How Much Does Merit Aid Actually Matter?
Revisiting Merit Aid and College Enrollment When Some Students "Come Anyway"

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Abstract
Merit aid is an increasingly important component of college scholarships, but policymakers are concerned that merit aid is often given to students who would enroll anyway. As a baseline we use a regression discontinuity (RD) framework to test an institution-level merit aid program at a public research university and find that the merit aid program successfully increases the likelihood of enrollment. We then add to the RD a structure that accounts for the probability that specific students would enroll (or not enroll) with certainty. This richer model, which allows us to identify students who are less certain about enrolling, indicates the merit aid is much more effective in convincing such students to enroll.

JEL Codes: I20, I22

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1. Introduction

Universities use merit aid as an important tool to strengthen the academic credentials of their student bodies.[1] Merit aid is awarded to students based on some measure of academic achievement, such as grade point average (GPA) or SAT scores. Typically, a threshold value is set and students with scores above the threshold earn the scholarship while students with lower scores do not. We consider three main questions in this paper. Does merit aid increase enrollment? Does merit aid go to students who would come to the school anyway? What implications does this have for traditional empirical studies on merit aid?

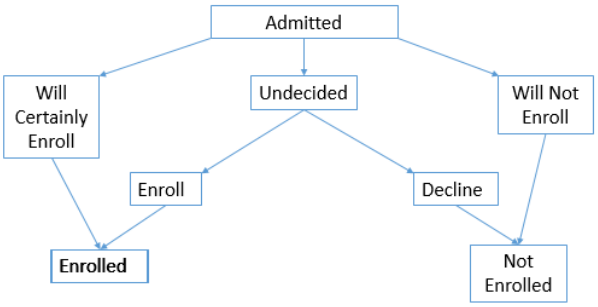
Our concern is that there is substantial heterogeneity among students with regard to their propensity to enroll. Some students may have strong family or local ties to a school. A student may see a particular school as a dream school. For some students, if they are admitted to a particular school, they will enroll with near certainty, regardless of financial aid. Likewise, there may be some students who view a given school as a "safety" school with no strong intention of ever enrolling, regardless of financial aid offers, unless they have no other choice. While it is not difficult to think of reasons why a student might be "certain" to enroll or "certain" to not enroll, this heterogeneity has received no attention in previous studies on merit aid.

Consider the framework in Figure 1. Once a student is admitted to a university, she must choose whether or not to enroll. Some students know that they likely will not enroll at the university; for example, it is their last choice. Other students have decided that, given the chance, they will enroll at the university[2]. It is the rest, the undecided students, for whom merit aid might actually make a difference. These students are the focus of our study. We want to know how merit aid affects their decisions.

[1] In the past 20 years, the percentage of undergraduates getting merit aid has increased more than 300% (Clark, 2014) and from one source amounts to $11 billion dollars a year (Baldwin, 2013).

[2] Our empirical approach allows us to estimate the probability that a student is in the "likely won't enroll" or "likely will enroll" group, for expository purposes use the terms "certainty" or "will always" to refer to these attitudes.

Figure 1: Student Enrollment Decision



Knowing which students won't come with near certainty would allow universities to more accurately predict financial aid needs, especially if financial constraints make administrators reluctant to commit resources. Having a better idea of which students will and will not enroll would aid university leaders in setting goals and program. Universities may waste financial resources if merit aid does not offset other grants given to students who would come anyway.[3]Additionally, the measured effect of merit aid may be biased if aid is offered disproportionately to students who will come with certainty, or not come with certainty, leading university leaders to incorrect conclusions of its usefulness compared to other initiatives for attracting students with strong credentials.

In this paper we use data from a public research university to study the effectiveness of merit aid, controlling for heterogeneity on intent to enroll in a regression discontinuity (RD) analysis. We find more "will never enroll" students than "will always enroll students," with disparities in the portion of each on either side of the merit aid cutoff. Moreover, after controlling for heterogeneity we find that the treatment effect, that is, the marginal impact of merit aid on enrolling, is approximately double in magnitude when compared to a simple RD treatment effect that does not control for heterogeneity in enrollment intentions. Our analysis allows us to estimate the amount of merit aid that is "wasted" on students who would have enrolled anyway. Our results indicate the need to control for heterogeneity in the intent to enroll when evaluating merit aid.

[3] Conversely, unless the amount of merit aid that may be offered is limited, there is no loss to giving it to students who won't come under any condition.

The paper is structured as follows. Section 2 highlights related literature. Section 3 explains the empirical strategy we use to address heterogeneity in students' intents to enroll. We describe the data in section 4 and present our results in section 5. Section 6 offers conclusions and discusses weaknesses in our paper.

2. Related Literature

Universities offer merit aid to increase a student's likelihood of enrolling. It is usually awarded based on student GPA, test scores, or other observable and measurable metric. Most programs rely on clear formulae such that students below some merit threshold do not receive the award and students above the threshold do. Merit aid has become a more important tool for attracting highly credentialed students in recent years (Doyle, 2010).

Comprehensive reviews of the merit aid literature and the various identification strategies involved can be found in Dynarski (2004), Reigg (2008), Klaauw (2008), and Dynarski et al. (2013). As merit aid grew in importance, it stimulated many studies that look at a diverse set of impacts such as where students apply (Curs and Harper, 2012; Goodman, 2008; Zhang et al., 2016), its effect on the racial composition of a student body (Dynarski, 2002), retention (Singell, 2003), degree completion (Bettinger et al., 2016; Sjoquist and Winters, 2015; Singell and Stater, 2006), and how students use time (DesJardins, 2010).

Most pertinent to us is research related to enrollment and student decisions. An early empirical analysis of merit aid was Cornwell, et al., (2006), who study the impact of the Georgia HOPE scholarship on enrollment, and find a positive effect. Van der Klaauw (2002) uses data from one university and shows that the merit aid has a positive effect on students' decisions to enroll. Using data on a merit aid program in Iowa, Leeds and DesJardins (2015) and Monks (2009) also find that it increases enrollment. But while Dynarski (2002) and Monks (2009) show that merit aid increases university enrollment and induces a shift from 2-year to 4-year schools, Bruce and Carruthers (2014) detect no merit aid effect on enrollment in Tennessee. None of these studies considered heterogeneity of the form we discussed above.

To address this heterogeneity, we draw on a model devised by Hausman et al. (1998) for estimating a binary choice model with misclassification. Footnote 1 in that paper describes using the same model for heterogeneity of the sort we identify in merit aid programs; a fraction a_0 of individuals who will always enroll, and a fraction a_1 who will never enroll. Both a_0 and a_1 are independent of the characteristics observed in the main equation. The remaining individuals follow the traditional binary choice model.

The Hausman model assumes the heterogeneity is random to observed variables that explain choice. A recent extension to the Hausman model (Tennekoon and Rosenman, 2016), which we term GHAS, allows heterogeneity probabilities to be systematically dependent by individual. In our context, GHAS allows us to make predictions about which group, coming with certainty, not coming with certainty, or "in play", most likely applies to individual students.

Despite the newness of the GHAS model, it has already been used in several applied settings. Murphy et al. (2015) use the model to study opioid use and self-reporting. It has also been used to study the prevalence of medical bankruptcies (Hackney et al., 2016) and the effectiveness of the BAPCPA means test (Hackney et al. 2015), which pertains to consumer bankruptcies. The original authors use it to study bias in measuring smoking behavior with different tools (Tennekoon and Rosenman, 2013).

3. Empirical Strategy

Heterogeneity

With no heterogeneity the enrollment decision can be characterized as

$$y_i^* = X_i\beta + \delta d_i + \varepsilon_i \tag{1}$$

where y_i^* is the latent individual propensity to enroll, X_i is a vector of individual characteristics except about merit aid, β is a vector of coefficients to be estimated, d_i is a dummy variable on receiving merit aid, δ is the marginal treatment effect (MTE) of merit aid, also to be estimated, and ε_i is an error term with a known common distribution. Given that y_i^* is latent, we only observe

$$y_i = 1(y_i^* \geq 0). \tag{2}$$

where $y_i = 1$ if the student enrolls, $y_i = 0$ otherwise and ϵ_i is the random error term.

In the absence of the heterogeneity we describe, (2), properly estimated, provides unbiased estimates of the marginal treatment effect. However, if merit aid disproportionately impacts students who either will always or who will never enroll, then estimates of (2) capture the average treatment effect (ATE) rather than the MTE.

