in the NA range represents a missing value and should be interpreted as a Null value (they were coded this way for modeling purposes after they were pulled out of SLCC's data warehouse).

Ethnicity and Terms were adjusted for using random effects for all of these models. The ethnicity results are presented in the next subsection. Term was held as a random effect to control for serially correlated variables and not presented here since it is beyond the scope of this analysis.

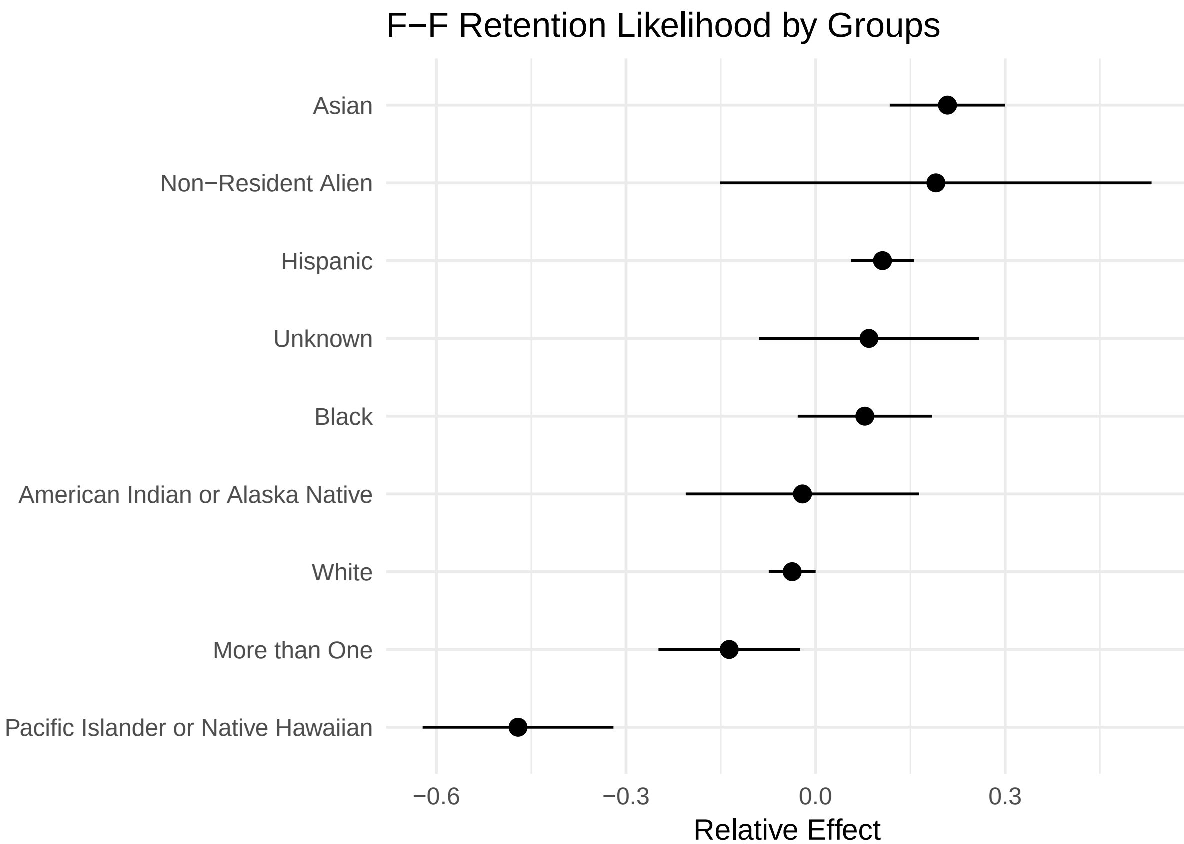
Random Effect: Ethnicity

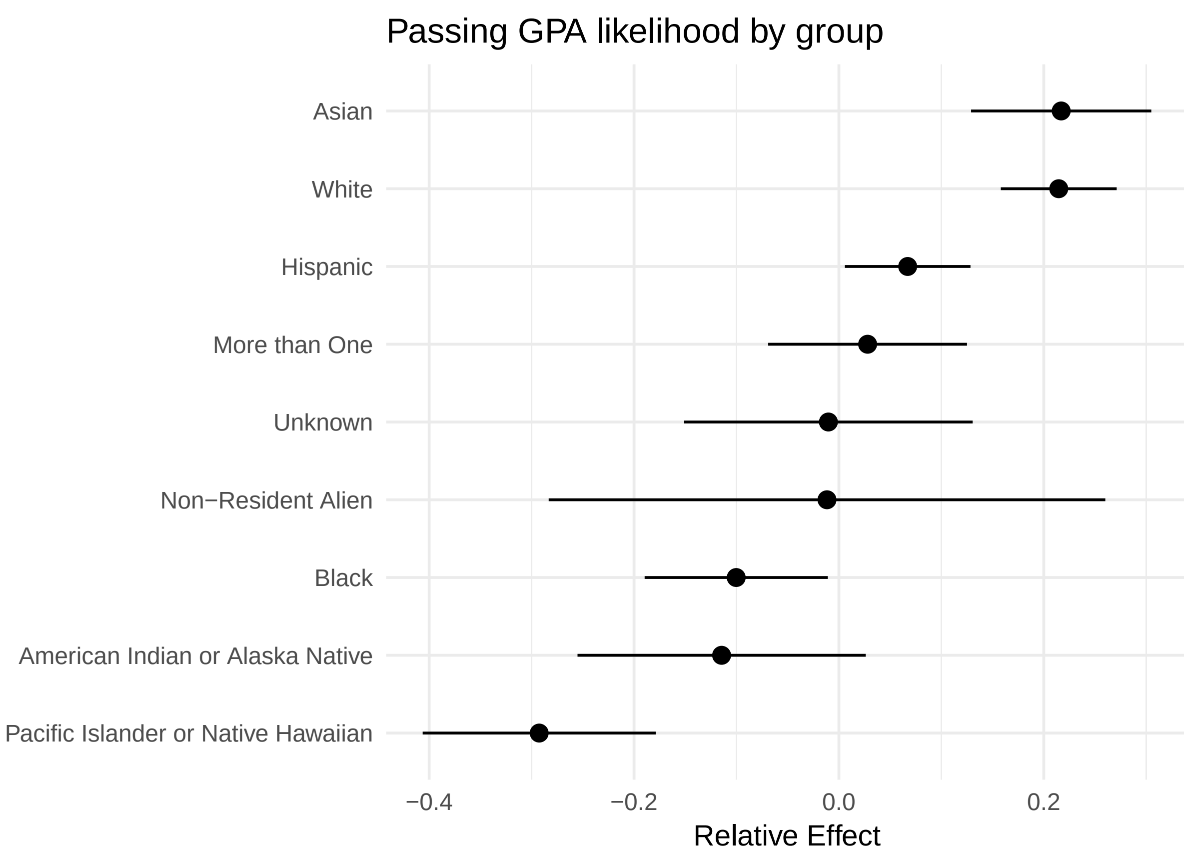
Below is a breakdown of the random effects differences between ethnicities at SLCC for F-F retention, Passing Term GPA and Term Credit Earned for both Promise and non-Promise Pell students at SLCC (this is just extra information we obtain about SLCC students in general while testing Promise). The black dot represents the group mean and the black horizontal line represents the likely mean estimate error. The x-axis is not directly interpretable so it is best to use these plots to note differences between groups that are large enough to be considered statistically significant (when the black horizontal lines indicating each groups error do not cross, the difference between these two groups can be considered statistically significant). Larger groups typically will have smaller error as the group mean is based on many more observations (note how small White and Hispanic group errors are as they are the two largest student ethnicity groups in this study). The first two plots x-axis display relative effects and are not directly interpretable without additional calculation.

Pacific Islander for instance are lagging far behind their peers in all three and should be focused on for achievement gap initiatives. For F-F retention there is a noticeable gap between 'Pacific Islanders or Native Hawaiian' and the rest of SLCC. The F-F gap indicates that this group lags behind all other groups at SLCC in a statistically significant (likely non-random) manner.

