

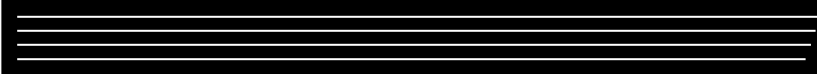


Working Paper Series
WP 2016-18

**Is it the Visit or the Scholarship? An analysis of a
special campus visitation program**

Matthew Birch and Robert Rosenman

September 2017



Is it the Visit or the Scholarship? An analysis of a special campus visitation program

Matt Birch & Robert Rosenman*

School of Economic Sciences

Washington State University

Pullman, WA 99164-6210

Neither author has any conflict of interest with regards to this research.

* Graduate student and professor, respectively

Birch, matthew.birch@wsu.edu

Rosenman, yamaka@wsu.edu (509) 335-1193

Is it the Visit or the Scholarship? An analysis of a special campus visitation program

Abstract

We analyze the impact of a campus visit program for admitted students on enrolling using data from a public research university. Differences in receiving the scholarship among those who participate in the visit program, combined with other financial aid information, allows us to decompose the effect of the program on enrolling into its component parts of visiting campus and receiving a scholarship, allowing us to identify the treatment effect of visiting by itself. Our results indicate a substantial effect of visiting on the likelihood that a student will enroll at the university.

JEL Codes: I22 I23

Keywords: college, enrollment, yield, visit, university

1. Introduction

Yield rates – the percent of admitted students who enroll at a university – is considered to be a measure of a college’s popularity and desirability (Powell, 2017; Baskin, 2015) and is often a component when assessing college selectivity (College Raptor, 2017) and in rankings (DIY College Rankings, 2017).¹ In this paper we address one popular form of recruitment effort that colleges use to improve yield – 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 predisposed to enrolling 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 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.

The effectiveness of campus visits has not been addressed empirically in a way that accounts for potential endogeneity bias from the confounding of visiting and enrollment, even when there is no scholarship involved. In an early work, Kealy and Rockel (1987) claim that

¹ The popular US New College Rankings used to use yield rate, but discontinued using in in the early 2000s.

attempting to identify a causal relationship between visiting and enrollment is 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 visiting with no corrections for potential 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 potential endogeneity of visiting.

In this paper, we analyze the impact of a campus visit program for admitted students on enrolling, using data from a public research university. Our empirical model controls for potential endogeneity bias of visiting. Differences in receiving the scholarship among those who visit, combined with other financial aid information, allows us to decompose the effect of the program into its component parts of visiting campus and receiving a scholarship. More specifically, we identify the treatment effect of visiting by itself. Our results indicate a substantial effect of visiting on the likelihood that a student will enroll at the university.

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 its main campus, one general and one marketed to students of color.² These are in-depth full day 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

² The program marketed only to admitted students of color 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.”

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.

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 alluded to earlier, some students, predisposed 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 as 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.³ 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.⁴ In August all admitted individuals, whether or not they participated in a visitation, choose to enroll or not. If an enrolled student participated in the program, she is eligible for the visitation scholarship.⁵

In this context we can think of participating in the visitation program as a treatment which is (at least partially) determined by the student's action, raising a concern of selection bias (Heckman, 1978). Our primary analysis considers the case in which students "select" by participating in the visitation program. In this construct, since registration opens at the same time for every eligible student and space fills up quickly, timing may decide whether or not the student gets the treatment. Highly motivated students, knowing there is limited space, apply for the program as soon as possible, and the selection is on participating in the visit program, not just trying to participate. Being motivated enough to get the treatment differentiates those who get to visit from those who do not. Hence, for our main analysis we include only visiting as a (potentially endogenous) explanatory variable for enrollment, ignoring students who request to be part of the visitation program, but do not get in.

Of course, that begs the question why anyone bothers to register late, or be asked to be put on a waiting list? Hence, we also consider, as a robustness check, two additional models. First, we change our selection variable from visiting to what we term "interested", which consists of all those who visit or are waitlisted for a visit. In essence, this assumes that getting to visit or not was due to random differences in when the students tried to register for the program, but those who were put on the waitlist were just as motivated as those who got to

³ We have no data on other universities, so we only consider choices only about enrolling at this one.

⁴ 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.

⁵ Approximately 16% of those who attended the visitation program did not receive the scholarship. We address this issue later in the paper.

visit. In this case, both visited and interested are used as explanatory variables, allowing a further decomposition of visiting from a predisposition towards enrolling at the university.

