Isolating the Mechanisms Behind the Test-Optional Admissions Policy

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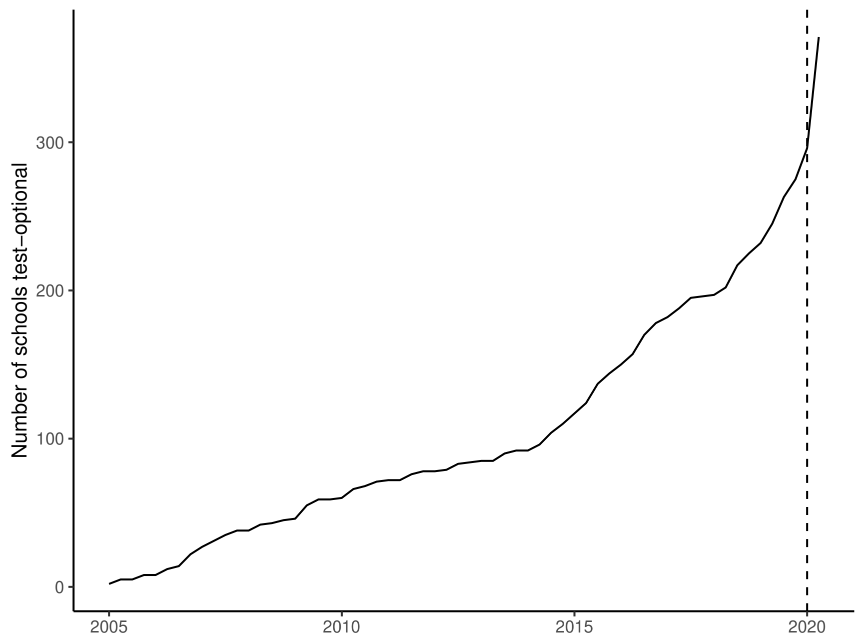
Abstract

The test-optional admissions policy is a growing tactic among four-year postsecondary institutions in the United States. While each institution decides individually whether or not to implement this policy, there has been limited research done in evaluating these collective decisions across colleges and universities. By using machine learning algorithms across a range of institutions, I am able to uncover trends across schools that shine a light on why institutions may be heading in this direction. I find that the motives for implementing this policy may be different depending on the selectivity of the school.

1 Introduction

Since 1969, institutions of higher education across the country have begun to adopt test-optional policies that allow prospective students to forgo sending their SAT or ACT scores along with their application. Postsecondary institutions have been adopting this policy at an exponential rate (Figure 1), and the COVID-19 outbreak of 2020 has exacerbated these trends. Several test-optional institutions suggest that this policy boosts both ethnic and economic diversity of their campuses (Bates College, 2004; Jaschik, 2006; McDermott, 2008). This policy is rooted in increasing diversity amongst applicants (Epstein, 2009; Ehrenberg, 2002), since there is strong

Figure 1:
Longitudinal Trends of Test-Optional Schools



Source: FairTest.org

evidence that suggests a correlation between test-taking and socioeconomic status (Rothstein, 2004). Therefore, by adopting this policy, institutions seek to remove barriers for underprivileged students to apply.

However, Belasco et al. (2015) find no evidence that suggests that becoming a test-optional school achieves this goal. Rather, they find an increase in both applications and reported SAT scores post-implementation. By becoming test-optional, colleges see increased application numbers and thus a larger proportion of students that they can reject, boosting their acceptance rate and consequently institutional rankings (Yablon, 2001).

This leads us to confusion as to why institutions are adopting this policy. Is it to increase minority and underrepresented enrollment, or is it to boost institutional rankings? Further, is it possible that institutions are adopting this policy with both goals in mind? What drives their decisions may be unique to each institution, but there has been limited research done in evaluating these collective decisions across institutions. Uncovering these trends are important from a policy perspective, since there may be ulterior motives at play. By using a decision tree classifier, I am able to isolate the key factors that are correlated with this policy implementation. In doing so, I find varying trends that depend largely on the prestige of the institution.

