Undergraduate Women in Science and Engineering: Effects of Faculty, Fields, and Institutions Over Time*

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Objective. Taking an institutional approach to the determinants of outcomes for women in science and engineering, we examine the effects on women’s percentages among undergraduate majors and among degree recipients of four basic factors: (1) the percentage of faculty who are women in the students’ major science/engineering area; (2) the students’ disciplines (biology, physical sciences, and engineering); (3) the type of institution in which students are enrolled (“Research I” vs. others); and (4) a time trend (1984–2000). Method. We use longitudinal, multivariate, and multi-institutional data from the Integrated Postsecondary Data System (IPEDS) and from a mail survey of registrars. Results. Over the observation period, the women’s percentages have risen steadily. The effects of disciplines and departments are stronger than those of institutions. Especially notable is that the percentages of women among undergraduate science/engineering majors and degree recipients are associated with the percentages of women among the faculty in these fields. Conclusion. The findings contribute empirically to the discussion about the effects of “role models” for the participation and performance of women in science and engineering—and point to the strong effects of departments, compared to institutions, in accounting for degrees awarded to undergraduate women.

Science and engineering are strategic research sites in the study of gender, education, and careers. First, science and engineering are crucially important for modern society. They are connected to powerful social institutions, particularly to the government and to the economy, and they have broad and deep consequences for the present and future in areas including health and healthcare, communication and data banks, consumer goods, transportation, irrigation, energy, pollution, and environmental controls (Fox, 2006; Sonnert and Holton, 2002). Science and engineering careers thus play an

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increasingly pivotal role in the overall workforce, and the size as well as the composition of the science and engineering workforce are focal concerns for the government, businesses, and the media.

Further, career paths in science/engineering are characterized by gender divisions in participation, ranks, and rewards that have tended to favor men compared to women (Long and Fox, 1995; Sonnert and Holton, 1995a, 1995b). These gender divisions in science and engineering are important to understanding processes of social inequality, as well as to devising potential means toward greater gender equity in education, professional employment, and rewards, not only within science and engineering, but also in society broadly. This is because, as critical and powerful institutions, science and engineering both reflect and reinforce levels of gender equity or inequity in society (Fox, 1999).

Undergraduate education, specifically, is crucial to understanding—and influencing—gender imbalances in science/engineering because this educational phase strongly shapes the composition of the science/engineering workforce. The undergraduate level of education is acknowledged to be the “latest point” for a standard entry into science/engineering fields (Xie and Shauman, 2003:96). This contrasts with many fields outside of science, which may be entered and pursued from both a wider range of educational backgrounds and at later stages in the lifecourse.

Women’s participation as undergraduate majors and degree recipients in science and engineering is thus an important area of analysis. Although women have been entering these fields in growing numbers over the past two decades, especially, women are still relatively rare among majors and degree holders outside the social, behavioral, and life sciences. This has been well documented, for example, by the periodic statistics compiled by the National Science Foundation and by the Commission on Professionals in Science and Technology on degrees awarded in science and engineering by field and gender over time (National Science Board, 2006; Commission on Professionals in Science and Technology, 2004:Tables 2-72, 2-73). For instance, in the United States between 1983 and 2002, the percentage of women among bachelor recipients in biology rose from 46.4 percent to 61.0 percent; in the physical sciences, the percentage increased from 28.5 percent to 42.7 percent; and in engineering, it went from 13.3 percent to still only 20.9 percent (National Science Board, 2006:Appendix Table 2-26).

Statistics of this kind have tended to present national averages. In this article, we provide a complementary perspective by looking at the representation of undergraduate women at individual institutions and departments. We present a quantitative assessment of the effects of institutions and departments on the participation of college-level women in science and engineering. These local situations are far from uniform and vary by institutions and departments; in turn, they are susceptible to practices and policies, including leadership exercised, to support significant participation and performance of women in scientific fields (Fox, 2000).
The dearth of women in most sciences and in engineering has increasingly been perceived as a public policy problem, both in terms of underutilizing talent and human resources and of perpetuating gender inequities (Hanson, 1996; Pearson and Fechter, 1994). An extensive literature has examined the causes of the persisting underrepresentation of women in science and engineering, attributing the underrepresentation to a complex set of factors, including: (1) social constructions of what is regarded as appropriate work for women, and thus issues of social and gender identity; (2) an educational “pipeline” that starts early in life and forms a sequence of study; (3) perceived barriers for women in science, compared to other fields; and (4) inequitable resources and opportunities offered to women compared to men in both education and employment in science/engineering (Fox, 1999:445).