We exploit the limited space in the visitation program further to conduct what we think of as a quasi-regression discontinuity design analysis to help control for possible confounding effects of interest in visiting the university from the effect of visiting itself. Students who were waitlisted expressed an interest in visiting but do not get the opportunity due to insufficient space. The same assumption as in our first robustness analysis (the difference in getting to visit or not is due to random differences in the timing of applying to the visitation program) creates a “bandwidth” of similar students – those wanting to visit, separated only by the small window for when space was available. Using only those students allows us to identify the treatment effect of visiting by itself. As with our primary analysis, 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.

Empirical Approach

We use a recursive bivariate probit model (Heckman, 1978) where the relationship between enrolling and visiting may rely upon underlying unobserved variables (such as motivation) that jointly enter both decisions. These unobserved factors enter the error structure of the model, and explicitly address the possibility that treatment is not randomly applied – those who participate in the visitation program are fundamentally different from those who do not. The model is recursive because most prospective students are unaware of the formal visitation program, and the details of the program are not made clear until admitted students are invited by email, approximately 8 weeks prior to registering for a visit. Moreover, the decision to visit is made months before the final decision to enroll.

Given this timing and nature of the decision process we have

$$\begin{aligned} y_{1i}^* &= X_{1i}\alpha_1 + y_{2i}\beta_1 + d_i\beta_2 + u_{1i}, y_{1i} = 1(y_{1i}^* > 0) \\ y_{2i}^* &= X_{2i}\alpha_2 + u_{2i}, y_{2i} = 1(y_{2i}^* > 0) \end{aligned} \quad \text{with} \quad \begin{bmatrix} u_{1i} \\ u_{2i} \end{bmatrix} \square N \left[0, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right]. \quad (1)$$

where 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

participating in the visitation program and we observe $y_{2i} = 1$ (the student visits) if $y_{2i}^* > 0$. Unobserved factors (the u_i) across the two equations may be correlated.⁶ The dummy variable $d_i = 1$ indicates the student attended the visit program. Heckman shows that maximum likelihood estimators of this model is consistent, asymptotically normal, and efficient.⁷ Given limitations on scholarships and grants, which cannot exceed the total cost of attending the university (including living expenses) some students who visit do not get the scholarship. For others the visit scholarship is the only source of non-loan aid. This allows us to separate the effect of the visit from the effect of the scholarship with dummy variables for these special cases. Data on financial aid helps control for the fact that students in these two groups may be different from others who participate in the visit program.

The limited space in the program allows us two robustness checks. We select on intent to participate rather than visiting. In this construct, y_2^* is a latent variable underlying *interest* in participating in the visitation program and we observe $y_{2i} = 1$ (the student either visits or is on the waitlist) if $y_{2i}^* > 0$. Selection is on interest in visiting rather than on visiting. This model is used as a robustness check because it implicitly assumes the motivation for those who get to visit and those placed on the waitlist are the same; getting to visit from among that group is random. This specification uses the entire sample. The dummy variable $d_i = 1$ now indicates the student applied to the visit program. We add another dummy variable indicating the

⁶ For convenience we call y_{2i}^* the selection variable.

⁷ A recursive bivariate probit system can be identified by conventional exclusion restrictions, $X_{2i} \not\subset X_{1i}$, or, if $X_{2i} \subset X_{1i}$, by its recursive nature as long as there is sufficient variation in the exogenous variables. Because of the recursive structure, a linear combination of the two equations differs structurally from the first equation in (1) and the classical identification problem of simultaneous equation does not exist (Wilde, 2000).

student attended the program, and it allows us to separate motivation impact from the effect of attending the visit program.

A second robustness analysis, as discussed above, is what we term a quasi-regression discontinuity design where the “bandwidth” consists of those who visited or were waitlisted for a visit. Such an analysis uses a univariate probit of only the enrollment equation, comparing those who visited to those who ended up on the waitlist. Since all observations in this limited sample expressed a desire to visit, we can isolate only the marginal effects of visiting and the scholarship. This approach provides another way to check the estimates from the primary analysis.

4. Data and Variables

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, if they enrolled. Table 1 provides a list of the variables used in our analysis and basic statistics. Appendix Table 1 compares students who participated in the visit program to those who did not. Among the highlights of the difference, those who visited are more likely to have a parent who is an alumnus, more likely to be from the state, county or region that the university is located, are less likely to be Black or Asian, have higher GPAs on average, but lower SAT scores. They filed FAFSAs more frequently, had a lower unmet need and higher total financial aid offers, with larger average amounts of all types of aid used in the analysis. At conventional p-values, there is no statistical difference in their average age or being a first-generation college student.