Following Hausman, et al (1998) and Tennekoon and Rosenman (2016), we allow for heterogeneity in enrollment intentions by letting the probability that a student will enroll with certainty to be

$$\alpha_{0i} = \Phi_0\left(Z_i^0\gamma_0\right) = \Pr(\text{Enrolls with certainty}). \tag{3}$$

The probability that a student is certain to not enroll is

$$\alpha_{1i} = \Phi_1\left(Z_i^1\gamma_1\right) = \Pr(\text{Does not enroll, with certainty}). \tag{4}$$

In (3) and (4) Φ_0 and Φ_1 are known distributions (usually the same) and the vectors Z_i^0 and Z_i^1 are, respectively, factors that affect the probabilities of enrolling, or not, with certainty. These factors may, but are not required to, be subsets of X_i. Vectors γ_0 and γ_1 are parameter to be estimated. Assuming $y_i \sim N$ so (1) can be estimated with a probit model, the expected value of enrolling is

$$E\left(y_i \middle| X_i, Z_i^0, Z_i^1\right) = \Pr\left(y_i \middle| X_i, Z_i^0, Z_i^1\right) = \Phi\left(Z_i^0\gamma_0\right) + \left(1 - \Phi\left(Z_i^0\gamma_0\right) - \Phi\left(Z_i^1\gamma_1\right)\right)\Phi(X_i\beta) \tag{5}$$

where $\Phi(\cdot) = \Phi_0(\cdot) = \Phi_1(\cdot)$ and the likelihood function is

$$\mathcal{L}(\beta, \gamma_0, \gamma_1) = n^{-1}\sum_{i=1}^{n}\begin{pmatrix} y_i \ln\left[\Phi\left(Z_i^0\gamma_0\right) + \left(1 - \Phi\left(Z_i^0\gamma_0\right) - \Phi\left(Z_i^1\gamma_1\right)\right)\Phi(X_i\beta)\right] + \\ (1 - y_i)\ln\left[1 - \Phi\left(Z_i^0\gamma_0\right) - \left(1 - \Phi\left(Z_i^0\gamma_0\right) - \Phi\left(Z_i^1\gamma_1\right)\right)\Phi(X_i\beta)\right] \end{pmatrix}. \tag{6}$$

Because Φ is symmetric identification requires $Z_i^1 \neq Z_i^0$. The maximum likelihood estimator is

$$\left[\hat{\beta}, \hat{\gamma}_0, \hat{\gamma}_1\right] = \arg\max L(\beta, \gamma_0, \gamma_1 | X, Z^0, Z^1). \tag{7}$$

The model predicts enrollment when

$$\Phi_0\left(Z_i^0\hat{\gamma}_0\right) + \left(1 - \Phi_0\left(Z_i^0\hat{\gamma}_0\right) - \Phi_1\left(Z_i^1\hat{\gamma}_1\right)\right)\Phi\left(X_i\hat{\beta}\right) \geq 0.5. \tag{8}$$

With these parameter estimates from equation 8, we can calculate the fraction of each kind of student as follows:

The fraction that always enrolls is

$$E(\Pr[\text{always enroll}]) = n^{-1}\sum_{i=1}^{n}\frac{y_i\Phi(-X_i\hat{\beta})\Phi(Z_i^0\hat{\gamma}_0)}{\Phi(-X_i\hat{\beta})\Phi(Z_i^0\hat{\gamma}_0)+\Phi(X_i\hat{\beta})\Phi(Z_i^1\hat{\gamma}_1)}; \tag{9}$$

while the fraction that never enrolls is

$$E(\Pr[\text{never enroll}]) = n^{-1}\sum_{i=1}^{n}\frac{(1-y_i)\Phi(X_i\hat{\beta})\Phi(Z_i^1\hat{\gamma}_1)}{\Phi(X_i\hat{\beta})\Phi(Z_i^1\hat{\gamma}_1)+\Phi(-X_i\hat{\beta})\Phi(-Z_i^0\hat{\gamma}_0)}. \tag{10}$$

For undecided students the probability of enrolling is given by $\Phi(X_i\hat{\beta})$.

Treatment Identification

We identify the treatment effect using a RD design. With a RD design, we limit our sample to a small neighborhood around the threshold for qualifying for merit aid. The idea underlying RD design is that students near the cutoff, on either side, have equivalent conditional propensities to enroll, hence the marginal treatment effect is the only difference between students just to the left of the aid cutoff and those just to the right. The only difference in our approach from a normal RD design is that we use (6) as the likelihood function rather than a simple probit.

4. Data

Our data were provided by Institutional Research (IR) at the university we are studying. IR provided cross sectional information on the students admitted as freshman for the 2015 fall term. We limit our analysis to students qualifying as "in-state" (including citizens and legal residents) not designated as athletes who were admitted to the university's main campus. The data includes demographic, geographic, and financial aid information for all admitted students and whether or not they enroll.

The merit aid program of interest has a sharp cut-off based on a student's "Q-value." The Q-value is a combination of the student's high school GPA and SAT score. It is calculated using the students best available math and verbal SAT scores as follows: $Q = SAT + 400GPA$. The institutional merit aid

program considered in this paper is awarded to all in-state students with a Q-value of 2400 or greater. For our main analysis we use an RD bandwidth of Q-values within 25 points of 2400, although we consider other bandwidths as a robustness check. A 25 point difference in Q-value is equal to a 0.0625 GPA point difference for 2 students with the same SAT score. Of the 14,200 admitted students, 624 have Q-values between 2375 and 2425. Table 1 provides a list of all variables used in our analysis and basic statistics.[4] Variables above the line are used in our primary analysis. Variables below the line are used in some of our robustness checks.

Of the students included in our main sample, 49 percent are eligible for the scholarship. Of students who do not receive the scholarship, 34 percent matriculate, compared to 42 percent of students who do receive the scholarship. Overall, 38 percent of students enroll. Approximately 10 percent of the students have at least one parent who is an alumnus at the university, 41 percent are male, 41 percent are ethnic minority students, the average age is 18.5, and 21 percent of the students are from the proximate geographic area of the university, the same side of the state as the university itself. In this range of Q-scores, the average best SAT score for a student is 1040 out of 1600. On average, students in our sample attended high school about 300 miles away from the university.[5]

The expected family contribution, or EFC, is how much the federal government expects a student's family to contribute to the cost of attendance. The EFC is a function of family income, accumulated wealth, and family size. Most universities use the EFC to determine need-based aid, meeting the difference between the (federal) cost of attendance and a student's EFC with a combination of grants, scholarships, loans and, in some cases, work-study. In our data, the average EFC is $22,351. By way of comparison, the cost of attendance for students at the university in 2015 was, on average, $27,824.

[4] Tables A1 and A2 in the appendix present the summary statistics for students below and above the merit aid threshold, respectively.

[5] Appendix table A1 reports summary the sample means and standard deviations for students below and above the eligibility threshold as well as test results for sample mean equivalence. Aside from Q-score measurements, only the student SAT scores are significantly different on either side of the cutoff, with higher scores being eligible for treatment. Less significant differences are that eligible students tend to be slightly more white, higher income, and from farther away.

The merit scholarship is $2000 a year, renewable for students maintaining a GPA of 3.0 or more and earning at least 24 semester credit hours each year. It helps recipients in one of two ways. If the student qualified for need-based financial aid of less than $2000, the merit scholarship directly reduced the amount she would have to pay to attend the university. If she qualified for need-based aid greater than $2000, the merit scholarship offsets loans. If such a student has loans of less than $2000 in her need-based package, the excess of the grant would again reduce the direct cost she would have to pay to attend the university.[6]

In our primary specification we chose three variables as predictors of students who enroll with certainty, and two variables as predictors of students who will not enroll with certainty. In the certain to not enroll equation, we include EFC and whether or not the student has at least one parent who is an alumnus. EFC is included here as a proxy for income, expecting that students with more financial means may be less interested in a state university, looking at it, perhaps, as their safety school. Parent an alumnus is included because students with family ties to the university are less likely to be certain about not enrolling than other students.

In the certain to enroll equation we include a dummy variable for being from the geographic area proximate to the university, a distance variable (measured in miles), and the student's SAT scores. The state has two large research universities located in different parts of the state. Local culture, preferences, or other factors, may play a role in a student's intent to enroll, perhaps approaching certainty. Distance is included because students from farther away are probably less likely to always enroll. Test scores affect a student's choice set. High test scores increase possibilities, making it less likely a student will enroll at this university with certainty.

GHAS is sensitive to the specifications for the certainty to or not to enroll. We include several variations of these specifications as a robustness check. We find that the MTE estimates tend to be larger

[6] Because need-based aid is the difference between the cost of attendance and EFC, including need-based aid along with EFC would impose (almost exact) multicollinearity; hence it is not included as an explanatory variable.

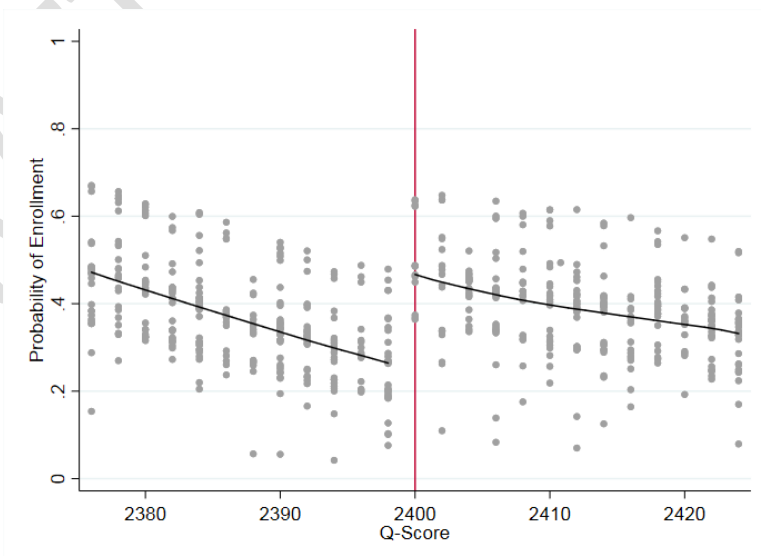
than simple RD estimates across a wide range of α_0 and α_1 specifications. Our chosen specification yields a more conservative estimate of the MTE than the others do.

5. Results

Table 2 reports the marginal treatment effect (MTE) for RD models of GHAS and probit at a bandwidth of 25 Q-value points.[7] Consistent with most previous studies, with both models, we find the merit scholarship increases the probability of enrollment. In the probit, students are 20 percent more likely to enroll with the merit aid than without. Using GHAS we estimate that undecided students with merit aid are 30 percent more likely to enroll than undecided students who do not qualify for merit aid. Correcting for heterogeneity in intent to enroll, we find the treatment effect is 50 percent larger than the average treatment effect estimated in the simple probit model. This difference is statistically significant with a p-value<0.01.

