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Abstract

Using data from a public research university we analyze the impact of a campus visit program on enrolling. We exploit a natural experiment – some students who express an interest in visiting do not get the opportunity due to insufficient space – and financial aid information to decompose the effect into its component parts of visiting campus and receiving a scholarship. We find evidence to suggest campus visits are effective tools for boosting enrolling and that the primary impact comes from visiting, not the scholarship. The marginal effectiveness is stronger for nonresidents and minorities compared to state residents and whites.

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1. Introduction

From 2007 to 2015 state per student funding (excluding medical students) for public higher education fell in 31 states, with an average decrease in those states of $771. For the 19 states that saw an increase in that period, the state per-student spending increased by $1141, Meanwhile, tuition revenue per capita in all states increased by $2379 (SHEEO, 2015), while all states except Louisiana saw an increase in student FTEs. The uncomfortable fiscal reality of relying more and more on tuition revenue while trying to attract and enroll the best students has increased the importance of recruiting and marketing efforts at many universities. In this paper we address one popular form of recruitment effort – special campus visit programs for students *already admitted* that award scholarships to participants who enroll at the university.

Participation in programs like this is often confounded with enrollment in two opposing ways. Students interested in a university but having other choices may be more likely to visit to enable a more informed decision, even if such students on average are less likely to enroll. Alternatively, an admitted student intending to enroll may be more likely to visit, maybe to gain an early hand on the campus and environment. In both cases the scholarship potential adds to the confounding.

Campus visits are considered, by and large, to be among the best recruitment tools available (Kealy and Rockel, 1987; Brown, 2010; Swann et al., 1998; Hesel, 2004) and even promote a higher likelihood of graduation (Goenner et al., 2013). In a recent study, Okerson (2016) uses survey data at multiple universities in an attempt to determine which parts of the visits are most important in attracting students, finding that personal interactions, understanding community and history of a university, and how the campus looks during the visit are the most influential factors. Universities believe that if they can just get a potential student on campus, the student will come; hence the justification for the scholarship tied to visit participation. It is important to many policy makers that the campus visit be as effective as possible, and some universities go to great lengths to do so (See Hoover, 2009). Most of these studies fits in with the higher education marketing literature rather than with any economic literature.

The effectiveness of campus visits has not been addressed empirically in a way that addresses the significant endogeneity bias from the confounding of visitation and enrollment, even when there is no scholarship involved. In an early work, Kealy and Rockel (1987) claim that attempting to identify a causal relationship with the visitation and enrollment is entirely misguided because of the complicated choice problem students face. Nonetheless, subsequent analysis has tried. Brown (2010) uses a logistic model to estimate matriculation, and directly includes visitation with no corrections for bias. Okerson (2016) uses survey data and a qualitative analysis, which is not without merit, but does little for those seeking quantitative analysis. Goenner et al. (2013) use a hazard model to estimate “stopout” behavior, but likewise fails to account for the endogeneity of visitation.

In this paper we analyze the impact of campus visits on enrollment using data from a public research university. Because we know which potential students wanted to participate in the visit program, we are able to separate interest in the university from the effect of visiting. Moreover, we are able to exploit a natural experiment – some students who express an interest in visitation do not get the opportunity due to insufficient space – and other financial aid information to decompose the effect on enrolling of the program into its component parts of visiting campus and receiving a scholarship. In other words, the limited capacity, along with other financial aid oddities enables us to fully separate a predisposition effect from the two treatment effect. Overall, we find considerable evidence to suggest campus visits are effective tools for boosting enrollment and that the primary impact comes from visiting, not the scholarship.

The rest of this paper is as follows. Section 2 give more detail on the specific visitation program we analyze, describes the conceptual framework of our analysis and presents our empirical approach. Section 3 describes our data. Section 4 gives our results and discusses robustness checks. Section 5 concludes the paper.

2. The Visitation Programs: Conceptual Framework

The Visitation Programs

The university has two formal visitation programs for students admitted to the its main campus, one general and one marketed to students of color.[1] These are in-depth full day visitation programs for admitted prospective students and their parents. Students who attend and fully participate earn a scholarship if they enroll in the term for which they applied. The visitation scholarship program began in 2014. Although other admitted prospective students may have informal visits to campus, we have no data on them. Hence, our analysis is only of these two formal visitation programs,

All admitted students who were applied by January 31 are invited by email to participate in the visitation programs. Scholarship details are on the program website but not in the email. Although the visitation program is typically offered in November, March, and April, the nature of our data means the only relevant sessions are March and April. Space is limited, and registration, which opens 8 weeks prior to the event, is on a first-come, first served basis. Not all students expressing a desire to attend one of the programs get in. Programs fill quickly and students not able to register are placed on a waitlist. For the 2015-16 school year, there were 2312 students who attended a visitation program and 213 who were on a waitlist and could not attend. Walk-ons are not allowed, even if there is space.