Dependent and endogenous (recursive) variables

Our dependent variable of interest is enrolling at the university (“Enrolled”), while the endogenous treatment we analyze is participating in the visitation program (“Visited”. Overall, 28% of our sample enrolled at the university. Table 2 breaks enrollment down by race and residence. Most students 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 3, for all students and decomposed 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 could participate in the visit program. Hence, 2132 students attended a visitation program; of those 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 190) 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. 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 difference in 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.

Explanatory Variables

The timing of decisions informs our specification. At the time students must register for the visitation program they know that they have been admitted to the university but do not yet have their financial aid offer. We broadly classify our explanatory variables into two subsets:

personal information, known when deciding whether to register for visitation or enroll, and financial aid information available only at the time the student makes the enrollment decision.

Personal information includes basic demographics (gender, race⁸ 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 in⁹) and if the student applied for financial aid by submitting a FAFSA. 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, which is the information the student will have when deciding to enroll or not in the upcoming semester. Variables used include expected family contribution (EFC, the amount the student and family would be expected to pay to attend the university), federal need (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. Only 72% of our sample filed a FAFSA. If a student did not file a FAFSA she was not eligible for need-based financial aid. For the enrollment equation, when no FAFSA was filed or if the EFC exceeded the cost of attendance we set the EFC 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. Although a very imperfect measure, EFC is correlated with income, so we used it as a proxy for

⁸ 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".

⁹ Including additional counties did not alter the conclusions.

income in the visit equation. Reported EFC is zero for those not filing a FAFSA so, in the visit equation, we included a cross term of $EFCx(1-FAFSA)$ to try to account for this missing value.

For those students who participated in the visitation program, we also included specific information on their visitation scholarship. 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, 456 did not enroll at the university, and 1676 enrolled. Just over 16% (350) of all 2132 were not offered the scholarship.¹⁰ Enrollment statistics provide some evidence that the scholarship matters. Of those who visited who did not enroll, 24% were not offered the scholarship, but of those who enrolled, only 14% did not get the scholarship. Appendix Table 2 compares, for those who visited, basic statistics of those who received the scholarship, and those who did not. Most pertinent in this table are variables related to financial aid. Those who did not get the visit scholarship had lower expected family contribution and financial aid offers, on average, but larger amounts of grants, scholarships and waivers. They were more likely to be Black, Hispanic or Asian and had lower high school GPAs and SAT scores, on average. We expect, from this information, that other forms of grants, scholarships and waivers "crowded out" the visit scholarship.

Additionally, for just under 24% of the visit participants the visit scholarship was the only form of non-loan aid offered. There was only a slight difference in the scholarship being the only form of an aid between those who enrolled or did not. The scholarship would have been the only form of aid for almost 25% of those who did not enroll; it was just under 24% for those who enrolled.

In the visitation equation we added a variable that accounts for the number of individuals from the same geographic area who indicated an interest in the visitation program. We hypothesize that students might be more likely to join the program if they know someone who is going or if more students like them participate (Epple et al., 2003). We use county level

¹⁰ We have no real information about why a student who visited did not get a scholarship. We thought perhaps it had to do with filing a FAFSA, since all other financial aid depends on doing so. But only 14% of the 350 who did not get the scholarship did not file a FAFSA, compared to 13% of those who did get the scholarship.

counts for in-state students, state level counts for domestic students from out of state, and country level counts for students not from the United States.¹¹ This variable identifies the enrollment equation through exclusion restrictions.

5. Results

Table 4 provides parameter estimates from various specifications and identification strategies. Our primary specifications, which use Visited as the selection variable, are in first and second results columns in the table. In model (1) we identify the parameters with exclusion restrictions – the financial aid variables are excluded from the Visited equation, and the number of students interested in visiting from the same geographic area, is used to identify the Enrolled equation. In model (2) we do not use the geographic area variable and identify the parameters through the recursive structure of the system, as discussed in footnote 7.

Somewhat surprising, the estimate of rho, the correlation between the errors of the two equations is tiny and not statistically significant near any conventional p-value. Although we expected unobserved factors might jointly determine visiting and enrolling, the evidence is that these are independent decisions.