2 Data

The data is primarily scraped from the The Urban Institute Education Data API. Urban Institute's Education Data Explorer is a robust ecosystem of higher education metrics, most of which are collected from the Integrated Postsecondary Education Data System (IPEDS) and College Scorecard data. In addition to this data, I merged additional metrics not available from the API but directly from IPEDS to complete my collection of relevant variables. The dataset includes 967 institutions, all degree-granting, four-year private or public institutions across 50 states and D.C.

The dependent variable of interest is the test-optional status: a flag for institutions that do not require test scores upon application. For my decision tree classifier, I include twelve feature variables, listed in Table (1). The test-optional policy is heavily distributed towards private institutions, so I break my summary statistics and classifier down by public vs. private control and focus my analysis primarily on private institutions. My key variables of interest are percent minority enrollment (percentage of full-time students from underrepresented groups),[1,2] percent

[1] Calculated as $[1 - (\%White) - (\%Asian)]$

[2] Since Asian students score higher on average than White students on the SAT (National Center for Education Statistics, 2018), I exclude this ethnicity from the URM group.

low-income enrollment (from College Scorecard Data), yield rate (percent of students accepted who decide to attend), and acceptance rate.

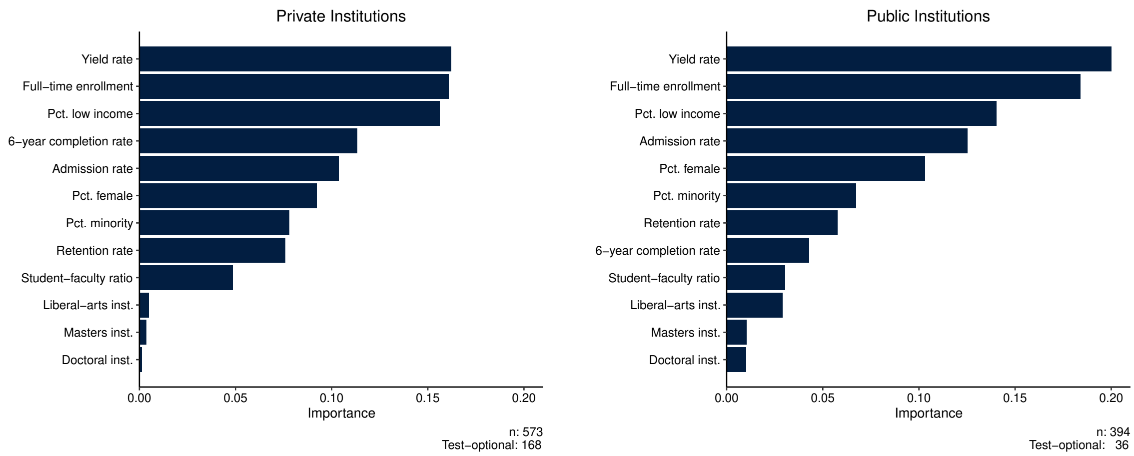
While prior research in this field has incorporated reported test-scores alongside this decision (Belasco et al., 2015), I found that including these features severely decreases my sample size needed for a robust analysis. Several schools, especially test-optional, neglected to report these metrics to IPEDS, resulting in a large proportion of missing features across schools. Thus, these covariates are not included in my report.

3 Methodology

To understand the factors that go into the test-optional policy, I employed a decision tree model on my data. This decision tree classifier allows me to calculate feature importances on each of my independent variables. Feature importance is calculated as the decrease in node impurity weighted by the probability of reaching that node (Rongahan, 2018). In other words, this model will output the features that are most important in predicting the test-optional policy. This model is highly intuitive and easy to visualize and can easily highlight the the essential variables, yet predictive accuracy may be lower.

Further, I plan on incorporating other classifiers, specifically K-nearest neighbors, Naïve Bayes and logistic regression to predict which schools may soon be heading in the direction of test-optional admissions, by looking specifically at schools classified as having the policy but do not (the false positives). This will allow me to identify schools that may soon be heading in the direction of test-optional. These algorithms have been used to predict many student-level metrics such as dropout and retention (de Sousa et al., 2018; Lehr et al., 2016), but to my

Figure 2: Feature importances by Sector



knowledge have not been frequently used at the institutional level for predicting this policy. These models will perform better on predictive accuracy, but may be hindered by imbalanced classes and correlated features.