Two major ways of thinking about women in science and engineering can be described as a matter of “individual issues” versus “institutional issues.” From the individual perspective, the status of women in science and engineering is attributed to, or thought to correspond to, women’s individual characteristics, such as attitudes, behaviors, aptitudes, skills, performance, experience, race, and socioeconomic status (Cronin and Roger, 1999; Dryburgh, 1999; Fox, 1998; Ong, 2005; Sonnert and Holton, 1995a, 1995b). From the institutional or structural perspective, the status of women in science and engineering is attributed to factors beyond individual characteristics, that is, to features of the settings in which women are educated and in which they work, such as available resources, patterns of interaction, and the type of institution, including a single-sex compared to co-ed environment (Cronin and Roger, 1999; Fox, 1995, 1996, 1998, 2001; Frehill, 1997; Robinson and McIlwee, 1989; Seymour and Hewitt, 1997; Sharpe and Fuller, 1995; Sonnert and Holton, 1995a, 1995b). A research tradition, pioneered by Kanter (1977a, 1977b), has pointed to the particular importance of gender proportions in organizational contexts.

Without claiming to provide a full analysis of all relevant factors influencing the representation of women among science and engineering undergraduates, we examine some key institutional determinants of the percentage of women among majors and among bachelor’s recipients. This reflects a perspective of institutional/structural factors as they influence women’s status in science/engineering. The specific research questions addressed are these: What are the effects on the women’s percentage among majors and among degrees awarded of: (1) the percentage of faculty in their major area who are women; (2) the students’ discipline (distinguishing the fields of biology, physical science, and engineering); (3) the type of institution (distinguishing between Research I institutions and other institutional types); and (4) a time trend (from 1984 through 2000)?

In assessing trends over time, using individual departments and institutions as units, this study goes beyond the limits of data collected at a single time point and in national aggregate, and it represents the longitudinal,
multivariate, multi-institutional analyses that have been relatively absent—and needed—in research on gender and outcomes among undergraduates in science and engineering (Astin and Sax, 1996:101). An increase in the overall percentage of undergraduate women in science and engineering has been observed over a few decades, in parallel with a general societal trend of women’s increasing participation in a variety of occupations. Such an increase cannot go on forever, of course, and the question is when and where the levels will stabilize (or even start an inverse trend). At issue then is the shape of the trajectories of women’s percentages both nationally and at the department level. Are the percentages of women rising steadily, or are there signs of new trends? If so, will the percentages eventually stabilize in a broadly defined band of gender equity, or will some disciplines pass a tipping point beyond which they will undergo rapid “feminization” in the sense of becoming overwhelmingly female? (Or might, at some point, the levels begin to drop?) Thus, we examine the type of increase (linear vs. nonlinear) and the differences between fields.

Addressing variation by fields of sciences and institutional types is important because “women in science” is not a single, monolithic concern but rather a complex issue of “where” and in which types of settings and fields women do or do not attain participation and performance (Fox, 1995). The differences between fields (in terms of the representation of women) have historically been large, with higher percentages of women in life sciences, and lower percentages in physical sciences (especially physics) and engineering. In other words, considerable gender segregation has existed by field. The question is whether these differences show any signs of attenuation over time.

Further, as to types of institutional settings, prior research in the mathematical sciences has indicated that women students have tended to congregate in the less prestigious types of institutions of higher education (Sharpe and Sonnert, 1999). Thus, in addition to gender segregation between fields, gender segregation has existed within a field, such that women have tended to be somewhat marginalized in less prestigious positions and work settings. We examine whether this is the case also in our study of undergraduates in biological and physical sciences and engineering.

Finally, the question of the relationship between the percentage of women among undergraduate majors and among degree recipients and the percentage of women faculty in departments is particularly important to address with actual institutional data. This is because, typically, studies on issues of “role modeling” (a presumed benefit bestowed by the presence of female faculty on women students) have not used data on percentages of students and faculty. Rather, they have asked women students about their “perceptions” of a range of factors (including women faculty) that may contribute to their career aspirations (see, e.g., Basow and Howe, 1980; Betz and Fitzgerald, 1987; Gilbert, 1985; Hackett, Esposito, and O’Halloran, 1989; Smith and Erb, 1986; Stake and Noonan, 1985; Stenta et al., 1994).
Exceptions to such methods of inference are the studies by Bettinger and Long (2005) across fields that are more, and less, technical and quantitative; Canes and Rosen (1995) across fields; Rothstein (1995) across fields, including humanities, social sciences, and sciences/engineering; and Sharpe and Sonnert (1999) of mathematical sciences.

Xie and Shauman (1997) point out two slightly divergent theories about the factors that influence women’s choice of an occupation. One school of thought emphasizes the importance of concrete individuals, such as peers, teachers, and parents, who might act as role models or supporters. The other school focuses on pervasive effects of the gender composition of occupations and the resulting perceptions of the gender appropriateness of occupations. Both approaches would expect a higher percentage of female faculty to be associated with a higher percentage of female undergraduate students.

Method

Data

Institutional-level data on student and faculty participation in science and engineering were collected from the Integrated Postsecondary Data System (IPEDS online) and through a survey of registrars for 499 U.S. universities and colleges. These data were collected for measures within three disciplinary areas—biology, physical sciences, and engineering—for the period between 1984 and 2000.