Despite the geographic variable being significant with a p-value<0.01 in the model identified by exclusion, the results from the two strategies are nearly identical. Except for First-generation college student (in the Enrolled equation) and being a state resident (in the Visited equation), the significance and sign of all parameters are the same. Most magnitudes are also similar, with those that differ being in the Visited equation. Hence, we discuss these models together.

The signs of the estimates make sense with a possible exception of Total financial aid offer, although since this includes merit aid, it is consistent with the signs of GPA and Best,

¹¹ 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 to those using county-level data for in-state students. For consistency between in-state aggregation and out-of-state aggregation, and to better support the variable being exogenous, we chose to use county-level counts for in-state students.

which indicate stronger students go elsewhere. First generation students are more likely to enroll (a long-standing tradition of the student body at this university). However, whether they are more likely to visit depends on which identification strategy is used. Our conjecture that the visitation program might attract students uncertain about this university compared to other offers is bolstered by finding that GPA increases the likelihood of visiting while having a negative coefficient on enrolling. The parameter of primary interest, on Visited in the Enrolled equation, is consistent in both magnitude and p-value between the two identification strategies.

Does the visitation/scholarship program work?

We are most interested in the marginal effects of participating in the visitation program and other variables associated with that program on enrolling. The other variables of primary interest include Visited but No Scholarship (which indicates an individual who visited did not get the scholarship) 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 visiting from 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 marginal effects are given in columns 2 and 3 of Table 5

All estimated marginal effects from our primary specification are significant with p-values < 0.01 with both identification methods. Students who participated in the visitation program were much more likely to enroll, after controlling for other differences. All else equal, attending the visitation program increases the likelihood of enrolling by about 58%. We measured the marginal effect of not getting the visitation scholarship (Visited but No Scholarship) or of it being the only non-loan source of aid only for those who visited as others are not eligible for the scholarship. The increase in enrollment attributable to visiting is attenuated if the scholarship is not received – the net effect of the program on the probability of enrolling falls to 44%, still very substantial. This indicates about 80 percent of the increase in

the probability of enrollment from participating in the program can be attributed to the visit, while 20 percent can be attributed to the scholarship. Having the visit scholarship as the only non-loan offer also attenuates the program effect on enrollment, but only by one-half as much, offering more evidence that the scholarship is not the major reason those who visit are more likely to enroll. In fact, it provides evidence against those who join the visitation program are those already intending to enroll, and they do so only for the scholarship.

As an extension of the analysis, we used the fact that some students showed interest in the visitation program but were closed out because of space limitations to try to decompose the program effect further. As noted earlier, this analysis assumes the difference between visiting and being waitlisted is essentially random. This is not our primary analysis because we do not have the times that students applied for the visit program, so cannot test this idea.

Model 3 in Table 4 uses Interested (which means the student either attended a visitation program or was waitlisted) as the selection variable.¹² Again there is no evidence that rho differs from zero. The magnitudes, signs and significance levels of all the estimated parameters mimic those of the model without Interested in visiting, although the magnitude of the parameter estimate on Visited in the Enrolled equation is appreciably smaller (and in fact, statistically different with a p -value $< .01$). At the same time, the parameter estimate on Interested in the Enrolled equation, while positive, has a p -value of 0.44. The sum of the parameters on Visited and Interested in this specification is not statistically different at conventional p -values from the estimate on Visited when Interested is not included in the specification. The marginal effects of this model are given in the fourth column of Table 5. As would be expected, visiting has a smaller impact on enrolling, although the sum of the marginal effects of being in the visitation program and being interested in the program is close to what we find when participation (Visited) is alone in the model.

¹² We identify the model via recursiveness. A bivariate probit that included the geographic variable did not converge, although a simultaneous equations Linear Probability Model which included the geographic variable produced similar marginal effects.

As a final check we conduct what we term a quasi-RD analysis, using a limited sample for the estimation of only those who expressed an interest in the visitation program. RD design models assume those used in the sample, usually limited to observations within a small bandwidth of the variable determining whether the treatment is received or not, are similar. Since we do not have the time a student applied for the visitation program, we use the entire set of those who visited or were waitlisted. Appendix Table 3 compares the means and standard deviations of students in the two groups. Compared to those waitlisted, students who visited are more likely to be legacies, state residence, be from the region or county of the university. They have higher expected family contributions, but their federal need is lower (which goes along with more likely being a state resident), and larger unsubsidized student loans. A greater share of the waitlisted students are minority. These results, model (4) are reported in the last column of Table 4. The estimates on Enrolled with this model show some differences from those in model (3), especially in statistical significance. However, the parameter of primary interest, on Visited, which shows the impact of participating in the visitation program, is similar in value and significance. In fact, the parameter estimates on Visited from models (3) and (4) are not statistically different at conventional p-values. The marginal effect of program participation is also similar to what we found with model (3), although there is no evidence of an attenuation by the visit scholarship being the only financial aid received.