4 Feature Importances

Pooling across all private institutions, I find that yield rate is the most important feature in determining whether or not a school is test-optional, displayed in Figure (2). This is validated through running a decision-tree classification model and plotting variable importances over 1000 simulations to get an unbiased result. The other main factors identified for private institutions are full-time enrollment and percentage of students low income. The same trends are seen in public institutions as well, also displayed in Figure (2).

However, these results should be generalized lightly. There is a wide range of the types of schools in the data displayed in Figure (2): schools from a mere acceptance rate of 5% to upwards of 99% are pooled together in this classification model. I wanted to investigate whether the motives for the most selective institutions differ from those on the least-selective side of the spectrum. To do so, I incorporated Barron's selectivity rankings to examine these differences.[3] Barron's *Profile of American Colleges* classifies colleges and universities on a range of competitiveness, ranging from "less competitive" to "most competitive." I constructed feature importance figures for schools in each of these categories from an average of 1000 simulations, displayed in Figure (3).

The feature importances of percent minority students tell a compelling story moving across Barron's classifications, shown in Figure (4). As schools move from the most competitive to the least competitive, the feature importance of percent minority in the test-optional decision tree creates a distinct U-shape.[4] It is an important factor for the most competitive and less competitive schools, yet for the middle Barron's category, "very competitive," it plays a rather insignificant role. Percent low-income enrollment tells less of a story, but follows roughly a linear path from most competitive to less competitive aside from a small bump in the "competitive" category.

The feature importances in Figures (2) and (3) validate that percent minority enrollment and percent of low income students do impact probability of being classified test-optional. However, Figure (4) suggests that the role that these metrics play is partly due to the prestige of the institution. To uncover this phenomenon I look at difference in means across Barron's Classifications in private institutions (Table 3). Amongst the most selective private institutions, there is a significant difference in means in minority enrollment percentage between test-optional and test-required schools: test-required schools have an average 7 percentage point advantage over test-optional schools in percent minority enrollment. As these in-

[3]This data was only available from 2004, yet these metrics do not significantly change over time (Kelchen, 2018).

[4]Though the sample size is small and the classes are unbalanced in the "most-competitive" sector, the same trends are followed, even when excluding this category.

Figure 3: Feature importances by Barrons Classification (Private)