In Figure 2 we present the predicted probability of enrollment (i.e., $\Phi(X_i\hat{\beta})$) from the probit model. We observe a strong downward trend in enrollment as Q-value increases, but the impact of the scholarship is very clear.

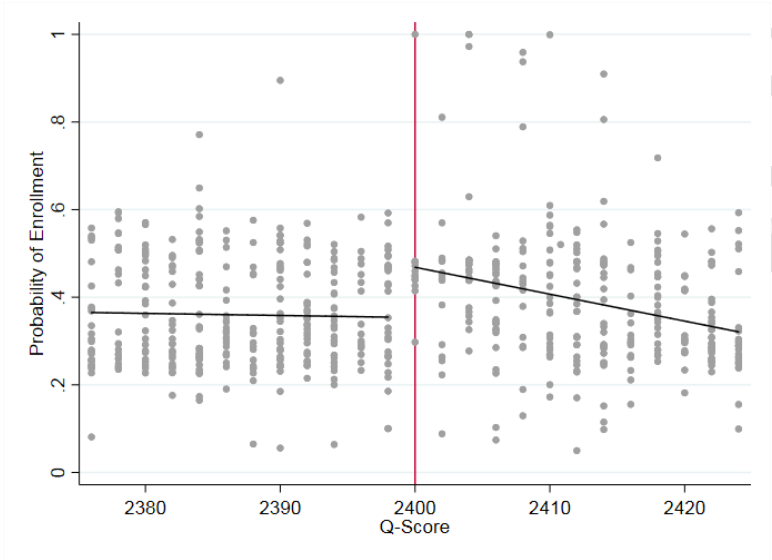
Figure 2: Predicted Probability of Enrollment -- Probit



[7] The full regression output, and a brief discussion of the results, is in Table A7 in the Appendix. In that table, column 1 shows the parameter estimates for the GHAS model, and column 2 has the estimates for the probit.

Figure 3 graphs the same relationship for the predicted probability of enrollment estimated with GHAS, which accounts for the heterogeneity – some students likely enrolling with certainty, and others likely not enrolling with certainty. In the figure we see much less of a relationship between the fitted values and Q-score but we again observe a discrete increase at 2400.

Figure 3: Predicted Probability of Enrollment – GHAS



Recognizing that the image of the treatment effect in Figure 3 is obfuscated by the presence of always enroll and never enroll students, we include present, in Figure 4, the probability of enrollment calculated only for students who are less than 50 percent likely to be an always enroll student and less than 50 percent likely to be a never enroll student. The points in Figure 4 are the $\Phi(X_i\hat{\beta})$ outcomes from the main equation only, which behaves like a probit. Notice that for these students who are most likely uncertain about attending, the probit portion of the model predicts a very large treatment effect at 2400 Q-score points. The difference between the treatment effect in Figure 3 and the treatment effect in Figure 4 helps to illustrate how the MTE for the undecided is very different from the ATE for the whole sample.

Figure 4: GHAS Predicted Probability of Enrollment Only for Students with Probability of Never Enrolling and Probability of Always Enrolling Both Less than 0.5

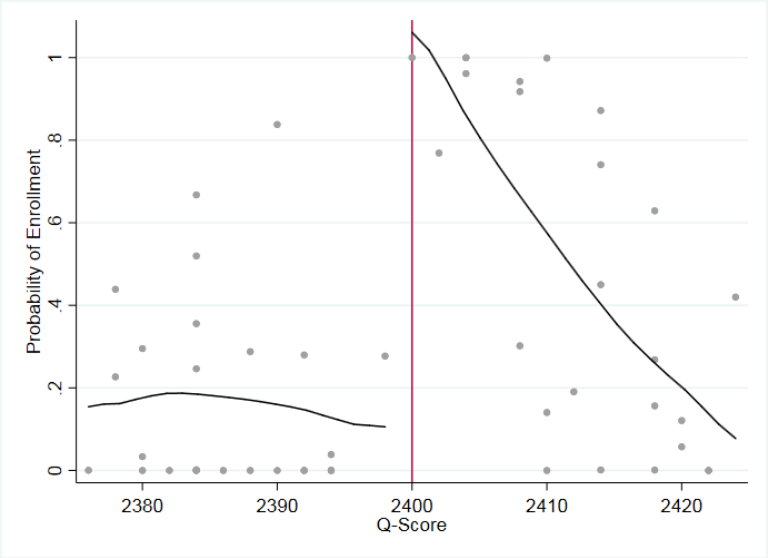
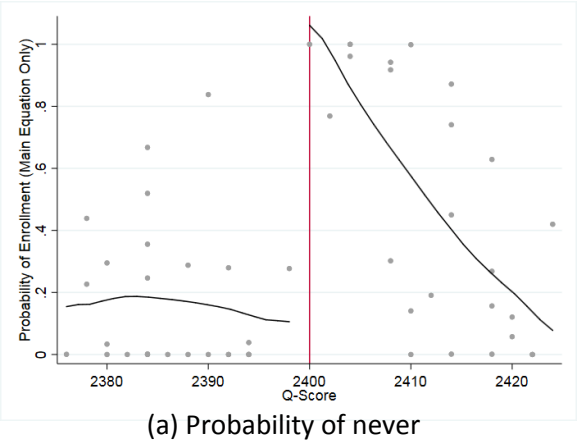


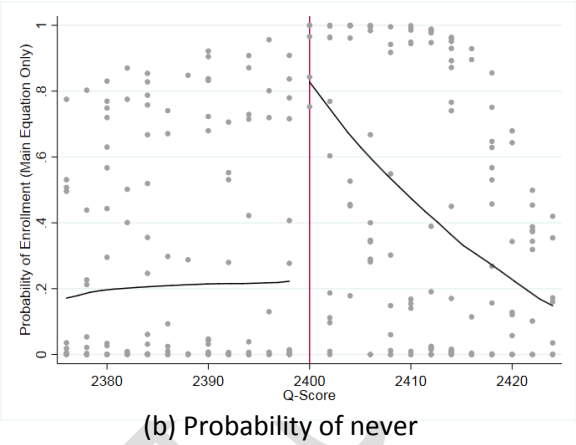
Figure 5 is an expansion on Figure 4. Panel (a) presents the same image as figure 4 with the same interpretation. Panel (b) presents the probability of enrollment calculated only for students who are less than 55 percent likely to be an always enroll student and less than 55 percent likely to be a never enroll student. Panel (c) does the same but with a cutoff at 60 percent and panel (d) with 70 percent. From panel (a) to (d) we progressively add more students to the undecided group, and see the MTE declines.

Figure 5: GHAS Predicted Probability of Enrollment Only for Students with Probability of Never Enrolling and Probability of Always Enrolling Both Less than 0.5, 0.55, 0.6, 0.7



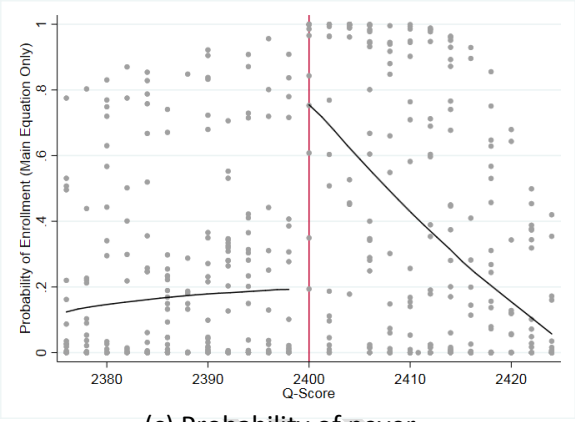
(a) Probability of never enrolling and probability of always enrolling are both less than 0.5.

Obs: 51



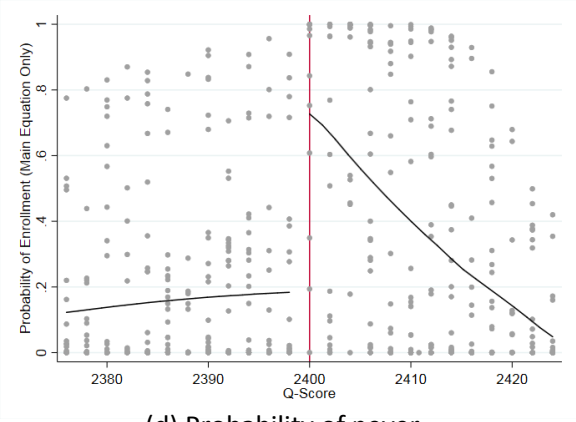
(b) Probability of never enrolling and probability of always enrolling are both less than 0.55.

Obs: 339



(c) Probability of never enrolling and probability of always enrolling are both less than 0.6.

Obs: 578



(d) Probability of never enrolling and probability of always enrolling are both less than 0.7.

Obs: 620

Using equations (9) and (10) we can compare the prevalence of always enroll students and never enroll students for those students who are above or below the threshold for the scholarship. In the total sample, 234 enrolled and 390 did not. We estimate that roughly 27.1 percent of the enrolled students would have enrolled independent of merit aid. Of students who did not enroll, roughly 11.6 percent would

not have enrolled regardless of merit aid. Just under 29% of those ineligible for merit aid are likely to always enroll. A slightly smaller 25% of those eligible for aid would always enroll, indicating that one-fourth of the merit aid funding is offered to students who would come anyway. A much larger difference is apparent for the percent of non-enrolled who would never enroll; only 7% of those ineligible for the merit aid fall into this group, compared to 16% of those who are eligible for the merit aid, consistent with our hypothesis that better students look at this university as a safety school, and thus enroll only as a last resort.