A survey at the end of the program suggest a strong increase in student intentions to enroll, from roughly one-half to about 80 percent. As a matter of comparison, approximately 15% of students who had formally indicated intentions to enroll were not enrolled at the 10th day of classes, and additional students prior to that time had formally indicated an intention to enroll and subsequently cancelled, the point being that there is a significant difference between expressing intentions to enroll, even formally, and enrolling.

[1] One program is marketed only to admitted prospective students of color, it is open to all prospective students, as is the general program. Because the programs are essentially the same, we treat them jointly under the term "visitation program."

The scholarship is conditional on enrollment and is worth $1000 per year for 4 years. Since the award is counted with the rest of the student's financial aid package, for some students it may reduce the amounts of loans offered or it may be crowded out by other grants and scholarships. As we noted earlier, some students, already intending to enroll, may come to the visitation program simply to gain the scholarship. This effect may be mitigated by the fact that students do not know their financial aid offer prior to the dates of the programs.

Conceptual Framework

We see the visitation and enrollment decisions are part of a sequential process with interactions between the school and the applicant. Students apply to the university and potentially other universities; for each application a student is either admitted or rejected.[2] When registration for the visit programs open admitted individuals decide whether to register or not, and if so, either get in or are put on the waitlist. If a registered individual decides not to visit and informs the university the slot is filled from the waitlist.[3] In August all admitted individuals, whether or not they participated in a visitation, choose whether or not to enroll. If an enrolled student participated in the program, she eligible for the visitation scholarship, and receives it, except if it is crowded out by other financial aid.

In this context we can think of participating in the visitation program as a treatment which is partially determined by the student's action, raising a concern of selection bias (Heckman, 1978). There are multiple ways to consider selection in this framework, but the two we focus on is selection into treatment and selection into trying to get treatment. We primarily consider the case in which students "select" by choosing treatment – that is to participate in the visitation program. In this construct a prospective student effectively knows that space fills up quickly (which is part of the information in both the email and on the website) so chooses to participate by registering sufficiently early. Of course that begs the question why register late? Moreover, since registration opens at the same time for every

[2] We have no data on other universities, so we only consider choices regarding individuals admitted to WSU.
[3] As noted earlier, walk-ins are not allowed, so if a registered individual does not show up for a visitation program, the space is unused.

eligible student and space fills up quickly, small perturbations in timing, likely to be random, may decide whether or not the student gets the treatment, making selection on registering and getting the treatment random among that group. Hence, we also consider, as a robustness check, this second case with two different modeling strategies.

Empirical Approach

Our foundational model is case 4, the multivariate probit model with structural shift, from Heckman (1978). As in his paper, let

$$\begin{aligned} y_{1i}^* &= X_{1i}\alpha_1 + d_i\beta_1 + y_{2i}^*\gamma_1 + u_{1i} \\ y_{2i}^* &= X_{2i}\alpha_2 + d_i\beta_2 + y_{1i}^*\gamma_2 + u_{2i} \\ d_i &= 1 \quad iff \quad y_{2i}^* > 0 \\ d_i &= 0 \quad \text{otherwise} \end{aligned} \qquad \text{with} \quad \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \sim N\left[0, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right].$$

For out purposes, y_1^* is a latent variable underlying the decision to enroll at the university; student i enrolls if $y_{1i}^* > 0$ and we observe $y_{1i} = 1$. Similarly y_2^* is a latent variable underlying the decision to participate in the visitation program and we observe $y_{2i} = 1$ if $y_{2i}^* > 0$. In our case neither endogenous variable directly affects the other, nor does $y_{2i}^* > 0$ cause any structural shift on visitation, hence $\beta_2 = \gamma_1 = \gamma_2 = 0$ and we are left with a recursive bivariate probit model,

$$\begin{aligned} y_{1i}^* &= X_{1i}\alpha_1 + d_i\beta_1 + u_{1i} \\ y_{2i}^* &= X_{2i}\alpha_2 + u_{2i} \\ d_i &= 1 \quad iff \quad y_{2i}^* > 0 \\ d_i &= 0 \quad \text{otherwise.} \end{aligned}$$

Heckman shows that maximum likelihood estimators of this model are consistent, asymptotically normal, and efficient (see also Wilde, 2000). Another approach sometimes used to estimate these models is a two-step IMR-based procedure to capture the endogenous treatment choice, but Freedman and Stekhon (2010) show it gives biased estimates. Terza, et al (2008) offer an alternative two-stage residual inclusion instrumental variables approach which we use as an additional robustness check.

