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ABSTRACT

This study evaluated the effectiveness of a variety of academic intervention programs designed to improve the success of "at risk" students at one university. Most programs were designed to either help students in a particular course (such as calculus or chemistry) or in a particular major. The performance benchmark used to assess program effectiveness was Spring 1997 semester grade point average in comparison with predicted grades based on a linear regression statistical model. Analysis indicated that the 13 academic intervention programs were generally effective in improving student performance as measured by the Spring semester GPA. Among four programs which appeared to be particularly effective were a program for forestry students and a program for students taking chemistry. Two programs, one for African-American students and one for at-risk biology majors, appeared to have a slight detrimental effect on spring grades. Further analysis suggested that the positive results for the effectiveness of the intervention programs seemed to be driven largely by the results for those students who participated in more than one program. (Contains 18 references.) (DB)

Assessing The Effect Of Programs Designed To Enhance Student Success

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Dolores Vura
Editor
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Abstract

When we implemented a new academic eligibility requirement, we also initiated some thirteen programs to improve student success. To evaluate the programs, we used a methodology to make comparisons across various programs ranging from those designed to build life skills to those designed to improve grades in specific courses. The basis of our methodology is to develop linear models to anticipate performance and then interpret the variables associated with various program characteristics. We discuss interpretation of results it terms of both methodological and programmatic issues along with next steps in developing the student programs.

Introduction and Background:

A student's lack of success and consequent dropping out from a higher educational institution can have costly consequences for both the student and the institution. For the student, a lack of success in college can impose both personal and financial costs, including such factors as lower self-esteem and more limited opportunities for self and career advancement. For the educational institution, on the other hand, the costs of student attrition include the intangible humanitarian costs associated with failing to help students live up to their full potential. There are also the tangible financial costs associated with trying to recruit new students, hence new sources of tuition income for the school, to replace the students lost through attrition.

As a result of these potentially very large tangible and intangible costs of student attrition, the question of how to retain students and, in general, to enhance student success at higher educational institutions has been a widely studied one over the past few decades. Even before 1980, this problem had received sufficient attention to merit a number of comprehensive literature reviews, including those of Spady (1970), Tinto (1975), Cope and Hannah (1975), and Pantages and Creedon (1978). Most of the earlier studies comprising this body of literature, however, had been atheoretical in terms of their descriptions of the influences on student attrition. So, starting with Spady (1971), a number of authors have proposed theoretical models to explain student attrition (e.g., Pascarella (1980) and Bean (1986)). However, probably the best known and most widely examined, tested, and accepted model of student attrition in the educational community is that of Tinto (1975, 1987, 1993) (see, e.g., Halpin (1990), Pascarella and Chapman (1983), Pascarella, Duby, and Iverson (1983), Terenzini and Pascarella (1977,1980), and Terenzini, Lorang, and Pascarella (1981)).

Tinto's model focuses on the fit between the student and the educational institution and emphasizes integration and commitment. According to this model, an individual's pre-entry attributes, such as family background, skill and ability, and prior schooling, interact with each other. They then influence the student's goals and commitments, most notably the student's initial commitment to the goal of college completion and initial commitment to the institution itself. These goals and commitments, in turn, interact over time with the student's academic and institutional experiences, in terms of both the formal and informal academic and social systems of the institution, to influence students' intellectual development and academic performance, which determine academic integration. The extent to which the student becomes academically and socially integrated into the formal and informal academic and social systems of an institution then determines the individual student's departure decision. A greater degree of goal and institutional commitment corresponds to a reduced probability of the student's dropping out.

Thus, in order to improve retention and reduce attrition, an institution should invest its time and energy on strengthening those factors that help improve the fit between the student and the institution. This is the role that programs aimed at improving student retention need to play. So, on the road to improving student retention, it is important first to develop such programs and then to ensure that such programs are performing their function effectively. As Congos and Schoeps (1997) state,

> Retention is an outcome, a result, a by-product of effective educational programs and services in and out of the classroom. Therefore, focus in postsecondary education should not be on retention itself but rather on the effectiveness of programs aimed at lowering attrition.

We have followed their advice and evaluating program effectiveness is the focus of this paper. We have included special emphasis on exploring a number of statistical and analytical issues that arise in trying to assess the effectiveness of such programs in the non-experimental environment in which they must operate.

Building on some of the insights from the vast body of research on student attrition and performance, and in conjunction with the development of a new academic eligibility policy, various projects were funded to investigate factors that seem to enhance academic success. Felicia Blanks, coordinator of these projects, asked IR to look at the effectiveness of these various intervention programs.

The academic intervention programs that will be studied in this paper were conducted during the Spring semester of the 1996-97 academic year. These programs were designed to help improve the academic success of students who were "at risk" in various regards. Some of the programs were designed to help students in a particular course, while others were not course-specific but were designed to help students of a particular major. Still other programs were designed to help students who were thought to be at-risk for other reasons that did not fall into these two specific categories. A listing of the programs analyzed (along with the abbreviations used to denote the programs in the analysis below) is as follows:

- "Excel above and beyond - a comprehensive intervention program for African-American Students" (CAAE)
- "Promoting Student Success in Calculus-Based Introductory Physics" (CALPHYSC)
- "Early Involvement with At Risk Biology Majors" (ERLINVBI)
- "The Emerging Scholars Program in Calculus (Math)" (ESPMATH)
- "Enhancing Success and Professional Development in Forestry" (PRODEVFO)
- "Fostering Student Success through Residential Advisors" (RESADADS)
- "Enhancing Student Success - High Risk Courses - Chemistry" (RSKCHEM)
- "Course-specific Moderated Study Groups to Increase Plan for African-American Students" (STDYUHSA)
- "Multifaceted Approaches to Increasing Retention in FCD" (SUCCFCD)
- "Developing Complete Student Through Team Advising - Biology" (TMADVBIO)
- "Training Project Success Facilitators (CAAE)" (TNGSUFAC)

The research goals for this study are twofold. First, the general effectiveness of the intervention system as a whole will be analyzed. The goal of this analysis will be to determine whether the performance of students who participated in a program improved relative to what it would have been if the student had not been a participant in the intervention system, regardless of the specific program or programs in which the student participated. Second, the performance of specific intervention programs will be examined.

Criteria For Analyzing The Programs:

There are multiple ways to evaluate improved performance. The intent of this effort is to select a criterion that is relevant to all programs. As was noted above, some of the intervention programs focus on specific courses (e.g., "Promoting Student Success in Calculus-Based Introductory Physics"). Other programs focus on specific majors (e.g., "Enhancing Success and Professional Development in Forestry"). Other programs target specific students or categories of students who want to improve their academic performance (e.g., "Excel above and beyond - a comprehensive intervention program for African-American Students" and "Fostering Student Success through Residential Advisors"). For the programs that are connected with a specific course, the effectiveness of the program could be assessed by comparing the students' actual performance in the course (e.g., letter or numerical grade) with the performance that would have been expected for the students had they not participated in the intervention program. For the programs for specific majors, the students' retention rate within the major and their subsequent Major GPA's could be used in evaluating the effectiveness of the programs.

However, none of these evaluation methods is unilaterally appropriate for all of the programs. Thus, a measure of performance must be chosen that IS applicable to the students in all of the programs. While specific programs seek to improve student performance in specific categories, from a university-wide perspective the purpose of the intervention process (as opposed to a specific intervention program) is ultimately to improve the chances that a student will (be able to) remain enrolled in school and eventually graduate. For the purposes of short-term evaluation, one performance benchmark students establish along the way toward remaining in school and ultimately graduating is the GPA they attain for the Spring term, a decisive factor in determining which students will be allowed to return in the Fall.

Thus, the prime performance benchmark that will be used to assess the effectiveness of the intervention programs is the Spring '97 semester GPA. But to use this as a performance benchmark for the programs means that we need to assess the difference between what are the students' performances, i.e., their Spring GPA's, given that they were involved in the intervention programs and what the Spring GPA's WOULD HAVE BEEN had they not been involved in the intervention program. This means that a model must first be developed for predicting students'

Spring semester GPA's before it will be possible to determine whether the intervention programs were successful in improving Spring semester GPA's. Of course, once such a model is in place, it could also be used to directly examine the effectiveness of the intervention programs in improving students' Spring semester GPA's.

Initial Data Analysis:

Before a statistical model for Spring GPA's can be developed that will enable an examination of the effectiveness of the intervention programs, however, the statistical features of the data must first be examined to determine what form such a model should take. Also, a set of possible independent variables must be selected that are likely to be able to explain or "capture" the observed variation in the dependent variable, the Spring GPA.

For GPA data, the most obvious possible explanatory data is past GPA data. Thus, an initial possible model entails modeling Spring GPA as a function of Cumulative GPA as of the end of the Fall term. For estimating the relationship between past GPA and present GPA, the relevant population is the entire student body. The ultimate purpose of our analysis, however, is to estimate the effectiveness of the intervention programs in improving student GPA's. Thus, to estimate how well the students may have performed had they not been involved in the intervention programs, it is necessary to find a control group of students not in the intervention programs that is as similar as possible to the treatment group of students who were in intervention programs. Because the ultimate purpose of the intervention programs is to improve student retention and ultimately graduation rates, we are most concerned at this point with students who have not yet reached their Senior year. Therefore, our relevant population of interest consists of Freshmen, Sophomores, and Juniors, but excludes Seniors. Out of the categories remaining in the population, Freshmen are ultimately the most important, and this group will also be analyzed separately.

For the complete analysis group of interest, including the Freshman, Sophomore, and Junior level students, the distributions of Spring '97 semester GPA's and Fall '96 cumulative GPA's each cover the full spectrum of possible GPA's from 0.0 to 4.0, each has a mean and median around 2.5, and each of the two distributions exhibits a slight degree of negative skewness. Furthermore, there is a slight amount of truncation at the 4.0 boundary, and a slight degree of trailing or tapering off toward the 0.0 boundary, but with a "stacking" of a large number of observations at 0.0, especially for the Fall 1996 data. However, apart from the truncation at the upper end and the "stacking" at the lower end of the range of possible values, the data fall close to having a symmetric, bell-shaped distribution. In this regard, the stacking of observations at 0.0 is particularly troublesome.