In this article, these disciplinary areas are referred to as “fields,” even if the actual organizational structure at many of the institutions does not correspond explicitly to those fields. For instance, the “physical sciences” often consist of several departments (e.g., a department of chemistry and a department of physics), and “engineering” might be organized as a “faculty” or “school” or a “college.” In instances when “field” might obfuscate the fact that we are referring to fields nested within particular institutions, we use the term “department,” again in a generic sense.

The institutions included were selected according to the following plan. All institutions in the “Research I,” “Research II,” “Doctoral I,” and “Doctoral II” categories of the Carnegie classification in use before 2000 were included. Within the large Masters Degree Granting (MAI) and Associate Degree Granting (AA) categories, the selection procedure was based on the existence of programs for undergraduate women students in science and engineering because those programs were important to the overall focus of the larger research project in which the data were collected. In these categories of the Carnegie classification, we matched the institutions with programs to institutions that were similar in institutional control (public/private) and urbanization (large city/midsize city/small town) of the community in which the institution was located. If the categories thus
determined were still too large to survey them fully—which occurred in the public/midsize, private/midsize, and public/small town groups—we selected the 40 institutions that matched the target program institution most closely in size of student population. This plan resulted in 499 institutions (45 institutions with programs, and 454 institutions without programs) in the study.

We collected data on the number of male and female students enrolled as majors in the biological sciences, physical sciences, and engineering, using the Integrated Postsecondary Education Data System (IPEDS) for the years available online. At the time these data were collected in 2000/2001, on-line data were available, specifically, for the number of male and female students enrolled as majors in 1994, 1996, 1998, and 2000. For the number of male and female students completing undergraduate degrees, we obtained IPEDS on-line data for all institutions in 1989–1990, 1994–1995, and 1999–2000. For the program institutions, we collected IPEDS data for all years from 1989–1990 through 1999–2000. Data on numbers of full-time tenured and tenure-track faculty at institutions in these years, 1984–2001, were not available online.

Thus, in 2001, a survey of registrars in the 499 institutions was conducted to obtain data on the number of male and female students enrolled, and the number completing undergraduate degrees, in biological sciences, engineering, and physical sciences for years in which these data were not available online; and to obtain the number of full-time tenured and tenure-track male and female faculty in the same fields, by year. For the number of students enrolled as majors, the survey covered all years from 1984 through 2000 that were not available through IPEDS (i.e., all years except 1994, 1996, 1998, and 2000). For the number of degree recipients, the survey covered all years from 1984–1985 through 2000–2001 for which we did not have IPEDS data (i.e., all years except 1989–1990 through 1999–2000) in the case of program institutions. In the case of nonprogram institutions, the survey obtained data for 1984–1985 (in addition to the IPEDS data for 1989–1990, 1994–1995, and 1999–2000). The survey furthermore asked for the number of male and female faculty for all years from 1984–1985 through 2000–2001 for the program institutions, and for 1984–1985, 1989–1990, 1994–1995, and 1999–2000 for nonprogram institutions. In conducting this survey, the registrars were identified in the published Membership Guide of the American Association of Collegiate Registrars and Admissions Officers; and all names/addresses were verified for accuracy using the websites for each of the 499 institutions. The mail survey was conducted in up to four timed waves of mailing with followups to those who had not responded initially (Dillman, 2000).

The response rate for institutions with programs was 51 percent. Response rates for institutions without programs were: 51 percent among Research I institutions; 37 percent among Research II institutions; 59 percent among Doctoral I institutions; 46 percent among Doctoral II institutions; 52
percent among MAI-I institutions; 41 percent among MAI-II institutions; 35 percent among MAI-III institutions; 30 percent among MAI-IV institutions; and 50 percent among AA institutions. The resulting number of respondents to the survey was 197 (45 percent response rate overall, after removing ineligibles \((N = 59)\) from the base). Combining IPEDS and our own survey data, we obtained 9,275 data points on majors, 4,835 data points on bachelor recipients, and 1,803 data points on faculty.

In sum, as far as IPEDS data were available, the data set was virtually complete and represented the population under study, rather than a sample. For the additional data, we conducted a survey of registrars, where, as is usual, rates of nonresponse, and hence missing values, existed, as described above. For a rough estimate of potential bias in who responded and who did not, we predicted the two outcome variables (percentage of women among undergraduate majors and among bachelor degree recipients) by the main independent variables (see descriptions below) and a dummy variable indicating response or nonresponse. The response variable made very little difference when added to the other independent variables (the women’s percentages were slightly lower: \(-0.16\) percent for majors (nonsignificant) and \(-1.3\) percent for bachelors \((p = 0.02)\)). In neither case did the addition of interactions of the response variable with all other independent variables make any statistically significant difference.

The analytical method chosen (hierarchical modeling) has the advantage that it is very robust concerning missing values. In addition, a method to estimate missing values by multiple imputation was applied (see below). This method would mitigate potential response bias, although, in light of the above response-bias analysis, one would expect only small, if any, differences between the two methods.