Our choice of actually participating in the visit program for y_2^* deserves further comment since registering is the student's action. As is conventional, the error terms account for unobserved causal factors – included in these factors are sometimes items outside of the individual's control, for example, how quickly other prospective students sign up for visitation. Hence, while we have elements of treatment selection, the treatment being getting a visit, it is not pure self-selection. Modeling on visiting rather than registering allows us to more appropriately identify the structural shift that visiting has on enrollment. In fact, if y_2^* is assigned to registering it would necessarily be the case that getting to attend once registered is a *completely* random process. While we do not think this is the case, we nonetheless make that assumption in our robustness checks, discussed later.

4. Data

Our data were provided by Institutional Research (IR) at the university. IR provided information on the 2015 new freshman applicants/admitted/enrolled at its main campus. Our analysis is for admitted domestic (resident and nonresident, including legal residents and citizens living overseas) students not designated as athletes. After eliminating four observations for bad data, we were left with a sample of 14,196 observations. The data includes detailed financial aid information and geographic, educational and demographic characteristics of all admitted students and, of course, whether or not they enrolled. Table 1 provides a list of the variables used in our analysis and basic statistics.

Dependent and endogenous (recursive) variables

Our dependent variable of interest is enrolling while participating in the visitation program is our primary endogenous (recursive) variable – we use visitation interest (attending or wait-listing for the program) as an alternative recursive variable. Overall, 28% of our sample enrolled. Table 2 breaks enrollment down by race and residence. Most students, not surprisingly, are white state residents. The yield of such students is also relatively high at almost 37%. Only residents who are Native Americans or those of other races have higher yields, but these two groups account for only 110 of the enrolled freshman. The lowest yields are non-residents who are either white or Asian.

Data on visitation participation and enrollment are given in Tables 3a (all students) and 3b-3e broken down by residency and minority status. Of the 14,196 in our sample, 2322 applied to attend one of the visitation programs. Because of capacity constraints 260 were put on the waitlist, but 70 of those on the waitlist eventually were allowed to register. Hence, 2132 students attended a visitation program and 1782 were offered the scholarship. Almost 79% of the visit program attendees (1676) enrolled, compared to 24% (2231 out of 9547) of students neither attending nor waitlisted for visitation, and 27% (52 out of 138) of those who never made it off the waitlist. Not in the table, but relevant, is that 1435 (67%) of the students offered the visit scholarship enrolled. Tables 3a and 3b indicate that participating in the program had a bigger effect on residents than on nonresidents, and on Whites compared to Minorities, although minority students in all groups were less likely to enroll. The spread of enrollment percent between visiting and showing no interest in visiting (not visiting and not being waitlisted) was 59.39% for Whites, and 56.25% for Minorities.

These raw enrollment ratios provide considerable understanding as to why policy makers at many universities see these visitation programs as so effective and, given the disparity, why we are concerned with endogeneity. We suspect there may be an unobserved differences between students who want to visit and students who do not.

Explanatory Variables

The timing of decisions informs our modelling. When students try to register for the visitation program, or not, they know only that they have been admitted to the university. Most importantly, they do not have their financial aid information. We broadly classify our explanatory variables into two subsets: personal information, available when deciding whether to register for visitation and beyond, and financial aid information available only at the time the student makes the enrollment decision.[4]

[4] For the 2SRI we need additional explanatory variables. These are discussed in the robustness check.

Personal information includes basic demographics (gender, race[5] and age), educational background (high school GPA on a four-point scale, the best composite SAT score, whether the students is a first-generation college student, and whether one of the student's parents is an alumnus), geographical information (state resident and if so, from the region of the state the university is located in, if the student resides in the same county that the university is located in[6], or if a citizen currently living overseas) and information of family finances and financial aid. We also include a dummy variable indicating if a student paid the application fee (if not, it was waived either for financial reasons or because the university was encouraging the application).