Apart from this potential problem of "non-normality," this GPA data also presents another possible problem in terms of its modeling, a problem that is also likely to be at least partially caused by the bounded nature of such data. This problem is one of a "nonlinear" relationship between the Fall and the Spring GPA's. A review of Fall vs. Spring GPA's indicated that as we move along the range of people with Fall '96 GPA's from 0.0 to 4.0, their average Spring GPA's start off at about 1.4, then gradually fall to a minimum of about 1.2 for people who received around a 0.3 Fall GPA, then the average Spring GPA's start to rise again, staying above the Fall GPA's until around the 2.25 to 2.5 range. For students with Fall GPA's above 2.5, their average Spring GPA's all fall below their Fall GPA's. The bounded nature of the GPA data may explain some of this observed behavior, because students who receive around a 2.0 in the Fall could easily do either better or worse in the Spring, depending on the relative ease or difficulty of the specific courses they take in the Spring, while a student whose cumulative GPA after the Fall was 0.0 would have nowhere the go but up (and of course would have a definite incentive to improve), while a student with a cumulative GPA of 4.0 in the Fall would have nowhere to go, gradewise, but down.

To simultaneously compensate for these two problems of non-normality and non-linearity, the students who had 0.0 cumulative GPA's as of the end of the Fall term were dropped from the sample, and squared GPA terms were calculated for use in the final model. The removal of the 0.0 GPA students from our sample reduced our "control" group by 379 students, down to 12,440 students, and reduced the "treatment" group by 54 students, down to 831 students. Aside from the empirical justification of trying to render the data set more "normal" by removing "outlying" observations, an additional justification for deleting students with GPA's of 0.0 from the sample is that such students are much more likely than other students to have been affected by such student-specific circumstances as deaths in the family, personal illnesses, etc., that cannot be captured adequately (mainly due to lack of any objective information about such factors) by any explanatory or "dummy" variables. They might also be an artifact of a census date for the database that does not coincide with various registrar and fee payment time lines. Thus, the circumstances faced by such students could be systematically different from those of other students, in which case their exclusion from the analysis would be appropriate for obtaining unbiased results. It is important to note that the previously mentioned nonlinear relationship between Fall and Spring GPA's was not a function of this stacking of Fall GPA observations at 0.0. For the subsequent sample excluding the students with 0.0 Fall GPA's, the nonlinear relationship between Fall and Spring GPA's was still clearly evident.

Regression Analysis Of Program Effectiveness:

A natural first thought when studying the effects of various treatments is to try to view the problem from an experimental design/ANOVA framework. However, there are clear ethical questions to be raised if students on the verge of failing out of school were to be randomly assigned not to be allowed into programs that may enable them to improve their academic performance and remain in school. Thus, as a consequence, there was not a random assignment of students to treatment versus control groups in our case, so we do not have an experimental design situation. As an alternative, the data for the students is analyzed within a regression framework.

The dependent variable for our regression analysis, our primary variable of interest, is the Spring '97 GPA. Our ultimate goal is to determine whether a student's being in an intervention program led to an increase in that student's GPA over what he would have received had he not been in the program. Boxplots of Spring '97 GPA's for the students in our sample, broken down into treatment vs. non-treatment, and freshman vs. non-freshman students, is shown in Figure 1.

Figure 1 about here

As can readily be seen, the students in each of the categories shown exhibit similar levels of variability (so that the use of ANOVA or regression analysis is not precluded on these grounds). However, there do seem to be systematic differences between these categories of students. The means of these categories (denoted by "+") appear to drop steadily as we move across these categories. Thus; the average Spring '97 GPA is lowest for Freshman students who were involved in an intervention program. The second lowest average was among post-Freshman students involved in an intervention program. The third lowest average belonged to Freshman students who were NOT involved in an intervention program, and the group with the highest average was post-Freshman students who weren't involved in an intervention program.

At first glance, these results would appear to show that involvement in an intervention program was detrimental to a student's grades. However, such a conclusion ignores the systematic differences that exist between the two groups, notably the fact that the students selected for the intervention programs are those who are, in general, encountering greater than average difficulties in their academic careers. Thus, all else equal, these students would also be expected to post lower Spring GPA's. So the real question is not how well the intervention program students did relative to the non-intervention students, but how well they did relative to their own, lower, expected Spring GPA's.

But to estimate this statistically, as many as possible of the remaining systematic differences between the treatment group (intervention program students) and the control group must be accounted for. For example, one systematic difference between the two groups is that the treatment group, containing a total of 831 students, is comprised of 72.1% Freshmen, while the control group of 12,440 students comprises only 32.7% Freshmen (see Table 1). As the above box-plots illustrated, the average GPA's for Freshman students tend to be lower than those of other students are. A survivorship bias among post-Freshman students helps to account for some of the difference. Thus, the high composition of Freshman students in the treatment group would further contribute to this group's having a lower expected Spring GPA relative to that of the control group. These results are shown in Table 1.

Table 1 about here

Additional variables across which the treatment group could systematically differ from the control group include a student's field of study (e.g., engineering vs. non-engineering), gender, and ethnic background. Given that courses required in engineering have a reputation of being more difficult than other courses, engineering majors may be expected to have lower GPA's than students with the same academic ability who are in other majors. Thus, the relative proportions of engineering majors in the groups would affect their relative expected GPA's. It is unclear what systematic effects the other categorical variables may have on the GPA's for the groups, but it is very likely for the treatment and control groups to differ across at least some of them. For example, a number of the intervention programs are designed specifically for African-American students, so that the treatment groups for those programs contain a much higher proportion of African-American students than do the other treatment groups or the control group.

Taking all the above into account, a linear regression model was estimated for the Spring '97 GPA data using Freshman and non-Freshman GPA's and squared GPA's and various categorical variables (for ethnicity, gender, field of study, etc.) as the independent variables, and a backward selection method (with a cutoff of .10) was used to remove the variables that did not seem to play a significant role in accounting for the variation in Spring GPA's. This process resulted in a final model for the full sample with an analysis of variance and model parameters as shown below: This model is shown in Table 2.

Table 2 about here

The R-squared of .4565 for this model indicates that the dependent variables remaining in the model can account for close to half of the variation in Spring 1997 semester GPA's. Thus, while there is a lot of variation in such GPA's that is left unexplained, a substantial proportion (nearly half) of the variation nonetheless can be accounted for. And the variables remaining that play a significant role in helping to explain this variation are a student's Fall 1996 cumulative GPA (GPA) and squared GPA (GPA_2), the interaction between whether the student is a Freshman and his GPA (GPA*FR) and squared GPA (GPA*FR_2), whether or not the student is an engineering major (ENGG), whether or not the student is female (FEMALE), whether or not the student is an African-American (AFRI_AM), and last, but most importantly for this study, whether or not the student is involved in an intervention program (D_TRT) and the interaction between this involvement and the student's GPA (GPA*TRT).

As would be expected, the coefficient for GPA is significant and positive, so that higher Fall cumulative GPA's are associated with higher Spring semester GPA's. Of course, due to variations in course loads, workloads, and levels of student motivation over time, the relationship between past and present GPA's is less than 1:1, but the relationship is nonetheless sizable and significant. As the saying goes, "the past is prologue," and the track record a student establishes via a cumulative GPA is a significant predictor of the student's future performance. For Freshmen, however, the track record reflected in the cumulative GPA represents a much smaller body of work, in most cases only one semester's worth of grades, so we would expect such "cumulative" GPA's to have less ability to predict future semester GPA's for Freshmen than for other students. This is precisely what the negative coefficient for GPA*FR tells us is the case. This means that the impact of Fall cumulative grades on Spring semester grades is less for Freshmen than for non-Freshman students. For non-Freshman students, the net coefficient (b_{GPA}) for the relationship between Fall cumulative GPA's and Spring semester GPA's is 0.554659. For Freshmen, the net coefficient (b_{GPA} plus b_{GPA*FR}) is 0.429341 (0.554659 - 0.125318). Thus, given its negative sign, the coefficient for GPA*FR represents somewhat of a "de-linkage" or "de-coupling" of Spring GPA's from Fall GPA's for Freshmen as compared to non-Freshmen.

The fact that the squared GPA terms (GPA_2 and GPA*FR_2) have significant coefficients indicates that, as the analysis of the previous section noted, there is in fact a nonlinear relationship between past and future GPA's. The positive signs of these coefficients indicates that there is a premium for stronger past performance, with this premium being nearly 50% greater for Freshmen as compared to non-Freshmen. This, when combined with the results for GPA and GPA*FR, would seem to indicate that for Freshmen as compared to post-Freshman students, poor past performance is more likely to be reversed while good past performance is more likely to be repeated. Or, the past is more likely to be prologue for Freshmen if they went ahead and performed well in the first place. But, for all students, the significance of the squared GPA term indicates that the influence of past grades on future grade performance is stronger for higher GPA's than for lower GPA's.

With regard to the remaining non-treatment-effect variables in the model, majoring in engineering would reduce a student's predicted GPA by 0.066145, while being a female rather than a male would improve the student's predicted performance by 0.094505 points. Hispanics and other ethnic groups were not found to have significantly different Spring GPA's than whites, but the story is different for African-American students. All else equal, the fact that a student is an African-American would lower the predicted Spring GPA by 0.197442. Thus, even if they started from the same Fall cumulative GPA, an African-American student would have a predicted Spring semester GPA that is 0.197442 points lower than that of a non-African-American student. But, beyond this, the mean and median Fall cumulative GPA's for African-American students are each approximately 0.4 points below those for non-African-American students, so the typical predicted Spring semester GPA difference would be even greater than that suggested by the AFRI_AM coefficient. This result provides additional justification for the existence of intervention programs specifically targeting African-American students. Note, however, that caution must be taken in the detailed interpretation of individual weights because of the multicollinearity among the variables in the model.