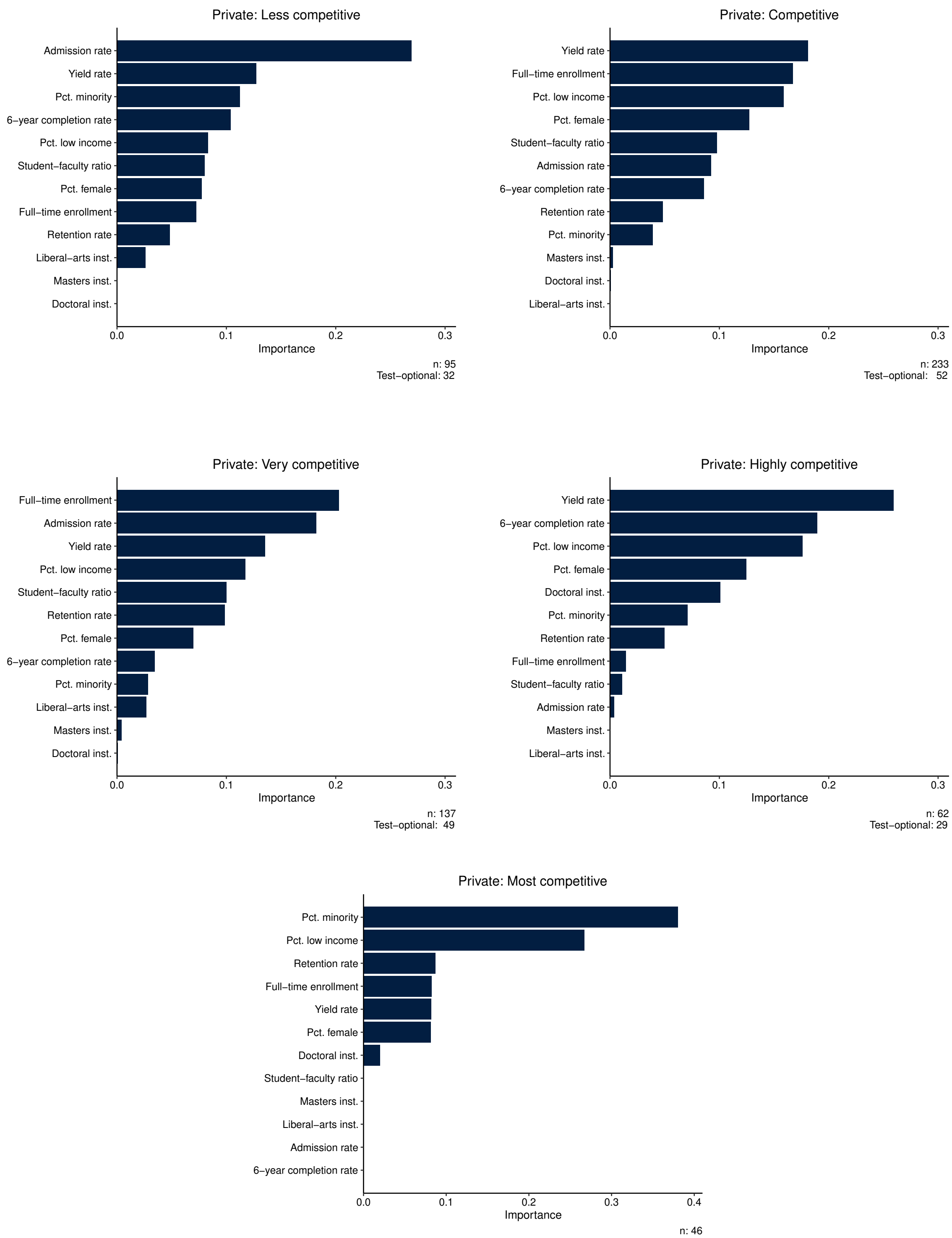
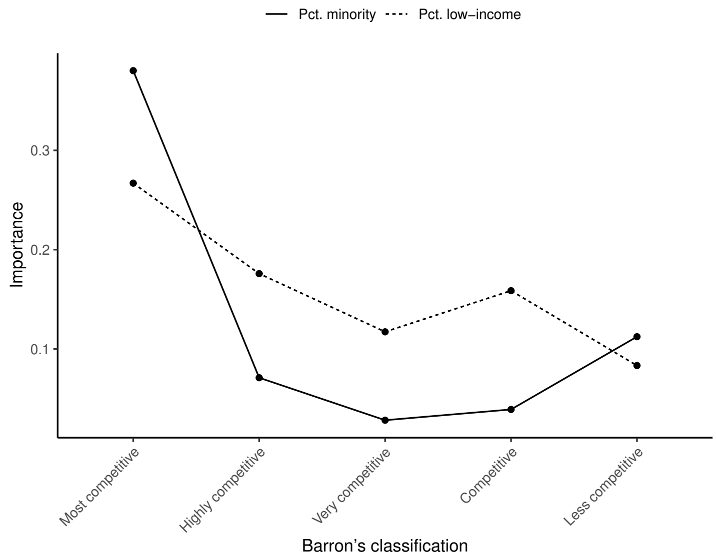