Table 6 shows the marginal effects of the visitation program, using our primary model with exclusion identification, disaggregated by residence and race.¹³ Overall, the findings on the marginal effects carry over to the smaller groups with two exceptions. Having the visit scholarship as the only financial aid has a much smaller impact on state residents than for the other groups (although this could be a function of using the LPM), and not getting the scholarship does not diminish the effect of visiting for nonresidents of the state.

¹³ The estimations underlying these marginal effects are available from the authors. Because of convergence problems, some marginal effects, as indicated, were estimated with a linear probability model (LPM).

Table 7 shows the marginal effects when Model (3) is used on the subgroups. Again, this allows us to decompose the impacts of Visited and Interested. Visiting has a slightly stronger impact on residents than nonresidents, although the attenuation effect of the visit scholarship being the only financial aid is much stronger for nonresidents – given the much greater cost of attending for nonresidents, this is not surprising. The visitation program affects minorities and Whites differently. At conventional p-values, the substantial marginal effects of visiting are not different but, Interested is not significant for White, while it is for Minority. In addition, the difference we see in the scholarship variables indicate the scholarship is more important for Minority students than for Whites. That is, getting no scholarship or having the visiting scholarship only reduces the probability of enrolling for minority individuals, but not for Whites.

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. Because not all students received the scholarship, we were able to decompose these two effects. In addition, because not all students interested in the program got in, in an extension we identified a potential difference between an interest in joining the program, and getting to participate.

Overall, we found a strong effect of the visitation program. For all students, participating in the campus visit attached to this program increased the probability of enrollment by 58%. To the extent we could decompose this estimate, 44% of it is due to the visit, and 14% due to the scholarship. The fact that students interested in the visitation program who did not get to had a much lower probability of attending indicates that the visit itself is important in the decision to enroll. This finding held up over several alternative estimations. There was some difference in the marginal effects between state residents and nonresidents, but, in our main specification, not between minority and White students.

Surprisingly, there was no statistical evidence that unobserved factors that motivated participating in the visitation program also motivated enrolling at the university.

Given estimates for parameters on the quality of students, 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 likely 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 conclusively 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 evidence 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 s(he) could get prospective students to the program without the scholarship, s(he) should still have a very impressive increase in the propensity to enroll.

References

- Baskin, Morgan, 2015. "As 'yield rates' fluctuate, colleges work to protect reputations", *USA Today College*. <http://college.usatoday.com/2015/02/07/as-yield-rates-fluctuate-colleges-work-to-protect-reputations/>. Accessed September 26, 2017.
- College Raptor. 2017. "Selectivity Index." <https://www.collegeraptor.com/college-rankings/details/Selectivity>. Accessed September 26, 2017.
- DIY College Rankings. 2017. "50-50 Highlights: Colleges Students Really Want to Go To." <http://www.diycollegerankings.com/50-50-highlights-colleges-highest-yield-rates/5983/>. Accessed September 26, 2017.
- Epple, D., R. Romano, and H. Sieg. 2003. "Peer Effects, Financial Aid, and Selection of Students into Colleges." *Journal of Applied Econometrics* 18 (5): 501-525.
- Goenner, Cullen F., Melissa Harris, and Kenton Pauls. 2013. "Survival of the Fittest: What Do Early Behaviors Tell Us About Student Outcomes?" *Journal of College Student Development* 54 (1): 43-61.
- Heckman, James J. 1978. "Dummy Endogenous Variables in a Simultaneous Equation System." *Econometrica* 46 (4): 931-959.
- Hesel, Richard A. 2004. *Campus Visit Drives College Choice*. Art & Science Group. Accessed Aug 10, 2016. http://www.artsci.com/StudentPOLL/v5n5/publishers_note.htm.
- Hoover, Eric. 2009. "'Golden Walk' Gets a Makeover from an Auditor of Campus Visits." *Chronicle of Higher Education* 55 (26).
- Kealy, Mary Jo, and Mark L. Rockel. 1987. "Student Perceptions of College Quality: The Influence of College Recruitment Policies." *The Journal of Higher Education* 58 (6): 683-703.
- Okerson, Justine Rebecca. 2016. *Beyond The Campus Tour: College Choice And The Campus Visit*. PhD Thesis, College of William and Mary, Dissertations, Theses, and Masters Projects at W&M

Powell, Farran. 2017. "Universities, Colleges Where Students are Eager to Enroll." *USNews*.
<https://www.usnews.com/education/best-colleges/articles/2017-01-18/universities-colleges-where-students-are-eager-to-enroll>. Accessed September 26, 2017.