Table 4 compares the predictive accuracy of the probit and GHAS estimates. GHAS correctly predicted 67 percent (415 students) of the cases while probit correctly predicted 65 percent (406 students). Other ratios included are the models' sensitivity, specificity, positive predictive value, and negative predictive value. From a merit aid perspective, the most important measure is likely sensitivity; the percent of correct predictions among students who actually enroll. GHAS (27%) does a much better job than probit (20%). Specificity is the percent of correct predictions of student who did not enroll. Here, GHAS is correct 90% of the time, while probit is correct 93% of the time. The positive predictive value (how likely someone is to enroll if the model predicts that they enroll) is 62%with GHAS and 60% with probit, while the negative predictive value (how likely someone is to not enroll if the model predicts that they will not enroll) is 67% with GHAS and 66% with probit. GHAS seems slightly better, overall, in predicting who will enroll.

Other Heterogeneity Specifications

GHAS can be sensitive to specification, especially on the variables explaining always enroll and never enroll. We include the MTEs from 6 alternative specifications in Table 5.[8] Column 1 is the base model. Columns 2 through 7 have alternate specifications. Column 8, for convenience, again reports the simple probit. Each of columns 1-7 indicates the different combination of covariates used for explaining

[8] Full regression results for heterogeneity changes are in Table A8 in the Appendix.

the always enroll and never enroll probabilities. The variables used in the main equation (that is, the Xs) are the same in each model.

For all specifications except that in column 6, the MTE is sizeable and statistically significant at a p-value≤0.05. Our primary specification was chosen, in part, because it produced the most conservative estimate of the marginal effect of merit aid. Hence, we have additional evidence that a simple probit underestimates the marginal effect of merit aid. Controlling for heterogeneity in likelihood to either always enroll or never enroll strongly increases the importance of merit aid in the decision of those students who fall in neither group.

Placebo Experiments

In Table 6 we address the possibility that the model is picking up spurious changes around treatment.[9] A common way to test for this is to conduct placebo experiments, in which an arbitrary threshold is chosen away from the true treatment effect. RD methods are employed at the artificial threshold. If the treatment effect is unique to the true treatment then the treatment effect should differ in the placebo trials.

For both GHAS (our primary specification) and probit, we conduct placebo tests at 2380, 2390, 2410, and 2420 Q-value thresholds. At each threshold, the bandwidth is consistently 25 points on each side of the threshold. With the largest adjustments, 2380 and 2420, we find no treatment effect with a placebo analysis. There is a negative effect at 2390 in both models. There is a positive and significant treatment effect in the GHAS at 2410, but it is less than half the size of the true treatment effect at 2400. The probit treatment effect is not statistically significant at 2410. These results suggest that our model is picking up a true treatment effect, and not some spurious change in the running variable.

[9] Full estimation of each placebo test is recorded in Table A9 of the Appendix.

Bandwidth Comparisons

In Table 7 we present the marginal treatment effects of the models with different bandwidths.[10] Small bandwidths make it difficult to capture a distinct treatment effect. Large bandwidths, however, increase the likelihood that the differences among the observations is due to something more than the treatment. To balance this tradeoff, Imbens and Kalyanamaran, (2012) devised a method for choosing a bandwidth to minimize mean squared error (MES). Calonico et al., (2014) expand on their method to allow covariates in addition to the running variable. Calonico et al., (2016) goes further, presenting a new method for bandwidth optimization that relies on coverage error (CE) optimization. We employ the methods used in Calonico et al., (2014, 2016) to determine the MSE optimal bandwidth and the coverage error optimal bandwidth.

These methods yield bandwidths of 150.323 and 95.432 respectively. We have concern that these ranges are too large from a conceptual standpoint. Comparing 2 students 95 (150) Q-value points in opposite directions from the threshold suggests comparing two students with equal SAT scores but a 0.475 (0.75) difference in GPA, or two students with similar GPAs but a 190 (300) point GAP on the SAT.

Nonetheless, we include these in our robustness checks. We also try bandwidths of 75 and 50. The marginal effects of these analyses are presented in Table 7, in order of descending bandwidth. For convenience, we also present our primary results using a bandwidth of 25. Merit aid is significant at conventional p-values only at the lowest bandwidth, although the GHAS MTE is always significantly larger than the probit MTE.

Running Variable Changes

In Table 8 we address the specification of the running variable.[11] In each of the preceding regressions, we included Q-value points to the left of 2400 as one variable and Q-value points to the right

[10] Full estimations of model by bandwidth are recorded in Table A10 of the Appendix.
[11] Full estimation results by running variable controls are recorded in Table A11 in the Appendix.

as another. In Table 8 we consider 2 additional specifications. In column 2 the running variable is the Q-value centered on 2400. In column 3 the centered Q-value and Q-value squared are included. For the probit the marginal treatment effect is nearly identical in all specifications. With GHAS the treatment effect is more sensitive to these running variable changes. The treatment ranges from 29 percent in the primary model to 38 percent in the cubic Q-value model, but is only significant in the primary model. Though the GHAS marginal effect is noisier, each treatment effect is markedly larger than the simple probit RD effects, and our primary model yields the treatment effect with the smallest magnitude of the four.

Changes in the Main Equation Specification

Finally we compare the results with different X variables in the main equation. We compare the results of 5 additional models in Table 9.[12] Which covariates for each specification are listed in the table. In all columns the probit MTE rounds to 20 percent and is significant to the 1 percent level.

The GHAS is more sensitive to these changes. The magnitude of the MTE in columns 2-6 ranges from 29 percent in our primary specification to 47 percent. Each alternate specification is larger in magnitude than our main specification, but columns 2 and 4, those with the individual race variables, are not significant at conventional levels. Once again our primary specification yields the smallest treatment effect, at 29 percent. In each case the marginal effect is larger in the GHAS than the probit.

6. Conclusions

We analyze a merit aid scholarship offered by a public research university. Using traditional RD methods and a novel data set, we estimate a positive marginal effect of approximately 20% on enrollment from a merit-based scholarship. However, after controlling for heterogeneity among our sample for those likely to enroll, and or those likely to not enroll, we find a much larger marginal effect (30%) for students who are not committed one way or the other. The treatment effect with decision heterogeneity is

[12] Full estimation results by main equation specification are recorded in Table A12 in the Appendix.

approximately 50 percent larger than the treatment effect in the simple RD model. In addition, we estimate that approximately 27% of students who enrolled would have enrolled no matter what, while 12% of non-enrolling students were likely never going to enroll. Only the remaining students were influenced by the merit aid, and approximately 25% of the scholarships went to students who would have enrolled anyway.

The importance of controlling for heterogeneity is robust over different specifications. However, our results are sensitive to bandwidth changes, although traditional bandwidth selection methods give bandwidths that, we believe, are too large to be appropriate for our analysis. The empirical magnitudes of our results are, of course, specific to the university studied. Both the percent of wasted resources and the marginal treatment effect are specific to the degree of heterogeneity among the student considering enrolling at the university. At the same time, our results point to the importance of controlling for such heterogeneity, especially at colleges with lower yield rates. Around 80% of those admitted to Harvard and Stanford enroll – merit aid probably matters for the undecideds, but that is likely a small percentage of the students who decide to enroll. But the average yield among universities considered "National Universities" by US News and World Report in its rankings for 2015 was 32.9 percent (Powell, 2017). Among National Liberal Arts Colleges the average yield was 27.5 percent for 2015. To the extent these universities have "never enroll" or "always enroll" students, the effectiveness of merit aid in building a select student body may be grossly underestimated. While money might be spent on those who would come anyway, the marginal effect on the undecided may be quite large.

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Tables

Table 1: Summary Statistics for RD Sample with Bandwidth 25

Variable	Obs	Mean	Std. Dev.	Min	Max
Enrolled	624	0.375	0.485	0	1
Eligible for Merit Aid	624	0.489	0.500	0	1
Q-value Points Left of the Cutoff	624	-6.590	8.100	-24	0
Q-value Points Right of the Cutoff	624	6.197	8.097	0	24
Male	624	0.410	0.492	0	1
Minority	624	0.407	0.492	0	1
Expected family contribution	624	22351	3.171	0	50.795
Age	624	18.513	0.383	17.667	20.75
Same geographic region	624	0.215	0.411	0	1
Distance	624	300.180	364.796	13.557	2900.865
Parent an alumni	624	0.098	0.297	0	1
Best combination of SAT scores	624	10.402	0.960	8.1	13.4
Q-value Points Centered Around the Cutoff	624	-0.393	14.593	-24	24
Squared Q-value Points Centered Around the Cutoff	624	212.777	185.028	0	576
Hispanic	624	0.186	0.389	0	1
Asian	624	0.095	0.293	0	1
Native American	624	0.006	0.080	0	1
Other	624	0.024	0.153	0	1
Multi-Race	624	0.090	0.286	0	1

Table 2: Average Marginal Treatment Effects of Merit Aid on Enrollment for Primary GHAS and Probit Estimations

Model	GHAS	Probit
Marginal Treatment Effect (MTE)	0.297**	0.197***
SE	[0.134]	[0.07]
Obs	624	624

*Main equation *X* variables are Q-Value Points to the Left, Q-value points to the right, Male, Minority, EFC, Age, Same geographic region, Distance; Always enroll variables are Best SAT Score, Distance, Same geographic region; Never enroll variables are EFC, Parent Alumni.

