1-1-2015

Increasing Retention in STEM: Results from a STEM Talent Expansion Program at the University of Memphis

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Abstract

MemphiSTEP is a five-year STEM Talent Expansion Program (STEP) at the University of Memphis sponsored by the National Science Foundation. The project focuses on retention and persistence to graduation to increase the number of STEM majors and graduates. The project includes a range of student retention programs, including a Summer Mathematics Bridge Bootcamp, Networking Program, Research Award Program, Travel Award program and STEM Learning Communities. Results from the first four years of the project suggest that MemphiSTEP is making a positive impact on student retention and performance in STEM fields. Our data indicate that even after controlling for gender, major, semester standing, race, and prior performance, STEM students taking part in MemphiSTEP activities are retained at higher rates and perform better than University of Memphis STEM students who have not participated in MemphiSTEP activities.

MemphiSTEP is a five-year Type 1 STEM Talent Expansion Program (STEP) funded by the National Science Foundation (NSF-DUE 0756738). MemphiSTEP is designed to significantly increase the number of STEM graduates (US citizens or permanent residents) at the University of Memphis (U of M) over the life of the grant and beyond. The project was put in place in June 2008 to address shortages of STEM graduates at the U of M and in the Mid-South region in general. Enrollment and graduation in STEM at the University had been declining consistent with a national downward trend. Enrollment in engineering majors had declined from 828 in fall 1997 to 650 in fall 2005 and had only recovered to 697 by fall 2007. The percentage of students in a STEM major in a given fall semester between 2007 and 2013 has been around 12%, whereas the percentage of the graduating class with a STEM major was 8.7% in the 2008-2009 academic year, 9.9% in the 2009-2010, 2010-2011, and 2011-2012 academic years, and 11.1% in the 2012-2013 academic year.

To address the shortage of STEM graduates, MemphiSTEP aimed to increase the total number of U of M STEM graduates from 212 per year (baseline measured in 2005 for the grant proposal) to 335 per year by 2013, representing an increase of over 60% in the number of STEM graduates. As outlined below, a range of student retention activities was developed to facilitate persistence to graduation in STEM. Data produced by the U of M Office for Institutional Research (www.memphis.edu/oir/retention/graduationgenerator.php) indicates that STEM graduation numbers have increased, reaching 320 by summer 2013. The objective of the current paper is to investigate whether MemphiSTEP student retention activities have played a role in student persistence to graduation and performance in STEM, factors critically related to graduation success.

This paper builds on a previous article published in the *Journal of STEM Education* (Russomanno, et al., 2010) regarding MemphiSTEP. The original paper outlines the MemphiSTEP student programs designed to increase persistence to graduation in STEM, organizational structure of the grant, objectives, and formative evaluation data relating to the first year of the project. Our goal for the original paper was to help others conduct or propose projects with similar objectives. The purpose of the present paper is to analyze the impact of the MemphiSTEP project and its individual components on persistence to graduation and performance, which should allow other retention projects to target interventions more successfully. This paper presents data and analysis of project program effectiveness for the first four years of the project (Year 1: 2008-2009; Year 2: 2009-2010; Year 3: 2010-2011; and Year 4: 2011-2012). For the purpose of assessing impact, GPA and retention in STEM are the key indicators used for predicting STEM student success and graduation increases.

Student Retention Programs

MemphiSTEP employs a range of retention programs that are informed and guided by the current research of numerous investigators; well-established best practices (e.g., Tinto 1993; Tinto, 2002); and results from funded projects, including U of M projects (Ivey & Lambert, 2005). Although the project concentrates on all STEM disciplines across the campus and each year of a student's undergraduate career, the mathematics used in science and engineering is a focus of one of the project programs, the Mathematics Bootcamp. It is well established that the lack of a solid preparation in mathematics is a deterrent to a student's success in a STEM major (Avallone, Geiger, & Luebke, 2008; French, Immekus, & Oakes, 2005).

Networking and research activities allow students to connect with faculty mentors, to learn from peers and graduate students, and to get a sense of the type of work involved in their fields (Kinkead, 2003). Furthermore, participation in cooperative educational experiences has a significant and positive effect on retention and degree completion (Nasr, Pennington & Andres 2004; Jaeger, Eagan & Wirt, 2008). Research opportunities have been found to increase students' identity in STEM fields, making them more likely to persist to graduation in their STEM discipline (Chang, Sharkness, Newman & Hurtado, 2010). Importantly, all retention programs implemented through MemphiSTEP have been found to be successful in retaining women and under-represented minorities in STEM fields (Building Engineering and Science Talent, 2004)—subgroups who are underrepresented in STEM.

There were five original MemphiSTEP student programs designed to foster persistence to graduation in STEM among a significant number of students. Each program is briefly outlined below. More details can be found in Russomanno, et al. (2010) and on the project website (www.memphis.edu/memphistem).

- *Summer Mathematics Bridge Bootcamp*: This is a two-week refresher program before the beginning of the fall semester. The Bootcamp is designed to help boost mathematics skills as well as offer opportunities to network and discover STEM career options. The Bootcamp is marketed to students enrolled in pre-calculus or Calculus 1 in the fall semester, but is not limited to those students.
- *Networking Program:* Offers opportunities for STEM students to network with fellow STEM students and faculty during large group events (e.g., mixers and field trips). Student Network Leaders (upper-level STEM students) are recruited to reach out to networking participants and interact with them during

networking events.

- *Undergraduate Research Program*: Offers students the opportunity to participate in paid STEM research under the supervision of STEM faculty.
- *Travel Award Program*: Offers funding for STEM students to attend conferences or national and regional STEM club activities to present work and network.
- *Learning Communities:* Facilitates social networking and study groups by having students take common classes during the semester they enter the University.