The data constitute a large part of the population under study, and if the missing values are estimated by multiple imputation, they represent the population. Hence, strictly speaking, this is not a case for the application of inferential statistics, but significance levels will be used as a pragmatic guideline for assessing the strength of observed associations.1 Normal probability plots for relevant regression models indicated that the residuals approximated a normal distribution.

Variables

**Dependent Variables.** Two dependent variables are used in these analyses. The first dependent variable (**MAJOR**) is the percentage of women among undergraduate majors in biological sciences, physical sciences, and engineering

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1Although there has been some debate about the appropriateness of significance testing when populations are studied, it is a common and widely accepted practice (Bollen, 1995; Leahey, 2005).
The second dependent variable (BACHELOR) is the percentage of women among bachelor degree recipients (1984–2000). Having these two dependent variables (MAJOR and BACHELOR) in conjunction permits an indirect glimpse at the issue of differential attrition by gender over the course of undergraduate science education. If women, on aggregate, tended to drop out of science or engineering majors at higher rates than men, one would expect the percentage of women to be lower among bachelor degree recipients than among majors.

Independent Variables. Four independent variables are used in these analyses. The first (CYEAR) is a centered time variable (in years). Instead of centering the time variable on the beginning of the observed time period, which is usually done, for example, starting the period under consideration with “Year 0,” we have centered it on the end, that is, on the year 2000 (CYEAR = YEAR – 2000). Because the slope term becomes zero in 2000, the intercept can be immediately interpreted as the value of the outcome variable in the year 2000, thus focusing attention on the current situation.

The second independent variable (FACULTY) is percentage of women among faculty in a particular field and year.

The third variable (FIELD) is a three-level categorical variable (biology, physical sciences, engineering). In the analyses, it is represented through two dummy variables (biology and physical sciences), with engineering as the absent “baseline” category.

The fourth variable (CARNEGIE) is based on the “older” Carnegie classification of institution type, in use before 2000. The dummy variable created distinguishes between Research I universities and all other types of institutions.

Issues of Analysis

Before reporting the findings, it is important to consider four issues in these analyses. The first concerns a linear compared to a nonlinear, specifically logistic, approach. Second is the issue of missing data, and an advanced way of dealing with it. Third is the methodological approach of using hierarchical modeling or multilevel analysis, as it applies to these data. Fourth is a description of the six basic diagnostic models employed as initial probes into the data.

Logistic Versus Linear Models. The two dependent variables, MAJOR and BACHELOR, are percentage variables and have a floor (0 percent) and a ceiling (100 percent) beyond which they cannot move. Therefore, a case could be made that a logistic growth model, with its S-shaped growth curve
asymptotically approaching 0 and 100, theoretically would be more appropriate than a linear model with its straight line. Nonetheless, a linear approach could be applied in this article. Whereas a ceiling effect can be immediately ruled out, the women’s percentages appear high enough, even at the beginning of our observation period, to disregard a floor effect. Inspection of the data showed that, within our observation period of about 15 years, the trajectories for the outcome variables looked remarkably linear. Furthermore, as a widely used rule of thumb, linearity can be assumed if the standard deviation of the dependent variable is larger than the standard deviation of the residuals, which was indeed the case here. All this prompted us to use the linear model, with its greater simplicity in interpretation.

The observed linearity of the time trends is also a substantive finding. We are still in the phase of relatively linear increases in the percentages of women undergraduates in science and engineering. It remains to be seen when and how this pattern will change.

**Missing Values.** In multivariate analysis, the standard procedure for dealing with missing values is to exclude the whole observation (case) even if only one variable has a missing value for that observation. This often leads to a considerable reduction in number of cases for analysis, and to a substantial loss of information because all the data from incomplete observations are discarded. In our data set, too, there are missing values, owing to nonresponse (e.g., in the non-IPEDS years). An advanced statistical method of dealing with missing values is that of “multiple imputation” (Rubin, 1976, 1987, 1996), and we used it in parallel to the standard analysis. This approach replaces each missing value with several plausible values that represent the uncertainty about that missing value. This leads, in turn, to the creation of several data sets—each of which is complete, but differs from the others in the values that have replaced the originally missing values. Each of these data sets is then subjected to the desired statistical procedures, which, of course, produce somewhat different parameter estimates in each case. In the last step, the different parameter estimates are combined to produce final estimates with appropriate standard errors (see Allison, 2002).

To carry out the multiple imputation method on the computer, we used PROC MI and PROC MIANALYZE in the 8.2 release of SAS. The former procedure creates several data sets by multiple imputation; the latter procedure combines the statistical results obtained for each imputation into the final results.