Table 3: Comparisons of Decision Heterogeneity Probabilities by Merit Aid Eligibility

	Ineligible for Merit Aid	Eligible for Merit Aid	Total
Percent of enrolled who would always enroll	0.288	0.254	0.271
Percent of non-enrolled who would never enroll	0.073	0.161	0.116
Number Enrolled	116	118	234
Number Not Enrolled	203	187	390

Table 4: Predictive Accuracy

Model	Portion Correctly Predicted	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value
GHAS	0.67	0.27	0.90	0.62	0.67
Probit	0.65	0.20	0.92	0.61	0.66

Table 5: Changes in Modelling Decision Heterogeneity, Average Marginal Effect of Merit Aid on Enrollment

Heterogeneity Specification	1	2	3	4	5	6	7	8
MTE	0.297**	0.324**	0.458***	0.325**	0.340**	0.373	0.405**	0.197***
SE	[0.134]	[0.157]	[0.152]	[0.152]	[0.162]	[0.455]	[0.181]	[0.070]
Obs	624	624	624	624	624	624	624	624
Always Enroll Covariates	Best SAT Score, Distance, Same geographic region	Distance, Same geographic region	Distance, Best SAT Score	Distance, Parent Alumni	EFC, Distance, Same geographic region	Distance, Parent Alumni	EFC, Distance	
Never Enroll Covariates	EFC, Parent Alumni	Parent Alumni	Same geographic region, Parent Alumni	EFC	EFC, Parent Alumni	Best SAT Score	EFC, Parent Alumni	

Main equation *X* variables are Q-Value Points to the Left, Q-value points to the right, Male, Minority, EFC, Age, Same geographic region, Distance.

Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Table 6: Marginal Placebo Treatment Effects

Placebo Shift	20 Q-Value points to the left	10 Q-Value points to the left	Centered	10 Q-Value points to the right	20 Q-Value points to the right
GHAS MTE	0	-0.331***	0.297**	0.122***	0
SE	.	[0.042]	[0.134]	[0.034]	.
Probit MTE	0	-0.162**	0.197***	-0.143	0
SE	.	[0.082]	[0.070]	[0.101]	.
Obs	591	623	624	609	578

Main equation *X* variables are Q-Value Points to the Left, Q-value points to the right, Male, Minority, EFC, Age, Same geographic region, Distance; Always enroll variables are Best SAT Score, Distance, Same geographic region; Never enroll variables are EFC, Parent Alumni.
Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Table 7: Marginal Treatment Effects by Bandwidth

Bandwidth	MSE Optimal: 150	CE Optimal: 93	75	50	25
GHAS MTE	0.056	0.070	0.031	0.089	0.297**
SE	[0.057]	[0.152]	[0.084]	[0.083]	[0.134]
Probit MTE	0.009	0.017	0.014	0.057	0.197***
SE	[0.032]	[0.040]	[0.045]	[0.054]	[0.070]
Obs	3307	2139	1705	1209	624

Main equation *X* variables are Q-Value Points to the Left, Q-value points to the right, Male, Minority, EFC, Age, Same geographic region, Distance; Always enroll variables are Best SAT Score, Distance, Same geographic region; Never enroll variables are EFC, Parent Alumni.
Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Table 8: Running Variable Comparisons, Marginal Treatment Effects

	1	2	3
GHAS MTE	0.297**	0.311	0.367
SE	[0.134]	[419.496]	[0.226]
Probit MTE	0.197***	0.194***	0.196***
SE	[0.070]	[0.070]	[0.070]
Obs	624	624	624
Running Variable Controls	Q-value points below cutoff, Q-value points above cutoff	Q-value (Centered on Cutoff)	Q-value, Squared Q-value

Main equation *X* variables are running variable controls above, Male, Minority, EFC, Age, Same geographic region, Distance; Always enroll variables: Best SAT Score, Distance, Same geographic region; Never enroll variables are EFC, Parent Alumni. Key: *, **, and *** denotes estimate is significant at the 0.1, 0.05, and 0.01 levels.

Table 9: X variable Comparisons, Average Marginal Effect of Merit Aid on Enrollment

X Specification	1	2	3	4	5	6
GHAS MTE	0.297**	0.408	0.416*	0.409	0.471***	0.318***
SE	[0.134]	[1.040]	[0.215]	[2.285]	[0.109]	[0.102]
Probit MTE	0.197***	0.200***	0.197***	0.203***	0.199***	0.200***
SE	[0.070]	[0.071]	[0.071]	[0.070]	[0.071]	[0.070]
Obs	624	624	624	624	624	624
X Covariates	Male, Minority, EFC, Age, Same geographic region, Distance	Male, Black, Hispanic, Asian, Native American, Other Race, MultiRace, EFC, Age, Same geographic region	Male, Minority, Age, Same geographic region, Distance	Male, Black, Hispanic, Asian, Native American, Other Race, MultiRace, EFC, Age, Same geographic region, Distance	Male, Minority, EFC, Age, Distance	Male, Minority, Age, Same geographic region, Distance, Parent Alumni

Always enroll variables are Best SAT Score, Distance, Same geographic region; Never enroll variables are EFC, Parent Alumni. Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Appendix: Additional Tables and Figures

Table A1: Summary statistics by merit aid eligibility

	Students Below Cutoff		Students Above Cutoff		T-Test $H_o: \bar{x}_{below} = \bar{x}_{above}$	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	T-Stat	P-Value
Enrolled	0.36	0.48	0.39	0.49	-0.60	0.55
Eligible for Merit Aid	0.00	0.00	1	0	.	.
Q-value Points Left of the Cutoff	-12.89	6.86	0	0	-32.82	0.00
Q-value Points Right of the Cutoff	0.00	0.00	12.68	7.20	-31.43	0.00
Male	0.40	0.49	0.42	0.49	-0.30	0.76
Minority	0.43	0.50	0.38	0.49	1.17	0.24
Expected family contribution	2.08	2.57	2.39	3.70	-1.23	0.22
Age	18.49	0.38	18.54	0.38	-1.58	0.11
Same geographic region	0.24	0.43	0.19	0.39	1.46	0.14
Distance	286.57	345.76	314.41	383.75	-0.95	0.34
Parent WSU alumni	0.10	0.31	0.09	0.29	0.49	0.63
Best combination of SAT scores	10.32	0.94	10.49	0.97	-2.23	0.03
Q-value Points Centered Around the Cutoff	-12.89	6.86	12.68	7.20	-45.41	0.00
Squared Q-value Points Centered Around the Cutoff	213.07	182.92	212.47	187.50	0.04	0.97
Hispanic	0.18	0.39	0.19	0.39	-0.27	0.79
Asian	0.10	0.31	0.09	0.28	0.78	0.44
Native American	0.01	0.10	0.00	0.06	0.96	0.34
Other	0.02	0.14	0.03	0.17	-0.87	0.38
Multi-Race	0.09	0.29	0.09	0.28	0.38	0.70
Observations	319		305			

Expected family contribution measured in $10,000's.

Table A2: Summary statistics for full university in-state data and summary statistics for RD sample data

	All Admitted In-State Students									
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Enrolled	8,843	0.34	0.48	0.00	1.00	624	0.38	0.49	0	1
Eligible for Merit Aid	8,843	0.38	0.49	0.00	1.00	624	0.49	0.50	0	1
Q-value Points Left of the Cutoff	8,843	-48.41	274.44	-2400.00	800.00	624	-6.59	8.10	-24	0
Q-value Points Right of the Cutoff	8,843	62.20	100.13	0.00	348.00	624	6.20	8.10	0	24
Male	8,843	0.44	0.50	0.00	1.00	624	0.41	0.49	0	1
Minority	8,843	0.41	0.49	0.00	1.00	624	0.41	0.49	0	1
Expected family contribution	8,843	2.63	4.29	0.00	100.00	624	22351.00	3.17	0	50.80
Age	8,843	18.52	0.45	16.67	27.75	624	18.51	0.38	17.67	20.75
Same geographic region	8,843	0.21	0.41	0.00	1.00	624	0.22	0.41	0	1
Distance	8,843	245.68	232.41	13.56	2900.87	624	300.18	364.80	13.56	2900.87
Parent an alumni	8,843	0.12	0.33	0.00	1.00	624	0.10	0.30	0	1
Best combination of SAT scores	8,843	10.66	1.73	0.00	16.00	624	10.40	0.96	8.1	13.4
Q-value Points Centered Around the Cutoff	8,843	13.79	302.27	-2400.00	800.00	624	-0.39	14.59	-24	24
Squared Q-value Points Centered Around the Cutoff	8,843	91546	2.86E+05	0.00	5.76E+06	624	212.78	185.03	0	576
Hispanic	8,843	0.16	0.37	0.00	1.00	624	0.19	0.39	0	1
Asian	8,843	0.11	0.31	0.00	1.00	624	0.10	0.29	0	1
Native American	8,843	0.00	0.07	0.00	1.00	624	0.01	0.08	0	1
Other	8,843	0.02	0.14	0.00	1.00	624	0.02	0.15	0	1
Multi-Race	8,843	0.09	0.29	0.00	1.00	624	0.09	0.29	0	1

Expected family contribution measured in $10,000's.

Summary statistics by bandwidth:

Table A3
Summary Statistics of Sample with Mean Squared Error Optimal Bandwidth: 150.32
(See Imbens and Kalanaraman, 2012; Calonico et al., 2014).

Variable	Obs	Mean	Std. Dev.	Min	Max
Enrolled	3,307	0.376474	0.484574	0	1
Eligible for Merit Aid	3,307	0.499546	0.500075	0	1
Q-value Points Left of the Cutoff	3,307	-36.6723	48.08485	-150	0
Q-value Points Right of the Cutoff	3,307	36.3567	47.85514	0	150
Male	3,307	0.437859	0.496199	0	1
Minority	3,307	0.397641	0.489485	0	1
Expected family contribution	3,307	25670	4.026112	0	85.1477
Age	3,307	18.51492	0.386996	16.83333	22.16667
Same geographic region	3,307	0.202903	0.402222	0	1
Distance	3,307	255.4942	248.6894	13.55669	2900.865
Parent WSU alumni	3,307	0.111884	0.315271	0	1
Best combination of SAT scores	3,307	10.48633	1.034098	7.4	14.2
Q-value Points Centered Around the Cutoff	3,307	-0.31557	85.26218	-150	150
Squared Q-value Points Centered Around the Cutoff	3,307	7267.541	6757.281	0	22500
Hispanic	3,307	0.15694	0.363799	0	1
Asian	3,307	0.101603	0.302171	0	1
Native American	3,307	0.006955	0.083118	0	1
Other	3,307	0.020865	0.142953	0	1
Multi-Race	3,307	0.094043	0.291933	0	1

Expected family contribution measured in $10,000's.