Funding from the grant also supports grants to STEM student societies and for the use of blended instruction in some calculus classes. Since the intervention in calculus classes started later and varied considerably from semester to semester, we have not included it in our analysis. Because data was not gathered on the membership or impact of student societies, we have not included these in our analysis.

With the exception of the Research Program and the Travel Award Program MemphiSTEP activities were open to all undergraduate students regardless of major (activities were opened up to students interested in pursuing STEM majors). However, for the purposes of our analysis we consider only declared STEM majors. The activities were conceived as retention and not recruitment activities.

Methods

As is the case with many program evaluations, our central problem is that of self-selection. Since the various programs that comprise the MemphiSTEP program are voluntary and participants are self-selected and not chosen by random assignment, we cannot simply consider the difference between outcomes between the MemphiSTEP participants and the group that did not participate in any MemphiSTEP programs. Observed differences could be due to the effect of the programs but could also be attributable to difference between the two groups.

One possible way to account for the differences in the two groups is to use regression to estimate a model of the outcome variable including all of the observed covariates and a treatment indicator. The effect is then the coefficient on the treatment indicator. However, when there are sufficiently large differences between the groups, the assumptions underlying the regression are unlikely to be valid. For this reason much of the literature in program evaluation instead uses semi-parametric methods, such as nearest neighbor matching on covariates, propensity score matching, or propensity score reweighting, to ameliorate the covariate bias before applying parametric methods.

For each MemphiSTEP program we consider two groups of students: the STEM majors that participated in that program (which we term *the treated group*) and the STEM majors who did not participate in any MemphiSTEP program (which we term *the untreated group*). For each student we consider that they have two possible outcomes: the outcome if they are treated Y_{1i} and the outcome if they are not treated Y_{0i}. To each student we also associate a treatment indicator: $D_i = 1$ if the student is treated (i.e. participated in the MemphiSTEP program being analyzed) and $D_i = 0$ if the student did not participate in any of the MemphiSTEP programs. When focusing on the effect of an individual program (e.g., the Mathematics Bootcamp), students who participated in some MemphiSTEP program but not in the program of interest are ignored, they are not considered part of either the treated or untreated group for that program.

General Framework

We aim to compute the average effect of the treatment on the treated (abbreviated ATT).

$$E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1)$$

Unfortunately, it is not possible to observe $E(Y_0|D = 1)$ since this represents the average outcome for the treated group had they not been treated (it is referred to as a counter-factual). In a random experiment, the assignment to treatment is independent of the individual and hence we may compute the average effect of the treatment on the treated (which is now the same as the average effect of the treatment on the untreated) by simply computing the difference of means.

As can be seen from the demographic data presented in Table 2 and Table 3, the group of students who participated in MemphiSTEP programs is quite dissimilar from the group of STEM students who did not participate in MemphiSTEP programs. Thus, we are far from being in a random experiment; assignment to the treatment group very much depends on the individual in question. Taking a simple difference of means in this case will overestimate the effectiveness of the MemphiSTEP programs.

Smith and Todd (2005) note that the work of Dehejia and Wahba (1999, 2002) had made "propensity score matching the estimator du jour in the evaluation literature." Unfortunately, at this time, there are no statistically justified methods for determining the standard errors of propensity score matching estimators. The propensity score matching literature typically relies on bootstrapping to obtain standard errors for the estimators. In the related case of matching on covariates, Abadie and Imbens (2006) showed that bootstrapping matching estimators is not asymptotically valid. There is little reason to suspect that the more complicated propensity score matching estimators fare any better with regards to bootstrapping for standard errors. The problem is that matching estimators are inherently non-smooth so the standard proofs of validity of bootstrapping do not apply. For this reason, we have chosen to use a related technique, propensity score reweighting, for which bootstrapping is better justified.

Regardless of whether we are doing matching or reweighting, the crucial statistic of interest is the *propensity score* introduced by Rosenbaum and Rubin (1983), which is the probability that an individual will be in the treatment group conditioned on their observed covariates. An excellent introduction to the practical implementation of both matching and reweighting schemes can be found in Nichols (2007). If we use X_i to denote the observed covariates then the propensity score may be defined as

$$p(X_i) = P(D = 1|X_i)$$

the probability of being treated conditioned on the observed covariates. Typically, this probability cannot be observed and so must be estimated. We compute the estimated propensity score, denoted $\hat{p}(X_i)$, using a logistic regression of the treatment assignment variable against all the covariates. The crucial assumption in the Rosenbaum and Rubin theory is that the assignment to treatment and the potential outcomes are independent after conditioning on the observed covariates.

To eliminate the differences between the treated and the untreated groups we seek to assign weights to the individuals in the untreated group so that after reweighting they have the same probability of being in either group. If we denote the weight for covariates X_i by $w(X_i)$ then we wish to have

$$P(D = 1|X_i) = w(X_i)P(D = 0|X_i)$$

Using

$$P(D = 1|X_i) = p(X_i)$$
$$P(D = 0|X_i) = 1 - p(X_i)$$

we can solve our expression to get the desired weights

$$w(X_i) = \frac{p(X_i)}{1 - p(X_i)}.$$

In practice we have only the estimated propensity score $\hat{p}(X_i)$ so we must make do with the estimated weight

$$\hat{w}(X_i) = \frac{\hat{p}(X_i)}{1 - \hat{p}(X_i)}.$$

These weights apply only to individuals in the untreated group. Individuals in the treatment group are assigned a weight of 1.

Once we have reweighted our untreated observations in this fashion we may compute

$$E(Y_0|D = 1) = E(wY_0|D = 0)$$

and hence compute the average effect of the treatment on the treated. In practice, having computed the weights, we compute the average effect of the treatment on the treated by using a weighted linear regression. We do this even in the case of our retention variable, which is binary valued. That this is both valid and meaningful is argued in Hellevik (2009). This has the effect of ameliorating any remaining covariate imbalances.