Because we are dealing with longitudinal data, imputations were performed for both the multiple-variable and the multiple-observation formats. Thus, we first produced five imputations in the multiple-variable
format, then converted each of these imputed data sets into the multiple-observation format, and finally produced another five imputations on each of the converted data sets. Hence, we had a total of 25 imputations that were then combined to arrive at the final estimates. Results for the multiple imputation procedure are shown in italics in Table 2, next to the results for a standard analysis (in which incomplete observations were deleted).

**Multilevel Data Structure.** In our data, repeated measurements over time (Level 1) of departments (Level 2) are nested within institutions (Level 3). This particular data structure suggests the adaptation of the statistical method called multilevel analysis or hierarchical modeling into a longitudinal framework.\(^3\) The structure of the data can be mathematically expressed in the following model, which contains the dependent variable MAJOR and only one independent variable, representing a linear time trend (CYEAR). (The following reasoning applies analogously also to the second dependent variable, BACHELOR.) Separate equations are written for each level in order to highlight how the higher-level equations specify coefficients in the lower-level equations.

**Level 1: Time Varying**

\[
\text{MAJOR}_{ijk} = \pi_{0ik} + \pi_{1ik} \text{CYEAR}_{ijk} + e_{ijk}
\]

**Level 2: Departments**

\[
\begin{align*}
\pi_{0ik} &= \gamma_{00k} + \xi_{0ik} \\
\pi_{1ik} &= \gamma_{10k} + \xi_{1ik}
\end{align*}
\]

**Level 3: Institutions**

\[
\begin{align*}
\gamma_{00k} &= \delta_{000} + \xi_{00k} \\
\gamma_{10k} &= \delta_{100} + \xi_{10k},
\end{align*}
\]

where \(e_{ijk} \sim N(0, \sigma_e^2)\) and

\[
\begin{bmatrix}
\xi_{0ik} \\
\xi_{1ik}
\end{bmatrix} \sim N\left(\begin{bmatrix}
0 \\
0
\end{bmatrix}, \begin{bmatrix}
\sigma_0^2 & \sigma_{01} \\
\sigma_{10} & \sigma_1^2
\end{bmatrix}\right)
\]

and

\[
\begin{bmatrix}
\xi_{00k} \\
\xi_{10k}
\end{bmatrix} \sim N\left(\begin{bmatrix}
0 \\
0
\end{bmatrix}, \begin{bmatrix}
\sigma_0^2 & \sigma_{01} \\
\sigma_{10} & \sigma_1^2
\end{bmatrix}\right).
\]

\(^3\)This analytical approach mainly follows Singer and Willett (2003).
When we substitute, the model becomes:

\[
\text{MAJOR}_{ijk} = \delta_{000} + \xi_{00k} + \zeta_{0ik} + (\delta_{100} + \xi_{10k} + \zeta_{1ik})\text{CYEAR}_{ijk} + \varepsilon_{ijk},
\]

and we see that the percentage of women majors at department \(i\) in institution \(k\) at time \(j\) is composed of an intercept component \((\delta_{000} + \xi_{00k} + \zeta_{0ik})\), a slope component \([(\delta_{100} + \xi_{10k} + \zeta_{1ik})\text{CYEAR}_{ijk}]\), and an error term specific to department and occasion \(\varepsilon_{ijk}\). The intercept and the slope coefficients each contain a grand mean (the \(\delta\)'s), a mean that is specific for each institution and varies randomly across institutions (the \(\xi\)'s), and a mean that is specific for each department and varies randomly across departments (the \(\zeta\)'s). For this model, note that terms for individual departments affect the intercept \(\zeta_{0ik}\) and the slope \(\zeta_{1ik}\), and that terms for individual institutions—going through two substitutions—also affect the intercept \(\xi_{00k}\) and the slope \(\xi_{10k}\).

At each of the levels, the appropriate independent variables can be added to this structure. FACTULTY is a Level-1 variable (time-varying variable). A Level-2 variable (a variable that characterizes departments) is FIELD. A Level-3 variable (a variable that characterizes institutions) is CARNEGIE.

Basic Diagnostic Models. The framework developed above may or may not fit the actual data. For diagnostic purposes, we estimate three unconditional means models (UM1, UM2, UM3) and three unconditional growth models (UG1, UG2, UG3) (see Table 1 for MAJOR and Table 3 for BACHELOR). The results from these simple models provide some basic insight into the structure of the data.

The first model (UM1) serves to partition the outcome variation across departments. It shows where the main variation occurs—within or between departments. The unconditional growth model (UG1), in addition, partitions the outcome variation within departments into the effect of time and the remaining within-department variation. This indicates whether a linear time trend exists in the percentage of women majors. UM2 and UG2 do the same, respectively, with the institution, rather than the department, as the unit. UM3 includes both the departmental and institutional levels, and UG3 partitions out the effects of institutions, departments, and time. Notice that UG3 is the model described above in Equations (1) and (2).