Table A4
Summary Statistics of Sample with Coverage Error Optimal Bandwidth: 95.43
(See Calonico et al., 2014)

Variable	Obs	Mean	Std. Dev.	Min	Max
Enrolled	2,139	0.377747	0.484937	0	1
Eligible for Merit Aid	2,139	0.504441	0.500097	0	1
Q-value Points Left of the Cutoff	2,139	-22.6749	30.12665	-94	0
Q-value Points Right of the Cutoff	2,139	23.16017	30.03811	0	94
Male	2,139	0.430575	0.495273	0	1
Minority	2,139	0.395979	0.489174	0	1
Expected family contribution	2,139	24888	3.817435	0	85.1477
Age	2,139	18.51021	0.372023	17	21.41667
Same geographic region	2,139	0.196353	0.397332	0	1
Distance	2,139	264.8375	278.4551	13.55669	2900.865
Parent WSU alumni	2,139	0.115007	0.319105	0	1
Best combination of SAT scores	2,139	10.47821	0.996989	7.8	14.2
Q-value Points Centered Around the Cutoff	2,139	0.485274	53.48554	-94	94
Squared Q-value Points Centered Around the Cutoff	2,139	2859.601	2681.01	0	8836
Hispanic	2,139	0.159888	0.366588	0	1
Asian	2,139	0.097709	0.296991	0	1
Native American	2,139	0.00748	0.086184	0	1
Other	2,139	0.020103	0.140385	0	1
Multi-Race	2,139	0.091632	0.288573	0	1

Expected family contribution measured in $10,000's.

Table A5
Summary Statistics of Sample with Bandwidth 75

Variable	Obs	Mean	Std. Dev.	Min	Max
Enrolled	1,705	0.388856	0.487634	0	1
Eligible for Merit Aid	1,705	0.507918	0.500084	0	1
Q-value Points Left of the Cutoff	1,705	-17.4707	23.33762	-74.8001	0
Q-value Points Right of the Cutoff	1,705	18.44903	23.64844	0	74
Male	1,705	0.421114	0.493883	0	1
Minority	1,705	0.399414	0.489922	0	1
Expected family contribution	1,705	25042	3.886837	0	85.1477
Age	1,705	18.50626	0.373881	17.16667	21.41667
Same geographic region	1,705	0.202933	0.402301	0	1
Distance	1,705	263.9395	278.2576	13.55669	2900.865
Parent WSU alumni	1,705	0.108504	0.311108	0	1
Best combination of SAT scores	1,705	10.4705	0.98075	7.8	13.7
Q-value Points Centered Around the Cutoff	1,705	0.978299	41.81994	-74.8001	74
Squared Q-value Points Centered Around the Cutoff	1,705	1748.839	1637.738	0	5595.047
Hispanic	1,705	0.166569	0.3727	0	1
Asian	1,705	0.096774	0.295737	0	1
Native American	1,705	0.008211	0.090269	0	1
Other	1,705	0.018768	0.135746	0	1
Multi-Race	1,705	0.08915	0.285043	0	1

Expected family contribution measured in $10,000's.

Table A6
Summary Statistics of Sample with Bandwidth 50

Variable	Obs	Mean	Std. Dev.	Min	Max
Enrolled	1,209	0.387097	0.487288	0	1
Eligible for Merit Aid	1,209	0.508685	0.500131	0	1
Q-value Points Left of the Cutoff	1,209	-11.8826	15.65214	-50	0
Q-value Points Right of the Cutoff	1,209	13.01141	16.59262	0	50
Male	1,209	0.413565	0.492676	0	1
Minority	1,209	0.411084	0.492234	0	1
Expected family contribution	1,209	24805	4.10952	0	85.1477
Age	1,209	18.5113	0.370371	17.41667	20.75
Same geographic region	1,209	0.200993	0.400908	0	1
Distance	1,209	278.9241	323.0425	13.55669	2900.865
Parent WSU alumni	1,209	0.099256	0.299129	0	1
Best combination of SAT scores	1,209	10.46559	0.97076	7.8	13.7
Q-value Points Centered Around the Cutoff	1,209	1.128867	28.80587	-50	50
Squared Q-value Points Centered Around the Cutoff	1,209	830.3661	769.607	0	2500
Hispanic	1,209	0.176179	0.38113	0	1
Asian	1,209	0.092639	0.290045	0	1
Native American	1,209	0.008271	0.090607	0	1
Other	1,209	0.020678	0.142364	0	1
Multi-Race	1,209	0.097601	0.296898	0	1

Expected family contribution measured in $10,000's.

Table A7: Primary Results: Estimation of Enrollment

Enrolled	2 GHAS Centered	1 Probit Centered
Eligible for Merit Aid	3.309	0.564***
	[2.164]	[0.218]
Q-value Points Left of the Cutoff	0.032	-0.024**
	[0.073]	[0.011]
Q-value Points Right of the Cutoff	-0.219*	-0.013
	[0.116]	[0.010]
Male	0.169	0.057
	[0.718]	[0.109]
Minority	-3.992**	-0.271**
	[1.946]	[0.111]
Expected family contribution	-0.670*	-0.010
	[0.375]	[0.020]
Age	0.150	0.058
	[1.125]	[0.137]
Same geographic region	-10.057	0.397***
	[1,953.064]	[0.133]
Distance	-0.002	-0.000*
	[0.002]	[0.000]
Constant	-0.724	-1.633
	[21.056]	[2.541]
Observations	624	624
A1: Never Enroll		
Expected family contribution	0.050	
	[0.131]	
Parent WSU alumni	-5.075	
	[188.793]	
Constant	0.038	
	[0.202]	
A0: Always Enroll		
Same geographic region	0.633***	
	[0.151]	
Distance	-0.000*	
	[0.000]	
Best combination of SAT scores	0.105	
	[0.068]	
Constant	-1.619**	
	[0.727]	

Expected family contribution measured in $10,000's.
Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Discussion of main results

Q-value points are only significant on the right in the GHAS and the left in the probit. Both have negative coefficients. The more able students in this range are less likely to enroll at this university, probably due to opportunities at other universities.

Minority students are less likely to enroll in both models. Students with higher EFC's are less likely to enroll, but this effect is only significant in the GHAS model. Younger students and female students are less likely to enroll in both models, but these effects are statistically insignificant at a p-

value<0.1. Students from farther away are less likely to enroll in both models, but this only significant with a conventional p-value in the probit.

In our primary specification, we predict that the probability that a student will always enroll as a function geographic variables and SAT scores. Students from the same geographic region are more likely to always enroll than are students from elsewhere, and students who are farther away are less likely to always enroll. Both effects are significant at conventional p-values. Students with higher SAT scores are also more likely to be in this group, but this effect is not statistically significant at the threshold levels used..

We model the student decision as if the probability of being a "never enroll" student as a function of EFC and parent alumni status. Richer students are more likely to never enroll, and students with parent alumnus are less likely to never enroll. These effects are not significant at conventional levels.

Table A8: Full Estimation Results by Changes in the Always Enroll and Never Enroll Specifications

Enrolled	1	2	3	4	5	6	7	8
Eligible for Merit Aid	3.309	3.018*	1.711	1.428	3.136	433.754	1.539	0.564***
	[2.164]	[1.732]	[1.107]	[1.243]	[1.985]	[571.578]	[1.424]	[0.218]
Q-value Points Left of the Cutoff	0.032	0.051	-0.052	-0.069	0.051	-22.499	-0.051	-0.024**
	[0.073]	[0.082]	[0.033]	[0.053]	[0.080]	[29.423]	[0.052]	[0.011]
Q-value Points Right of the Cutoff	-0.219*	-0.219**	-0.060	-0.047	-0.224**	-10.817	-0.051	-0.013
	[0.116]	[0.100]	[0.057]	[0.071]	[0.113]	[14.522]	[0.060]	[0.010]
Male	0.169	0.314	0.187	0.116	0.311	-374.091	0.255	0.057
	[0.718]	[0.740]	[0.371]	[0.458]	[0.706]	.	[0.403]	[0.109]
Minority	-3.992**	-3.932**	-0.550	-1.138	-3.893**	-197.120	-0.691	-0.271**
	[1.946]	[1.794]	[0.425]	[0.771]	[1.807]	[258.680]	[0.723]	[0.111]
Expected family contribution	-0.670*	-0.784*	-0.153	-0.058	-0.780*	-12.292	-0.256	-0.010
	[0.375]	[0.418]	[0.152]	[0.088]	[0.408]	[15.699]	[0.226]	[0.020]
Age	0.150	0.205	0.058	0.451	0.244	163.407	0.119	0.058
	[1.125]	[1.169]	[0.387]	[0.694]	[1.082]	[214.236]	[0.454]	[0.137]
Same geographic region	-10.057	-3.145*	-0.035	0.930	-3.150*	500.104	0.544	0.397***
	[1,953.064]	[1.861]	[0.545]	[0.929]	[1.821]	.	[1.107]	[0.133]
Distance	-0.002	-0.002	-0.000	-0.004	-0.003	0.159	-0.000	-0.000*
	[0.002]	[0.002]	[0.000]	[0.003]	[0.002]	[0.209]	[0.000]	[0.000]
Constant	-0.724	-1.380	-1.652	-8.030	-1.999	-3,370.943	-2.590	-1.633
	[21.056]	[21.767]	[7.219]	[12.960]	[20.088]	[4,418.454]	[8.506]	[2.541]
Observations	624	624	624	624	624	624	624	624
A1: Never Enroll								
Expected family contribution	0.050			0.055	0.027		-0.022	
	[0.131]			[0.050]	[0.137]		[0.111]	
Same geographic region			-0.698					
			[0.525]					