In order to quantify the change we give an estimated value for the outcome of the treatment on the treated and an estimate for the counterfactual value of the outcome given no treatment on the treated. We use logistic regression for our retention variable. This leads to a very slight difference between the difference of the two estimates and our computed version of ATT (due to the difference between linear regression and logistic regression). This difference provides an alternative to the linear results reported for retention but the two results agree to a high degree.

Exact Matching In A Reweighting Context

We will give several different model specifications. All of these models use the reweighting analog of exact matching. Suppose that Z takes values from 1 to k. We compute propensity scores and their associated weights $\widehat{w}_j(X_i)$ separately within each group $Z = j$ and then normalize. If an untreated individual $\boldsymbol{i}$ is in group $\boldsymbol{j}$, i.e., $Z_i = j$ then we define $\widehat{w}(X_i)$as follows

$$\widehat{w}(X_i) = \frac{\#\{k: Z_k = j \text{ and } D_k = 1\}}{\sum_{k:Z_k=j \text{ and } D_k=0} \widehat{w}_j(X_k)} \widehat{w}_j(X_i).$$

The result of this is that the proportions of the untreated in group j is, after reweighting, exactly equal to the proportion of the treated in group j.

Enforcing Common Support

Ideally, we would hope that for every observation in the treatment group there is a similar observation in the untreated group. Unfortunately, it is often the case that for some observations in the treated group there are no similar observations in the untreated group. Computations of the treatment effects should probably be limited to the smallest connected area of common support (Nichols, 2007). For this reason, we take the smaller of the maximum propensity score for the treated group and the maximum propensity score for the untreated group and drop any observations whose propensity score exceeds this. Typically this means we drop observations from the treated group whose propensity scores are higher than any of the observations in the untreated group, there are a couple of cases, however, when this involves eliminating some observations from the untreated group whose propensity scores are higher than any observation in the treated group. Similarly, we take the larger of the minimum propensity score for the treated group and the minimum propensity score for the untreated group and drop any observations whose propensity score is below this (in practice the minimum propensity score for the treated group is always larger and we drop observations from the untreated group whose propensity score is lower than any observation in the treated group). In the case of exact matching this common support is enforced within each subgroup separately. For all our analyses we list the number of observations excluded from both the treatment group and the untreated group in order to enforce the common support and give the estimates of ATT had common support not been enforced. In our analyses these always broadly agree which indicates that there is sufficient overlap between treated and untreated group to feel confident in the estimate of the ATT.

One criticism of enforcing a common support is that it is no longer clear what the treatment group, to which the ATT applies, actually is. Wherever we have close agreement of the ATT with and without enforcing common support we may feel reasonably confident in interpreting the result as an ATT for the full treatment group.

Bias Measures

In order to compare the effectiveness of the reweighting scheme on individual covariates we compute a measure of bias suggested by Rosenbaum and Rubin (1985). They define a bias measure based on a normalized difference of means between the treated and the untreated groups. The same normalization factor is used both before and after reweighting namely the averaged standard deviations of the treated and untreated groups.

$$\sigma_{bias} = \sqrt{\frac{\sigma^2_{untreated} + \sigma^2_{treated}}{2}}.$$

The measures of bias are then

$$bias_{before} = \frac{\mu_{treated} - \mu_{untreated}}{\sigma_{bias}}$$

$$bias_{after} = \frac{\mu_{treated,reweighted} - \mu_{untreated,reweighted}}{\sigma_{bias}}$$

This measure of bias is signed. The sign of the number indicates the direction of bias while the magnitude of the number indicates the size of the bias. Reweighting alters the mean of the untreated group. The mean of the treated group is different after reweighting only if observations are dropped in order to enforce a common support.

Data

The goal of this paper is to investigate the efficacy of the MemphiSTEP programs in fostering persistence to graduation in STEM. To this end, we investigated performance and retention of students with declared STEM majors that participated in MemphiSTEP activities. In our analysis we consider only students who were declared STEM majors. A student was classified as retained in a STEM major if either they remained in a STEM major or had graduated in a STEM major at the start of the following academic year (the year after they had participated in MemphiSTEP). Our performance measure is overall GPA for all courses taken during the academic year.

We will examine the effect on retention and performance of the project overall and for each of the project programs.

For each student, treated (MemphiSTEP students) or untreated (non-project STEM students), we considered the following 5 covariates:

1. Gender: Male or Female.
2. Race: Alaskan Native, American Indian, Asian, Black (including African American), Hispanic, White, Native Hawaiian.
3. Major: Biology, chemistry, computer science, earth sciences, mathematical sciences, physics, and all engineering majors.
4. Class standing: Freshman, sophomore, junior, senior.
5. Prior performance: High school GPA for freshman students, cumulative U of M GPA for non-freshman students.
6. Year Indicator: Year 1, year 2, year 3, year 4.

The prior performance measures are two separate variables: a high school GPA variable that holds the high school GPA for freshman students and 0 for non-freshman students, and a cumulative GPA variable that is 0 for freshman students and holds the cumulative GPA for non-freshman students. We have separated the two prior performance measures in this way because high school GPA is quantitatively different from cumulative college GPA and therefore necessitates a different coefficient.

Some students with either a non-STEM major or no declared major participated in some of the MemphiSTEP activities. Given the focus of this paper on retention within a STEM major, these students are not considered in this paper. Counting only declared STEM majors, MemphiSTEP engaged 107 students in Year 1, 173 students in Year 2, 187 students in Year 3, and 281 students in Year 4.

We do not include students who chose not to declare a racial group, freshman students that do not have a high school GPA on record, and transfer students who have no cumulative college GPA from the U of M; in total 69 MemphiSTEP students and 631 non-MemphiSTEP students were dropped.

Demographics

This section outlines demographic information on the declared STEM majors that participated in MemphiSTEP activities during the first four years of the project that is compared to demographic information of all the declared STEM majors over that period.