Findings

To begin, it is important to examine the results of the diagnostic probes in order to choose an appropriate model for the subsequent analysis.
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<td>()</td>
<td>(0.0356)</td>
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<td>In rate of change, INST</td>
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<tr>
<td>$\sigma^2_1$</td>
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<td>0</td>
<td>0.07586**</td>
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<td></td>
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<td>()</td>
<td>(0.03531)</td>
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<tr>
<td>Covariance, DEPT</td>
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<tr>
<td>$\sigma_{01}$</td>
<td>5.65***</td>
<td></td>
<td>5.63***</td>
<td></td>
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<tr>
<td></td>
<td>(0.57)</td>
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<td>(0.58)</td>
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<td>Covariance, INST</td>
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<tr>
<td>$\sigma_{01}$</td>
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<td>0.93</td>
<td>-0.3497</td>
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<td></td>
<td></td>
<td>(0.59)</td>
<td>(0.56)</td>
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</tbody>
</table>

**Goodness of Fit**

- Deviance (-2LL)
  - UM1: 64976.3
  - UM2: 78632.1
  - UM3: 64976.3
  - UG1: 61854.6
  - UG2: 78276.4
  - UG3: 61842.4
- AIC
  - UM1: 64982.3
  - UM2: 78638.1
  - UM3: 64982.3
  - UG1: 61866.6
  - UG2: 78286.4
  - UG3: 61858.4
- BIC
  - UM1: 64998.2
  - UM2: 78650.7
  - UM3: 64994.9
  - UG1: 61908.5
  - UG2: 78307.4
  - UG3: 61892.1
- N
  - UM1: 9,275
  - UM2: 9,275
  - UM3: 9,275
  - UG1: 9,275
  - UG2: 9,275
  - UG3: 9,275

**Notes:** Standard errors in parentheses. Significance levels: $\sim p<0.10$; $p<0.05$; **$p<0.01$; ***$p<0.001$. 

**TABLE 1**

Basic Diagnostic Models for MAJOR (Percentage of Women Among Undergraduate Majors)
Basic Models for Undergraduate Women’s Percentage Among Majors

In UM1, the average percentage of women majors across all departments ($\gamma_{00}$) is estimated at 40.2 percent. Both the within-department and between-department variances are highly significant ($p < 0.0001$). As one would expect, individual departments vary over time, and they differ from each other in women’s percentage among majors. However, the intra-class correlation coefficient is 0.89,\(^4\) indicating that differences between departments contribute 89 percent of the total variation in the percentage of women majors, and thus dwarf the differences that occur within departments over time.

When we estimate UM2, the unconditional means model on the basis of institutions (rather than departments), a very similar figure obtains for the grand mean (41.1 percent), as one would expect. However, the examination of the variances reveals a radically different picture—and thus justifies the strategy of estimating these simple models first. Here, the intra-class correlation coefficient is only 23 percent, indicating that the differences within institutions by far outweigh the differences between institutions. Although both variance components are highly significant, this casts some doubt on the initially hypothesized model structure, and those doubts are confirmed by the third model (UM3), which includes both the departmental and institutional levels. In this model, the variance structure was not regular because no variance could be attributed to the institution.\(^5\) Hence, we find that institutions are a negligible source of variance in this type of model.

UG1 (the first of our unconditional growth models) introduces a linear time variable. In this model, the average percentage of women majors across all fields in 2000 ($\gamma_{00}$) is estimated at 43.9 percent. We also estimate that this percentage has been increasing by 0.8 percent every year.

Comparing UG1 with UM1, we find that the inclusion of the time trend reduces the within-department variation ($\sigma_i^2$) by 38.6 percent. Thus, more than a third of the variation within departments is accounted for by the inclusion of a linear time trend.

In UG2, no variance could be attributed to the institutional rate of change.

UG3 includes both the departmental and institutional levels, in addition to the time-varying level. As one might already expect from the results of UM3 and UG2, this model had no regular variance structure for the institutional intercept.

These results lead to the conclusion that a three-level hierarchical model structure is not viable. Interestingly and importantly, what appears to matter for the percentage of women among undergraduates is the department, whereas the institution has no additional significant impact. A two-level structure (with the longitudinal and the departmental levels) is sufficient,

\(^4\) The intra-class correlation coefficient is defined as $\rho = \frac{\sigma_i^2}{\sigma_b^2 + \sigma_i^2}$.

\(^5\) The estimated G matrix was not positive definite.
and will be used in subsequent analyses. The Level-3 variable, **Carnegie**, indicating an institution’s Carnegie classification, will be treated as a Level-2 variable.

### Main Effect Models for Majors

We created a variety of two-level models with various combinations of main effects and interactions. (**Faculty** was treated as a fixed effect.) The relevant models are presented in Table 2. In this table, the results based on the multiple-imputation method of handling missing values are listed next to the results obtained in the ordinary way. Through multiple imputation, many more data points (from 2.1 times to 12.4 times as many) become available for analysis. Overall, the similarity between the two sets of results is striking. In the following discussion, we use the results obtained by the standard method, but we note where the newer method of multiple imputation brought about divergent findings (in terms of the respective significance levels).

