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These attributes may confer a comparative advantage to STEM students. The engineers have statistically significant differing response elasticities than the non-engineers, and show evidence of persistence that may arise from learning-by-doing. A successful engineering STEM major at Binghamton has good mathematics preparation, and disproportionately is of Asian ethnicity. Women are few in numbers as engineers. Other STEM fields see less emphasis on mathematics preparation, but more emphasis on the presence of AP course work. Women have the same presence in these other STEM fields as in the whole university.

Keywords

science, technology, engineering, math, STEM, Binghamton University, gender, race

Comments

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Who succeeds in STEM studies? An analysis of Binghamton University undergraduate students

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ABSTRACT

Using student level data, the characteristics of STEM and Non-STEM students are examined for attributes associated with academic success. We use fixed effects models to analyze the variables' role in attaining graduation and college GPA and find preparation and ability, as evidenced by Advanced Placement course work, mathematical ability, gender, ethnicity, high school GPA and college experience are all statistically significant indicators of success. These attributes may confer a comparative advantage to STEM students. The engineers have statistically significant differing response elasticities than the non-engineers, and show evidence of persistence that may arise from learning-by-doing. A successful engineering STEM major at Binghamton has good mathematics preparation, and disproportionately is of Asian ethnicity. Women are few in numbers as engineers. Other STEM fields see less emphasis on mathematics preparation, but more emphasis on the presence of AP course work. Women have the same presence in these other STEM fields as in the whole university.

1. Introduction

The question of academic success is important for American society and the apparent paucity of STEM students is of national concern. As an example, the number of undergraduate students earning a degree in engineering and engineering technologies has fallen about 16 percent over a twenty-year period (1985–86 to 2005–06). The first fifteen of these years saw a decline of 25%. But, the last five saw the number of degrees conferred in engineering and engineering technologies increase 12%, though the numbers did not reach the level of 1985–86. The decline was uneven when specific fields are considered. For example, Chemical and Civil Engineering had positive growth from 1985–86 to 1995–96. But from 1996–97 to 2001–02 all the engineering fields declined (National Academies, 2006; Snyder & Dillow, 2010; US Department of Education, 2009).

If one looks at the history of people who are successful in the arts such as music or dance, or one considers people who are successful in highly technical fields such as astrophysics, we find these individuals often had an interest in their area since early childhood or at the least, since middle school. So it should be no surprise that the successful students in STEM courses probably had an interest in STEM fields for many years before college. Is this early interest evidence of a comparative advantage? Or does this early experience provide learning-by-doing?

Following that line of thought, researchers have considered STEM precursors in K-12 schools. For example, various international surveys on high school students' science and mathematics performance are conducted (Baldi, Jin, Skemer, Green, & Herget, 2007; Gonzales et al., 2008).

However, less attention has been focused on the problem in higher education and the observed high drop-out

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rates from science and mathematics majors. Women and/or non-white students opt out of STEM majors at disproportionate rates. And US universities have not kept pace with rest of the world in the production of STEM graduates. Even though a young student's interest in a STEM career may start before she enters college or a university, it's the postsecondary education that creates the career path and prepares the student for work in a STEM occupation. Hence, it is important to analyze the university/college experience with STEM courses and the reasons for the high attrition rates from STEM majors.

Our paper examines the characteristics of STEM students at Binghamton University (State University of New York at Binghamton) and explores the differences between STEM students and Non-STEM students in an attempt to shed light on the question of academic success. We also test the validity of some of the hypotheses that have been offered to explain the gap between intended and completed STEM field majors. We must caution the reader that we have not found a clear answer to these questions, but we have found some things that are important including the differential of the correlates of a student's academic success in various STEM and Non-STEM fields.

In the following sections, we first consider some definitional issues, and next discuss STEM research. This is followed by a description of our model for subsequent econometric analysis. The fifth section is a description of Binghamton data and the sixth section gives the results of the econometric analysis. Finally, we discuss and conclude.

2. STEM students and academic success

The National Center for Education Statistics of the US Department of Education (2006) developed a definition of a STEM degree listing degree programs that include science, technology, engineering, or mathematics degrees. The National Science Foundation defines STEM fields more broadly and includes not only the common categories of mathematics, natural sciences, engineering, and computer and information sciences, but also social/behavioral sciences as psychology, economics, sociology, and political science. This classification issue is discussed in Chen and Weko (2009). We applied the first definition, eliminating the social sciences from our study. Using the Binghamton list of majors, we found 18 engineering majors and 34 other non-engineering STEM fields in which degrees were offered.

The definition of success is more difficult; grades, graduation rates, persistence, completion time, or time to degree are often used. Measures such as Grade Point Average (GPA)[2] and time to degree are relatively easy to measure, but persistence is not. A student may 'persist' in their quest for education and a degree at many campuses and schools over the course of many years. This may mitigate the perceived high drop-out rates. And the scientific and engineering communities have need for substantial numbers of support personnel such as lab assistants and technical writers. These may be provided from the ranks of those who formally drop out of STEM studies but are better trained individuals for their academic experience. We are not able to follow such a student or drop-out with our data and thus this issue is not addressed.

A further criticism of graduation or grades as a measure of a successful outcome is that they do not reflect the quality of the education of the student. The time students spend in exploring different majors and taking elective courses may better prepare them to be life-long learners and better citizens. From this perspective, measures of the educational output are the intelligence, the existence of a breadth of knowledge, understanding, their ability to adapt and learn on the job and thus become more productive, and personal satisfaction of the citizenry as well as their contribution to the commonweal.