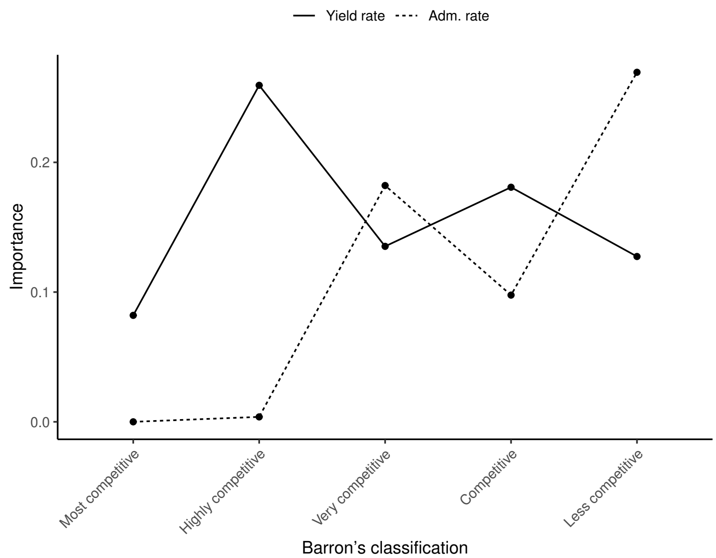
Figure 4:
Importances of Pct. Minority and Pct. Low-Income by Barron's Classification (Private)



stitutions become less selective, this difference becomes insignificant and the sign flips. Amongst the "competitive" and "less competitive" colleges and universities, test-optional institutions have a greater share of minority enrollment than their test-required counterparts.

Lastly, looking at two additional metrics across Barron's rankings in Figure (5), we see that yield rate plays the greatest factor in the "highly competitive" institutions. Additionally, while acceptance rate plays little-to-no role in the most competitive and highly competitive institutions, it plays a rather significant factor in the less-selective institutions. Table (4) shows that across all classifications, test-optional schools boast a significantly lower yield rate and higher acceptance rate.

Figure 5:
Importances of Yield Rate and Admission Rate by Barron's Classification



5 Classification Algorithms

To classify institutions as having and not having this policy, I employed the decision tree model outlined above as well as three additional models: Naïve Bayes, K-nearest neighbors, and a logistic regression. In addition to the feature variables listed in Table (1), I also added variables for the Census division each school is located in for these classification models. Adding these variables to my classification algorithms increased predictive accuracy greatly, although they were left out of the decision tree model due to institutions having no power over these attributes. Test-optional schools are greatly concentrated in the New England and Mid-Atlantic divisions, so adding this Census data allows for greater predictive accuracy.

The models were initially fit using training data (80% of the sample) and evaluated on the testing data (the remaining 20%) each dwith scaled feature matrices. The accuracy metrics for private institutions are listed in Table (5). The logistic regression yields the greatest balanced accuracy and F-measure scores, while KNN scored highest of the algorithms on recall and Naïve Bayes on precision.[5] It is harder for these algorithms to classify public institutions as having this policy since the classes are very unbalanced (only 9% of public institutions have this policy in place). The accuracy metrics for public institutions are displayed in Table (6), although these results do not tell us much given the severe imbalance of classes.

2020 has created a policy window for several schools to implement this policy. Given the COVID-19 outbreak, several SAT and ACT testing centers have closed, prodding schools to forgo the testing requirement for the upcoming admissions cycle (Jaschik, 2020). It will not be surprising if institutions decide to not revert back to their previous admissions policies even after the pandemic. To evaluate the admissions-implications of this ongoing phenomenon, I investigated the false positives from the private institutions. I took the subset of schools falsely identified as having this policy in the logit model: the algorithm yielding the highest balanced accuracy. Thirty-nine schools were identified as having this policy but do not. Of these schools, twenty-two institutions have since decided to go test optional, most citing the pandemic as the main motivator in this decision (including Amherst College, Babson University, Middlebury College, and Rhodes College). As more institutions decide to head in this direction post-2020, these classification algorithms and feature importances will become more accurate and can help uncover more hidden trends in the institutional data.

6 Discussion and Policy Implications

As most schools cite increasing underrepresented minority enrollment as a main reason to go test optional, the feature importances displayed in Figure (2) suggest

[5] Balanced accuracy was used to account for the unbalanced classes.

otherwise. Instead, the key factors driving the classification of this policy were found to be yield rate, full-time enrollment, and low-income enrollment. Further, the factor that minority enrollment has on this decision is varying across Barron's selectivity classification (Figure 4). This metric has a larger impact on the most competitive and less competitive classes of private institutions, while the factor it plays on the middle selectivity-range of institutions is not as big.