Model A indicates a significant effect of **Faculty** ($p < 0.0001$): the percentage of women among faculty predicted the percentage of women among majors. The size of this effect was rather small, however. When the percentage of women faculty increases by 10 percent, the percentage of women majors is expected to increase by 1.2 percent. Owing to the statistical power of the analysis, even such a minor effect can become highly significant.

Model B shows the huge effect of **Field**. The estimated percentage of women among engineering majors in 2000 is only 21.5 percent. By contrast, the corresponding number for female biology majors is 59.8 percent, and the percentage for women with majors in the physical sciences is between these two extremes (42.4 percent).

Adding **Carnegie** as a main effect made no significant difference, and neither did its interaction with the time trend; thus this variable was dropped from further consideration (models not shown).

### Interaction Models

The following models probe for the existence of interactions between the variables. Whereas there was no significant interaction between **Faculty** and **Field** (not shown), both **Faculty** and **Field** interacted with the time variable (Models C and D, respectively). The final model (Model E) includes all main effects, plus the interactions between the percentage of women faculty and time, and between field and time. The first interaction indicates that the growth trajectory of the percentage of female undergraduate majors was somewhat steeper in the presence of a larger percentage of women faculty. This again underscores the importance of the presence of women on the
### TABLE 2
Predictors of the Percentage of Women Among Undergraduate Majors and Among Bachelor Degree Recipients

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
<th>Model D</th>
<th>Model E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>40.60***</td>
<td>43.13***</td>
<td>21.47***</td>
<td>19.26***</td>
<td>18.13***</td>
</tr>
<tr>
<td>CYEAR</td>
<td>0.7428***</td>
<td>0.7103***</td>
<td>0.8091***</td>
<td>0.6317***</td>
<td>0.3013***</td>
</tr>
<tr>
<td>FACULTY</td>
<td>0.1175***</td>
<td>0.0294 ~</td>
<td>0.1286***</td>
<td>0.0580*</td>
<td>0.0528*</td>
</tr>
<tr>
<td>FIELD Biology</td>
<td>38.31***</td>
<td>36.68***</td>
<td>37.81***</td>
<td>36.40***</td>
<td>40.82***</td>
</tr>
<tr>
<td>Physical sciences</td>
<td>20.95***</td>
<td>18.87***</td>
<td>20.34***</td>
<td>18.81***</td>
<td>23.19***</td>
</tr>
<tr>
<td>CYEAR x FACULTY</td>
<td>0.01434***</td>
<td>0.00319*</td>
<td>0.01414***</td>
<td>0.00317*</td>
<td>0.009697*</td>
</tr>
<tr>
<td>Deviance (–2LL)</td>
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<td>60477.4</td>
<td>10132.4</td>
<td>10108.9</td>
<td>10103.1</td>
</tr>
<tr>
<td>AIC</td>
<td>10800.3</td>
<td>60493.4</td>
<td>10152.4</td>
<td>10130.9</td>
<td>10127.1</td>
</tr>
<tr>
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<td>60535.9</td>
<td>10193.4</td>
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<td>10176.3</td>
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<td>1,598</td>
<td>19,873</td>
<td>9,275</td>
<td>19,873</td>
<td>1,598</td>
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TABLE 2—continued

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>34.89***</td>
<td>39.62***</td>
<td>19.23***</td>
</tr>
<tr>
<td>CYEAR</td>
<td>0.4595***</td>
<td>0.5342***</td>
<td>0.5906***</td>
</tr>
<tr>
<td>FACULTY</td>
<td>0.3625***</td>
<td>0.0603</td>
<td>0.1337***</td>
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<tr>
<td>FIELD</td>
<td></td>
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<tr>
<td>Biology</td>
<td>35.31***</td>
<td>34.70***</td>
<td>34.01***</td>
</tr>
<tr>
<td>Physical sciences</td>
<td>17.79***</td>
<td>15.69***</td>
<td>17.62***</td>
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<tr>
<td>Deviance (– 2LL)</td>
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<td>37969.3</td>
<td>12441.3</td>
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<tr>
<td>N</td>
<td>1,671</td>
<td>19,873</td>
<td>1,671</td>
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</table>

Notes: Results from multiple-imputation approach in italics. Significance levels: \( p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001 \).
faculty for outcomes among undergraduate women students. The latter interaction, showing that the rates of increase are different by field, is particularly interesting. Whereas the percentage of women engineering majors has been increasing by an estimated annual rate of only 0.3 percent, biology and the physical sciences each had estimated annual rates that were about three times that high. The level of women’s participation among undergraduate majors is highly uneven by field, and these disparities have been growing over time.

The following divergences between the ordinary and multiple-imputation analyses were found. In the multiple-imputation approach, the percentage of women among the faculty played less of a role than in the regular approach (the coefficients were consistently smaller than in the regular models and, in most cases, only marginally significant). Moreover, departments at Research I institutions, on average, had a somewhat lower expected percentage of women among the majors than did departments at other types of institutions (that expected difference was only 1.4 percent, but statistically significant).