A breakdown of the number of students involved in

Program/Activity	Year 1	Year 2	Year 3	Year 4	Total
Math Bridge Bootcamp	35	70	40	47	192
Networking/Mentoring Program	59	80	123	206	468
Learning Communities	10	24	20	30	84
Undergraduate Research Program	32	23	27	19	101
Travel Award Program	17	21	14	58	110

Table 1. Number of MemphiSTEP Participants in Years 1 through 4

Demographics	Combined Years					Combined Years			
	MemphiSTEP		All STEM			MemphiSTEP		All STEM	
Gender	**N**	**%**	**N**	**%**	**Major (Arts and Sciences)**	**N**	**%**	**N**	**%**
Males	528	70.6%	4744	60.3%	Biology	75	10.0%	2720	34.6%
Females	220	29.4%	3119	39.7%	Chemistry	41	5.5%	891	11.3%
Ethnicity					Computer Science	38	5.1%	593	7.5 %
Black	215	28.4%	2686	33.2%	Earth Sciences	11	1.5%	117	1.5%
White	445	58.9%	4367	53.9%	Mathematical Sciences	47	6.3%	339	4.3%
Other	74	9.8%	713	8.8%	Physics	24	3.2%	112	1.4%
Unspecified	22	3.89%	330	4.1%	**Major (Engineering)**				
Classification					Biomedical Eng.	95	12.7%	400	5.1%
Freshman	292	39.0%	1948	24.8%	Civil Eng.	120	16.0%	485	6.2%
Sophomore	130	17.4%	1749	22.2%	Computer Eng.	69	9.2%	391	5.0%
Junior	140	18.7%	1721	21.9%	Electrical Eng.	67	9.0%	448	5.7%
Senior	186	24.9%	2445	31.1%	Mechanical Eng.	102	13.6%	687	8.7%
Major College					Eng. Technology	680	7.9%	689	8.7%
Arts and Sciences	225	30.5%	4655	60.1%					
Engineering	512	69.5%	3091	39.9%					

Table 2. STEM Student Demographic and Major Data for Combined Project Years 1 through 4.

	MemphiSTEP			Non-MemphiSTEP			Test for Difference		
Measure	N	Mean	Std. Dev.	N	Mean	Std. Dev.	Diff.	Std. Err.	p-Value
High school GPA (for freshmen)	287	3.49	0.50	1585	3.21	0.62	0.29	0.04	0.0000
Cumulative college GPA (for non-freshmen)	434	3.08	0.63	5155	2.85	0.64	0.23	0.03	0.0000
GPA	745	2.91	0.99	6906	2.58	0.99	0.33	0.04	0.0000
Retained	748	85.3%	-	7155	64.7%	-	20.6%	1.8%	0.0000

Standard t-test performed for high school GPA, cumulative college GPA, and for GPA outcome measure. Standard test for proportions used for the retention percentage.

Table 3. Prior Performance Measures, and Outcome Variables for MemphiSTEP And Non- MemphiSTEP Groups

Variable		MemphiSTEP	MemphiSTEP	Bias	p-Score
Freshman	Unweighted	3.4833	3.2008	49.9	0.0000
GPA	Weighted	3.4775	3.4370	7.2	0.3137
Non-Freshman	Unweighted	3.0760	2.8433	36.6	0.0000
GPA	Weighted	3.0739	3.0865	-2.0	0.6299

Reweighting with all covariates (indicators for White race, biology major, and sophomore class standing omitted) except project year. Exact matching on project year. Common support enforced (4 students out of 699 treated excluded 720 out of 6473 untreated excluded).

Table 4. Effect of Reweighting on Prior Performance Measures Using Exact Matching on Project Year, and Enforcing Common Support. All STEM Students Considered

each activity is presented in Table 1. Note that some students participated in multiple activities and thus the sum of students reported under each activity exceeds the project participant totals outlined above.

Demographics for declared STEM majors can be seen in Table 2. As evidenced in the table, MemphiSTEP has engaged a diverse range of students during years 1 through 4, including women and under-represented minorities. As shown in Table 2, we see that the distribution of majors in the MemphiSTEP group is very different from the distribution of majors within the group of all STEM majors. In particular biology and chemistry are underrepresented while the engineering majors, with the exception of engineering technology, are overrepresented.

Though we have exhibited the effects of self-selection on the distribution of races and majors we have yet to exhibit the effect of this self-selection on the crucial prior performance measures. It is also instructive to see the outcomes for the MemphiSTEP and the non-MemphiSTEP students. These comparisons are shown in Table 3.

MemphiSTEP students are retained at significantly higher rate and perform significantly better than their non-MemphiSTEP counterparts. However, MemphiSTEP students also have significantly better prior performance than their non-MemphiSTEP counterparts. The question now becomes whether the observed differences in prior performance (and race, gender and major) account for all of the improvement in outcomes or whether there is an additional positive effect that can be attributed to the MemphiSTEP project.

Results

A preliminary regression analysis of the group of non-MemphiSTEP students showed that the covariates with the strongest effect on our outcome measures, retention and performance (GPA), were the prior performance measures (cumulative college GPA for non-freshman students and high-school GPA for freshman students). For retention only, covariates that are significant at the $p<.05$ level are gender, the prior performance measures, the indicator variables for the majors (biomedical engineering, civil engineering, computer engineering, electrical engineering, mathematical sciences, mechanical engineering, and engineering technology), and the indicator variables for the class standings. No racial effects are observed on retention. For GPA, the only covariates that are significant at the $p < .05$ level are the Black racial class, the indicator variable for the major in engineering technology, the indicator variables for the class standings, the prior performance measures, and the project year variable. The largest effect sizes for GPA are from the two prior performance measures with cumulative college GPA having the largest effect size. The largest effect sizes for the retained variable are from the indicator variable for the senior class standing and the cumulative college GPA.