The remaining variables in the model are the variables designed to capture the treatment effects, D_TRT and GPA*TRT: Notably, the parameter estimate is positive for D_TRT and negative for GPA*TRT. These are precisely the signs we would expect if the treatment programs were having a beneficial impact. The direct effect of the academic intervention programs on predicted Spring semester GPA's is captured by the D_TRT variable, the coefficient of which indicates that, all else equal, participation in an intervention program will increase a student's predicted Spring semester GPA by 0.239948, or nearly a quarter of a letter grade. But this effect cannot be examined in isolation. The GPA*TRT interaction term is designed to capture the indirect effects of participation in an intervention program. Similar in effect to the GPA*FR variable, a negative value for the coefficient to GPA*TRT represents a "decoupling" of the Spring semester grades from the previous performance of the student as the Fall GPA increases.

For Freshmen, the Fall cumulative grades provide a track record that is too short to provide a good representation of the student's performance. For the intervention program students, on the other hand, this track record may be long enough to be representative, but the intervention programs would hopefully change the attitudes of the student toward his academic work, so that the past performance would no longer be representative of the student's current attitudes and resulting academic abilities. Thus, a negative value for the coefficient of GPA_TRT means that a student's being in an intervention program will reduce the extent to which his predicted Spring semester grades are dependent upon his past grades. In other words, the GPA_TRT variable would reflect a "starting over" effect. So, taken together, the significant positive coefficient for D_TRT and the significant negative coefficient for GPA_TRT indicate that participation in an intervention program reduces the impact of past grades on current GPA and, simultaneously, provides a direct improvement to current GPA. In other words, these results indicate that the academic intervention programs provide for a statistically significant improvement in students' academic performance, regardless of their past performance.

For a quick review of the variables in the model, a brief example is as follows. For a Hispanic male Psychology major in his Sophomore year who is not involved in any of the intervention programs, his predicted GPA for Spring '97, as a function of his Fall cumulative GPA (GPA), is:

$$\text{Predicted Spring GPA} = 0.844310 + 0.554659*(\text{GPA}) + 0.051327*(\text{GPA})^2$$

If he were a Freshman rather than a Sophomore, the following amount would be ADDED to the above figure to obtain the final prediction of the Spring GPA:

$$-0.125318*(\text{GPA}) + 0.024446*(\text{GPA})^2$$

Thus, the predicted GPA in this case would be:

$$\text{Predicted Spring GPA} = 0.844310 + (0.554659 - 0.125318)*(\text{GPA}) + (0.051327 + 0.024446)*(\text{GPA})^2$$

or,

$$\text{Predicted Spring GPA} = 0.844310 + 0.429341*(\text{GPA}) + 0.075773*(\text{GPA})^2$$

Once again, the reason for incorporating the squared GPA term is to account for the nonlinear relationship between past GPA's and present GPA's.

As a final example, if the student were a Freshman, female, engineering major enrolled in one of the programs, her predicted Spring semester GPA, as a function of her Fall cumulative GPA, would be:

$$\text{Predicted Spring GPA} = (0.844310-0.066145+0.094505+0.239948) + (0.554659-0.125318-0.081114)*(\text{GPA}) + (0.051327+0.024446)*(\text{GPA})^2$$

or,

$$\text{Predicted Spring GPA} = 1.112618 + 0.348227*(\text{GPA}) + 0.075773*(\text{GPA})^2$$

Next, because Freshmen retention is a particular concern, a separate analysis was undertaken to focus exclusively on the Freshman students in the sample. The results of this analysis are shown in Table 3.

Table 3about here

This model exhibits an R-squared only slightly higher than that of the model for all of the students, but the model coefficients exhibit some key differences from those of the full sample model. The intercept term is 0.133 points higher for the Freshman sample model than for the full sample model, while the GPA term is 0.106 lower than the GPA term for the full model, even after adjusting for the GPA*Freshman interaction term. Among the demographic variables, each of these has the same sign as for the full sample model, but the magnitudes of their coefficients are substantially larger for the Freshman sample model than for the full sample model. Thus, the predicted Spring semester GPA's of Freshman women are better relative to those of Freshman men than were the predicted Spring semester GPA's of all the women in the full sample relative to those of all the men. Unfortunately for Freshman men, this disparity is only compounded if they also happen to be African-Americans and/or are majoring in engineering. Freshmen students in these two categories seemed to have even lower grades relative to their peers than did Junior and Senior students who fell into these categories. Thus, intervention programs tailored toward such Freshman students may be particularly beneficial.

But the most dramatic differences between the two models concern the treatment effects. First, the direct impact of the intervention programs on Spring semester GPA's, the D_TRT term, has a much smaller coefficient in the Freshman sample model relative to the full sample model, 0.063346 versus 0.239948. More dramatically, the GPA*treatment interaction effect does not even appear in the Freshman sample model (its p-value was 0.1252, above the 0.10 cutoff for the backward selection). One possible explanation for these surprising results is that they are consequence of the fact that the Freshman sample contains a much higher proportion of students involved in the intervention programs, so that part of the treatment mean and GPA interaction effects have been subsumed into the direct intercept and GPA effects for this sample. As an illustration, the intercept and D_TRT coefficients sum to 1.040 for the Freshman sample model, and they sum to the similar amount of 1.084 for the full sample model. But the distribution of these sums between the intercept and the D_TRT coefficients are very different in each case of the two cases, with 22% of the sum being allocated to the D_TRT coefficient for the full model but only 6% being allocated to the D_TRT coefficient for the Freshman sample model. Similar results hold for the GPA effects. For the Freshman sample model, the GPA effect has a coefficient of 0.323, and there is no significant GPA*treatment interaction effect. For the full sample model, on the other hand, the net GPA effect for Freshmen in intervention programs is 0.348 (0.554659 –0.125318 –0.081114). Even without a significant interaction term to "decouple" current grade performance from past grade results, the coefficient for the Freshmen-only sample is still somewhat lower even than what would be suggested by the full-sample model for treatment-group Freshmen. Thus, it appears that, for the Freshman sample, the entire GPA*treatment interaction effect has simply, but completely, been subsumed into the direct GPA effect.

This explanation is lent validity by the changes in results that occur if the GPA*treatment interaction term is left in the model, so that this effect is forcefully separated out from the direct GPA effect. In this case, the coefficient for the direct GPA effect increases from 0.323 shown in Table 3 to 0.351, with a coefficient of –0.053 for the interaction term (with a p-value of 0.1252), for a net GPA effect for Freshmen enrolled in the intervention programs of 0.298. Furthermore, and most dramatically, the direct treatment effect in this case nearly triples in magnitude to a level of 0.179, a value that is much closer to what would be suggested by the full sample model.

An alternative explanation for the Freshman model results as presented is that, for Freshman students, the academic intervention programs had little marginal effect toward encouraging a higher level of performance among "at-risk" students beyond the impetus produced simply by the shock of receiving poor first semester grades. Thus, under this account, where the programs would seem to have been particularly helpful would be among the students who were able to maintain a sufficiently high GPA to make it past their Freshman year but were not able, on their own, to substantially improve their performance. In such cases, the academic intervention programs would have provided the students with the skills they needed to improve their performance but were not able simply to acquire or develop on their own.

The above models examine the effect of participation in an academic intervention program on the more immediate performance measure of a student's Spring semester GPA. The next step in our analysis of the programs was to examine their effect of the somewhat longer-term measure of whether a student returned to school for the following Fall semester. For these models, the coefficients for the treatment effect variables all had the "correct" signs, but unfortunately these effects were not of a large enough magnitude to be statistically significant. Thus, the results in this direction are encouraging but inconclusive.

Examination Of The Effects Of Individual Programs On Predicted GPA's:

The previous section found that participation in an academic intervention program does tend to improve a student's predicted Spring semester GPA. However, because all students who participated in an intervention program were simply lumped together into one all-encompassing treatment group in the models used, such analysis implicitly assumed that all the programs were equally effective and that there was no marginal benefit to being in more than one program. Given the diversity of types and focuses of the programs involved, however, such an assumption of homogeneity is probably unrealistic. So in this section, the models of the previous section are re-estimated with variables included to capture the effects of the program or programs in which a student participated.

This first model estimated is the one that contains all the demographic and GPA variables that were in the full sample model of the previous section. However, the variables for the direct treatment effect and the GPA*treatment interaction effect have been replaced by the concomitant variables for each of the individual programs in which a student could have participated.

Table 4 about here

Overall, the results for this model are consistent with those of the simple full sample treatment effect model of the previous section. The coefficients of all of the GPA and demographic variables have the same signs and magnitudes very close to those of the variables in the original model. Furthermore, for all but two of the intervention program groups, the direct and interaction treatment effect variables also have the anticipated signs, as did the concomitant variables for the previous model. Thus, after taking into account the direct effects of the Fall cumulative GPA's, the effects of the demographic variables, and the effects of the other intervention programs, most of the programs provide a direct boost (positive weight) to the students' Spring semester GPA's while reducing the impact (negative weight) of the students' past grades on this measure.

Of the eleven programs covered by this study, only two, CAAE and ERLINVBI, had signs implying that participation in the program by a student led to poorer performance, and each of these had the "wrong" signs for both the direct treatment effect and the GPA*treatment interaction effect. Notably, however, neither of these effects was significant for either of these intervention programs. Of the remaining nine intervention programs, all of them had the desired signs for both of their effects. But, of these nine, only four had significant direct effects on student grades, while, of these four, three also had significant GPA*treatment interaction effects. Overall, for each of the programs it is either the case that both the direct and the interaction effects for the program indicate that the given program is beneficial to student performance or they both indicate that the program is "detrimental" to student performance. But all the programs that had significant effects on students' predicted performance were programs whose effects appeared to be beneficial. Thus, to the extent that two of the programs appeared to have detrimental effects on student performance, these effects were of a small enough magnitude to be attributable simply to random variation.