All financial information we have come from the Federal Application for Federal Student Aid (FAFSA) which is used to determine need-based financial aid awards. For financial aid information we use the offer made in May. Among the variables we use are expected family contribution (EFC), federal need (which is the cost of attending the university minus the EFC), the total financial offer, how much of that is in grants, scholarships and waivers, the amounts of loans (subsidized and unsubsidized) and how much of federal need is unmet by financial aid. Although a very imperfect measure, EFC is correlated with income. Only 72% of our sample filed a FAFSA – this is included as an explanatory variable. If a student did not file a FAFSA she was not eligible for need-based financial aid. Since we have no information about the EFC we set it equal to the federal cost of attendance at the university, which was $27,824 for residents and $41,408 for non-residents for the academic year 2015-16. The average EFC in the data set is $19,234, inflated somewhat by those not filing a FAFSA.

The visitation scholarships are not need-based although they are counted in a student's financial aid offer. Of the 2132 students who participated in the program, 350 did not get the scholarship, 50 of whom who did not file a FAFSA. For 33% of those who received the visitation scholarship it was the

[5] Because they were too few in number to yield meaningful results, for the remainder of the analysis Native Americans and minority students who are not Black, Asian or Hispanic, are combined with those students indicating they are of multiple races into a single category we designate as "Other minority".
[6] Including additional counties did not alter the results.

only form of non-loan aid reported. On the other side, 43% of those eligible for the visitation scholarship did not receive it because other grants and scholarships crowded it out.

5. Results

Estimates and z-scores of the primary model, with participation in the visitation program as the endogenous recursive variable, are given in columns 2 and 3 respectively of Table 4.[7] Most parameter estimates are statistically significant at conventional levels and signs make sense with a possible exception of Total Offer, although since this includes merit aid, it is consistent with the signs of GPA and Best, which indicate better admitted students go elsewhere. One interesting issue of note in the models is that First Generation students are more likely to enroll (a long-standing tradition of the student body) but less likely to visit. The same is true of older students. Our conjecture that the visitation program might attract students uncertain about this university compared to other offers is bolstered by two findings – first that the GPA increases the likelihood of visiting while having a negative coefficient on enrolling, and that the estimated ρ is negative (with a p-value<0.10).

Do the visitation/scholarship programs work?

We are most interested in the marginal effects of participating in the visitation program and other variables associated with that program on enrolling. These other variables include Interested, No Scholarship, which indicates an individual who visited did not get the scholarship (probably because it was crowded out by other financial aid), and Visit Scholarship Only which indicates the only financial aid the individual received was the visitation scholarship. Being able to identify these different characteristics allows us to decompose the impact of visitation from a latent interest in the university, and the importance of the scholarship on convincing someone to enroll.

All these variables are dummy variables, so to measure the marginal effects we predicted the probability of enrollment when they equaled 0 or 1, holding all other variables at their means. These

[7] The remaining columns are discussed in the robustness analysis.

marginal effects are given in columns 2 and 3 of Table 5a.[8] Table 5b disaggregates the marginal effects by residency and race.

Looking at the entire sample, all the estimates are significant with p-values<0.01. The visitation program has a large marginal effect on the probability of an accepted applicant enrolling. All else equal, attending the visitation program increases the likelihood of enrolling by 57%. This is over and above the latent interest captured by Interested, which equal 1 for those either waitlisted or who got to visit. Showing this interest makes an individual 12% more likely to enroll.

We measured the marginal effect of not getting the visitation scholarship (No Scholarship) or it being the only non-loan source of aid. The marginal effects for these variables are relevant only for those who visited as others are not eligible for the scholarship. The increase in enrollment attributable to visiting is attenuated somewhat if the scholarship is not received – the net effect of visiting on the probability of enrolling falls to 47%, still very substantial. The net result is that the marginal increase in enrolling due to the scholarship is about 10%, while the marginal effect of visiting campus and going through the program is 47%. Having the Visit Scholarship as the only non-loan offer also attenuates the visitation effect on enrollment, but only by one-half as much.

Table 5b shows the marginal effects of the visitation program from estimations disaggregated by residence and race.[9] Except for residents, the direction of the marginal effects carry over to the smaller groups, sometimes with different magnitudes. Visiting has the strongest impact on nonresidents, and a stronger effect on minority individuals than on Whites. For residents, statistically visiting has no impact on their propensity to enroll. This may be from a more intimate knowledge of the university to start and the likely higher probability that the individuals had been on campus previously. Interested residents are more likely to enroll than interested nonresidents, and the attenuation effects of getting no scholarship or having the visiting scholarship be the only non-loan source of financial aid are larger. We also see differences between whites and minority students. While the substantial marginal effects of visiting are

[8] Again, the remainder of this table is discussed in the robustness analysis.
[9] The estimations underlying these marginal effects are available from the authors.

not different at any conventional p-value, interested white students are more likely to enroll when compared to interested minority students. Moreover, getting no scholarship or having the visiting scholarship only reduces the probability of enrolling for minority individuals, but not for whites.