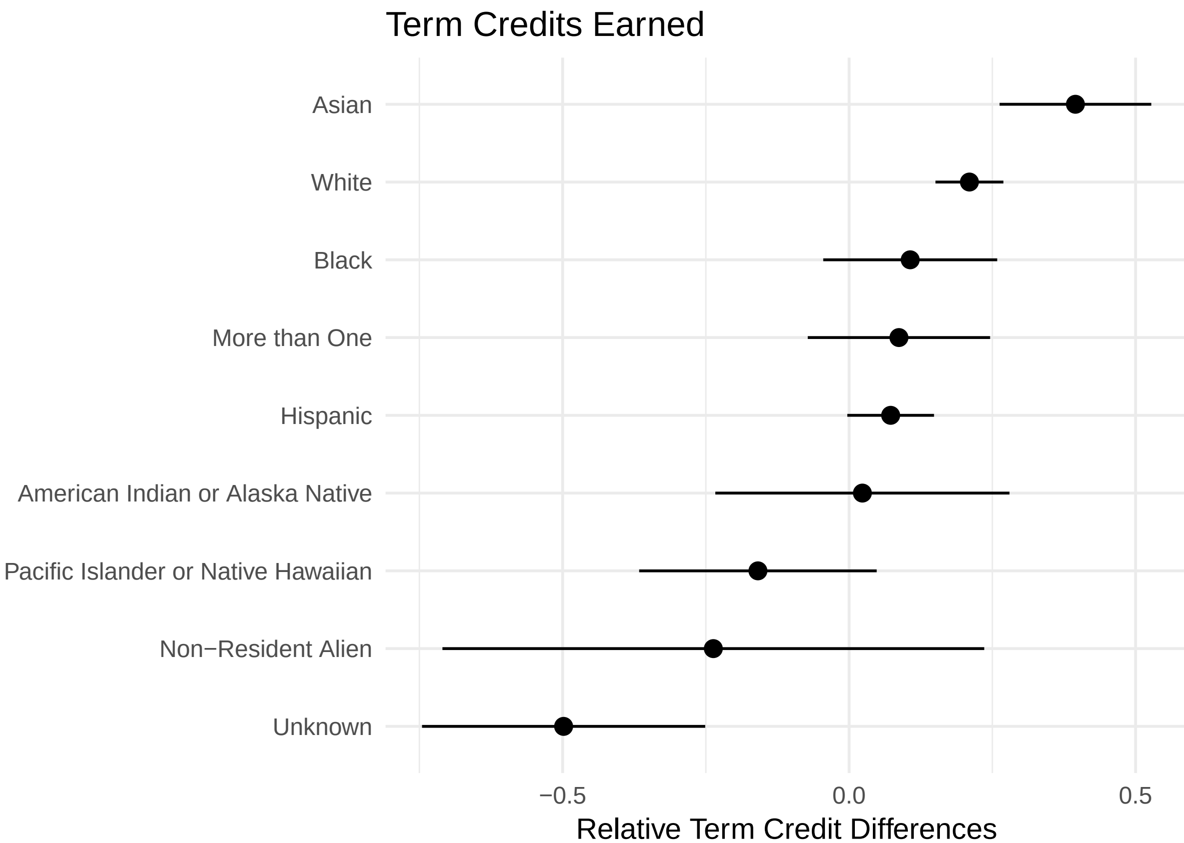
Table 3: Results From all 3 models

	Dependent variable:		
	Fall-to-Fall Retention	Passed	Term UG Credits Passed
	generalized linear mixed-effects	*generalized linear mixed-effects*	*linear mixed-effects*
	(1)	(2)	(3)
Promise	0.076	0.153***	3.502***
Credits Attempted: Scaled	0.141***	0.274***	
Age on first day: Scaled	0.014	−0.050***	−0.579***
Male	−0.033	−0.230***	−0.001
Married	−0.118***	0.239***	0.236***
College Ready English: Yes	−0.001	−0.030	0.250***
College Ready Math: Yes	0.152***	0.087***	0.484***
First Generation: Yes	−0.048**	−0.069***	−0.059**
First term non-concurrent: Yes	0.001	−0.048	2.138***
Ever Concurrent: Yes	−0.037	0.239***	−0.792***
Prior UG GPA: Scaled	−0.346***	0.083***	0.045**
S.L. Co.	0.126***	−0.030	−0.170***
High School GPA: 1-2	−1.420	−0.471	0.576
High School GPA: 2-2.5	−1.375	−0.258	0.887
High School GPA: 2.5-3	−1.096	0.008	1.492
High School GPA: 3-3.5	−1.093	0.257	1.804*
High School GPA: 3.5-4	−1.075	0.921*	2.045*
High School GPA: NA	−1.289	0.120	1.315
Prior UG GPA: 1-2	0.461***	0.464***	1.206***
Prior UG GPA: 2-2.5	0.912***	0.790***	2.198***
Prior UG GPA: 2.5-3	1.167***	1.278***	3.126***
Prior UG GPA: 3-3.5	1.242***	2.008***	4.313***
Prior UG GPA: 3.5-4	1.275***	2.775***	5.227***
Prior UG GPA: NA	0.578***	1.243***	1.229***
Constant	0.015	−0.841	1.365
Observations	40,622	88,986	88,986
Log Likelihood	-27,239.010	-45,648.240	-256,883.600
Akaike Inf. Crit.	54,532.030	91,350.470	513,821.300
Bayesian Inf. Crit.	54,764.550	91,604.170	514,075.000
Note:			*p<0.1; **p<0.05; ***p<0.01