To account for changes in the student body over the period of the project, we performed exact matching on project year, ensuring that students were only compared to other students in the same calendar year. Reweighting affects all covariates, but we will focus on its effects on the prior performance measures since these are crucial in determining our outcome measures. Examining the prior performance measures after reweighting with exact matching on only project year shows that that even with common support enforced, groups are insufficiently balanced (see Table 4 below).

Reweighting with exact matching on both project year and freshman standing (and enforcing common support) provided better balancing of the observed covariates between the MemphiSTEP and non-MemphiSTEP groups. In particular, Table 5 shows that the means of the performance measures now have biases less than 2.9%.

Before reweighting, the maximum bias in the crucial prior performance measures is 49.9%. After reweighting, the maximum bias in the crucial prior performance measures is 2.9%.

Examining the success of the reweighting scheme by examining the covariates in this fashion is rather space intensive. The following section therefore summarizes the effects of reweighting by examining a regression of the treatment variable against the covariates (see Table 6). Assuming that the reweighting scheme is effective at removing the differences between the two groups all the non-constant coefficients should be zero. This can be tested using an F-test. The p-value for the F-test will be our single number measure of the effectiveness of re-

Variable		MemphiSTEP	Non-MemphiSTEP	Bias	p-Score
Freshman GPA	Unweighted	3.4833	3.2008	49.9	0.0000
	Weighted	3.4736	3.4902	-2.9	0.6876
Non-Freshman GPA	Unweighted	3.0760	2.8433	36.6	0.0000
	Weighted	3.0687	3.0648	0.6	0.8822

Reweighting with all covariates (indicators for White race, biology major, and sophomore class standing omitted) except project year and freshman indicator. Exact matching on project year and freshman indicator. Common support enforced (13 students out of 699 treated excluded 1441 out of 6473 untreated excluded).

Table 5. Effect of Reweighting on Prior Performance Measures Using Exact Matching on Project Year and Freshman Status, and Enforcing Common Support. All STEM Students Considered.

	R^2	Adj. R^2	F Statistic	p-Value
Unweighted	0.1022	0.0991	F(24,7147)=33.88	0.0000
Weighted	0.0008	-0.0030	F(22,5695)=0.2146	1.0000

F-test for joint insignificance of the non-constant coefficients.

Table 6. Effectiveness of Reweighting for the Entire MemphiSTEP Project.

	Observed Coeff.	Bootstrap Std. Err.	Z	P > |z|	Predicted Non-Prog.	Prog.
MemphiSTEP Project						
ATT (GPA)	0.2066	0.0364	5.67	0.000	2.703	2.910
ATT (Retained)	0.1686	0.0179	9.43	0.000	0.683	0.856
MemphiSTEP Project on Freshman Students						
ATT (GPA)	0.2817	0.0606	4.65	0.000	2.537	2.819
ATT (Retained)	0.2578	0.0344	7.49	0.000	0.537	0.792
MemphiSTEP Project on Non-Freshman Students						
ATT (GPA)	0.1639	0.0447	3.66	0.000	2.807	2.970
ATT (Retained)	0.1129	0.0196	5.77	0.000	0.775	0.892
MemphiSTEP Project on Female Students						
ATT (GPA)	0.2582	0.0755	3.42	0.001	2.656	2.914
ATT (Retained)	0.2098	0.0447	4.70	0.000	0.645	0.864
MemphiSTEP Project on Male Students						
ATT (GPA)	0.2004	0.0434	4.66	0.000	2.704	2.905
ATT (Retained)	0.1469	0.0215	6.84	0.000	0.703	0.851
MemphiSTEP Project on Black Students						
ATT (GPA)	0.2444	0.0761	3.21	0.001	2.208	2.452
ATT (Retained)	0.2437	0.0363	6.71	0.000	0.586	0.835
MemphiSTEP Project on Non-Black Students						
ATT (GPA)	0.1869	0.0452	4.14	0.000	2.917	3.103
ATT (Retained)	0.1489	0.0230	6.46	0.000	0.715	0.861
MemphiSTEP Project on Black Freshmen Students						
ATT (GPA)	0.5745	0.1618	3.55	0.000	1.854	2.428
ATT (Retained)	0.3677	0.0757	4.86	0.000	0.440	0.811

Based on 500 Bootstrap replications resampling within treatment status using student ID to cluster. Reweighting with all appropriate covariates except project year and freshman status (where appropriate). Exact matching on project year and freshman status. Common support enforced for all regressions: for the overall project 13 students out of 699 treated are excluded and 1441 out of 6473 excluded, for the project restricted to freshmen 5 students out of 272 treated are excluded and 457 out of 1497 untreated are excluded, for the project restricted to non-freshmen 8 students out of 419 treated are excluded and 984 out of 4976 untreated are excluded, for the project restricted to females 25 students out of 206 treated are excluded and 930 out of 2625 untreated are excluded, for the project restricted to males 7 students out of 493 treated are excluded and 926 out of 3848 untreated are excluded, for the project restricted to Black students 3 students out of 205 treated are excluded and 682 out of 2258 untreated are excluded, and for the project restricted to non-Black students 14 students out of 494 treated are excluded and 1380 out of 4215 untreated are excluded, and for the project restricted to Black freshmen 2 students out of 68 treated are excluded and 313 out of 578 untreated are excluded.

Table 7. Results for the MemphiSTEP Project Using Reweighting.

weighting. A p-value near 0 indicates that the covariates are statistically significant in determining whether a student uses a MemphiSTEP program, while a p-value near 1 indicates that the covariates are not statistically significant in determining whether a student uses a MemphiSTEP program.

Before reweighting, it is evident that the covariates explain a significant amount of the variation in the treatment assignment. After reweighting, the covariates no longer explain a significant amount of the variation in the treatment assignment.