Swann, Claire, Stanley E. Henderson, and American Association of Collegiate Registrars and Admissions Officers. 1998. *Handbook for the College Admissions Profession*. Greenwood Publishing Group.

Wilde, Joachim. 2000. "Identification of multiple equation probit models with endogenous dummy regressors." *Economics Letters* 69: 309-312.

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
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 state region where the 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	2.82	4.26	0	99.99
Best combination of SAT scores	14196	10.72	1.71	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	1.22	1.41	0	4.14
Unmet need^	14196	.289	0.85	0	4.14
Total financial aid offer^	14196	1.97	1.56	0	5.24
Total grants, scholarships, and waivers ^	14196	0.56	0.63	0	3.35
Subsidized loans^	14196	0.16	0.22	0	0.75
Unsubsidized loans^	14196	0.19	0.21	0	3.20
Number of interested students from same geographic location	14196	31.75	101.32	0	502
<u>For those who visited</u>	2132	0.24	0.43	0	1
Visited, No Scholarship	2132	0.24	0.43	0	1
Visit Scholarship Only Financial Aid	2132	0.16	0.37	0	1

Key: ^ in \$10,000; * the highest possible value for reported EFC is \$999,999. Our data had 5 observations which reported EFC exceeding \$900,000 and 17 reporting EFC exceeding \$500,000.

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
Multiracial	946	9.15	314	33.19	361	9.35	58	16.07
Total	10336	100	3406	32.95	3860	100	605	15.67

Table3: Visit Program Participation and Enrollment				
All Students	Not enrolled	Enrolled	% enrolled	Total
No interest in visit	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
State Residents	Not enrolled	Enrolled	% enrolled	Total
All Students	6,558	1,925	22.68%	8,487
No interest in visit	51	32	38.55%	83
Waitlisted	321	1,449	81.86%	1,770
Total	6,930	3,406	32.94%	10,33
Nonresidents	Not enrolled	Enrolled	% enrolled	Total
All Students	3,033	358	10.56%	3,391
No interest in visit	87	20	18.69%	107
Waitlisted	135	227	62.71%	362
Total	3,255	605	15.67%	3,860
Whites	Not enrolled	Enrolled	% enrolled	Total
All Students	5,407	1,391	20.45%	6,802
No interest in visit	64	26	28.89%	90
Waitlisted	257	1,115	81.27%	1,372
Total	5,728	2,532	30.64%	8,260
Non-White	Not enrolled	Enrolled	% enrolled	Total
All Students	4,184	892	17.57%	5,076
No interest in visit	74	26	26.00%	100
Waitlisted	199	561	73.82%	760
Total	4,457	1,479	24.92%	5,936