This suggests varying motives for implementing this policy depending on the selectivity of the institution. For the most selective colleges and universities, including institutions such as Wake Forest University (test-optional) and Stanford University (test-required), it appears that this policy is implemented to increase access amongst underrepresented groups. However, for the tier below the most selective (institutions like test-optional George Washington University and test-required Grinnell College), the driving factor in this decision is primarily yield-rate. These institutions aspire to compete with the schools in the most-competitive classification. To do so, these colleges and universities aim to increase their yield rate by implementing this test optional policy. Similar motives are identified for institutions in the bottom-tiers of Barron's classifications, yet minority enrollment becomes increasingly important as the institution becomes less selective.

While previously suggested that college administrators are adopting this policy to increase underrepresented postsecondary access (Bates College, 2004; Jaschik, 2006; McDermott, 2008), this trend is only apparent in the most selective schools. Otherwise, the feature importances suggest that minority enrollment plays only a small role in this decision. Percentage of students from a low income background, on the other hand, does play a significant factor in this decision. This validates some hypotheses that postsecondary access is correlated with standardized test-taking (Blau et al., 2004).

There is much research that can be done in this field of institutional research across colleges and universities. Post-2020, more schools will be implementing this policy, creating a more balanced set of classes and thus more accurate classification algorithms can be implemented. This may uncover more trends in the data. Secondly, incorporating a panel-data approach to implement a difference-in-difference model with this new data can help understand some of the post-policy effects and can help identify more factors in the decision to go test-optional. Further, why is this such a growing trend among private institutions, yet public institutions are hesitant to move in this direction? Lastly, there are arguments that the opposite policy, requiring high-school students to take standardized tests, can also be a mechanism for increasing low-income and minority enrollment (Dynarski, 2018). Though the test-optional policy and this test-required policy are both rooted in increasing underrepresented postsecondary access, they are complete opposites. Using this new data, we can identify which policy better closes these attainment gaps. Nonetheless, this research has added to the literature on the growing postsecondary test-optional movement, shining a light on some of the factors that go into this decision and uncovering that motives may be different depending on the selectivity of an institution.

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Table 1: Pooled summary statistics of Private and Public Institutions

	Private Institutions				Public Institutions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Mean	Std. Dev.	Min.	Max	Mean	Std. Dev.	Min.	Max
School characteristics								
Test-optional	0.29	0.46	0	1	0.09	0.28	0	1
Full-time enrollment	2,756	3,034	280	28,012	11,066	8,642	647	44,975
Admission rate	0.62	0.21	0.05	0.99	0.70	0.17	0.16	1.00
Yield rate	0.24	0.12	0.05	0.83	0.31	0.10	0.11	0.76
Retention rate	0.78	0.11	0.40	0.99	0.78	0.09	0.46	0.97
6-year completion rate	0.65	0.16	0.11	0.98	0.57	0.14	0.22	0.93
Student-faculty ratio	12.08	2.67	3	28	17.66	3.39	10	30
Pct. female	0.58	0.10	0.18	0.98	0.57	0.08	0.12	0.90
Pct. minority	0.34	0.18	0.05	0.99	0.37	0.22	0.08	0.99
Pct. low-income	0.29	0.11	0.09	0.76	0.37	0.12	0.10	0.93
Doctoral inst.	0.17	0.37	0	1	0.44	0.50	0	1
Masters inst.	0.43	0.50	0	1	0.49	0.50	0	1
Liberal-arts inst.	0.06	0.24	0	1	0.06	0.23	0	1
Barrons: Most competitive	0.08	0.27	0	1	0.01	0.10	0	1
Barrons: Highly competitive	0.11	0.31	0	1	0.05	0.21	0	1
Barrons: Very competitive	0.24	0.43	0	1	0.17	0.48	0	1
Barrons: Competitive	0.41	0.49	0	1	0.51	0.50	0	1
Barrons: Less competitive	0.17	0.37	0	1	0.25	0.44	0	1
Observations	573				394			

Notes: Barron's metrics from 2004. All other metrics from 2016.