After reweighting, the average treatment effect on the treated (the average treatment effect on the MemphiSTEP group) was extracted by performing a weighted linear regression of the outcome variable against all the covariates and the MemphiSTEP treatment indicator (see Table 7). The result is then the coefficient on the treatment indicator. An alternative is simply to take the difference in the means of the outcome variables in the two groups. For all the results reported, the two methods yield similar point estimates but the more extensive regression gives a value with a lower standard error (by helping to account for any remaining covariate imbalance) and this is the method we use for the analyses in the paper. This analysis is repeated for the project restricted to subpopulations of interest.

We compute a value that predicts how project students would have performed if they were not in the project by using the reweighted observations of the non-project students. Using reweighting, we compute that participation in MemphiSTEP increased GPA from a predicted 2.70 to 2.91, and increased retention from a predicted 68% to 86%, an increase of 18%. The increase of 0.21 (about a fifth of a letter grade) in GPA is exactly the ATT (GPA) for the MemphiSTEP project reported in the table. Without enforcing a common support an ATT (GPA) of 0.2095 and an ATT (Retained) of 0.1698 would have been obtained for the whole MemphiSTEP project so enforcing a common support does not meaningfully alter the results. Similarly, without enforcing common support for Black freshmen we would have obtained an ATT (GPA) of 0.5807 and an ATT (Retained) of 0.3593. For this reason we may reliably interpret these results as applying to the entire treatment group.

The effectiveness of the program is not uniform across subpopulations (see Table 7). The project shows itself to be most effective in addressing at-risk populations. For freshmen, 39% of project students, participation increased GPA from a predicted 2.54 to 2.82 and increased retention from a predicted 54% to 79%. For Black students, 28% of project students, participation increased GPA from a predicted 2.20 to 2.45 and increased retention from a predicted 59% to 84%. For Black freshmen participation increased GPA from a predicted 1.85 to 2.43 and increased retention from a predicted 44% to 81%.

	R^2	Adj. R^2	F statistic	p-Value
Bootcamp Program				
Unweighted	0.0711	0.0677	F(24,6623)=21.1205	0.000
Weighted	0.0004	-0.0083	F(20,2295)=0.0499	1.000
Networking Program				
Unweighted	0.0797	0.0764	F(24,6881)=24.8303	0.000
Weighted	0.0010	-0.0035	F(22,4918)=0.2248	1.000
Research Program on Non-Freshman Students				
Unweighted	0.0327	0.0285	F(22,5042)=7.7403	0.000
Weighted	0.0045	-0.0053	F(19,1935)=0.4578	0.978
Travel Award Program on Non-Freshman Students				
Unweighted	0.0397	0.0355	F(22,5050)=9.4850	0.000
Weighted	0.0017	-0.0106	F(20,1623)=0.1415	1.000
Learning Communities Program on Freshman Students				
Unweighted	0.0861	0.0749	F(19,1553)=7.7031	0.000
Weighted	0.0114	-0.0181	F(16,535)=0.3862	0.986

F-test for joint insignificance of the non-constant coefficients (linear regression).

Table 8. Effectiveness of Reweighting for the Individual Programs

	Observed Coeff.	Bootstrap Std. Err.	Z	P > |z|	Predicted Non-Prog.	Prog.
Bootcamp Program						
ATT (GPA)	0.1989	0.0742	2.68	0.007	2.526	2.725
ATT (Retained)	0.2259	0.0385	5.86	0.000	0.569	0.795
Bootcamp Program on Freshman Students						
ATT (GPA)	0.2404	0.0867	2.77	0.006	2.522	2.762
ATT (Retained)	0.2533	0.0442	5.73	0.000	0.543	0.798
Bootcamp Program on Female Students						
ATT (GPA)	0.2915	0.2250	1.30	0.195	2.521	2.812
ATT (Retained)	0.3263	0.1301	2.51	0.012	0.513	0.840
Bootcamp Program on Black Students						
ATT (GPA)	0.4026	0.1695	2.38	0.018	1.953	2.355
ATT (Retained)	0.3304	0.0732	4.51	0.000	0.488	0.816
Bootcamp Program on Black Freshmen						
ATT (GPA)	0.6961	0.1695	3.33	0.001	1.738	2.424
ATT (Retained)	0.3827	0.1067	3.59	0.000	0.411	0.793

Based on 500 Bootstrap replications resampling within treatment status using student ID to cluster. Reweighting with all covariates (indicators for biology major and sophomore standing omitted) except project year. Exact matching on project year and freshman standing (where appropriate). Common support enforced: for the Bootcamp 2 out of 175 treated were excluded but 4330 out of 6473 untreated were excluded, for the Bootcamp restricted to freshmen 2 out of 137 treated were excluded but 583 out of 1497 untreated were excluded, for the Bootcamp restricted to Black students 3 out of 57 treated excluded and 1574 out of 2285 untreated excluded, and for the Bootcamp restricted to Black freshmen 2 out of 35 treated were excluded but 345 students out of 578 untreated were excluded

Table 9. Results for the Bootcamp Program Using Reweighting.

Results for the Individual Programs.

In this section the results of the impact analysis outlined in the previous section for the individual program components are duplicated. The same model for the analysis, using all the covariates with exact matching on the project year and freshman status (except when restricting to freshman or non-freshman students), is used. We test the effectiveness of this reweighting scheme using our standard F-test (see Table 8).

Again, the reweighting is successful at removing the covariate bias. For each of the weighted and unweighted cases we run a regression with the dependent variable being treatment status and with all appropriate covariates for independent variables. The p-value shown is the probability of getting the fitted model given that all the covariate coefficients are zero i.e. the probability of getting the fitted model given that the covariate had no influence on treatment status. A p-value near 0 means that the covariates are important in determining treatment status while a p-value near 1 means that the covariates are not important in determining treatment status. Prior to reweighting all p-values are 0 to 3 decimal places meaning that the covariates are very important in determining treatment status. After reweighting all p-values are very near 1 indicating that covariates are not important in determining treatment status.