Table 4: Full Model Estimates

(Model number) and Selection Variable	(1) Visited		(2) Visited		(3) Interested		(4)
Identification Method	Exclusion		Nonlinearity		Nonlinearity		Limited sample
Dependent Variable	Enrolled	Visited	Enrolled	Visited	Enrolled	Interested	Enrolled
Visited	1.758***		1.703***		1.271***		1.137***
Interested in visiting					0.321		
Visited, No Scholarship	-0.464***		-0.465***		-0.465***		-0.380***
Visit Scholarship Only Financial Aid	-0.246***		-0.239***		-0.242***		-0.089
Parent is an alumnus	0.296***	0.212***	0.298***	0.156***	0.303***	0.145***	0.188*
State resident	0.441***	0.064	0.443***	0.222***	0.454***	0.093***	0.898***
From same region of the state as the university	0.109***	0.545***	0.114***	0.254***	0.122***	0.237***	-0.058
From same county as the university	0.363**	0.188	0.364**	-0.050	0.359**	-0.022	0.038
Male	0.122***	-0.004	0.122***	-0.010	0.122***	-0.01	0.003
Black	-0.033	-0.686***	-0.038	-0.440***	-0.048	-0.337***	-0.022
Hispanic	-0.120***	-0.118**	-0.121***	-0.097**	-0.124***	-0.06	-0.073
Asian	-0.247***	-0.567***	-0.251***	-0.437***	-0.259***	-0.412***	-0.473***
Other minority	-0.017	-0.048	-0.018	-0.056	-0.019	-0.052	-0.062
Paid application fee	0.498***		0.497***		0.503***		0.565***
High School GPA	-0.420***	0.319***	-0.418***	0.094***	-0.416***	0.087**	-0.162
Best combination of SAT scores	-0.085***	-0.056***	-0.085***	-0.050***	-0.086***	-0.053***	-0.076***
Filed a FAFSA	0.168**		0.175**		0.188**		-0.044
Federal need	0.011		0.011		0.01		0.180*
Unmet need	-0.036		-0.037		-0.04		-0.058
Expected family Contribution (EFC) capped at tuition	-0.032		-0.032		-0.034		0.145
Total financial aid offer	-0.156***		-0.156***		-0.160***		-0.206***
Total nonloan aid	0.294***		0.293***		0.292***		0.454***
Subsidized loans	0.413**		0.413**		0.419**		0.296
Unsubsidized loan	0.936***		0.939***		0.953***		1.467***
First gen. college student	0.079***	0.010	0.078**	-0.116***	0.076**	-0.114***	0.018
Age	0.041	0.019	0.041	-0.022	0.04	-0.025	0.013
Expected family contribution		-0.133***		-0.171***		-0.179***	
EFC x Fafsa		0.129***		0.175***		0.182***	
Number interested in visiting from the same geog. area		0.014***					
Constant	-0.307	-2.494***	-0.301	-0.409	-0.282	-0.145	-0.952
Observations	14,196		14,196		14,196		2,322
Rho (Wald chi square test of rho)	-0.050 (2.20)		0.005 (0.00)		0.071 (0.10)		----

Table 5: Marginal Effects				
<i>Recursive variable/identification</i>	<i>Visited/Exclusion</i>	<i>Visited/Nonlinearity</i>	<i>Interested/Nonlinearity</i>	<i>Interested/Sample</i>
Visited	0.58*	0.56*	0.43*	0.38*
Interested	---	---	0.09*	---
Visit Scholarship Only	-0.07*	-0.07*	-0.07*	-0.01
Visited but No Scholarship	-0.14*	-0.14*	-0.15*	-0.11*

Key: * p-value<0.01

Table 6: Marginal Effects by Subgroup				
	<i>State Residents</i> [^]	<i>Nonresidents</i>	<i>Minority</i>	<i>White</i> [^]
Visited	0.59***	0.54***	0.58***	0.57***
Visit Scholarship Only	-0.03***	-0.17***	-0.16***	-0.13***
Visited but No Scholarship	-0.13***	-0.11	-0.15***	-0.15***

Key * p-value<0.10; ** p-value<0.05; *** p-value<0.01; ^ from Linear Probability Model

Table 7: Marginal Effects by Subgroup, Interested included in the estimation				
	<i>State Residents</i> [^]	<i>Nonresidents</i>	<i>Minority</i>	<i>White</i> [^]
Visited	0.42**	0.37***	0.44***	0.45***
Interested	0.18	0.09**	0.11**	0.14
Visit Scholarship Only	-0.04*	-0.17**	-0.16***	-0.03
Visited but No Scholarship	-0.13***	-0.11	-0.16***	-0.06

Key * p-value<0.10; ** p-value<0.05; *** p-value<0.01; ^ from Linear Probability Model