We use both Grade Point Average and graduation rates as measures of success in this paper. We do note there are limitations to both; Bretz (1989), using Meta analysis, found success in a field is weakly related to GPA for some fields (e.g. teaching) but not related to success in most fields. Further, graduation rates are partially controlled by institutional characteristics, particularly funding. A good introduction to modern research on this issue together with a good bibliography is given in Calcagno, Bailey, Jenkins, Keens, and Leinbach (2008). Also see DesJardins, Kim, and Rzonca (2002–2003) and Braxton and Hirschy (2004, 2005). Many of the issues are identified in Habley and McClanahan (2004). Adelman (1999) is also useful.

Neither the use of grades nor that of graduation, considers variations in the length of a degree program. The idea of a traditional four-year degree program is not universal and this is relevant to STEM studies as many engineering and architectural programs are five years in length. Some other programs, such as three-two programs, where the student spends time in industry or some other field of study such as business, often require five years of study also. Finally, certification in some sub-field, employment, earnings subsequent to graduation, marriage, citizenship, and literacy are some further possible measures of success. There is some evidence that certification or its equivalent is useful in the STEM field of computers or information technology (Chen & Weko, 2009).

3. STEM research

Much of the literature of these metrics is descriptive and/or discusses the relationship among various student and institutional characteristics and the outcome. Baseline studies by Tinto (1975, 1982), ~~Bean (1980),~~ Pascarella and Terenzini (1991) and Astin and Astin (1992) omit the role of resources, other than student financial assistance (see Archibald & Feldman, 2008). Others like Kuh (2003) who conducted research into student engagement found most, if not all, of the educational engagement factors studied have significant financial implications for the institution. And work by Kokkelenberg, Blose, and Porter (2006) found that institutional expenditures, adjusted for types of majors, to be most important in helping students achieve timely graduation.

Very few studies analyzing university/college education of STEM use longitudinal data, but two recent, notable

[2] See Cohn, Cohn, Balch, and Bradley (2004).

studies are by Xie and Shauman (2003) and Ohland et al. (2008).[3] Xie and Shauman addressed the low participation of women in science fields by considering at the entire science career trajectory starting from high school and ending in doctoral degrees. They analyzed seventeen large datasets to assess the performance of high school students in science and mathematics considering the mean gender difference in mathematics and science achievement scores. They found the mean gender differences in scores to be small in magnitude, and there was no significant difference in mathematics and science scores of females compared to males. Continuing in STEM major or early entry (within first two years of baccalaureate education) into STEM major from a Non-STEM major was found to be the most important factor contributing to achieving baccalaureate degree in science. Late entry into a STEM major or re-entry into a STEM major (students who switched from a STEM major to a Non-STEM major and back to a STEM major) does not necessarily lead to a science degree. The rates of persistence of men and women in engineering majors were found to be similar and no significant differences existed among racial/ethnic groups even though the gender distribution of engineering majors is skewed more towards males.

Ohland et al. (2008) looked at engagement in an engineering major by analyzing the eight engagement metrics and six outcome scales from National Survey of Student Engagement (2006). Engineering majors were found to be no different from other major groups in terms of involvement in working on campus and time spent on various leisure activities. Substantial positive differences existed in terms of internships, experience, and involvement in research projects with faculty; and negative differences exist for those taking foreign language classes and participating in study abroad programs. They found that students who persisted in engineering majors disengaged from both liberal arts courses and other fields of engineering.

The question of persistence, engagement and migration (both in and out) in baccalaureate engineering programs is also addressed by Ohland et al. They proposed that engagement is a precursor to persistence. The focus of the paper was only on engineering programs and comparisons were made against students in other academic programs (which included STM programs) in terms of persistence in the major they matriculated in and staying on in the same university where they enrolled for the first time. The difference in the rates of persistence between the engineering major and the other academic majors was found to be small except that in-migration of students into engineering majors from other majors is very low compared to other majors who attract students away from engineering majors. Hence students who graduate in engineering are the ones who moved into it quite early on in their academic career, a result that was also found by Xie and Shauman and that we found as shown below.

Most research on factors determining persistence and graduation in engineering degrees point out that having an interest in engineering, science or mathematics is crucial to pursue a degree in engineering. Among those we note McCormack (2000–2009), Zhang, Anderson, Ohland, Carter, and Thorndyke (2004), Fleming, Engerman, and Griffin (2005), Eris et al. (2007), McCain, Fleming, Williams, and Engerman (2007), Alting and Walser (2007), and Kilgore, Atman, Yasuhara, Barker, and Morozov (2007). All appear to find that a long interest is a common trait of successful students.

Along with interest in STEM subjects, the kind of college experience an engineering student faces in the first two years of college was found to be very important as attrition rates among engineering students is high during the first two years. For example, see Brainard and Carlin (1997) who studied six hundred women students in six cohorts at the University of Washington. They found that perceived job outlook influenced persistence during the freshman year. It seems that the first two years in college play a significant role in helping a student focus more on engineering majors or to make a move away from such a major toward pursuing something else. The question of how students initially choose their major is addressed by Maple and Stage (1991), by Montmarquette, Cannings, and Mahseredjian (2002), and by Malgwi, Howe, and Burnaby (2005).

In summary, the vast research literature sheds much light on the nuances and identifies interesting and useful details. One of these is that early interest and continued experience in STEM work is advantageous. We test some of these findings, and extend some of this work, using Binghamton University longitudinal data.