Note, however, that in interpreting the effects of these variables it is important to remember that these are marginal effects given other characteristics and other program participation. They do not tell what the effects of these programs would be in isolation. Instead, these coefficients tell what the effect of a given variable is given that the effects of other relevant variables have been taken into account. Because a number of students participated in more than one of the academic intervention programs, this means that the model coefficients shown represent the effects that a given program has on a student's performance after the effects of any other programs in which a student has participated have already been taken into account.

If the variables that do not have significant effects are removed from the model and only variables that have significant effects remain, the results are as shown in Table 5:

Table 5 about here

In comparison to the previous model in which the effects of all of the intervention programs were included, this edited model holds no surprises. All of the non-treatment-effect variables have coefficients very close to those of the complete model, and the treatment effect variables that remain in the model are precisely the same ones that were significant in the complete model. Namely, PRODEVFO, RSKCHEM, SUCCFCD, and TNGSUFAC each provides a significant direct boost to students' predicted Spring semester GPA's, while three of these same programs, PRODEVFO, RSKCHEM, and TNGSUFAC each also significantly reduces the weight of students' past GPA track record on their Spring GPA performance.

The next two sets of results are the complete model and edited model results for the Freshman-only sample of students. For these models, only one of the treatment programs appears to have reversed signs for its direct and GPA interaction effects, namely ERLINVBI. But, as was the case for the full sample model, neither of the coefficients for this treatment program is statistically significant. Among the other nine programs (CALPHYSC had no Freshman students), only PRODEVFO, RSKCHEM, SUCCFCD, and TNGSUFAC have significant direct effects on predicted Spring semester GPA's. Of these four programs, two, PRODEVFO and TNGSUFAC, also have significant GPA interaction effects. These results are shown in Tables 6 and 7.

Tables 6 and 7 about here

Thus, for both the full student sample and the Freshman sample, most of the treatment programs seemed to have a positive effect on student performance. Only four of these programs, however, PRODEVFO, RSKCHEM, SUCCFCD, and TNGSUFAC, have significant treatment effects, but they are significant for both the full sample and the Freshman-only sample models. Of these four, PRODEVFO, RSKCHEM, and TNGSUFAC also have significant GPA interaction effects for the full sample model, while PRODEVFO and TNGSUFAC have significant GPA interaction effects for the Freshman-only sample model. The fact that the Freshman model in this case has such significant GPA*treatment interaction terms is most likely a consequence of the fact that we allowed for differences between the programs in this case, rather than simply assuming that all programs were equally effective. Conversely, the results of this section indicate that it is the marginal effects of these four programs that are driving both the direct treatment effect and the GPA*treatment interaction effect for the generic treatment group of the previous section's model. While most of the remaining treatment programs also appear to be have beneficial effects on students' predicted Spring semester GPA's, the results for these programs were of too small a magnitude to preclude the possibility that the direction of these effects was due solely to random variation.

Analysis of the Total "Own-Program" Effects of the Individual Intervention Programs:

The previous section examined the marginal effects of the various academic intervention programs. In other words, what the results show us are the effects of each of the programs given that the effects of all the other programs have already been taken into account. The purpose of this section, on the other hand, is to try to study the total effects, rather than just the marginal effects, of each of the programs. That is, the goal is to see how effective each program was on its own, irrespective of the effects of the other programs. If each of the programs had completely separate rosters of students enrolled in them, so that the programs were mutually independent in terms of the specific students they tried to benefit, then the marginal effects measured in the previous section would be the same as the average "own-program" effects, and the results of the previous section would simultaneously answer the question of whether these own-program effects are significant. Unfortunately, because there was substantially degree of overlap of students across the programs (see Table 8 for a breakdown of students in multiple programs), the results of the individual programs are not independent of each other. Thus, there is no statistically valid means of analyzing the effects of each program completely independently of those of the other programs. Although there is no statistically valid means of segregating the effects of the individual programs from each other in order to accurately examine the total rather than the marginal effects of each program, this section will nonetheless look at this question from a couple of different directions.

Table 8 about here

Before continuing on to a more formal analysis of the total "own-program" effects of the various academic intervention programs, the individual effects of each of the programs will first be examined informally, via the following method. First, the model for predicting Spring semester GPA's was fitted, but without including any of the treatment effect variables, and then the mean levels of the residuals from this model are calculated for each of the programs. The results of this step, for both the complete sample and the Freshman-only sample, are shown in Table 9. In this case, the residuals for students in multiple programs were simply counted multiply, and were included in the results of each of the programs in which the student participated.

Table 9 about here

As can be seen from Table 9, only the CAAE students had negative mean residuals for both the complete and the Freshman-only samples. This would imply that, on average, students who participated in the CAAE program actually did worse than they would have been expected to do in the absence of such a program. In both the

Freshman-only and complete sample cases, though, the mean level of the residuals is close enough to zero, only 0.152 standard deviations of the mean away from zero for the total sample case and 0.780 for the Freshman-only sample case, so that chance or random variation cannot be ruled out. This is similar to the results of the previous section, in which CAAE also yielded negative, though insignificant, marginal effects on students' predicted GPA's. For the Freshman-only sample, aside from CAAE all of the programs had positive mean residuals, so that they are all associated, even if insignificantly or weakly, with better student performance than would otherwise be predicted in the absence of such programs. This is even the case for ERLINVBI, which is the only program associated with detrimental marginal effects in the Freshman-only sample.

For the complete sample model, the CALPHYSC displayed the poorest results, with actual Spring semester GPA's on average 0.16 points below what would otherwise have been expected. However, due to the small number of participants in this program, this result is only 1.22 standard deviations of the mean away from zero, so it is too small a result to be conclusive. The ESPMATH and RESADADS programs also have negative mean residuals, though the means in these two cases are even closer to zero. At the other end of the performance spectrum, PRODEVFO, TNGSUFAC, TMADVBIO, and SUCCFCD all have substantial positive mean residuals, in terms of both absolute magnitude and standard deviations of the mean away from zero. Three of these programs, PRODEVFO, TNGSUFAC, and SUCCFCD, were also among the four programs with significantly positive marginal effects on expected GPA's. The fourth program that had significantly positive marginal effects was RSKCHEM. The mean residuals for this program were somewhat smaller in magnitude than those of the other three programs, though they were still fairly large in relation to the standard deviation of the mean for this program. Thus far, the overall results for the own-program total effects of each program seem to be similar to those for the marginal effects for each program, with positive effects being associated with most of the programs, and the same four programs PRODEVFO, RSKCHEM, SUCCFCD, and TNGSUFAC, being associated with the largest relative effects in both cases.

As was noted previously, the above analysis is one attempt to try to capture the "own-program" effects, or the total effects on a student's Spring semester GPA that can be attributed to a given program. One major problem with this analysis, however, is that the results for each of the students who participated in multiple programs are included in the results for each of the programs in which the student participated. This confounds the results for the individual programs. Such a student may in fact have performed well as a consequence of his participation in a given program. On the other hand, the student may have derived no benefit whatsoever from that program but instead performed well as a result of the influence of another program. In this case, the student's good performance would tend to reflect well on both the program that had a beneficial influence on him as well as the program that did not provide him any benefit. Similarly, it may be the case that none of the programs individually provided much benefit to the student, but instead it was the constant reinforcement the student faced by virtue of participating in multiple programs that led to an improved performance by the student.

One means to try to correct for the impact of this potential effect is to perform the above analysis with all of the students who participated in more than one program being separated out into a separate, unique "MULTIPLE" category. Thus, for example, a student enrolled in both the CAAE and the TNGSUFAC programs would be included in neither of those groups, but would instead be categorized as MULTIPLE category students. Then, all of the students who remained in the categories of the various intervention programs would be students who participated only in those programs, so that any effects that were reflected in their performance would be attributable largely to the program in question, not to any of the other programs. Of course, even then the impact of other programs cannot be completely eliminated from the results, due to the fact that the students enrolled in only one of the programs may have indirectly gained useful insights from other programs as a result of interaction with their multiple-program classmates. Presumably, however, such an effect would be relatively minor. A more serious problem with this approach, though, is that the students involved in multiple programs are also much more likely to be the more ambitious, more active students who would put more effort into these programs and consequently be more likely to benefit from each of them. Excluding such students from the analysis of the individual programs, therefore, would deprive these programs of their brightest representatives, so that the perceived performances of these programs would be biased downward.

Ultimately, therefore, there are serious problems associated with including the results for multiple-program students in with the results of the individual programs in which they participated, and there are equally serious problems associated with removing them to a separate category. Nonetheless, examining the data from both of these approaches will, it is hoped, lead to a better overview of the total and relative levels of effectiveness of each of the programs that were funded. Thus, after the multiple-program students have been segregated to a separate "MULTIPLE" category, the mean levels of residuals for the students in this category and for the remaining students in the individual intervention programs are as shown in Table 10.

Table 10 about here

The most notable results resulting from this categorization are that, on average, the students enrolled in multiple programs had by far the best performance relative to what would otherwise be expected, and, concomitantly, removing these students from the analysis of the individual programs substantially reduces the average results for these programs. This effect is particularly detrimental to the results of TNGSUFAC, nearly a third of whose students were also involved in other programs (notably CAAE), ERLINVBI, fully half of whose students also participated in other programs, and STDYUHSA, which had proportionately fewer multiple-program students, but whose mean results nonetheless fell from +0.089 to -0.129 when these students were removed from the analysis. The results for the Freshman-only sample are similar to those for the complete sample, though in this case the change in results for the TNGSUFAC program when the multiple-program students are excluded are particularly dramatic, from an average of +0.183 with the multiple-program students to -0.154 without. Thus, it seems clear that, for whatever reason, whatever the program, its most-improved students were those who were also involved in other programs. Furthermore, when these students were removed from the analysis of the programs, the remaining students of more than half (seven out of eleven) of the programs actually received lower Spring semester GPA's than would have been expected for them in the absence of such programs. This result could be doing no more than representing the fact that if you remove the best performers from a group, the group's average will necessarily fall. On the other hand, this may suggest that there was a substantial benefit from the reinforcement that participation in multiple programs provides.