Appendix Table 1: Comparison of students who Visited to those who did not					
Variable	No Visit, n=12064		Visit, n=2132		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
Parent is alumnus	0.082	0.275	0.131	0.337	-6.31
State resident	0.710	0.454	0.830	0.376	-13.16
From state region where the university is located	0.142	0.349	0.258	0.438	-11.59
From same county as the university	0.007	0.082	0.012	0.108	-2.01
Male	0.421	0.494	0.410	0.492	0.95
Black	0.045	0.208	0.024	0.154	5.43
Hispanic	0.173	0.378	0.178	0.383	-0.63
Asian	0.107	0.310	0.051	0.219	10.28
Other minority	0.024	0.153	0.020	0.139	1.33
Paid application fee	0.768	0.422	0.805	0.396	-3.93
High School GPA	3.355	0.456	3.396	0.434	-3.97
Best combination of SAT scores	10.742	1.727	10.595	1.578	3.91
Filed a FAFSA	0.696	0.460	0.870	0.337	-20.65
Federal need^	1.218	1.437	1.218	1.259	0.00
Unmet need^	0.313	0.887	0.153	0.560	11.00
Expected family contribution^	2.817	4.193	2.884	4.625	-0.62
Total financial aid offer^	1.896	1.591	2.401	1.257	-16.36
Total grants, scholarships, and waivers ^	0.534	0.619	0.721	0.674	-11.95
Subsidized loans^	0.153	0.217	0.198	0.221	-8.62
Unsubsidized loans^	0.173	0.202	0.259	0.226	-16.31
First gen. college student	0.381	0.486	0.367	0.482	1.25
Age	18.496	0.515	18.504	0.403	-0.82

Key: ^ in \$10,000

Appendix Table 2: Comparison of Visited students who received the scholarship to those who did not					
Variable	Scholarship, n=1782		No Scholarship, n=350		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
Parent is alumnus	0.142	0.349	0.074	0.263	10.39
State resident	0.804	0.397	0.966	0.182	-30.28
From state region where the university is located	0.247	0.432	0.311	0.464	-5.93
From same county as the university	0.012	0.108	0.011	0.106	0.14
Male	0.416	0.493	0.380	0.486	3.13
Black	0.013	0.113	0.083	0.276	-11.53
Hispanic	0.119	0.324	0.480	0.500	-32.15
Asian	0.037	0.189	0.120	0.325	-11.44
Other minority	0.020	0.139	0.020	0.140	-0.11
Paid application fee	0.879	0.326	0.429	0.496	40.48
High School GPA	3.405	0.431	3.347	0.450	5.51
Best combination of SAT scores	10.734	1.519	9.886	1.680	21.79
Filed a FAFSA	0.872	0.334	0.857	0.350	1.82
Federal need^	1.118	1.248	1.726	1.187	-21.64
Unmet need^	0.121	0.494	0.315	0.797	-10.87
Expected family contribution^	3.175	4.871	1.400	2.624	24.63
Total financial aid offer^	2.469	1.250	2.051	1.236	14.38
Total grants, scholarships, and waivers ^	0.674	0.626	0.957	0.839	-14.87
Subsidized loans^	0.185	0.214	0.264	0.242	-14.16
Unsubsidized loans^	0.275	0.232	0.174	0.165	24.39
First gen. college student	0.314	0.464	0.637	0.482	-28.69
Age	18.499	0.393	18.530	0.452	-3.07

Key: ^ in \$10,000

Variable	Waitlisted, n=190		Visited, n=2132		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
Parent is alumnus	0.032	0.175	0.131	0.337	-27.24
State resident	0.437	0.497	0.830	0.376	-10.80
From state region where the university is located	0.079	0.270	0.258	0.438	-22.38
From same county as the university	0.005	0.073	0.012	0.108	-14.09
Male	0.368	0.484	0.410	0.492	-1.47
Black	0.079	0.270	0.024	0.154	9.49
Hispanic	0.268	0.444	0.178	0.383	4.54
Asian	0.079	0.270	0.051	0.219	4.85
Other minority	0.100	0.301	0.103	0.304	-0.42
Paid application fee	0.653	0.477	0.805	0.396	-3.03
High School GPA	3.316	0.397	3.396	0.434	-0.32
Best combination of SAT scores	10.429	1.687	10.595	1.578	-0.21
Filed a FAFSA	0.889	0.314	0.870	0.337	0.30
Federal need^	2.040	1.588	1.218	1.259	5.47
Unmet need^	0.442	1.101	0.153	0.560	8.96
Expected family contribution^	2.333	4.030	2.884	4.625	-3.05
Total financial aid offer^	2.798	1.650	2.401	1.257	1.90
Total grants, scholarships, and waivers ^	0.771	0.650	0.721	0.674	0.86
Subsidized loans^	0.244	0.254	0.198	0.221	2.52
Unsubsidized loans^	0.201	0.185	0.259	0.226	-3.66
First gen. college student	0.395	0.490	0.367	0.482	0.92
Age	18.455	0.499	18.504	0.403	-0.04
Number of interested students from same geographic location	174.795	145.009	195.845	179.278	-1.57

Key: ^ in \$10,000