Probit-based Robustness Checks

The first set of robustness checks estimates two different models related to our main model. The first explicitly uses Interested in participating in the visitation program (by either visiting or being on the waitlist) as the endogenous recursive variable and estimates a bivariate probit as before, the second implicitly uses the same variable by limiting the sample for the estimation only to those who have expressed an interest in the visitation program and estimates a univariate probit of only the enrollment equation, comparing those who visited to those who ended up on the waitlist.. The estimates for these models are given in columns 4 and 5, and 6 and 7, respectively, in Table 4. The marginal effects of the variables of interest are likewise given in Table 5a. Both these models implicitly assume that once a student has expressed an interest in visiting, whether she actually visits or is relegated to the waitlist is random.

Not surprisingly, the results of these two models are almost identical – differences for the most part can be attributed to the loss of information about students not interested in the visit program, which shows up in the bivariate probit through the estimate of ρ. There is no difference at any conventional level of significance for Visited, No Scholarship or Visit Scholarship Only. The bivariate model provides a marginal effect for Interested which the Limited Sample estimate cannot.

Compared to our main estimation, the marginal effects of No Scholarship and Visit Scholarship Only are identical. However, when Visited was used at the endogenous recursive variable the marginal effect of Visited is much stronger, compared to using Interested as the endogenous recursive variable, and the marginal effect of interest is much weaker. But, the *sum* of the two marginal effects is the same. Since the sum is the total effect on someone who actually visits, they predict the same impact of visiting on enrollment.

So why the difference in the distribution of the impact? Looking again at Table 4, both models estimate ρ, the correlation in errors between the enrolling and the recursive variable, at approximately 0.30. Through this correlation, our primary model attributes more of the impact of enrolling on Visited, while the second model attributes it to the variable it finds enrolling correlated with – Interest. The overall effect being the same is also not surprising since the correlation between Interested and Visited is 0.95, and only 9% of those interested do not get to visit. Nonetheless, this provides sufficient variation to decompose the two effects.

Two Stage Residual Inclusion Estimators

As a final robustness check we use a two-stage residual inclusion (2SRI) estimator to address the endogeneity of Visited when estimating the enrollment equation. Unlike the two-stage predictor substitution model, a direct nonlinear extension of the linear two-stage least squares estimator, the 2SRI gives consistent estimates for nonlinear models with endogenous covariates (Terza, Basu, and Rathouz, 2008). With the 2SRI estimator, instead of replacing endogenous variables with first-stage predictors, first-stage residuals are simply included as additional regressors.

Like other instrumental variable techniques, the 2SRI requires one or more exogenous instruments included with other covariates in the first stage. We use two variables we believe are related to the visitation decision but not to enrollment – a geographically based count of the number of students admitted from the same county (if a state resident), the same state (if from another US state), or the same country (if not US) which for convenience we call Geocount, and the number of days before 1-31-15 that application was deemed complete by the university.

We use application completion date rather than the date the student applies to impose additional separation between the student's latent intention with respect to enrollment and the instrument. The completion date is correlated with the application date, but requires actions by the university, the student's high school, and potentially others, hence is exogenous to student choices.

Geocount captures a completely different idea of what might affect visitation and enrollment (Epple, 2003). Students facing similar experiences, for example, from the same geographic area, might look for the same things in a university, an especially pertinent fact when the data consists of admitted students, not applying students. There can also be a social factor involved in both visiting and enrolling, where number of friends and acquaintances known to a student to be visiting or enrolling may affect a student's own interest in one or both activities. Finally, a student might be more or less curious about a university if many people she already knows are also interested in visiting or enrolling. The count aggregation we chose reflects two realities. The first is that students from within and outside the state are treated differently in admissions, financial aid, and enrollment and that international students face a decision process that is different from the one domestic students face. The other is more data driven, and it is that the frequency of students inside and outside the state and within and without of the U.S. differ widely. We expect that county level aggregation for in-state students is sufficiently aggregated so as to remove endogeneity from the student visitation and enrollment choices, yet still offers sufficient variability and interpersonal association potential of those within the country to serve as an adequate instrument.[10]