The next step in our analysis is to try to more directly quantify the significance of both the direct effects of each of these programs on predicted Spring semester GPA's and their interactions on the Fall cumulative GPA effect. But, as with the above analysis, simply fitting regression models for each of these programs is fraught with complications. Because the treatment group's students were more heavily concentrated toward the lower end of the GPA spectrum than was the student body in general, simply deleting all of the treatment group students, save the ones in the specific program being examined, from the sample used to fit the regression model would result in a non-representative sample, potentially biasing any regression results that are obtained. The other possibility is to keep such students in the sample used to fit the model, but then to ignore their programs' direct and interaction effects in fitting the regression model. This, however, would entail ignoring systematic differences among the students, creating an omitted-variables bias among the model parameters that are estimated. This latter problem seems to be the more serious, so the former approaches is taken.

Thus, a series of regressions was run, each with the same control group and the same basic model form as for the regression model used to analyze the general treatment effects. The treatment group in each case, however, consisted only of the students within a specific intervention program. Table 11 shows the results for the direct treatment effect and the GPA*treatment interaction effect model variables for the complete (i.e., Freshman, Sophomore, and Junior) sample models for which all of the students who participated in a given program are included in the treatment group for that program's model, regardless of whether they also participated in other intervention programs. Table 12 shows the equivalent results for the Freshman-only sample models. Notably, in Table 11 the programs that appear to have significant direct effects are TNGSUFAC, PRODEVFO, SUCCFCD, and RSKCHEM, the same four programs that had significant direct marginal effects when all were included in the same model. Thus it appears that, with the multiple-program students included in the measurement of the total effects, the marginal and the total effects of the various programs seem to be roughly equivalent. Notably, these results suggest that the TNGSUFAC program is especially beneficial, with a positive direct effect on its students' Spring semester GPA's of more than a full grade point. For the Freshman-sample models, the results are also similar to those of the model in which the intervention programs are all included simultaneously, though the variables for the individual program models seem in general to be somewhat more significant.

Tables 11 and 12 about here

Tables 13 and 14 present the regression model results for the data sets with the multiple-program students categorized separately from any of the specific individual programs in which they participated. These results contain little surprise. Among both the complete and the Freshman-only sample models the "MULTIPLE" category exhibits the strongest treatment effect, in terms of both the direct treatment effect and the GPA*treatment interaction effect. None of the other programs, however, exhibits any strongly significant results, either positive or negative. These results provide confirmation that it is the students who are involved in more than one program who are driving most of the results for each of the individual programs. But even the removal of the multiple-program students from their ranks, two of the programs, PRODEVFO and SUCCFCD, still manage to obtain marginally significant results, with p-values less than 0.10 for the Freshman, Sophomore, and Junior model. ERLINVBI exhibits marginally significant results for both the Freshman-Sophomore-Junior model and the Freshman-only model, but in this case the results imply that this program is actually marginally detrimental to students' academic performance. This program exhibits negative performances throughout much of the analysis in this paper, but for the most part it is of a small enough magnitude that it can be attributed to random variation. Removing the multiple-program students from the analysis, however, actually drops this program to the marginally detrimental range. Of course, if the multiple-program students are, in general, the more promising students, then the ERLINVBI program, half of whose students do participate in multiple programs, would be expected to be quite adversely affected by the removal of such students.

Tables 13 and 14 about here

Overall, the estimated coefficients for the treatment effects for the individual programs are fairly consistent with their mean residuals from the regression models without the treatment effects. Furthermore, when the results for the multiple-program students are included with those for each of the programs in which they participate, the results for the total effectiveness of these programs is similar to the results for the marginal effects of these programs. Unfortunately, there is no way to completely isolate the effects of the programs from each other, so there is no way to analyze the effectiveness of the programs in isolation. The key group in causing this statistical complication is the subset of students who participated in more than one program, and it is this group per se, rather than any of the intervention programs in which they may have participated, that posts the most dramatically positive results, and the most dramatic results in general. Separating these students out from the programs in which they participated also has a dramatic impact on the posted performances of those programs, so that none of the programs individually posted a highly significant performance. In such a case, whether a program's treatment effect regression coefficients have a positive or a negative sign could be simply due to natural random variation among the student body, and would thus provide little or no information about whether a program was beneficial or not. The fact that a number of programs contained relatively few students means that any positive results achieved by the program could easily be overwhelmed by such natural variation. As noted in the previous section, when the students within all the programs are combined, the aggregate effect of the programs is significantly positive. But the results of this section, in which it is the multiple-program students who seem to be driving most of the results for each of the individual intervention programs, raises the question of how much this same category of students is driving these overall results. This question will be examined more closely in the next section.

The Effectiveness of Multiple vs. Single Programs:

In an earlier section of this paper, it was shown that the intervention programs, taken as a whole, do make a significant contribution to the expected Spring semester GPA's of the students enrolled in these programs. The results of the previous section, meanwhile, indicated that of all the students in intervention programs, the ones who had the best performance were those who participated in more than one program. The results for these students are dramatically better than the results for the students enrolled only in one program, while for a majority of these programs, the average results for the students in these individual programs are actually worse than what would otherwise have been expected in the absence of such programs. This raises the question of whether the positive overall results for the treatment programs as a whole are also being driven by these multiple-program students.

To examine this question, the same general methods as in the previous section were followed. To get a preliminary overview of the relative effectiveness of single versus multiple programs, the residuals of the GPA regression model without the "treatment" term were examined. The average residuals for each of the resulting three categories, when all levels of students are included in the model, are shown in Table 15.

Table 15 about here

As the results of this table clearly illustrate, the students in multiple programs exhibited a dramatic improvement in performance, while the students enrolled in only a single program exhibited a performance that was, on average, negligibly better than the non-treatment group students. Among only the Freshman students, the results were even a bit more dramatic, with an even higher average performance of the multiple-program students relative to what was expected, and average results for the single-program students that is slightly negative. These results indicate that, all else equal, the students who participated in only one program received little if any benefit from these programs relative to being in no program at all. The students involved in more than one program, on the other hand, performed much better than would otherwise have been expected in the absence of such programs, indicating that these students received substantial benefits for their participation.

To more formally test this conclusion, the regression model from above was refitted, with the treatment group dichotomized into single-program students and multiple-program students. The ANOVA tables and estimated regression coefficients are shown below for, first, the model fit to all the students and, second, the model fit to only the Freshman students. The clear result in both of these cases is that participation in multiple programs led to a significant increase in a student's expected Spring semester GPA of more than eight tenths of a grade point and simultaneously also significantly reduced the impact of past grades on the student's current GPA. Participation in only one program, on the other hand, had no significant impact on either students' expected grades or the impact of their past grades on their present grades. These results are shown in Tables 16 and 17.

Tables 16 and 17 about here

Thus, the treatment group effect that was reported previously is in reality very heavily a multiple-program-student effect, or a multiple-treatment-program effect. In other words, it was the students who participated in multiple programs who predominately drove the significant results for the treatment program effects. There are a number of possible reasons why this is the case. One possibility is simply that participation in multiple programs provides sufficient reinforcement so that the students involved more readily internalize the lessons taught by these programs. A variation on this takes note of the fact that students learn in different ways and have poor academic performance for a variety of reasons, while each of the individual academic intervention programs must necessarily be designed to target student archetypes and reasons for poor performance that seem likely to be representative. Due to the natural variation among students, some of the students in a given program will match these target archetypes and will benefit accordingly, while other students would not really be a good match for the programs and would find them largely irrelevant and providing of little benefit, regardless of how well the individual programs are developed. But given that each of the programs targets somewhat different types of students, a student who participates in multiple programs is more likely to find at least one program that does match the student's needs, so that the more programs in which the student is involved, the more likely is the student to benefit from at least one of them.

The above explanations for the superior performance of students in multiple programs focus on the characteristics of the programs themselves. An alternative explanation focuses on the characteristics of the students who participate in multiple programs. Namely, the students involved in multiple programs are also much more likely to be the more ambitious, more active students who would put more effort into these programs and consequently be more likely to benefit from each of them. Thus, under this explanation, the additional benefit that multiple-program students receive from the intervention programs relative to that of single-program students and those who did not participate in any program is a direct result of the additional work that these multiple-program students put into learning from these programs and improving their grades.

Of course, these explanations are not mutually exclusive, so that each of these factors could come into play. Being taught a wider variety of study skills, for example, would make it easier for any student, especially a more actively participant one, to find study skills that are well-suited to him, and being more constantly involved in such programs would make it even easier for a student who is actively trying to change his academic habits to do so. But while these factors can help explain the performance of the students in multiple programs, they do not directly address the problem of the apparent lack of beneficial effects of the academic intervention programs among those students who were involved in only one program. A partial explanation, though, would follow if in fact the students involved in multiple programs were in fact the "best and brightest" among the intervention program students. If these are the "upper tail" students of the overall sample, then removing them from the analysis, as separating them out into a separate "MULTIPLE" category does, would necessarily reduce the average performance of the remaining students who were enrolled only in single programs. Furthermore, the distribution of the GPA performances of these remaining single-program students would be negatively skewed, so that the relatively poor performances of the "lower tail" students remaining in the sample would have a disproportionate influence on the averages for this sample of students. Going beyond this possible simple mathematical explanation, however, would require either accumulating additional years' worth of GPA data about these programs, which would mean delaying any conclusions about these programs, or obtaining more detailed information about the specific activities of these programs and the students who participated in them. Unfortunately, both of these options are beyond the scope of this paper, so that the question of the apparent lack of performance of single-program students must remain unresolved.