For the two largest programs, the Bootcamp and Networking programs, we examine their effectiveness on various subgroups. Results for the Bootcamp are reported in Table 9 and results for Networking are reported in Table 10. Results for remaining programs (Research, Travel and Learning Community programs) are reported in Table 11.

One must be very careful when comparing the treatment affects between different programs since the treatment group differs. The Bootcamp program shows statistically significant effects on both retention and performance. Participation increases GPA from a predicted 2.53 to 2.73 and increases retention from a predicted 57% to 80%. For the Bootcamp, if common support was not enforced, an ATT (GPA) of 0.1772 and an ATT (Retained) of 0.2447 would have been obtained. When restricted to freshmen the Bootcamp program has statistically significant effects on both retention and performance. Among freshmen, participation increases GPA from a predicted 2.52 to 2.76 and increases retention from a predicted 54% to 80%. Among freshmen, without enforcing a common support, an ATT (GPA) of 0.4833 and an ATT (Retained) of 0.3257 would have been obtained. It is perhaps surprising that the program most directly targeted at academic performance does not produce stronger gains. This will be examined more closely using grades in their subsequent mathematics course in a following paper.

The Networking program shows statistically significant effects on both retention and performance both overall and in all the subpopulations analyzed. Participation increases GPA from a predicted 2.69 to 2.96 and increases retention from a predicted 68% to 88%. Without enforcing a common support an ATT (GPA) of 0.2704 and an ATT (Retained) of 0.1922 would have been obtained. When restricted to freshmen the Networking program has large statistically significant effects on both retention and performance. Among freshmen, participation increases GPA from a predicted 2.54 to 3.04 and increases retention from a predicted 51% to 85%. Among freshmen, without enforcing a common support, an ATT (GPA) of 0.4833 and an ATT (Retained) of 0.3257 would have been obtained. When restricted to non-freshman, the Networking program has statistically significant effects on both retention and performance. Among non-freshmen, participation increases GPA from a predicted 2.76 to 2.93 and increases retention from a predicted 76% to 89%. The effect is not so pronounced as for freshmen since more non-freshman persist without any intervention. Among Black freshmen, participation increases GPA from a predicted 1.89 to 2.67

	Observed Coeff.	Bootstrap Std. Err.	Z	P > |z|	Predicted Non-Prog.	Prog.
Networking Program						
ATT (GPA)	0.2698	0.0408	6.62	0.000	2.689	2.959
ATT (Retained)	0.1924	0.0211	9.13	0.000	0.683	0.881
Networking Program on Freshman Students						
ATT (GPA)	0.5040	0.0821	6.14	0.000	2.535	3.039
ATT (Retained)	0.3313	0.0428	7.73	0.000	0.514	0.845
Networking Program on Non-Freshman Students						
ATT (GPA)	0.1699	0.0483	3.52	0.000	2.756	2.926
ATT (Retained)	0.1306	0.0232	5.62	0.000	0.759	0.896
Networking Program on Female Students						
ATT (GPA)	0.2965	0.0873	3.40	0.001	2.645	2.941
ATT (Retained)	0.2373	0.0476	4.98	0.000	0.596	0.851
Networking Program on Black Students						
ATT (GPA)	0.2788	0.0933	2.99	0.003	2.235	2.514
ATT (Retained)	0.2454	0.0469	5.24	0.000	0.154	0.337
Networking Program on Black Freshman Students						
ATT (GPA)	0.7829	0.2194	3.57	0.000	1.885	2.668
ATT (Retained)	0.4334	0.1105	3.92	0.000	0.450	0.884

Based on 500 Bootstrap replications resampling within treatment status using student ID to cluster. Reweighting with all covariates (indicators for Biology major and sophomore standing omitted) except project year. Exact matching on project year and freshman standing (where appropriate). Common support enforced: for the Networking program 5 out of 433 treated were excluded and 1960 out of 6173 untreated were excluded, for the Networking program restricted to freshmen we have 4 out of 137 treated excluded and 749 out of 1497 untreated excluded, for the Networking program restricted to female students 14 out of 143 treated were excluded and 1315 out of 2625 untreated were excluded, for the Networking program restricted to Black students 5 out of 131 treated were excluded and 992 out of 2258 untreated were excluded and for the Networking program restricted to Black freshmen 4 out of 35 treated were excluded and 437 out of 578 untreated were excluded,

Table 10. Results for the Networking Program Using Reweighting

	Observed Coeff.	Bootstrap Std. Err.	Z	P > |z|	Predicted Non-Prog.	Prog.
Research Award Program on Non-Freshman Students						
ATT (GPA)	0.1556	0.0721	2.16	0.031	2.981	3.137
ATT (Retained)	0.0791	0.0375	2.11	0.035	0.819	0.899
Travel Grant Program on Non-Freshman Students						
ATT (GPA)	0.1627	0.0777	2.10	0.036	2.991	3.153
ATT (Retained)	0.1140	0.0312	3.66	0.000	0.847	0.956
Learning Communities on Freshman Students						
ATT (GPA)	0.1473	0.1287	1.14	0.252	2.547	2.694
ATT (Retained)	0.2087	0.0674	3.10	0.002	0.549	0.755

Based on 500 Bootstrap replications resampling within treatment status using student ID to cluster. Reweighting with all covariates (indicators for biology major and sophomore standing omitted) except project year. Exact matching on project year and freshman standing (where appropriate). Common support enforced: for the Research Grant program on non-freshmen 1 student out of 89 treated was excluded but 3109 out of 4976 untreated were excluded, for the Travel Grant program on non-freshmen 9 students out of 97 treated were excluded and 3420 out of 4976 untreated were excluded, for the learning communities on freshmen 4 students out of 76 treated were excluded and 1017 out of 147 untreated were excluded.

Table 11. Results for the Remaining Programs Using Reweighting

and increases retention from a predicted 45% to 88%. The effect is to eliminate the racial disparity in retention rate amongst the treated students.