The estimates of the 2SRI model are given in the last two columns of Table 4. All variables used in this model are the same as in the bivariate probits, with the two additional variables added to the Visited equation. Geocounts has a mean of 1478.45 and a standard deviation of 1324.44. The respective values for the days before January 31 the application was complete are 38.52 and 62.43. Estimates for both equations are quite similar to those found in the bivariate estimation using Visited as the endogenous variable. There is virtually no difference in the estimates of the Enrolled equation between the two techniques, and the additional regressor, uhat, is not statistically significant with 2SRI. Of the two

[10] For 239 students we did not have home residence. For these students we used the location of their high school. Estimates aggregating count at the school and city levels had similar results, but we worried they may not be sufficiently independent of enrollment.

instruments in the Visited equation, days before is significant with a p-value<0.01, but Geocounts is not statistically significant at conventional levels.

The marginal effects and standard errors of visitation program variables on enrollment from the 2SRI are given in the last two columns of Table 5. As would be expected given the closeness of the model estimates, the marginal effects are very close, although Visited has a significantly smaller marginal effect on enrollment if the estimates from the 2SRI are used instead of the estimate of the bivariate probit. Overall, however, it is very clear that this alternative technique produces results about the visitation program that are qualitatively and quantitatively equivalent to what we found in our primary model.

6. Conclusion

In this work we have analyzed the impact of visitation scholarship programs at a high research public university. These programs invite students to visit the university and if they complete the visit, earn a scholarship if they enroll at the university, of course confounding the effect of visiting with the potential draw of the scholarship. Unlike previous analyses of visitation programs we were able to decompose these two effects because not all students interested in the program got in, and not all students who completed the program received scholarships.

Overall we found a strong effect of the visitation program. For all students, participating increased the probability of enrollment by 57%, which decomposes into 10% due to the scholarship and 47% due to visiting campus. There was considerable differences between state residents and those from outside the state. Nonresidents were 83% more likely to enroll if they visited, and this effect was not diminished by not getting the scholarship. The marginal effect on residents of visiting was, however, nonexistent, unless they were not offered the scholarship, in which case they were less likely to enroll. Whites and minorities also differed in their response to the visitation program, with the marginal effect of enrolling by minorities exceeding that for whites by about 12%. Not getting the scholarship attenuated this difference somewhat, but not completely.

Given estimates for parameters on the quality of students and the sign of the covariance of the error terms in the equations, we are also able to intuit why students come to the visitation program. It is more likely that those uncertain about the university (presumably compared to other options) are more like to participate than those who strongly intend to enroll. This is consistent with our decomposition that finds the scholarship is not the major reason for enrolling after participating in a visitation program. At the same time, we are not able to discern whether the possibility of the scholarship attracts students to the program.

Our results should be comforting for those charged with recruiting and enrolling students at a university. Although such programs are popular, it is often worried that the students who come do so only to gain the scholarship. While we cannot preclude the possibility of the scholarship being an attractant to visiting, we do find it is not the primary impact of the program on enrollment. In discussing the program with the Provost of the university which provided our data, (s)he said, "We know once we get them to campus, we get them enrolled." If you can get prospective students to campus without the scholarship, you should still have a very impressive increase in the propensity to enroll.

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Table 1: Summary Statistics for Total Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Enrolled	14196	0.28	0.45	0	1
Visited	14196	0.15	0.36	0	1
Waitlisted for Visitation	14196	0.01	0.11	0	1
Interested in visitation	14196	0.16	0.37	0	1
Parent is alumnus	14196	0.09	0.29	0	1
State resident	14196	0.73	0.44	0	1
From region university is located	14196	0.16	0.37	0	1
From same county as the university	14196	0.01	0.09	0	1
Male	14196	0.42	0.49	0	1
Black	14196	0.04	0.2	0	1
Hispanic	14196	0.17	0.38	0	1
Asian	14196	0.1	0.3	0	1
Other minority	14196	0.1	0.3	0	1
High School GPA	14196	3.36	0.45	0	4
Expected family contribution	14196	28268.52	44040.92	0	999999
Best combination of SAT scores	14196	1072.01	170.6	0	1600
First gen. college student	14196	0.38	0.49	0	1
Age	14196	18.5	0.5	16.58	34.25
Paid application fee	14196	0.77	0.42	0	1
Filed a FAFSA	14196	0.72	0.45	0	1
Federal need	14196	12178.83	14118.64	0	41408
Unmet need	14196	2893.8	8477.72	0	41408
Total financial aid offer	14196	19718.75	15563.07	0	52408
Total grants, scholarships, and waivers	14196	5616.65	6306.92	0	33525
Subsidized loans	14196	1598.34	2178.14	0	7500
Unsubsidized loans	14196	1861.62	2083.46	0	32000
For those who visited No visitation scholarship received	2132	0.24	0.43	0	1
Visitation scholarship is the only non-loan aid	2132	0.16	0.37	0	1