4. Modeling college success

The basic model for tests of outcomes we employed is a fixed effects estimator. This model is specified as follows:

$$y^*_{itjh} = \alpha + x'^*_{itjh}\beta + \varepsilon^*_{itjh} \quad (1)$$

where i denotes the individual student, t denotes the academic level of the student, j denotes the course, and h denotes the high school of the student. We define

$$y^*_{itjh} \equiv y_{itjh} - \bar{y}_{h(i)},$$

$$x^*_{itjh} \equiv x_{itjh} - \bar{x}_{h(i)}, \text{ and}$$

$$\varepsilon^*_{itjh} \equiv \varepsilon_{itjh} - \bar{\varepsilon}_{h(i)}$$

Here $\bar{y}_{h(i)}, \bar{x}_{h(i)}$, and $\bar{\varepsilon}_{h(i)}$ are the average observations of the i-th individual student's high school, h, averaged over all observations for that high school in that year. Hence, y^*_{itjh} is the individual student's deviation from the mean of students from the relevant high school, etc. This is a fixed effects model that estimates intercepts for each high school. The dependent variable, y, denotes the undergraduate GPA at various stages of the college career, or the awarding of a degree. A vector of explanatory variables is denoted by x, and epsilon is an error vector.

This fixed effects method reduces heterogeneity that arises from such things as size and type of high school, area of the country, the social environment, the issue of varying academic and sports emphasis, and possibly, to some degree, the parental economic status. Importantly, it also attempts to address the role of differential high

[3] A slightly older one is Brainard and Carlin (1997).

Table 1
Characteristics of Binghamton students 1997 through 2007 March 2, 2010.

	Number of degrees awarded	Average SATV	Average SATM	HS average	Number of AP hours credit	Percent female	Percent Black	Percent Hispanic	Percent Asian	Average final GPA
All	24251	571.1	614.1	91.69	4.48	54%	4%	5%	14%	3.22
Median		575.6	620.0	91.85	0.00	100%	0%	0%	0%	3.25
Engineers	604	563.2	638.4	91.75	2.68	13%	1%	3%	16%	3.07
Median		570.0	640.0	91.74	0.00	0%	0%	0%	0%	3.05
Non-Eng. STEM	1267	565.7	624.6	92.16	4.31	51%	5%	3%	18%	3.16
Median		570.0	630.0	92.10	0.00	100%	0%	0%	0%	3.18
Chemistry	82	546.0	626.0	92.09	3.80	49%	6%	1%	26%	3.18
Median		540.0	633.6	92.13	0.00	0%	0%	0%	0%	3.16
Economics	803	551.2	614.1	90.99	2.76	37%	2%	4%	26%	3.04
Median		550.0	620.0	91.10	0.00	0%	0%	0%	0%	3.05
English	1049	581.0	582.8	90.97	2.88	71%	5%	6%	9%	3.30
Median		590.0	580.0	91.18	0.00	100%	0%	0%	0%	3.31

school guidance counselors. Anecdotal evidence suggests that K-12 schools and school districts or systems devote different levels of resources to guidance activities with some providing minimal mandated efforts and others meeting prospective college students and their parents even as much as monthly for their last three years of high school. The fixed effects model should accommodate this suspected important variation in the intercept term.

A number of hypothesis concerning STEM majors preparation and success can be tested with this model. We tested the following hypothesis: 1. Correlates of successful outcomes as measured by GPA or degree awarded do not vary between STEM and Non-STEM majors; 2. STEM majors and Non-STEM majors do not differ in preparation, gender, or ethnicity; 3. The Instructor's gender makes no difference; and 4. STEM courses have higher grading standards and this is discouraging to students. The above tests might weakly reveal some insight into the hypothesis that by the time students enroll as undergraduates, many have developed some comparative advantage for a specific discipline and the ancillary hypothesis that the opportunity costs of changing majors post matriculation is high.

Several other hypotheses were also tested but we found many of these tests to yield inconclusive results because of the absence of sufficient observations. For example, we looked at how the ethnicity of the faculty was related to the drop-out rate but such data on faculty ethnicity are only collected for recent years and the drop-out rates were strongly related to grades making such tests inconclusive. Several other hypotheses we attempted to test included: students' interests are awakened by introductory courses; a lack of preparation for STEM work; and AP courses may build over-confidence. The tests we were able to devise with the data we had in hand for these also were inconclusive and we can neither sustain nor challenge these hypothesis.

5. Binghamton data

The data for Binghamton University was provided by the Office of Institutional Research at Binghamton and was garnered from various administrative and student records. The Data consists of 926,759 observations at the student-course level for 176 variables, and covers 1997 Fall Term through 2007 Spring Term. There are over 44,000 individuals or subjects.

The summary characteristics of Binghamton students in this data set who were awarded a degree are given in Table 1. Data is provided for all Binghamton students, engineers, other STEM students, chemistry students (a STEM field), economics and English. These last three are for illustrative purposes with Economics being considered a hard grading Non-STEM Department and English an easy grading Non-STEM Department.[4] Engineers have lower verbal SAT scores than the school average, higher mathematics SAT scores, comparable high school averages, and present fewer AP credits when they enroll. Engineers have a higher percentage of Asian students but lower percentages of Blacks and Hispanics and a far lower percentage of women (13 percent versus 54 percent) than the school as a whole. The average and the median values are quite close for nondemographic variables; the most notable exception is gender where women dominate the English discipline. We have found that about 50 percent of the incoming engineering majors switch out of engineering. There are virtually no Binghamton students who switch from some other field into engineering. This may be because the engineering programs precede lock step through a curriculum leaving little room for electives and the STEM courses build upon each other in the sequence and this observation is consistent with the literature cited above. In short, Binghamton STEM students exhibit characteristics common to those of many other schools.

In brief, Binghamton engineers present lower ability scores (except for math) than other STEM graduates, are more likely to be transfer students, and graduate fewer women and non-Asian minorities. Both engineers and non-engineers as graduates experience a considerable reduction in numbers from those initially intending to be a STEM student.