Conclusions:

The purpose of this paper was to study the effectiveness of a variety of academic intervention programs funded by the university during the Spring term of 1997. A number of technical issues arose to complicate this study, however. One of these was related to the fact that the data available for studying the programs was ultimately observational rather than experimental data. An experiment would require a random assignment of the subjects to the treatment and the control groups, but in the case of the intervention programs, however, there are clear ethical questions to be raised if students on the verge of failing out of school were to be randomly assigned not to be allowed into programs that may enable them to improve their academic performance and remain in school. Consequently, there was no such random assignment, and we do not have an experimental design/ANOVA situation. Instead, the data for these programs were analyzed within a regression framework. Such a framework enables us to determine whether the relationship between student performance and participation in the various intervention programs is significant, though it does not allow us to make any conclusions about causality. A second complicating factor was the fact that the data available for analysis were not normally distributed. The deletion from the sample of all students with 0.0 Fall cumulative GPA's helped to remedy this problem. A final complicating factor was the nonlinear nature of the GPA data. While Fall cumulative GPA's in general were positively correlated with Spring term GPA's, this relationship did not hold over the entire range of the data. Rather, for Fall GPA's along the range of just over 0.0 to around 0.3, increases in Fall cumulative GPA's were actually associated with lower Spring term GPA's. Squared GPA terms were included in the final regression model to help control for this effect.

The results of the regression analysis indicate that the academic intervention programs were effective, as a whole, in improving student performance, as measured by Spring semester GPA. When considering all the programs jointly, four programs, PRODEVFO, RSKCHEM, SUCCFCD, and TNGSUFAC, were each associated with significantly higher Spring semester GPA's. Of these four programs, two of them, PRODEVFO and TNGSUFAC, also significantly reduce the impact of past grades on the Spring GPA's, and a third program, RSKCHEM, significantly weakens this linkage between past grades and Spring GPA's for the full sample of students including Freshmen, Sophomores, and Juniors, though it did not do so among the Freshman-only sample. Two programs, CAAE and ERLINVBI, appeared to detrimentally affect their students' GPA's, but the magnitude of this effect was much too small to be significant. While the effects of the remaining programs all appeared to be beneficial, these effects were also of too small a magnitude to rule out random variation.

Attempts to isolate the effects of the programs on each other led to similar conclusions about the effectiveness of the individual programs. However, another interesting result was revealed by this analysis, namely that the positive results for the effectiveness of the intervention programs seem to be driven largely by the results for those students who participated in more than one program. When the analysis included only the results for those students who participated in only one program, the magnitudes of the effects for the various intervention programs were dramatically reduced, to the point where the effects of these programs on students' GPA's were no longer significant. There are number of possible explanations for the positive results for the multiple-program students, but explaining the lack of significance for the single-program students is more difficult.

References:

Bean, J.P. (1986). Assessing and reducing attrition. In D. Hossler (Ed.). *Managing College Enrollments: Number 53. New Directions for Higher Education* (pp. 47-61). San Francisco: Jossey-Bass, Inc.

Congos, D.H., and Schoeps, N. (1997). A model for evaluating retention programs. *Journal of Developmental Education*. 21(2), 2-8, 24.

Cope, R.G., and Hannah, W. (1975). *Revolving college doors: The causes and consequences of dropping out, stopping out and transferring*. New York: Wiley.

Gillespie, M., and Noble, J. (1992). Factors affecting student persistence: A longitudinal study. *ACT Research Report Series*. 92(4).

Halpin, R.L. (1990). An application of the Tinto model to the analysis of freshman persistence in a community college. *Community College Review*, 17(4), 22-32.

Myers, R. H. (1990). 2nd Edition. *Classical and Modern Regression with Applications*. Boston: PWS-Kent.

Pantages, T.J., and Creedon, C.F. (1978). Studies of college attrition: 1950-1975. *Review of Educational Research*, 48, No.1, 49-101.

Pascarella, E.T. (1980). Student-faculty informal contact and college outcomes. *Review of Educational Research*, 50, No. 4, 545-595.

Pascarella, E.T., and Chapman, D.W. (1983). A multiinstitutional, path analytic validation of Tinto's model of college withdrawal. *American Educational Research Journal*, 20, No. 1, 87-102.

Pascarella, E.T., Duby, P.B., and Iverson, B.K. (1983). A test and reconceptualization of a theoretical model of college withdrawal in a commuter institution setting. *Sociology of Education*, 56, 88-100.

Spady, W. (1970). Dropouts from higher education: An interdisciplinary review and synthesis. *Interchange*, 1, 109-121.

Spady, W. (1971). Dropouts from higher education: Towards an empirical model. *Interchange*, 2, 38-62.

Terenzini, P.T., and Pascarella, E.T. (1977). Voluntary freshman attrition and patterns of social and academic integration in a university: A test of a conceptual model. *Research in Higher Education*, 6, 25-43.

Terenzini, P.T., and Pascarella, E.T. (1980). Towards the validation of Tinto's model of college student attrition: A review of recent studies. *Research in Higher Education*, 12, No. 3, 271-282.

Terenzini, P.T., Lorang, W.G., and Pascarella, E.T. (1981). Predicting freshman persistence and voluntary dropout decisions: A replication. *Research in Higher Education*, 15, 2, 109-127.

Tinto, V. (1975). Dropouts from higher education: A theoretical synthesis of the recent literature. *A Review of Educational Research*, 45, 89-125.

Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition*. Chicago: The University of Chicago Press.

Tinto, V. (1993). 2nd Edition. *Leaving college: Rethinking the causes and cures of student attrition*. Chicago: The University of Chicago Press.

Figure and Tables

Figure 1

Student Sample Sub-category Box-Plots
Spring '97 GPA's

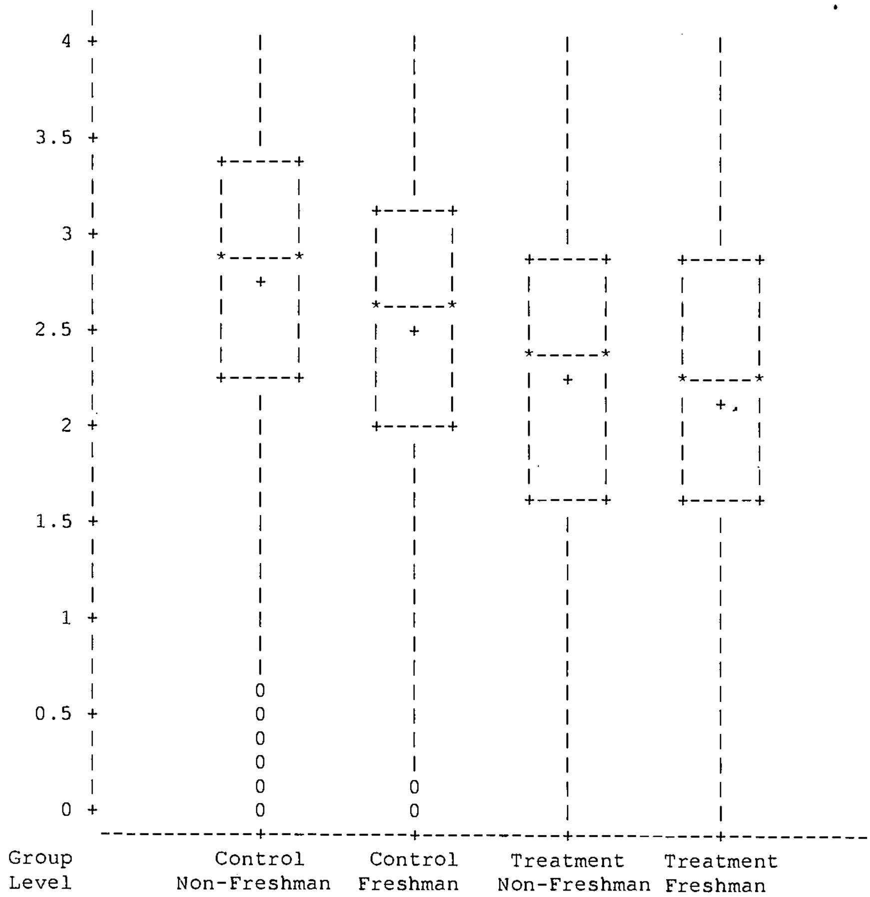

Table 1

Breakdown of Sample by Intervention Program and Freshman Status

Program	Total Students	Freshmen	% Freshmen
CAAE	128	64	50.0
CALPHYSC	20	0	0.0
ERLINVBI	18	18	100.0
ESPMATH	142	131	92.3
PRODEVFO	49	37	75.5
RESADADS	65	47	72.3
RSKCHEM	217	168	77.4
STDYUHSA	19	16	84.2
SUCCFCD	170	143	84.1
TMADVBIO	33	30	90.9
TNGSUFAC	75	36	48.0
Combined Treatment Group	831	599	72.1
Control Group	12440	4063	32.7
Total Sample	13271	4662	35.1

Note(1): A number of students were enrolled in multiple intervention programs, so the number of students listed in "Combined Treatment Group" is less than the sum of the students enrolled in the individual intervention programs.
Note(2): The "Total Sample" essentially consists of all Freshman, Sophomore, and Junior students who had a cumulative Fall 1996 GPA of greater than 0.0. The "Control Group" consists of the subset of students in this Total Sample who were not enrolled in any of the academic intervention programs.