F−F Retention Likelihood by Groups
Asian
Non−Resident Alien
Hispanic
Unknown
Black
American Indian or Alaska Native
White
More than One
Pacific Islander or Native Hawaiian
−0.6
−0.3
0.0
0.3
Relative Effect


Passing GPA likelihood by group
Asian
White
Hispanic
More than One
Unknown
Non−Resident Alien
Black
American Indian or Alaska Native
Pacific Islander or Native Hawaiian
−0.4
−0.2
0.0
0.2
Relative Effect

The x-axis values for the final plot, 'Term Credits Earned', are in term credit level since this output was generated from a linear model. For this plot we see that while there are differences based on ethnicity these differences are at a maximum difference of less than 1 term credit earned.



Financial Aid Interviews

There were several notable points about the success of the Promise program at SLCC that were the result of interviews with staff from Financial Aid (FAS). Promise has remained a small program at SLCC despite a continuous marketing effort across campus, according to FAS there were several reason in their minds for this.

- Students are increasingly receiving enough Pell money and there are fewer and fewer students in the "Pell gap" range.
- There are many other funding sources for students that fall into the need based aid category that do not require meeting the standards of Promise.
- The degree plan as a requirement was seen as a hurdle that many students, even after being notified of Promise eligibility, were not willing to overcome (i.e. meet with an divisor and file a plan).
- Promise is administratively 'high maintenance'. There is a lot of manual checking of students to see if they meet the requirements throughout the semester.