But non-engineering STEM graduates have profiles quite close to that of the Non-STEM student in all of the

[4] As would be expected, English majors excel in verbal SAT scores, and women account for 71 percent of the English majors, almost 1.5 times higher than in the whole school and over 5 times more than in engineering. The final GPA is of interest with the English majors having a much higher final GPA than various STEM groups or Economics.

dimensions presented except attrition from major. Consider the fields of biology, chemistry, and physics. We use data for the freshman cohorts, 1997 to 2003 and map how these students proceeded through their college career (Appendix). The first result is that while 16,380 students took a course in one of these fields, only 1803 declared one of these three fields to be their major. Thus, Binghamton appears to have few STEM majors, but many STEM courses that are taken by Non-STEM students to fulfill distribution requirements. This is compounded as the engineering school also requires course work in mathematics, chemistry and physics, again increasing the distributional loading in these STEM departments.[5]

The second point is that only 46–60 percent of these who declared one of these majors graduated in that field. One conclusion is that Binghamton students have a high rate of attrition from non-engineering STEM courses. A second observation is that many of these STEM courses are probably fulfilling educational distributional requirements in the main; only 873 students over eight years of entrants or five point six percent of the students who initially declared one of these three fields as their major, graduated in that major.[6]

But the third and most important point is that AP work is consistent with graduation in a STEM field. A higher percentage of those who graduate in any of these three majors had AP work in that field when compared to the percentage of graduates from the group with no AP work. This is possibly an indication of comparative advantage or learning-by-doing for these graduates.

6. Econometric results

Our paper tests if STEM majors have different correlates of graduation rates (a binary variable, 1 for graduation and 0 for non-graduation within six years of entering the university) and correlates of GPA (a continuous variable in the range 0–4), compared to the correlates for the Non-STEM majors. It does so with respect to the following explanatory variables: SAT verbal Score, SAT mathematics score, high school GPA, advanced placement grades, fulltime or part-time status, gender, and ethnicity.

6.1. Fixed effects models

We first investigated the issue of success by denoting GPA as the dependent variable for all Binghamton students ($n = 44{,}045$). Using a fixed effects model[7] in SAS (we repeated much of our work in STATA where we obtained the same results), we tested a version of Eq. (1). There are two models presented in Table 2 differing in the number of explanatory variables. Model 1 includes the issuance of a bachelor's degree, "Rec'vd Degree", and is the better model in terms of fit.[8] The inclusion of the degree variable is justified on both an econometric basis and a statistical basis: it adds a way to partition the sample into successful students (attained a degree) and those who have as yet to achieve success and it is a statistically significant dimension. All of the estimators are statistically significant by a t-test statistic. We found women do better than men (coefficient is the second largest in value at 0.139), entering as a freshman is advantageous as is prior ability indicated by SAT and AP scores. Blacks, Hispanics and Asians are at a disadvantage, and STEM students have lower GPAs. The basic difference between the results of Model 1 and Model 2 are that allowing for the issuance of a degree reverses the negative sign on the correlation between GPA and STEM majors (engineers and non-engineering STEM). We interpret this to mean that of all students, STEM students do better (Model 2) but when allowing for the attainment of a degree, STEM students have a lower GPA than Non-STEM graduating undergraduate students.

Similar results to those reported above and below were obtained over a variety of model specifications, some of which included high school grades, full versus part-time students, and parental income as explanatory variables, and some of which explored non-linear models. The results were not substantially enhanced and the conclusions are the same.

We next ran parallel fixed effects analysis for STEM students and a breakdown of these into non-engineering and engineering STEM students. These results are given in Table 3. In these cases, the degree variable was insignificant so the runs shown did not include that explanatory variable. In all of these STEM results, the relative size of the estimators is about the same. However, the correlation between women and GPA weakens and becomes statistically insignificant as we look at more detail. In other words, the advantage women hold as shown in Table 2 disappears when we partition the data into different major STEM groups. The negative correlation between GPA and the ethnic groups is weakened as the estimators become less significant in the partitioning between engineers and other STEM. Prior ability as denoted by the SAT and AP variables continues to be strongly correlated with success in non-

[5] The Watson School of Engineering at Binghamton University requires four specific mathematical courses, two specified Physics courses and one specified chemistry course.

[6] The Harpur College Bulletin states; "Harpur students must complete additional requirements designed by Harpur College of Arts and Sciences to compliment and extend the general education requirements and further their liberal arts education. These requirements include: two courses in the Division of Humanities, two courses in the Division of Science and Mathematics, two courses in the Division of Social Sciences, and an additional four liberal arts courses chosen from each of the two divisions outside the division of the student's major department."Harpur College is the College of Liberal Arts and Sciences at Binghamton University and it is the largest college by far at that University.

[7] Initially, we tried to analyze many issues using a Tobit procedure. We then looked at grades using ordered Logit, but were not certain the data met the proportionality assumption and indeed, there is evidence that the data probably violated this assumption (see Kokkelenberg, Dillon, & Christy, 2008). Thus, we used a fixed effects model.

[8] While the differing number of observations makes a strict comparison via log likelihood Chi squared test uncertain, as the sample size approaches infinity, the likelihood ratio approaches Chi squared and this forms the basis for an approximate statistical test. In our case, the differences in the sample size are 0.63%, 44,324 versus 44,045 observations. The less restricted model is better by a Chi squared test; the calculated value is 12,535 whereas the critical value is about 8 for one degree of freedom at the 99.5% confidence level.

Table 2
Fixed effects model for all Binghamton students 1997 through 2007 dependent variable is last observed cumulative GPA fixed effect is high school.