Table 2: Admitted and Enrolled by Race and Residence

	State Residents				Nonresidents			
Race	Admitted	Percent	Enrolled	% Yield	Admitted	Percent	Enrolled	% Yield
White	5734	55.5	2104	36.69	2277	58.99	345	15.15
Black	495	4.79	140	28.28	103	2.67	17	16.5
Hispanic	1842	17.81	553	30.02	620	16.06	107	17.26
Asian	1031	9.97	185	17.94	373	9.66	54	14.48
Native Am	56	0.54	23	41.07	24	0.62	6	25.00
Other	231	2.23	87	37.66	102	2.64	18	17.65
Multirace	946	9.15	314	33.19	361	9.35	58	16.07
Total	10336	100	3406	32.95	3860	100	605	15.67

Table3a: Visit Program Participation and Enrollment

	not enrolled	enrolled	% enrolled	Total
no visit or waitlist	9,591	2,283	19.22%	11,878
waitlisted	138	52	27.37%	190
attended	456	1,676	78.61%	2,132
Total	10,185	4,011	28.25%	14,196

Table 3b: Visit Program Participation and Enrollment, State Residents

	not enrolled	enrolled	% enrolled	Total
no visit or waitlist	6,558	1,925	22.68%	8,487
waitlisted	51	32	38.55%	83
attended	321	1,449	81.86%	1,770
Total	6,930	3,406	32.94%	10,33

Table 3c: Visit Program Participation and Enrollment, Nonresidents

	not enrolled	enrolled	% enrolled	Total
no visit or waitlist	3,033	358	10.56%	3,391
waitlisted	87	20	18.69%	107
attended	135	227	62.71%	362
Total	3,255	605	15.67%	3,860

Table 3b: Visit Program Participation and Enrollment, Whites

	not enrolled	enrolled	% enrolled	Total
no visit or waitlist	5,407	1,391	20.45%	6,802
waitlisted	64	26	28.89%	90
attended	257	1,115	81.27%	1,372
Total	5,728	2,532	30.64%	8,260

Table 3c: Visit Program Participation and Enrollment, Minority

	not enrolled	enrolled	% enrolled	Total
no visit or waitlist	4,184	892	17.57%	5,076
waitlisted	74	26	26.00%	100
attended	199	561	73.82%	760
Total	4,457	1,479	24.92%	5,936

Table 4: Estimates of different probit models

All runs use robust errors

EQUATION	---------------Recursive Probit (RP)----------------							
	---------Visited---------		------Interested------		----Limited Sample----		-----------2SRI-----------	
enrolled	**estimate**	**z-score**	**estimate**	**z-score**	**estimate**	**z-score**	**estimate**	**z-stat***
Visited	1.75	6.82	1.21	9.83	1.12	9.58	1.27	11.54
Interested in visitation	0.44	4.44	1.01	3.10	----	----	0.47	4.25
No scholarshp	-0.45	-5.28	-0.45	-5.24	-0.39	-3.96	-0.46	-5.12
Visit Scholarship Only	-0.24	-3.07	-0.24	-3.07	-0.08	-0.81	-0.24	-2.88
Parent is alumnus	0.28	6.06	0.28	6.00	0.19	1.78	0.30	6.85
State Resident	0.44	9.31	0.45	9.65	0.75	6.55	0.48	10.73
From region university is located	0.07	1.67	0.07	1.78	-0.06	-0.78	0.11	3.00
From same county as the university	0.36	2.48	0.36	2.44	0.03	0.09	0.37	2.51
Male	0.12	4.56	0.12	4.57	0.00	0.02	0.12	4.71
Black	0.00	-0.05	-0.01	-0.11	-0.02	-0.09	-0.04	-0.62
Hispanic	-0.11	-2.92	-0.12	-3.04	-0.08	-0.81	-0.12	-3.12
Asian	-0.21	-3.99	-0.20	-3.87	-0.47	-3.60	-0.25	-5.11
Other minority	-0.01	-0.32	-0.01	-0.33	-0.06	-0.59	-0.02	-0.42
Paid application fee	0.50	11.97	0.50	11.89	0.56	5.38	0.50	12.24
High School GPA	-0.43	-11.70	-0.43	-11.72	-0.16	-1.56	-0.42	-11.23
Best combination of SAT scores	0.00	-7.60	0.00	-7.26	0.00	-2.86	0.00	-8.56
Filed a FAFSA	0.20	3.45	0.20	3.44	-0.13	-0.88	0.21	3.30
Federal need	0.03	0.93	0.03	0.93	0.07	1.16	0.03	0.98
Unmet need	-0.04	-1.14	-0.04	-1.13	-0.06	-0.64	-0.04	-1.17
Expected family contribution	-0.01	-1.99	-0.01	-1.95	0.00	-0.31	-0.01	-1.84
Total financial aid offer	-0.16	-5.20	-0.16	-5.19	-0.18	-2.55	-0.17	-5.38
Total grants, scholarships, and waivers	0.29	9.43	0.29	9.40	0.44	5.95	0.30	9.44
Subsidized loans	0.40	2.47	0.41	2.49	0.15	0.42	0.42	2.49