Parent Alumni	-5.075	-4.878	-4.908		-4.630		-1.174
	[188.793]	[133.037]	[131.165]		[112.496]		[1.848]
Best combination of SAT scores						-0.259**	
						[0.107]	
Constant	0.038	0.083	0.066	-0.231	0.051	2.577**	-0.178
	[0.202]	[0.143]	[0.238]	[0.203]	[0.196]	[1.078]	[0.444]
A0: Always Enroll							
Expected family contribution					0.020		0.040
					[0.018]		[0.034]
Same geographic region	0.633***	0.592***			0.635***		
	[0.151]	[0.154]			[0.160]		
Distance	-0.000*	-0.000*	-0.002	-0.000	-0.000	-0.002***	-0.003
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.001]	[0.002]
Parent Alumni				1.388**		0.881***	
				[0.666]		[0.209]	
Best combination of SAT scores	0.105		0.118				
	[0.068]		[0.124]				
Constant	-1.619**	-0.523***	-1.362	-0.809**	-0.603***	0.083	-0.307
	[0.727]	[0.117]	[1.474]	[0.352]	[0.137]	[0.233]	[0.629]

Expected family contribution measured in $10,000's.
Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Column 2 omits SAT scores from the always enroll equation and EFC from the never enroll equation, and the Average Marginal Effect of treatment increases from .297 to 0.324. Column 3 moves same geographic region from the always enroll equation to the never enroll and the treatment effect is 0.458. Columns 4-7 compare other variations of the specifications and yield treatment effects ranging from 0.325 to 0.405. In each regression the treatment effect is much larger than the probit effect of 20 percent, and is at least somewhat larger than in our main specification.

Table A9: Full Estimation of Placebo Trials

Enrolled	1 GHAS Minus 20	2 GHAS Minus 10	3 GHAS Centered	4 GHAS Plus 10	5 GHAS Plus 20	6 Probit Minus 20	7 Probit Minus 10	8 Probit Centered	9 Probit Plus 10	10 Probit Plus 20
Eligible for Merit Aid	-	-8.203*	3.309	150.558	-	-	-0.477*	0.564***	-0.384	-
		[4.450]	[2.164]	[8,637.794]			[0.268]	[0.218]	[0.269]	
Q-value Points Left of the Cutoff	0.406*	0.529**	0.032	20.746	0.201	0.000	0.031*	-0.024**	0.022	-0.014
	[0.243]	[0.260]	[0.073]	[956.041]	.	[0.024]	[0.018]	[0.011]	[0.015]	[0.024]
Q-value Points Right of the Cutoff	0.008*	0.012**	-0.219*	-0.476	-0.002	0.000	0.001*	-0.013	-0.000	0.000
	[0.005]	[0.005]	[0.116]	[22.940]	.	[0.000]	[0.000]	[0.010]	[0.000]	[0.000]
Male	0.795	1.961**	0.169	129.199	1.945	0.088	0.126	0.057	0.138	0.050
	[0.963]	[0.918]	[0.718]	[9,512.748]	.	[0.109]	[0.107]	[0.109]	[0.110]	[0.112]
Minority	-1.503*	-6.453***	-3.992**	-439.192	4.759	-0.432***	-0.406***	-0.271**	-0.284**	-0.258**
	[0.898]	[2.317]	[1.946]	[20,144.432]	.	[0.113]	[0.110]	[0.111]	[0.115]	[0.116]
Expected family contribution	-0.259	-0.880**	-0.670*	-17.554	0.102	-0.017	-0.009	-0.010	-0.001	0.009
	[0.163]	[0.392]	[0.375]	[878.691]	.	[0.019]	[0.019]	[0.020]	[0.018]	[0.010]
Age	0.888	-2.051*	0.150	-4.573	-0.759	0.016	0.074	0.058	-0.108	-0.049
	[0.955]	[1.129]	[1.125]	[3,187.730]	.	[0.140]	[0.136]	[0.137]	[0.150]	[0.156]
Same geographic region	-5.500	-3.349**	-10.057	-677.415	-0.011	0.264*	0.343***	0.397***	0.390***	0.369***
	[4.512]	[1.422]	[1,953.064]	[36,085.005]	.	[0.139]	[0.131]	[0.133]	[0.137]	[0.142]
Distance	-0.001	-0.002	-0.002	-0.588	0.016	-0.000	-0.000	-0.000*	-0.000**	-0.000
	[0.001]	[0.002]	[0.002]	[29.963]	.	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-9.417	44.450**	-0.724	383.313	2.636	-0.522	-1.287	-1.633	1.916	0.883
	[17.487]	[21.719]	[21.056]	[72,619.175]	.	[2.634]	[2.524]	[2.541]	[2.774]	[2.891]
Observations	591	623	624	609	578	591	623	624	609	578
A1: Never Enroll										
Expected family contribution	-0.036	-0.078	0.050	0.053*	-0.019					
	[0.030]	[0.102]	[0.131]	[0.027]	[0.017]					
Parent WSU alumni	-0.405*	-6.964	-5.075	-0.943***	-10.198					
	[0.211]	[37,961.575]	[188.793]	[0.222]	[9.793e+08]					
Constant	0.283**	0.118	0.038	0.253***	0.747***					
	[0.126]	[0.188]	[0.202]	[0.096]	[0.109]					
A0: Always Enroll										
Same geographic region	6.136	0.632***	0.633***	0.985***	0.629					
	[86.095]	[0.152]	[0.151]	[0.222]	[0.390]					
Distance	0.000	-0.000	-0.000*	-0.000	0.001					
	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]					
Best combination of SAT scores	0.149	0.029	0.105	0.119	0.011					
	[0.195]	[0.071]	[0.068]	[0.097]	[0.080]					
Constant	-7.656	-0.878	-1.619**	-2.160**	-0.590					
	[86.142]	[0.746]	[0.727]	[1.017]	[1.076]					

Expected family contribution measured in $10,000's.

Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Table A10: Full Estimation Results by Bandwidth

Enrolled	1 GHAS MSE: 150	2 GHAS CE: 93	3 GHAS 75	4 GHAS 50	5 GHAS 25	6 Probit MSE: 150	7 Probit CE: 93	8 Probit 75	9 Probit 50	10 Probit 25
RD Treatment Effect	0.555	0.213	0.087	0.242	3.309	0.024	0.046	0.039	0.154	0.564***
	[0.458]	[0.467]	[0.238]	[0.228]	[2.164]	[0.087]	[0.108]	[0.121]	[0.147]	[0.218]
Q-Value Points Left of the Cutoff	-0.005	0.006	-0.001	-0.008	0.032	0.000	0.001	-0.001	-0.006*	-0.024**
	[0.004]	[0.007]	[0.004]	[0.006]	[0.073]	[0.001]	[0.001]	[0.002]	[0.004]	[0.011]
Q-Value Points Right of the Cutoff	-0.002	-0.007	0.000	-0.001	-0.219*	-0.001	-0.002	0.000	-0.000	-0.013
	[0.004]	[0.007]	[0.004]	[0.005]	[0.116]	[0.001]	[0.001]	[0.002]	[0.004]	[0.010]
Male	0.365	0.190	0.141	0.099	0.169	0.054	0.082	0.077	0.085	0.057
	[0.275]	[0.267]	[0.132]	[0.116]	[0.718]	[0.046]	[0.057]	[0.064]	[0.076]	[0.109]
Minority	-2.188	-1.175*	-0.594**	-0.372***	-3.992**	-0.255***	-0.296***	-0.340***	-0.292***	-0.271**
	[1.693]	[0.699]	[0.275]	[0.132]	[1.946]	[0.047]	[0.059]	[0.066]	[0.078]	[0.111]
Expected family contribution	0.033	-0.035	0.001	0.007	-0.670*	0.001	-0.004	-0.004	0.004	-0.010
	[0.043]	[0.035]	[0.017]	[0.015]	[0.375]	[0.006]	[0.008]	[0.009]	[0.009]	[0.020]
Age	0.854**	0.030	-0.088	-0.047	0.150	0.038	0.022	-0.021	-0.007	0.058
	[0.427]	[0.382]	[0.188]	[0.150]	[1.125]	[0.058]	[0.076]	[0.085]	[0.100]	[0.137]
Same geographic region	-5.241	0.599	0.014	-0.297	-10.057	0.189***	0.210***	0.219***	0.331***	0.397***
	[4.023]	[1.164]	[0.456]	[0.822]	[1,953.064]	[0.060]	[0.075]	[0.083]	[0.097]	[0.133]
Distance	-0.001***	-0.000	-0.000	-0.001	-0.002	-0.000***	-0.000***	-0.000**	-0.000*	-0.000*
	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-13.219*	-0.042	1.368	0.879	-0.724	-0.859	-0.521	0.233	-0.229	-1.633
	[7.869]	[6.875]	[3.348]	[2.812]	[21.056]	[1.080]	[1.406]	[1.570]	[1.853]	[2.541]
Observations	3,307	2,139	1,705	1,209	624	3,307	2,139	1,705	1,209	624
A1: Never Enroll										
Expected family contribution	-0.001	0.031	0.028	0.015	0.050					
	[0.007]	[0.024]	[0.031]	[0.023]	[0.131]					
Parent WSU alumni	-0.340***	-0.438*	-6.259	-10.084	-5.075					
	[0.086]	[0.263]	[118.890]	[0.000]	[188.793]					
Constant	0.301***	-0.034	-0.559**	-0.690**	0.038					
	[0.043]	[0.224]	[0.234]	[0.334]	[0.202]					
A0: Always Enroll										
Same geographic region	3.192	-0.008	0.078	1.154	0.633***					
	[34.154]	[0.332]	[0.434]	[0.842]	[0.151]					
Distance	-0.001	-0.002*	-0.003*	0.000	-0.000*					
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]					
Best combination of SAT scores	0.039	0.063	0.015	0.110	0.105					
	[0.054]	[0.074]	[0.074]	[0.134]	[0.068]					
Constant	-3.628	-0.714	-0.419	-2.747	-1.619**					
	[34.163]	[0.871]	[0.907]	[1.674]	[0.727]					

Expected family contribution measured in $10,000's.

Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Table A11: Full estimation Results by Running Variable Controls

	1	2	3	5	6	7
Enrolled	GHAS 1	GHAS 2	GHAS 3	Probit 1	Probit 2	Probit 3
RD Treatment Effect	3.309	390.835	3.746	0.564***	0.554**	0.560**
	[2.164]	[28,256.685]	[3.394]	[0.218]	[0.216]	[0.217]
Q-Value Points Left of the Cutoff	0.032			-0.024**		
	[0.073]			[0.011]		
Q-Value Points Right of the Cutoff	-0.219*			-0.013		
	[0.116]			[0.010]		
Q-Value Points Centered Around the Cutoff		-6.215	-0.112		-0.018**	-0.019**
		[444.388]	[0.133]		[0.007]	[0.007]
Squared Q-Value Points Centered Around the Cutoff			-0.006			0.000
			[0.006]			[0.000]
Male	0.169	281.163	0.051	0.057	0.059	0.056
	[0.718]	[769,806.268]	[0.825]	[0.109]	[0.109]	[0.109]
Minority	-3.992**	-494.685	-4.148**	-0.271**	-0.268**	-0.271**
	[1.946]	[770,297.514]	[1.921]	[0.111]	[0.111]	[0.111]
Expected family contribution	-0.670*	-56.009	-0.661*	-0.010	-0.010	-0.010
	[0.375]	[3,757.344]	[0.347]	[0.020]	[0.019]	[0.020]
Age	0.150	9.435	0.481	0.058	0.060	0.061
	[1.125]	[1,908.288]	[1.468]	[0.137]	[0.137]	[0.137]
Same geographic region	-10.057	-636.525	-3.585	0.397***	0.394***	0.396***
	[1,953.064]	[770,767.007]	[2.347]	[0.133]	[0.133]	[0.133]
Distance	-0.002	-0.480	-0.002	-0.000*	-0.000*	-0.000*
	[0.002]	[36.070]	[0.002]	[0.000]	[0.000]	[0.000]
	-0.724	68.785	-7.361	-1.633	-1.591	-1.660
Constant	[21.056]	[41,428.679]	[27.780]	[2.541]	[2.542]	[2.542]
	624	624	624	624	624	624
Observations	3.309	390.835	3.746	0.564***	0.554**	0.560**
A1: Never Enroll						
Expected family contribution	0.050	0.186***	0.057			
	[0.131]	[0.048]	[0.112]			
Parent WSU alumni	-5.075	-0.811***	-12.023			
	[188.793]	[0.244]	[0.000]			
Constant	0.038	-0.012	0.028			
	[0.202]	[0.121]	[0.197]			
A0: Always Enroll						
Same geographic region	0.633***	0.628***	0.632***			
	[0.151]	[0.161]	[0.156]			
Distance	-0.000*	-0.000*	-0.000*			
	[0.000]	[0.000]	[0.000]			
Best combination of SAT scores	0.105	0.215***	0.101			
	[0.068]	[0.081]	[0.072]			
Constant	-1.619**	-2.707***	-1.583**			
	[0.727]	[0.843]	[0.756]			

Expected family contribution measured in $10,000's. Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.

Table A12: Full Estimation Results by Main Equation Specification

Enrolled	1	2	3	4	5	6	7	8	9	10	11	12
X-Specification	GHAS 1	GHAS 2	GHAS 3	GHAS 4	GHAS 5	GHAS 6	Probit 1	Probit 2	Probit 3	Probit 4	Probit 5	Probit 6
RD Treatment Effect	3.446*	3.966*	1.426	5.145**	2.514**	2.592	0.564***	0.572***	0.564***	0.585***	0.563***	0.580***
	[2.092]	[2.233]	[1.312]	[2.308]	[1.194]	[1.907]	[0.218]	[0.219]	[0.218]	[0.220]	[0.217]	[0.219]
Q-Value Points Left of the Cutoff	0.035	-0.063	-0.038	-0.034	-0.061	-0.131	-0.024**	-0.026**	-0.024**	-0.025**	-0.024**	-0.024**
	[0.076]	[0.054]	[0.035]	[0.061]	[0.048]	[0.089]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Q-Value Points Right of the Cutoff	-0.231*	-0.178*	-0.048	-0.261**	-0.109	-0.049	-0.013	-0.013	-0.013	-0.014	-0.014	-0.014
	[0.119]	[0.104]	[0.055]	[0.130]	[0.078]	[0.043]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Male	0.310	-0.534	-0.152	-0.686	0.296	-0.399	0.057	0.041	0.048	0.029	0.053	0.027
	[0.774]	[0.581]	[0.421]	[0.655]	[0.526]	[0.445]	[0.109]	[0.110]	[0.108]	[0.110]	[0.108]	[0.108]
Black		-7.215		-8.445				-0.475		-0.421		
		[525.221]		[1,620.730]				[0.333]		[0.337]		
Hispanic		-1.791		-2.330*				-0.275*		-0.240*		
		[2.036]		[1.332]				[0.145]		[0.146]		
Asian		-2.933**		-4.842**				-0.581***		-0.531***		
		[1.312]		[2.383]				[0.200]		[0.204]		
nativeam		14.396		13.928				0.442		0.448		
		[34,273.582]		[446.626]				[0.697]		[0.698]		
other		0.063		-0.895				-0.234		-0.246		
		[3.474]		[1.772]				[0.333]		[0.334]		
multrace		0.695		1.067				-0.133		-0.109		
		[0.892]		[1.031]				[0.188]		[0.188]		
Expected family contribution	-0.704*	-0.554*		-0.721**	-0.314		-0.010	-0.009		-0.011	-0.016	
	[0.381]	[0.282]		[0.332]	[0.226]		[0.020]	[0.019]		[0.020]	[0.021]	
Age	0.299	0.422	0.068	0.334	0.246	0.637	0.058	0.080	0.052	0.075	0.067	0.059
	[1.127]	[0.709]	[0.319]	[0.849]	[0.563]	[0.496]	[0.137]	[0.136]	[0.137]	[0.137]	[0.135]	[0.137]
Same geographic region	-3.076	-8.344	-1.142	-10.294		0.309	0.397***	0.454***	0.408***	0.378***		0.391***
	[2.000]	[239.732]	[1.775]	[415.366]		[0.662]	[0.133]	[0.130]	[0.132]	[0.136]		[0.133]
Minority	-4.009**		-0.457		-1.442	-0.571	-0.271**		-0.263**		-0.235**	-0.222**
	[1.861]		[0.470]		[1.037]	[0.386]	[0.111]		[0.110]		[0.110]	[0.111]
Distance	-0.002		-0.000	0.001	0.000	0.000	-0.000*		-0.000*	-0.000*	-0.001**	-0.000*
	[0.002]		[0.001]	[0.001]	[0.001]	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]	[0.000]
Parent WSU alumni						9.790						0.519***
						[23,125.481]						[0.179]
Best combination of SAT scores	-3.476	-7.436	-1.564	-5.286	-5.343	-15.025	-1.633	-2.138	-1.550	-1.948	-1.653	-1.736
Constant	[20.950]	[13.230]	[6.053]	[15.731]	[10.304]	[10.514]	[2.541]	[2.523]	[2.541]	[2.536]	[2.504]	[2.550]
	3.446*	3.966*	1.426	5.145**	2.514**	2.592	0.564***	0.572***	0.564***	0.585***	0.563***	0.580***
Observations	624	624	624	624	624	624	624	624	624	624	624	624
A1: Never Enroll												
Expected family contribution	0.041	0.015	-0.001	0.039	0.001	0.113*						
	[0.127]	[0.105]	[0.026]	[0.093]	[0.128]	[0.064]						
Parent WSU alumni	-14.704	-9.357	-8.079	-9.232	-11.418	2.053						
	[0.000]	[5.257e+08]	[8685626.151]	[1.695e+08]	[0.000]	[2.165]						
Constant	0.038	0.146	-0.060	0.157	-0.128	-2.601						
	[0.199]	[0.165]	[0.415]	[0.145]	[0.233]	[2.246]						

A0: Always Enroll						
Same geographic region	0.624***	0.735***	1.180	0.652***	0.539***	0.347
	[0.155]	[0.242]	[1.399]	[0.200]	[0.189]	[0.278]
Distance	-0.000*	-0.001	-0.001	-0.001	-0.001	-0.001
	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
Best combination of SAT scores	0.100	0.168*	0.222	0.152**	0.130	0.097
	[0.070]	[0.098]	[0.252]	[0.077]	[0.080]	[0.071]
Constant	-1.562**	-2.343*	-3.367	-2.057**	-1.857**	-1.352
	[0.740]	[1.205]	[4.025]	[0.881]	[0.863]	[0.850]

Expected family contribution measured in $10,000's.

Key: *, **, and *** denotes that estimate is significant at respectively the 0.1, 0.05, and 0.01 levels.