Variable	Model 1			Model 2		
	F value of test of fixed			*F* value of test of fixed		
	Estimate	*T*-statistic	Effects	Estimate	*T*-statistic	Effects
Intercept	2.301	107.09		2.577	114.09	
Freshman	0.012	2.68	7.2	0.008	1.67	2.8
SAT verbal	0.0004	16.11	259.5	0.0003	10.49	110.1
SAT math	0.0004	13.08	171.1	0.0003	10.1	102.1
AP credits	0.015	44.00	1935.7	0.016	44.73	2000.8
Female	0.139	32.89	1081.5	0.165	36.78	1353.0
Non-engineering STEM degree	−0.056	−4.37	19.1	0.101	7.67	58.8
Engineering degree	−0.086	−4.72	22.3	0.082	4.32	18.7
Black	−0.192	−19.03	362.0	−0.208	−19.34	374.0
Hispanic	−0.129	−13.65	186.4	−0.158	−15.70	246.5
Asian	−0.071	−11.47	131.5	−0.058	−8.83	77.9
Receivd degree	0.337	79.72	6354.6			
N	44045			44324		
Log likelihood	50996.7			57264		

engineering STEM courses, though SAT, both Mathematics and Verbal, become statistically insignificant for engineering students, while AP work continues to be important.

The results of a further parallel fixed effects analysis for all Non-STEM students were explored and we found that all the estimators with the exception of that for freshman in Model 2 are significant, and the results are basically the same as above; ability is important, women do better, and ethnic groups are negatively correlated with GPA (See Table 4).

One of the chief conclusions from this analysis is that after allowing for the student's background as proxied by the high school (the fixed effect), ability, as proxied by SAT scores and AP credits, is important regardless of discipline in terms of final GPA. Any advantage that women have is confined to the Non-STEM fields, and Blacks, Hispanics, and Asians do not do as well as other ethnic groups.

6.2. *Declaration of major*

Most STEM tracks at Binghamton require a fairly lock-step series of courses be taken. At any level of the student's career, he or she must take certain specified courses to prepare them for the next level of study, and enrollment in certain upper division level courses is restricted to those with the prerequisites and frequently to department majors. Hence it is important that a student follow the proscribed path of study and declare their major early in their career. Yet the evidence is that Non-STEM students often wait until their junior year to declare, the exception being Economics Majors who must be a declared major to register for many courses. We thus looked at the initial declaration of major to test how important this is by running comparative fixed effects models to investigate the factors that correlate with getting an engineering degree and a non-engineering STEM degree. These results are discussed next, and are shown in Tables 5 and 6.

In Table 5, we report the correlation of the initial declaration of a major with the receipt of an engineering degree as the dependent variable. While the explanatory variables are for the most part the same as those reported above, here we include the student's choice of first and second major as added explanatory varibles. Using the log likelihood value, we see the regression with the inclusion of first major

Table 3
Fixed effects model for all Binghamton STEM students non-engineering STEM students engineering STEM students 1997 through 2007 dependent variable is last observed cumulative GPA fixed effect is high school (FE) Model 2.

Effect	All STEM			Non-engineering STEM			Engineering STEM		
	Test of FE *F* value			Test of FE *F* value			Test of FE *F* value		
	Estimate	*T*-statistic	Type 3	Estimate	*T*-statistic	Type 3	Estimate	*T*-statistic	Type 3
Intercept	2.556	24.89		2.429	19.74		2.775	15.08	
Freshman	0.032	1.47	2.15	0.093	3.41	11.66	−0.083	−2.31	5.36
SAT verbal	0.0003	3.00	9.02	0.0005	3.27	10.68	0.0001	0.44	0.19
SAT math	0.0005	3.59	12.87	0.0006	3.56	12.65	0.0004	1.68	2.81
AP credits	0.013	*111*	60.37	0.011	5.82	33.88	0.015	4.06	16.5
Female	0.060	3.11	9.67	0.027	1.20	1.45	0.066	1.29	1.67
Black	−0.109	−2.16	4.68	−0.093	−1.77	3.12	−0.302	−2.07	4.29
Hispanic	−0.101	−1.89	3.57	−0.103	−1.66	2.74	−0.094	−0.93	0.87
Asian	−0.060	−2.39	5.72	−0.070	−2.35	5.54	−0.035	−0.76	0.57
Number of FE	581			481			295		
N	1871			1267			604		
Log likelihood	1917.3			1262.1			683.9		

Table 4
Fixed effects model for all Binghamton Non-STEM students 1997 through 2007 dependent variable is last observed cumulative GPA fixed effect is high school.

Variable	Model 1			Model 2		
	F value of test of fixed			*F* value of test of fixed		
	Estimate	*T*-statistic	Effects	Estimate	*T*-statistic	Effects
Intercept	2.300	104.85		2.581	111.57	2.36
Freshman	0.012	2.53	6.4	0.008	1.54	101.72
SAT verbal	0.0004	15.87	251.8	0.0003	10.09	92.47
SAT Math	0.0004	12.63	159.4	0.0003	9.62	1939.40
AP Credits	0.015	43.3	1874.6	0.016	44.04	1363.20
Female	0.142	33.05	1092.3	0.169	36.92	368.20
Black	−0.195	−18.89	357.0	−0.212	−19.19	242.90
Hispanic	−0.130	−13.48	181.8	−0.160	−15.58	71.00
Asian	−0.072	−11.19	125.1	−0.058	−8.44	52.35
Receivd degree	0.337	79.37	6299.5			
N	42,250			42,453		
Log likelihood	49,175			55,298		

Table 5
Fixed effects model for all Binghamton engineering STEM students 1997 through 2007 dependent variable is awarding of degree fixed effect is high school correlation of initial declaration of major with engineering degree receipt.