Table 2

Regression Analysis with Spring Semester GPA as the Dependent Variable
Full Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	9	4394.62248	488.29139	1237.415	0.0001
Error	13261	5232.87036	0.39461		
C Total	13270	9627.49284			

Root MSE	0.62818	R-square	0.4565
Dep Mean	2.62818	Adj R-sq	0.4561
C.V.	23.90162		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.844310	0.05701596	14.808	0.0001
GPA	1	0.554659	0.04455065	12.450	0.0001
GPA*FR	1	-0.125318	0.02142626	-5.849	0.0001
GPA_2	1	0.051327	0.00876229	5.858	0.0001
GPA*FR_2	1	0.024446	0.00714279	3.422	0.0006
GPA*TRT	1	-0.081114	0.03071281	-2.641	0.0083
D_TRT	1	0.239948	0.07043296	3.407	0.0007
ENGG	1	-0.066145	0.01350847	-4.897	0.0001
FEMALE	1	0.094505	0.01158336	8.159	0.0001
AFRI_AM	1	-0.197442	0.02762766	-7.147	0.0001

Table 3

Regression Analysis with Spring Semester GPA as the Dependent Variable
Freshman Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	6	1796.00977	299.33496	769.507	0.0001
Error	4655	1810.77564	0.38900		
C Total	4661	3606.78541			

Root MSE	0.62370	R-square	0.4980
Dep Mean	2.46603	Adj R-sq	0.4973
C.V.	25.29142		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.977127	0.06628763	14.741	0.0001
GPA	1	0.323196	0.05575570	5.797	0.0001
GPA_2	1	0.093603	0.01154666	8.107	0.0001
D_TRT	1	0.063346	0.02849266	2.223	0.0262
ENGG	1	-0.093945	0.02201267	-4.268	0.0001
FEMALE	1	0.149471	0.01950895	7.662	0.0001
AFRI_AM	1	-0.269764	0.04456575	-6.053	0.0001

Table 4

Regression Analysis Allowing for Effects of Individual Programs
Full Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	29	4415.06267	152.24354	386.740	0.0001
Error	13241	5212.43017	0.39366		
Total	13270	9627.49284			

Root MSE	0.62742	R-square	0.4586
Dep Mean	2.62818	Adj R-sq	0.4574
C.V.	23.87290		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.827976	0.05738526	14.428	0.0001
GPA	1	0.565967	0.04498700	12.581	0.0001
GPA_FR	1	-0.133450	0.02148730	-6.211	0.0001
GPA_2	1	0.049442	0.00885515	5.583	0.0001
GPA_FR_2	1	0.026911	0.00715644	3.760	0.0002
GPA_CAAE	1	0.025053	0.13990542	0.179	0.8579
GPA_CALP	1	-0.164265	0.30704092	-0.535	0.5927
GPA_ERLI	1	0.271867	0.19866688	1.368	0.1712
GPA_ESPM	1	-0.086890	0.05903353	-1.472	0.1411
GPA_PROD	1	-0.218837	0.12050867	-1.816	0.0694
GPA_RESA	1	-0.115105	0.12819734	-0.898	0.3693
GPA_RSKC	1	-0.101601	0.04912197	-2.068	0.0386
GPA_STDY	1	-0.191315	0.19844559	-0.964	0.3350
GPA_SUCC	1	-0.106399	0.07723095	-1.378	0.1683
GPA_TMAD	1	-0.153780	0.18148099	-0.847	0.3968
GPA_TNGS	1	-0.429724	0.18111107	-2.373	0.0177
D_CAAE	1	-0.067975	0.23767676	-0.286	0.7749
D_CALPHY	1	0.227911	0.73737866	0.309	0.7573
D_ERLINV	1	-0.465047	0.39531932	-1.176	0.2395
D_ESPMAT	1	0.165367	0.13316824	1.242	0.2143
D_PRODEV	1	0.794993	0.30049601	2.646	0.0082
D_RESADA	1	0.241390	0.31268317	0.772	0.4401
D_RSKCHE	1	0.284574	0.11397057	2.497	0.0125
D_STDYUH	1	0.505762	0.48934578	1.034	0.3014
D_SUCCFC	1	0.382406	0.16200499	2.360	0.0183
D_TMADVB	1	0.642225	0.55255680	1.162	0.2451
D_TNGSUF	1	0.973258	0.32320319	3.011	0.0026
ENGG	1	-0.066060	0.01362065	-4.850	0.0001
FEMALE	1	0.093364	0.01159612	8.051	0.0001
AFRI_AM	1	-0.169722	0.03045409	-5.573	0.0001

Table 5

Regression Analysis Allowing for Effects of Individual Programs - Edited - Full Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	14	4409.79117	314.98508	800.245	0.0001
Error	13256	5217.70166	0.39361		
C Total	13270	9627.49284			

Root MSE	0.62738	R-square	0.4580
Dep Mean	2.62818	Adj R-sq	0.4575
C.V.	23.87145		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.838728	0.05501853	15.244	0.0001
GPA	1	0.557652	0.04326031	12.891	0.0001
GPA_FR	1	-0.129943	0.02135789	-6.084	0.0001
GPA_2	1	0.050951	0.00857139	5.944	0.0001
GPA_FR_2	1	0.025643	0.00711635	3.603	0.0003
GPA_PROD	1	-0.220835	0.12037137	-1.835	0.0666
GPA_RSKC	1	-0.120934	0.04826922	-2.505	0.0122
GPA_TNGS	1	-0.444993	0.17982413	-2.475	0.0134
D_PRODEV	1	0.799385	0.30011154	2.664	0.0077
D_RSKCHE	1	0.336318	0.11146961	3.017	0.0026
D_SUCCFC	1	0.167484	0.04912896	3.409	0.0007
D_TNGSUF	1	1.001700	0.32115931	3.119	0.0018
ENGG	1	-0.067281	0.01351013	-4.980	0.0001
FEMALE	1	0.093784	0.01157199	8.104	0.0001
AFRI_AM	1	-0.176597	0.02703433	-6.532	0.0001

Table 6

Regression Analysis Allowing for Effects of Individual Programs Freshman Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	25	1814.30937	72.57237	187.699	0.0001
Error	4636	1792.47604	0.38664		
C Total	4661	3606.78541			

Root MSE	0.62181	R-square	0.5030
Dep Mean	2.46603	Adj R-sq	0.5003
C.V.	25.21481		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.900123	0.07157409	12.576	0.0001
GPA	1	0.370129	0.05931359	6.240	0.0001
GPA_2	1	0.087037	0.01205157	7.222	0.0001
GPA_CAAE	1	-0.119168	0.16343953	-0.729	0.4660
GPA_ERLI	1	0.273484	0.19745845	1.385	0.1661
GPA_ESPM	1	-0.078709	0.05964032	-1.320	0.1870
GPA_PROD	1	-0.224993	0.13087386	-1.719	0.0857
GPA_RESA	1	-0.236316	0.14549682	-1.624	0.1044
GPA_RSKC	1	-0.059485	0.05506861	-1.080	0.2801
GPA_STDY	1	-0.267652	0.20787767	-1.288	0.1980
GPA_SUCC	1	-0.067302	0.07942161	-0.847	0.3968
GPA_TMAD	1	-0.163175	0.19442854	-0.839	0.4014
GPA_TNGS	1	-0.522836	0.19507281	-2.680	0.0074
D_CAAE	1	0.065781	0.26836733	0.245	0.8064
D_ERLINV	1	-0.472928	0.39327320	-1.203	0.2292
D_ESPMAT	1	0.192384	0.13644169	1.410	0.1586
D_PRODEV	1	0.808430	0.32218923	2.509	0.0121
D_RESADA	1	0.560671	0.36056977	1.555	0.1200
D_RSKCHE	1	0.214040	0.12405646	1.725	0.0845
D_STDYUH	1	0.788284	0.52773076	1.494	0.1353
D_SUCCFC	1	0.282538	0.16893798	1.672	0.0945
D_TMADVB	1	0.666949	0.57903397	1.152	0.2495
D_TNGSUF	1	1.019574	0.34296993	2.973	0.0030
ENGG	1	-0.099477	0.02228488	-4.464	0.0001
FEMALE	1	0.148039	0.01956389	7.567	0.0001
AFRI_AM	1	-0.217678	0.05208098	-4.180	0.0001

Table 7

Regression Analysis Allowing for Effects of Individual Programs - Edited Freshman Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	11	1807.65747	164.33250	424.731	0.0001
Error	4650	1799.12794	0.38691		
C Total	4661	3606.78541			

Root MSE	0.62202	R-square	0.5012
Dep Mean	2.46603	Adj R-sq	0.5000
C.V.	25.22350		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.939088	0.06618705	14.188	0.0001
GPA	1	0.344636	0.05584173	6.172	0.0001
GPA_2	1	0.090737	0.01155792	7.851	0.0001
GPA_PROD	1	-0.234245	0.13059844	-1.794	0.0729
GPA_TNGS	1	-0.549693	0.19328917	-2.844	0.0045
D_PRODEV	1	0.830251	0.32147661	2.583	0.0098
D_RSKCHE	1	0.108901	0.04964373	2.194	0.0283
D_SUCCFC	1	0.139968	0.05339758	2.621	0.0088
D_TNGSUF	1	1.083095	0.34037161	3.182	0.0015
ENGG	1	-0.094557	0.02200845	-4.296	0.0001
FEMALE	1	0.148507	0.01946977	7.628	0.0001
AFRI_AM	1	-0.247493	0.04389627	-5.638	0.0001

Table 8

Breakdown of Students in Multiple Programs

Program	Total Students	Total in Multiple	Freshmen Students	Freshmen in Multiple
CAAE	128	24	64	15
CALPHYSC	20	1	0	0
ERLINVBI	18	9	18	9
ESPMATH	142	25	131	24
PRODEVFO	49	6	37	6
RESADADS	65	20	47	16
RSKCHEM	217	47	168	44
STDYUHSA	19	5	16	4
SUCCFCD	170	31	143	30
TMADVBIO	33	5	30	5
TNGSUFAC	75	24	36	18
Multiple	92	92	80	80

Table 9

Mean Levels Of Residual GPA's For Students In Intervention Programs

	All Students			Freshmen		
Program	No. Obs.	Mean	Std. Dev.	No. Obs.	Mean	Std. Dev.
All Prgms.	831	0.052558	0.707347	599	0.0506726	0.6860604
PRODEVFO	49	0.274730	0.590868	37	0.2897860	0.6442918
TNGSUFAC	75	0.239294	0.797998	36	0.1830086	0.7857806
TMADVBIO	33	0.188050	0.385802	30	0.1845771	0.4073902
SUCCFCD	170	0.169997	0.704626	143	0.1430916	0.7100588
STDYUHSA	19	0.089055	0.716960	16	0.1577565	0.7032586
RSKCHEM	217	0.086213	0.707818	168	0.1199940	0.6803429
ERLINVBI	18	0.048986	0.658556	18	0.0431744	0.6625851
RESADADS	65	-0.004820	0.598953	47	0.0170576	0.5882535
ESPMATH	142	-0.009030	0.696843	131	0.0376169	0.6700399
CAAE	128	-0.010740	0.797883	64	-0.0792842	0.8130732
CALPHYSC	20	-0.161520	0.592037	0	n.a.	n.a.
CONTROL	12440	-0.003511	0.622434	4063	-0.0074706	0.6136210
Total Sample	13271	0	0.628205	4662	0	0.6236246

NOTE: Programs are ranked in order of their mean residuals from the complete sample model.