Table 2: Pooled summary statistics of Private Institutions by Admissions Policy

	Test-Optional				Test-Required			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Mean	Std. Dev.	Min.	Max	Mean	Std. Dev.	Min.	Max
School characteristics								
Full-time enrollment	2,342	2,405	280	21,774	2,928	3,247	389	28,012
Admission rate	0.66	0.18	0.14	0.99	0.61	0.22	0.05	0.98
Yield rate	0.20	0.09	0.05	0.54	0.25	0.13	0.08	0.83
Retention rate	0.78	0.11	0.43	0.97	0.79	0.12	0.40	0.99
6-year completion rate	0.65	0.16	0.27	0.94	0.64	0.16	0.11	0.98
Student-faculty ratio	12.33	2.89	7	28	11.98	2.57	3	20
Pct. female	0.59	0.10	0.18	0.98	0.58	0.10	0.21	1.00
Pct. minority	0.34	0.18	0.11	0.99	0.35	0.18	0.05	1.00
Pct. low-income	0.28	0.13	0.09	0.76	0.29	0.10	0.09	0.67
Doctoral inst.	0.08	0.27	0	1	0.21	0.41	0	1
Masters inst.	0.40	0.49	0	1	0.44	0.50	0	1
Liberal-arts inst.	0.05	0.23	0	1	0.06	0.24	0	1
Barron's: Most competitive	0.04	0.19	0	1	0.09	0.30	0	1
Barron's: Highly competitive	0.17	0.38	0	1	0.08	0.27	0	1
Barron's: Very competitive	0.29	0.46	0	1	0.22	0.41	0	1
Barron's: Competitive	0.31	0.46	0	1	0.45	0.50	0	1
Barron's: Less competitive	0.19	0.39	0	1	0.16	0.36	0	1
Observations	168				405			

Notes: Barron's metrics from 2004. All other metrics from 2016

Table 3: Differences in Means in URM Metrics across Barron's Classification (Private Institutions)

	Pct. minority			Pct. low-income		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Test-optional	Test-required	Diff.	Test-optional	Test-required	Diff.
Barron's classification						
Most competitive	0.28	0.35	-0.07**	0.21	0.25	-0.04
Highly competitive	0.28	0.30	-0.02	0.19	0.20	-0.01
Very competitive	0.26	0.27	0.01	0.22	0.24	-0.02*
Competitive	0.39	0.37	0.02	0.34	0.31	0.03
Less competitive	0.45	0.42	0.03	0.36	0.37	-0.01
All institutions	0.34	0.35	-0.01	0.28	0.29	-0.01

Notes: *p<0.1; **p<0.05; ***p<0.01.

Table 4: Differences in Means in Admissions Metrics across Barron's Classification (Private Institutions)

	Yield rate			Admissions rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Test-optional	Test-required	Diff.	Test-optional	Test-required	Diff.
Barron's classification						
Most competitive	0.37	0.46	-0.09	0.26	0.16	0.10***
Highly competitive	0.20	0.26	-0.05**	0.53	0.47	0.06
Very competitive	0.18	0.23	-0.05***	0.68	0.67	0.02*
Competitive	0.20	0.23	-0.03**	0.69	0.69	0.00
Less competitive	0.21	0.23	-0.02	0.78	0.67	0.11***
All institutions	0.20	0.25	-0.05***	0.66	0.61	0.05**

Notes: *p<0.1; **p<0.05; ***p<0.01.

Table 5: Accuracy Metrics on Classification Algorithms (Private)

	Balanced Accuracy	Precision	Recall	F-measure
Algorithm				
Decision Tree (max depth = 8)	0.57	0.29	0.40	0.34
Naïve Bayes	0.66	0.29	0.90*	0.44
Logistic Regression	0.74*	0.51	0.63	0.57*
KNN (K=17)	0.68	0.52*	0.47	0.49

Notes: *denotes best classifier for that metric.

Table 6: Accuracy Metrics on Classification Algorithms (Public)

	Balanced Accuracy	Precision	Recall	F-measure
Algorithm				
Decision Tree (max depth = 9)	0.53	0.25*	0.10	0.14
Naïve Bayes	0.58*	0.12	1.00	0.21*
Logistic Regression	0.50	0.00	0.00	0.00
KNN (K=3)	0.50	0.00	0.00	0.00

Notes: *denotes best classifier for that metric.