Variable	*F*-statistic	*P* value	*F*-statistic	*P* value	*F*-statistic	*P* value	*F*-statistic	*P* value
Freshman	3.95	0.0470	11.27	0.0008	4.51	0.0336	7.07	0.0078
SAT verbal	6.44	0.0112	73.56	<0.0001	6.18	0.0129	82.7	<0.0001
SAT math	21.76	<0.0001	87.73	<0.0001	23.51	<.0001	111.55	<0.0001
AP credits	7.48	0.0062	38.1	<0.0001	9.27	0.0023	66.19	<0.0001
Female	97.68	<0.0001	850.98	<0.0001	97.72	<.0001	886.98	<0.0001
Black	1.87	0.1720	9.39	0.0022	1.63	0.2018	7.16	0.0075
Hispanic	0.97	0.3241	3.38	0.0661	0.91	0.3408	3.21	0.0730
Asian	11.35	0.0008	13.61	0.0002	12.57	0.0004	25.57	<0.0001
First major ENG	40048.30	<0.0001			39896.60	<0.0001		
Second major ENG			3571.03	<0.0001			3550.90	<0.0001
Second major Non-ENG STEM					25.45	<0.0001		
First major Non-ENG STEM							404.67	<0.0001
N	24,251		24,251		24,251		24,251	
Log likelihood	−20394.7		−83.9		−20411.4		−476.3	

choice as engineering is the best explanatory model. Thus, students who graduate as engineers, start their academic career by majoring in engineering. Students who graduated in non-engineering STEM fields have a weaker correlation with declaring engineering as their first or second major. In other words, the non-engineering STEM students do not, on average, seem to be engineering students who switched majors to some other STEM field. Similar tests and results for non-engineering STEM students are reported in Table 6; the initial declaration of a non-engineering STEM major

Table 6
Fixed effects model for all Binghamton non-engineering STEM students 1997 through 2007 dependent variable is awarding of degree fixed effect is high school.

Effect	*F*	Pr > *F*	*F*	Pr > *F*	*F*	Pr > *F*		Pr > *F*
Freshman	58.88	<.0001	64.12	<.0001	63.68	<.0001	59.67	<.0001
SAT verbal	3.59	0.0581	5.57	0.0183	3.15	0.0758	12.22	0.0005
SAT math	23.71	<.0001	70.87	<.0001	26.78	<.0001	94.60	<.0001
AP credits	153.26	<.0001	298.46	<.0001	154.24	<.0001	327.24	<.0001
Female	7.59	0.0059	0.70	0.4038	3.93	0.0474	23.65	<.0001
Black	1.05	0.3063	0.70	0.4039	1.03	0.3099	0.30	0.586
Hispanic	1.64	0.1999	0.78	0.3774	1.93	0.1645	1.37	0.241
Asian	11.39	0.0007	78.82	<.0001	11.39	0.0007	84.07	<.0001
First Maj Non-STEM	36365.10	<.0001			36328.80	<.0001		
Second Maj Non-STEM			3739.29	<.0001			3673.35	<.0001
Second Maj ENG					66.19	<.0001		
First Maj ENG							371.42	<.0001
N		24,251		24,251		24,251		24,251
Number of FE		1788		1788		1788		1788
Log likelihood		−5910.9		12823.8		−5969.7		12463.1

Table 7
Elasticities of response cumulative GPA Response to a one percent increase in explanatory variable.

Explanatory variable	All students	Non-STEM students	All STEM students	Non-engineering STEM	Engineers
Freshman	0.012	0.009	0.036	0.090	−0.066
SAT verbal	0.243	0.259	0.169	0.000	−0.006
SAT math	0.210	0.179	0.467	0.001	0.569
AP credits	0.066	0.062	0.094	0.012	0.090
Female	0.133	0.140	0.104	0.066	0.101
Black	−0.197	−0.201	−0.157	−0.163	−0.214
Hispanic	−0.133	−0.139	−0.070	−0.087	−0.053
Asian	−0.068	−0.076	−0.030	−0.052	0.003
nengstem	−0.040				
eng	−0.095				

is strongly correlated with receiving a degree in a non-engineering STEM field. These findings are consistent with, but not conclusive concerning the existence of dedication, persistence, and possibly of a comparative advantage for these STEM students.

6.3. Elasticities

Elasticities as response percentages of mean cumulative GPA based on these models and data are reported in Table 7. The change in response of cumulative GPA for all students, Non-STEM students, and STEM students are shown. STEM students' grades were more responsive to the variable of having entered as freshman, more responsive to better mathematics scores and more responsive to reported AP course hours, than were Non-STEM students. The difference between engineers and other STEM students is also shown. A one percent change in mathematics scores results in a 0.569 percent change in graduation grades for engineers, but a very small, almost nonexistent, result for non-engineering STEM students. Again, it appears engineering STEM students need to concentrate on mathematics skills and not verbal ones.

6.4. Gender issues

We were able to test the conclusion of "Mathematical Self-Concept: How College Reinforces the Gender Gap," Sax (1994) that found the prevalence of female students on campus improves the mathematical confidence among female students enrolled in mathematics courses. We tested this for Biology and Mathematics courses using the dichotomous variable of "received an A" or "did not receive an A" as the dependent variable. A variable that was percentage of female students enrolled in a specific course of interest was introduced across all course levels in a regression model and was found to be significant and positive for sophomore level mathematics courses, but negative for junior level courses. In other words the percentage females in a class was beneficial in terms of a grade of A for sophomore mathematics classes, but not for other levels. Similar results were found for the grades of A minus, B plus, B and B minus.