Unsubsidized loans	0.95	5.32	0.95	5.32	1.52	4.17	0.98	5.45
First gen. college student	0.09	2.85	0.09	2.87	0.01	0.11	0.08	2.50
Age	0.04	1.51	0.04	1.52	0.01	0.18	0.04	1.33
Constant	-0.53	-0.93	-0.56	-1.00	-0.43	-0.28	-0.41	-0.69
Uhat							-0.04	-0.48
					Pseudo R2=0.1		Pseudo R2=0.24	
visited or interested					n=2322			
Parent is alumnus	0.14	3.23	0.13	3.01			0.21	4.18
State Resident	0.30	8.93	0.18	5.64			0.12	2.15
From region university is located	0.28	7.84	0.26	7.35			0.56	15.31
From same county as the university	-0.09	-0.06	-0.06	-0.45			0.18	1.34
Male	-0.02	-0.77	-0.02	-0.81			-0.01	-0.20
Black	-0.38	-4.91	-0.28	-3.85			-0.65	-3.51
Hispanic	-0.08	-2.10	-0.04	-1.10			-0.11	-2.15
Asian	-0.43	-7.99	-0.40	-7.81			-0.56	-4.98
Other minority	-0.03	-0.78	-0.03	-0.73			-0.03	-0.59
High School GPA	0.13	3.80	0.13	3.82			0.34	5.69
Expected family contribution	0.00	1.50	0.00	0.87			0.00	-1.18
Best combination of SAT scores	0.00	-4.72	0.00	-5.15			0.00	-3.88
First gen. college student	-0.07	-2.26	-0.07	-2.23			0.04	1.00
Age	-0.03	-1.30	-0.04	-1.46			0.01	0.29
Constant	-0.60	-1.18	-0.34	-0.68			-2.67	-3.00
Number of individual admitted from the same geographic area							0.01	19.40
Days before January 31 application was complete							0.00	1.15
rho	-0.28	-1.93	-0.30	-1.88			* bootstrap std err	
num obs	14196		14196				14196	
Wald chi2 on rho	3.30		2.90					
Prob>chi2	0.07		0.09					

Table 5a: Marginal Effects in Enrolled Equation

	--------------------Recursive Probit---------------------							
	---------Visited---------		-----Interested------		----Limited Sample----		-----------2SRI-----------	
enrolled	**estimate**	**std err**	**estimate**	**std err**	**estimate**	**std err**	**estimate**	**std err**
Visited	0.57	0.07	0.39	0.05	0.38	0.04	0.42	0.04
Interested	0.12	0.03	0.32	0.11	----	----	0.14	0.04
No Scholarship*	-0.10	0.03	-0.10	0.03	-0.11	0.03	-0.14	0.03
Visit Scholarship Only*	-0.05	0.02	-0.05	0.02	-0.02	0.03	-0.07	0.02

* for subsample with Visited=1

Table 5b: Marginal Effects in Enrolled Equation by Subpopulation

	Washington Res		Nonresident		White		Minority	
enrolled	**estimate**	**std err**	**estimate**	**std err**	**estimate**	**std err**	**estimate**	**std err**
Visited	-0.08	0.16	0.83	0.02	0.47	0.13	0.59	0.17
Interested	0.19	0.05	0.07	0.00	0.18	0.05	0.10	0.04
No Scholarship*	-0.14	0.05	-0.02	0.01	-0.06	0.05	-0.13	0.06
Visit Scholarship Only*	-0.06	0.03	-0.01	0.01	-0.02	0.02	-0.14	0.06

* for subsample with Visited=1