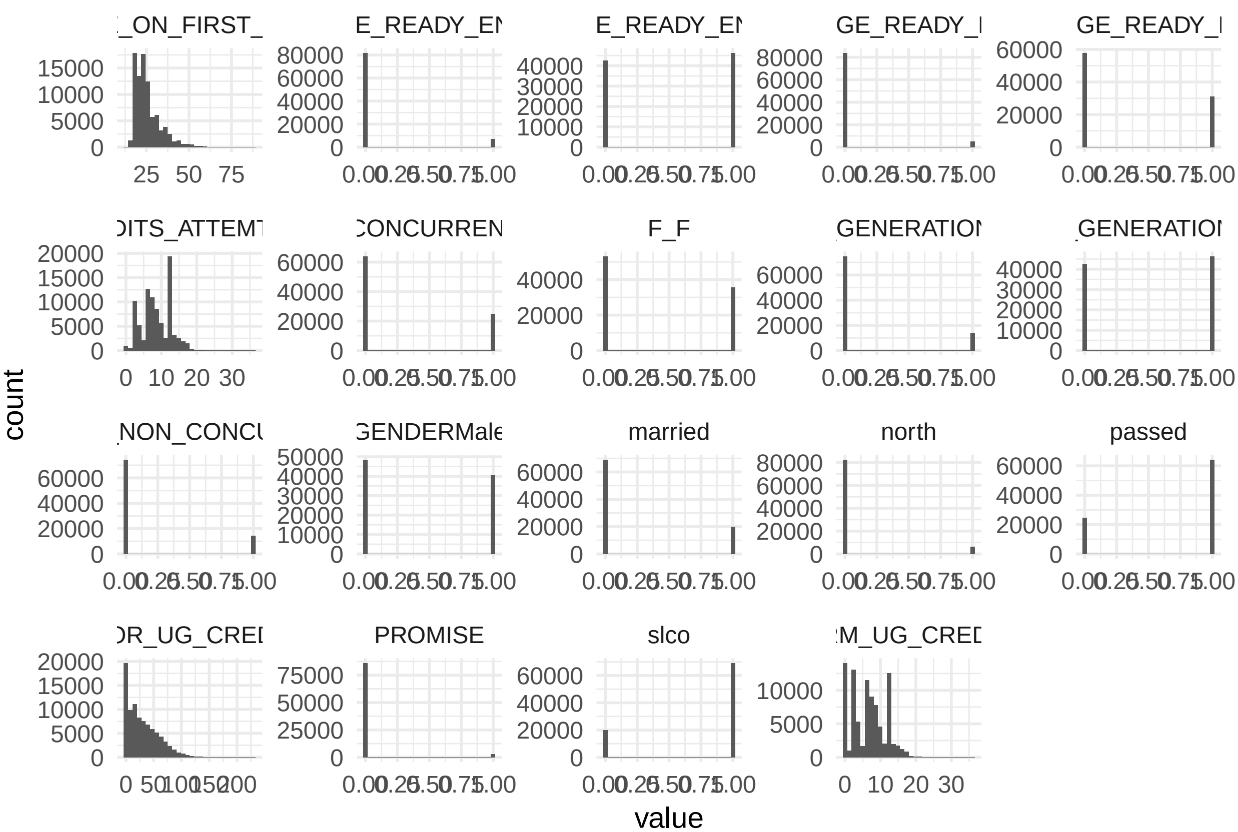
Data checks

This section will display some data quality checks and some pre-modeling processing steps take for future replication purposes and will not be discussed.

Near-zero Variance check. GENDERUnknown was removed from the analysis as a variable.

	freqRatio	percentUnique	zeroVar	nzv
F_F	1.487936	0.0022475	FALSE	FALSE
passed	2.597720	0.0022475	FALSE	FALSE
TERM_UG_CREDITS	1.125380	0.0516935	FALSE	FALSE
AGE_ON_FIRST_DAY	1.058193	0.0775403	FALSE	FALSE
GENDERMale	1.201098	0.0022475	FALSE	FALSE
GENDERUnknown	350.723320	0.0022475	FALSE	TRUE
FIRST_GENERATION_INDU	5.305697	0.0022475	FALSE	FALSE
FIRST_GENERATION_INDY	1.089903	0.0022475	FALSE	FALSE
married	3.464703	0.0022475	FALSE	FALSE
COLLEGE_READY_MATHU	16.527280	0.0022475	FALSE	FALSE
COLLEGE_READY_MATHY	1.863035	0.0022475	FALSE	FALSE
COLLEGE_READY_ENGLISHU	11.491016	0.0022475	FALSE	FALSE
COLLEGE_READY_ENGLISHY	1.086914	0.0022475	FALSE	FALSE
PRIOR_UG_CREDITS	5.016490	1.1541141	FALSE	FALSE
FIRST_TERM_NON_CONCURRENT_INDY	5.121767	0.0022475	FALSE	FALSE
EVER_CONCURRENT_INDY	2.560722	0.0022475	FALSE	FALSE
slco	3.494242	0.0022475	FALSE	FALSE
north	12.764269	0.0022475	FALSE	FALSE
CREDITS_ATTEMTPED	1.091541	0.0842829	FALSE	FALSE
ETHNICITY	2.740225	0.0101140	FALSE	FALSE
TERM_CODE	1.065546	0.0078664	FALSE	FALSE
HIGH_SCHOOL_GPA	7.037909	0.0078664	FALSE	FALSE
PRIOR_UG_GPA	1.065487	0.0078664	FALSE	FALSE

All variable histograms



Propensity Model Matching used for Mediation modeling

Table 5: Propensity Score GLM model

	Dependent variable:
	Promise
Age on First Day: Scaled	−0.217*** (0.046)
Male	0.009 (0.061)
Married	0.092 (0.080)
College Ready English: Yes	0.387*** (0.071)
College Ready Math: Yes	0.164** (0.066)
First Generation: Yes	0.040 (0.060)
First Term Non Concurrent: Yes	1.002*** (0.101)
Ever Concurrent: Yes	−0.433*** (0.084)
Prior UG Credits: Scaled	−0.093** (0.043)
S.L. Co.	−0.259*** (0.070)
High School GPA: 1-2	16.536 (6,304.299)
High School GPA: 2-2.5	16.954 (6,304.299)
High School GPA: 2.5-3	16.844 (6,304.299)
High School GPA: 3-3.5	17.136 (6,304.299)
High School GPA: 3.5-4	17.070 (6,304.299)
High School GPA: NA	17.017 (6,304.299)
Prior UG GPA: 1-2	−0.158 (0.418)
Prior UG GPA: 2-2.5	0.619 (0.380)
Prior UG GPA: 2.5-3	0.900** (0.369)
Prior UG GPA: 3-3.5	1.119*** (0.367)
Prior UG GPA: 3.5-4	1.363*** (0.365)
Prior UG GPA: NA	0.183 (0.371)
White	0.145 (0.089)
HLL	−0.012 (0.104)
Term 2016	17.412 (144.457)
Term 2017	17.565 (144.457)
Constant	−38.772 (6,305.954)
Observations	40,622
Log Likelihood	−4,723.804
Akaike Inf. Crit.	9,501.608
Note:	*p<0.1; **p<0.05; ***p<0.01