An Interaction term of the percent female students variable together with a term denoting the gender of instructor was not found to be significant in all cases except in beginning Biology where the relationship was negative (see Table 8).

Therefore there is evidence of a gender peer effect; having more females in a class, improves a female student's individual performance in a class. We caution that the reason behind this peer effect could be that female students perform better than male students, as the gender of the student variable is often significant and positive in other studies (Polachek, 1978; Kokkelenberg et al., 2006, 2008). But, even though having female faculty, and though the female students generally having better grades, the joint effect of these two variables was not found to be statistically significant in our tests.

The reader should note that we only investigated grades which are but one of the products of college education and even if female instructors do not provide extra encouragement or better results for female students when it comes to grades, they may provide other forms of encouragement such as counseling and career advice that are not captured in our study.

Finally, having more female students in a specific class helps the grades of all the females in that class. Gender peer

Table 8
Influence of percent female in class and gender of instructor in biology and mathematics courses all students earning grade of A.

Variable	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Course level	400		300		200		100	
Biology courses								
Number of observations	1065		2741		360		1966	
Instructor gender	−0.070	0.030	0.006	0.019	0.155	0.245	−0.051	0.023
Percent female	0.227	0.087	−0.041	0.066	0.300	0.171	0.217	0.123
Math courses								
Number of observations	715		2909		3342		1088	
Instructor gender	0.062	0.059	0.010	0.025	0.026	0.015	0.021	0.039
Percent female	0.038	0.117	−0.259	0.078	0.673	0.086	0.165	0.149

Table 9
Correlation of STEM and Non-STEM AP exams taken with receipt of engineering degree, non-engineering STEM degree, or any STEM degree.

Variable	Engineers			Non-engineering STEM			Any STEM		
	Estimate	*T*-statistic	*F* value of test of fixed effects	Estimate	*T*-statistic	*F* value of test of fixed Effects	Estimate	*T*-statistic	*F* value of test of fixed effects
Intercept	−0.006	−0.54		−0.098	−6.96		−0.099	−5.82	
Freshman	0.005	2.21	4.9	0.026	7.87	61.96	0.030	7.56	57.15
SAT verbal	0.000	−1.18	1.39	0.000	4.64	21.5	0.000	2.88	8.29
SAT math	0.000	4.06	16.45	0.000	4.71	22.19	0.000	6.5	42.25
STEM AP	0.009	6.26	39.14	0.023	11.94	142.55	0.033	14.19	201.4
Non-STEM AP	−0.006	−4.43	19.63	−0.003	−2.02	4.09	−0.009	−4.51	20.36
Female	−0.020	−9.59	91.94	0.007	2.34	5.46	−0.015	−4.46	19.88
Black	−0.007	−1.46	2.14	−0.009	−1.33	1.77	−0.017	−2.06	4.25
Hispanic	−0.004	−0.9	0.8	−0.008	−1.23	1.52	−0.013	−1.55	2.4
Asian	0.009	2.96	8.74	0.010	2.54	6.45	0.020	4.11	16.93
First major ENG	0.768	198	39203.8						
2nd major Non-ENG STEM	−0 026	−5.3	28.05						
1st major Non-ENG STEM				0.759	189.67	35,974			
2nd major ENG				−0.086	−8.54	73			
1st major STEM							0.738	177.49	31504
N	24,251			24,251			24,251		
Log likelihood	−20441.5			−5953			3198		

effect was found to be significant for Biology and Mathematics courses, i.e. having greater percentage of women in a class will raise the average performance of the class (except for 300 level mathematics courses). Again there are a complex possible set of causes generating this result which needs further study.

6.5. AP work, persistence and comparative advantage

The next model includes the number of AP credits as one of the explanatory variables. Specifically, this is the total number of credits reported by a student once he or she declares the AP exams were taken and the respective grades on them are known. A student can take AP exams in STEM fields-physics, biology, mathematics, chemistry, statistics, and computer science and also in Non-STEM fields-Literature, history, music, psychology, art studio and economics. The number of STEM AP exams and Non-STEM AP exams reported may show past interest or disinterest in STEM fields and evidence of prior training in a discipline. To explore the correlation between the of number of STEM and Non-STEM AP exams taken and the choice of major, the regression model for major choice (attainment of a degree is the dependent variable) is modified to include two new explanatory variables in place of the AP credits variable. The two new explanatory variables are STEM AP that equals the number of STEM AP exams reported by the student, and Non-STEM AP that equals the number of Non-STEM AP exams reported by the student. These two variables were significant in the degree choice models with opposite signs (See Table 9). Taking a larger number of STEM AP exams is associated with an increased chance of graduating with an engineering or non-engineering STEM degree. The opposite results hold if a larger number of Non-STEM AP exams are taken. We interpret this as an indication that interest in STEM fields may start at the high school level which inspires a student to take more STEM AP related courses and eventually graduate with a STEM degree from college. It also is consistent with a hypothesis that certain STEM-destined students have a comparative advantage in STEM work and this is exhibited by appropriate AP work. Such work is also consistent with the idea of learning-by-doing. Sadly, we cannot disentangle this further with our data.

A further result from this analysis shown in Table 9 is that the successful STEM majors, whether engineering or non-engineering STEM, initially declare their major to be in the field in which they finally receive their degree.

We next looked at all students who declared engineering as their first major choice and who then received a bachelor's degree. We further separated this group into those who graduated with an engineering degree and those who received a degree in some other field, STEM or Non-STEM. We decided that a regression using cumulative GPA as a dependent variable was not useful as it is well known that engineering grades harder than most other disciplines. Hence, we looked at the characteristics of these two groups and these results are presented in Table 10. There we show the mean of the ability variables together with a Satterthwaite test of the significance for the difference between the two means.[9]

The relative ability variables are all higher for those who received an engineering degree in terms of the means, and the means are statistically significantly different from each other with the only exception of the verbal SAT scores. This is consistent with a comparative advantage or with learning-by-doing, but may also be the result of some other cause.[10] Hence those who persist in engineering declare it as their first major and have better ability credentials compared to those who switch out of engineering.