Table 10

Mean Levels Of Residual GPA's For Students In Intervention Programs: Multiple-Program Students Counted Separately

Program	All Students No. Obs.	Mean	Std. Dev.	Freshmen Sample No. Obs.	Mean	Std. Dev.
All Prgms.	831	0.052558	0.707347	599	0.0506726	0.6860604
MULTIPLE	92	0.349137	0.622271	80	0.3834308	0.6115044
PRODEVFO	43	0.215529	0.554632	31	0.2103994	0.6035106
TMADVBIO	28	0.178926	0.358225	25	0.1763793	0.3761050
SUCCFCD	139	0.133029	0.721601	113	0.0846861	0.7290945
TNGSUFAC	51	0.113417	0.856568	18	-0.1536067	0.8288045
RSKCHEM	170	-0.002440	0.705365	124	0.0099554	0.6693863
RESADADS	45	-0.048960	0.644954	31	-0.0811828	0.6332558
CAAE	104	-0.057190	0.821348	49	-0.1758328	0.8396075
ESPMATH	117	-0.106250	0.662733	107	-0.0559626	0.6326468
STDYUHSA	14	-0.128520	0.650261	12	-0.0510993	0.6179936
CALPHYSC	19	-0.141000	0.600914	0	n.a.	n.a.
ERLINVBI	9	-0.168990	0.584758	9	-0.1732081	0.5920609
CONTROL	12440	-0.003511	0.622434	4063	-0.0074706	0.6136210
Total Sample	13271	0	0.628205	4662	0	0.6236246

NOTE: Programs are ranked in order of their mean residuals from the complete sample model.

Table 11

Direct and Interaction Effects of Individual Programs on GPA's

Program	b(trt)	t-stat	p-value	b(GPA*trt)	t-stat	p-value
All Prgms.	0.223053	3.131	0.0017	-0.073889	-2.380	0.0173
CAAE	-0.094834	-0.403	0.6871	0.050540	0.365	0.7151
CALPHYSC	0.235545	0.322	0.7475	-0.167578	-0.550	0.5823
ERLINVBI	-0.460723	-1.175	0.2399	0.281036	1.427	0.1537
ESPMATH	0.193761	1.455	0.1458	-0.095634	-1.622	0.1049
PRODEVFO	0.833271	2.796	0.0052	-0.231735	-1.939	0.0525
RESADADS	0.345123	1.123	0.2613	-0.146208	-1.161	0.2456
RSKCHEM	0.358579	3.188	0.0014	-0.124885	-2.574	0.0101
STDYUHSA	0.762210	1.584	0.1131	-0.282234	-1.445	0.1486
SUCCFCD	0.437608	2.722	0.0065	-0.127839	-1.671	0.0947
TMADVBIO	0.735636	1.348	0.1778	-0.183017	-1.021	0.3074
TNGSUFAC	1.049955	3.285	0.0010	-0.460033	-2.570	0.0102

Table 12

Direct and Interaction Effects of Individual Programs on GPA's for Freshman Students

Program	b(trt)	t-stat	p-value	b(GPA*trt)	t-stat	p-value
All Prgms.	0.239555	3.409	0.0007	-0.105336	-3.440	0.0006
CAAE	0.070183	0.265	0.7907	-0.120204	-0.751	0.4527
CALPHYSC	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
ERLINVBI	-0.474279	-1.224	0.2209	0.278207	1.432	0.1523
ESPMATH	0.243467	1.809	0.0705	-0.095372	-1.621	0.1052
PRODEVFO	0.867095	2.729	0.0064	-0.243254	-1.885	0.0595
RESADADS	0.585208	1.655	0.0979	-0.236527	-1.661	0.0967
RSKCHEM	0.326029	2.684	0.0073	-0.095885	-1.777	0.0757
STDYUHSA	0.934548	1.808	0.0707	-0.316078	-1.551	0.1210
SUCCFCD	0.365018	2.187	0.0288	-0.104043	-1.330	0.1837
TMADVBIO	0.660616	1.165	0.2442	-0.164328	-0.863	0.3884
TNGSUFAC	1.137292	3.375	0.0007	-0.567556	-2.967	0.0030

Table 13

Direct and Interaction Effects of Individual Programs on GPA's Multiple-Program Students Categorized Separately

Program	b(trt)	t-stat	p-value	b(GPA*trt)	t-stat	p-value
All Prgms.	0.223053	3.131	0.0017	-0.073889	-2.380	0.0173
MULTIPLE	0.726163	4.388	0.0001	-0.208462	-2.459	0.0140
CAAE	-0.326830	-1.269	0.2043	0.165448	1.084	0.2783
CALPHYSC	0.272429	0.371	0.7104	-0.173962	-0.571	0.5682
ERLINVBI	-0.824623	-1.715	0.0864	0.359280	1.533	0.1253
ESPMATH	-0.108326	-0.692	0.4890	0.005247	0.079	0.9371
PRODEVFO	0.555099	1.673	0.0944	-0.137850	-1.046	0.2955
RESADADS	0.270478	0.527	0.5985	0.124724	-0.621	0.5345
RSKCHEM	0.114502	0.855	0.3924	-0.047804	-0.860	0.3901
STDYUHSA	0.195354	0.295	0.7683	-0.130408	-0.492	0.6231
SUCCFCD	0.363340	1.881	0.0600	-0.107641	-1.171	0.2418
TMADVBIO	0.634502	0.907	0.3646	-0.147505	-0.658	0.5107
TNGSUFAC	0.495255	1.229	0.2190	-0.206054	-0.935	0.3496

Table 14

Direct and Interaction Effects of Individual Programs on GPA's for Freshman Students Multiple-Program Students Categorized Separately

Program	b(trt)	t-stat	p-value	b(GPA*trt)	t-stat	p-value
All Prgms.	0.239555	3.409	0.0007	-0.105336	-3.440	0.0006
MULTIPLE	0.765262	4.590	0.0001	-0.212598	-2.525	0.0116
CAAE	-0.141017	-0.479	0.6317	-0.045967	-0.254	0.7999
CALPHYSC	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
ERLINVBI	-0.842471	-1.776	0.0758	0.361065	1.563	0.1182
ESPMATH	-0.049046	-0.308	0.7578	0.002795	0.042	0.9665
PRODEVFO	0.527631	1.462	0.1438	-0.129979	-0.897	0.3698
RESADADS	0.528936	0.770	0.4411	-0.235342	-0.891	0.3730
RSKCHEM	0.009353	0.063	0.9496	0.007019	0.111	0.9116
STDYUHSA	0.345279	0.517	0.6050	-0.157797	-0.599	0.5491
SUCCFCD	0.208666	1.023	0.3065	-0.054149	-0.567	0.5710
TMADVBIO	0.499148	0.674	0.5002	-0.107647	-0.444	0.6574
TNGSUFAC	0.431898	0.975	0.3297	-0.323030	-1.373	0.1697

Table 15

Mean Levels Of Residual GPA's For Students In Single vs. Multiple Intervention Programs:

Program	All Students No. Obs.	Mean	Std. Dev.	Freshmen Sample No. Obs.	Mean	Std. Dev.
All Prgms.	831	0.052558	0.707347	599	0.0506726	0.6860604
MULTIPLE	92	0.349137	0.622271	80	0.3834308	0.6115044
SINGLE	739	0.015636	0.708969	519	-0.0006196	0.6830846
CONTROL	12440	-0.003511	0.622434	4063	-0.0074706	0.6136210
Total Sample	13271	0	0.628205	4662	0	0.6236246

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Table 16

Regression Analysis with Single- vs. Multiple-Program Students
Complete Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	11	4405.45715	400.49610	1016.879	0.0001
Error	13259	5222.03569	0.39385		
C Total	13270	9627.49284			

Root MSE	0.62757	R-square	0.4576
Dep Mean	2.62818	Adj R-sq	0.4571
C.V.	23.87866		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.835320	0.05701109	14.652	0.0001
GPA	1	0.563817	0.04456166	12.653	0.0001
GPA_FR	1	-0.127238	0.02141033	-5.943	0.0001
GPA_2	1	0.049450	0.00876481	5.642	0.0001
GPA_FR_2	1	0.024989	0.00713693	3.501	0.0005
GPA_SNGL	1	-0.039754	0.03252106	-1.222	0.2216
GPA_MULT	1	-0.241102	0.08480797	-2.843	0.0045
D_SNGL	1	0.118288	0.07513378	1.574	0.1154
D_MULT	1	0.813128	0.16493847	4.930	0.0001
ENGG	1	-0.067416	0.01350199	-4.993	0.0001
FEMALE	1	0.093508	0.01157382	8.079	0.0001
AFRI_AM	1	-0.204062	0.02765399	-7.379	0.0001

Table 17

Regression Analysis with Single- vs. Multiple-Program Students
Freshman Sample Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	9	1809.42734	201.04748	520.360	0.0001
Error	4652	1797.35807	0.38636		
C Total	4661	3606.78541			

Root MSE	0.62158	R-square	0.5017
Dep Mean	2.46603	Adj R-sq	0.5007
C.V.	25.20567		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.925132	0.07114648	13.003	0.0001
GPA	1	0.364218	0.05843510	6.233	0.0001
GPA_2	1	0.086616	0.01183907	7.316	0.0001
GPA_SNGL	1	0.000350	0.03663825	0.010	0.9924
GPA_MULT	1	-0.225065	0.08516368	-2.643	0.0083
D_SNGL	1	0.017413	0.08624068	0.202	0.8400
D_MULT	1	0.811986	0.16827853	4.825	0.0001
ENGG	1	-0.099747	0.02197652	-4.539	0.0001
FEMALE	1	0.146835	0.01945596	7.547	0.0001
AFRI_AM	1	-0.293894	0.04477054	-6.564	0.0001

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