Of the 101 research grants made under the Research Award Program 53 were awarded to seniors, 30 were awarded to juniors, 14 were awarded to sophomores, and 4 to freshmen. Even when we consider the effect on all students the four freshmen students are dropped when enforcing common support. We therefore report results only for non-freshman students. There were thirteen students who each received two research awards and one student who received three awards. The 101 awards therefore represent 86 students supported. The Research Award program shows statistically significant effects on performance and retention. For non-freshmen participation increased GPA from a predicted 2.98 to 3.14 and retention from 82% to 90%. Without enforcing a common support an ATT (GPA) of 0.1582 and an ATT (Retained) of 0.0744 would have been obtained.

Of the 110 travel grants 60 were awarded to seniors, 29 were awarded to juniors, 10 were awarded to sophomores, and 11 were awarded to freshmen. For this reason, we again choose to report only the effect on non-freshman students. There were seven students who each received two awards. The 110 awards thus represent 103 students supported. The Travel Grant program shows statistically significant effects on performance and retention. For non-freshmen participation increased GPA from a predicted 2.99 to 3.15 and retention from 84% to 95%. Without enforcing a common support we would obtain an ATT (GPA) of 0.1661 and an ATT (Retained) of 0.1177.

The Learning Communities program targets incoming freshman students so our attention is restricted solely to freshman students (there were 3 non-freshman listed – possibly due to transfer credits from high school). The Learning Communities shows no statistically significant effect on performance but does produce a statistically significant increase in retention. Participation increased retention from a predicted 55% to 76%.

Though steps have been taken to be as rigorous as possible in our statistical analysis, there is no assurance that the observed differences are not, at least in part, attributable to some unobserved characteristic of the MemphiSTEP students. In particular, students who become involved in such a program are probably less likely to be employed off-campus or to be child-care providers. We currently have no means of tracking such background information, although the University's Center for Research and Innovation in STEM Teaching and Learning (CRISTAL) is looking into ways of gathering data about student characteristics (e.g., work and family commitments). Despite limitations on what is known about our students, it appears certain that the observed differences are not explained by differences in race, gender, major, or prior performance.

Discussion and Conclusion

Through extensive statistical analysis, there is strong evidence that the MemphiSTEP project is playing an important role in facilitating both STEM student performance and retention. Overall, it is estimated that participation in MemphiSTEP increased GPA by 0.21 and increased retention by 17%.

Importantly, the analysis pointed to the importance of MemphiSTEP programs for helping subgroups of students, particularly those most "at risk" from withdrawing from STEM. Our findings indicated that MemphiSTEP activities are highly effective for freshmen and Black students. We estimate that participation produced increases of 25% in retention and marked increases in GPA for students in both subgroups. For Black freshmen, participation increased GPA from a predicted 1.85 to 2.43 and increased retention from a predicted 44% to 81%.

In our analysis of individual programs all were found to positively impact retention. In particular, the Networking program was most effective in increasing retention. Moreover, the Bootcamp and Networking activities were particularly effective in facilitating retention in the "at risk" subgroups—freshmen and Black students.

All programs were shown to positively impact performance (GPA) though the increase for the Learning Communities was not statistically significant. Performance gains were most marked for at risk subgroups of students (freshmen and Black students) for the Networking program. It is perhaps surprising that the Bootcamp program did not produce a stronger effect on grades given that it is specifically aimed at academic support. One possible explanation for that is the broadness of both our measure of prior performance and our measure of GPA. Neither our prior performance measures nor our measure of GPA are STEM specific. We intend to reanalyze our Bootcamp data using the grade of the student in their first mathematics course taken after their participation in the Bootcamp.

Overall, our analysis indicates that STEM retention efforts, such as the programs forming MemphiSTEP, play an important role in bolstering retention and performance of STEM students, which likely impact STEM graduation rates. In line with previous research, our findings highlight the importance of networking in terms of supporting student success in STEM courses (Nasr, et al., 2004; Jaeger, et al. 2008).

The MemphiSTEP Networking program has gained considerable momentum and interest over the course of the MemphiSTEP grant. Attendance numbers have grown from about 10-20 students per activity in the first year of the project to around 100 per activity.

While many of the MemphiSTEP programs require significant funding, certain activities can be implemented at little cost (e.g., the Networking program), or can be a lasting part of the university structure (e.g., the learning communities).

It is our goal to sustain all MemphiSTEP activities beyond the life of the grant. In addition to the Networking program, which requires minimal funding, project personnel have developed a reduced length, lower cost model of the Bootcamp (piloted in August 2013) that has been institutionalized by the Department of Mathematical Sciences. Encouragingly, evaluation data indicate that the immediate learning outcomes from the reduced length Bootcamp were the same as for the two-week version. Learning communities have already been institutionalized and are part of the university infrastructure. Much of the infrastructure established for the Research and Travel Grant programs is now a part of the Center for Research and Innovation in STEM Teaching and Learning (CRISTAL). One of CRISTAL's roles is to connect STEM students and faculty with available grant opportunities and to coordinate interdisciplinary applications for grants related to STEM education.

In closing, the reported data will play a critical role in future plans for retaining and helping STEM students, particularly "at risk" subgroups at the U of M. For instance, we are aware of the importance of STEM undergraduate networking and will continue to be active in implementing networking activities. We also anticipate that our findings will be of key importance to other institutions taking steps to increase student success in STEM, especially among vulnerable groups (e.g., freshmen) at high risk of withdrawing from STEM majors. It is envisioned that other institutions may refer to the MemphiSTEP data to make decisions about (cost effective) ways of implementing activities that serve to retain students in STEM and promote performance in STEM courses.

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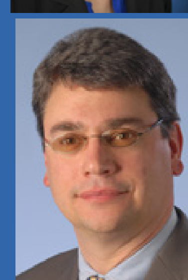

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