[9] This test requires that the samples are assumed to be independent, but may not have the same variance and is thus the Satterthwaite approximation of the degrees of freedom of the *t*-test.

[10] This may be also interpreted as evidence of persistence but that term begs the question of why persistence may exist whereas comparative advantage and learning-by-doing may be the ultimate cause of persistence.

Table 10
Satterthwaite test of equality of means of ability of all graduates who declare engineering as first major.

Ability metric	Degree awarded in engineering mean	Degree awarded in non-engineering mean	Satterthwaite test statistic	
			t-Test	Pr > |t|
Math SAT	647	635	−2.73	0.0070
Undergrad cumulative GPA	3.14	3.04	−4.37	<0.0001
No. of AP credits	5.80	4.52	−3.36	0.0008
No. of STEM AP credits	0.81	0.63	−3.01	0.0027
Verbal SAT	563	568	0.95	0.3440

6.6. Other results

Finally, we looked at the possibility that STEM fields grade harder and this discourages continuation in these fields. It has been suggested that academics in STEM fields see their role, in part, to weed out the less motivated and the incompetents and do so more strongly than academics of other fields. Teachers of STEM courses do not see a societal good in inept designers of vehicles, bridges, and manufactories. Hence, they challenge applicants to be motivated and competent. This would result in higher grading standards and practices in STEM fields, which is a testable hypothesis and indeed we found evidence of this differential grading. But we cannot link this statistically as causal of excessive drop-outs. So the answer is yes, the average grades are lower for STEM courses but this is difficult to relate to the encouragement or discouragement of students. It is well known that Economics Departments grade harder than English Departments, yet there are majors in both fields, and the drop-out rates are not as severe as those of STEM fields but we have no measure of encouragement in this case either.

7. Discussion and conclusion

The attributes of a successful STEM major at Binghamton can be summarized briefly. Engineers who have good mathematics preparation, who declare and enter engineering as freshmen, or transfer in with prior STEM work, and are of Asian ethnicity have better chances of success. Women are few in numbers as engineers. All other STEM fields see less emphasis on mathematics preparation, but far more on the presence of any advanced placement course work, and are not as rigorous in a lock-step program necessitating freshman entry. Women also seem to have the same presence in these other STEM fields as they do in the whole university.

After reviewing the rates at which students change majors, it is evident that these rates are varied. If we partition students into two groups, STEM and Non-STEM, we find differential rates of changing from either to the other with very few students embracing a STEM major after starting out as a Non-STEM student (similar to engineers). But the rate of switching out of a STEM field is high, over 50% in some of our data. This may be a rough measure of the opportunity costs of switching majors; high to switch into a STEM field and low to switch out of STEM work. Measures of this are beyond the scope of this paper.

Hence, we postulate that success in a STEM field, success here defined as declaring STEM as a major and graduating from a STEM field, accrues to those who have been interested and studying and working in STEM fields from high school or even possibly earlier. Both the existence of a long-term interest in STEM fields and prior middle and high school experience with STEM work are consistent with the development of a student's comparative advantage and/or with learning-by-doing in STEM work. Our data only allows us to test this very weakly using the presence of high school AP credits as evidence of early commitment to studying a STEM field. Again, we caution that this does not allow us to conclude with any certainty that either a comparative advantage exists nor that there exists considerable learning-by-doing.

There are several issues that remain untested, issues that may be important. These include the early life experiences of a student, the effect of peers, and the career outlook. Inspiration for STEM interest can come from various scientific toys, such as chemistry sets and *Legos*, from middle school science fairs,[11] and from family and neighbor role models. Peer effects can come from various levels of school and include dorm mates, Greek Houses, clubs, athletics, summer school, siblings and other relatives, and work. The perceived job outlook for most pre-college and for many undergraduates is based on anecdotal evidence until they see a placement officer at their college. Such things as expected income, working conditions, geographic location, and opportunities are only slowly developed but they may influence the choice of major. Our models also may mis-measure several complex variables such as drop outs as students switch colleges, do not measure idealism, and are functionally specified as log-linear in variables.

Future work to answer the question of why there is such a large drop-out rate from STEM majors nationally probably should consider survey methods to elucidate the answers from a large sample of students, faculty, and K-12 teachers and counselors; econometrics alone may be less useful given the data limitations we now have about the motivations to enter STEM, the possible existence of comparative advantage, the issue of learning-by-doing, and the many possible reasons for success.

Indeed, we think the question to address about STEM students is better phrased as "Why do students select and excel in STEM studies?" rather than "Why do the other students drop out?"

Appendix A.

[11] Economist, Technology Quarterly, June 12–18, 2010. p25.

2 Disposition of non-engineering, non-math STEM students, number of students or percent.

Field	Declare as first major	Declare as second major	Declare as third major	Presented no AP work: Took a course in this field	Presented no AP work: Graduates in this major	Presented no AP work: Percent of those who took a course	Presented AP work: Took a course in this field	Presented AP work: Graduates in this major	Presented AP work: Percent of those who took a course
Biology	1336	122	3	3947	443	11.2	1251	237	53.4
Chemistry	209	46	4	4809	103	2.1	542	51	9.4
Physics	17	39	26	5141	28	1.6	690	11	1.6
Totals	1562	207	33	####	574	12	2483	299	12

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