**Undergraduate Women’s Percentage of Degrees Received**

The second dependent variable is the percentage of women among the bachelor recipients in science and engineering. The analysis of BACHELOR paralleled that of MAJOR. Hence, we can go to the major findings without revisiting the rationale for our analysis (see Table 3 for basic models). As was the case for MAJOR as the dependent variable, UM3, UG2, and UG3 of the BACHELOR models did not generate valid results, indicating that the departmental level was by far more important than the institutional level in terms of influencing the outcomes for the percentage of bachelor’s degrees awarded to women in science and engineering. Nonetheless, the effect of the institution on degree recipients was stronger than the effect of the institution on majors, which can be gauged from the intra-class correlation coefficient in UM1 (0.67) being lower than its counterpart for MAJOR (0.89). This may indicate that the institution, while exerting very little impact on students’ choice of major, had at least a somewhat stronger effect on the final outcomes in degrees received.

In the unconditional growth model UG1, the average percentage of women bachelor recipients across all departments in 2000 ($g_{00}$) was estimated at 42.7 percent. Also estimated was that this percentage had been increasing by 0.7 percent every year during our observation period.

By comparing UG1 with UM1, we found that the inclusion of the time trend reduced the within-department variation ($\sigma^2_e$) by 23.0 percent. Thus, almost a quarter of the variation in women’s percentage of undergraduate degrees received within departments is accounted for by a linear time trend—which is less than the corresponding figure for the percentage of
TABLE 3

Basic Diagnostic Models for BACHELOR (Percentage of Women Among Bachelor Degree Recipients)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>UNcondition Means</th>
<th>UNcondition Growth</th>
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<td>DEPT, INST</td>
<td>DEPT, INST</td>
<td>DEPT, INST</td>
<td>DEPT, INST</td>
<td>DEPT, INST</td>
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<tr>
<td>Fixed Effects</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>γ₀₀</td>
<td>38.0084***</td>
<td>38.5624***</td>
<td>38.0084***</td>
<td>42.6779***</td>
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<tr>
<td></td>
<td>(0.5151)</td>
<td>(0.4762)</td>
<td>(0.5151)</td>
<td>(0.5866)</td>
<td>(0.5393)</td>
</tr>
<tr>
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</tr>
<tr>
<td>Intercept</td>
<td>γ₁₀</td>
<td>0.7124***</td>
<td>0.6220***</td>
<td>0.7394***</td>
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<tr>
<td></td>
<td>(0.04409)</td>
<td>(0.05642)</td>
<td>(0.05316)</td>
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<tr>
<td>Variance Components</td>
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</tr>
<tr>
<td>Within-dept./institution</td>
<td>σₑ²</td>
<td>126.08***</td>
<td>323.25***</td>
<td>126.08***</td>
<td>97.0479***</td>
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<tr>
<td></td>
<td>(2.93)</td>
<td>(6.91)</td>
<td>(2.93)</td>
<td>(2.83)</td>
<td>(2.85)</td>
</tr>
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<td>In mean/end status, DEPT</td>
<td>σ₀²</td>
<td>258.69***</td>
<td>258.68***</td>
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<td>298.03***</td>
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<tr>
<td></td>
<td>(12.65)</td>
<td>(12.64)</td>
<td></td>
<td>(16.70)</td>
<td>(16.92)</td>
</tr>
<tr>
<td>In mean/end status, INST</td>
<td>σ₀²</td>
<td>61.34***</td>
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<td>33.33***</td>
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</tr>
<tr>
<td></td>
<td>(6.97)</td>
<td>(-)</td>
<td></td>
<td>(12.17)</td>
<td>(-)</td>
</tr>
<tr>
<td>In rate of change, DEPT</td>
<td>σ₁²</td>
<td>0.7952***</td>
<td>0.3690***</td>
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<tr>
<td></td>
<td>(0.1152)</td>
<td>(0.1194)</td>
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<td></td>
</tr>
<tr>
<td>In rate of change, INST</td>
<td>σ₁²</td>
<td>0.4963***</td>
<td>2.31*</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.1129)</td>
<td>(1.06)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Covariance, DEPT</td>
<td>σ₀₁</td>
<td>5.13***</td>
<td>2.19</td>
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<tr>
<td></td>
<td>(1.06)</td>
<td>(0.99)</td>
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<td>(0.11)</td>
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</tr>
<tr>
<td>Covariance, INST</td>
<td>σ₀₁</td>
<td></td>
<td></td>
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</table>

Goodness of Fit

Deviance (−2LL)  
AIC             
BIC             
N

<table>
<thead>
<tr>
<th></th>
<th>UM1</th>
<th>UM2</th>
<th>UM3</th>
<th>UG1</th>
<th>UG2</th>
<th>UG3</th>
</tr>
</thead>
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<tr>
<td>39507.6</td>
<td>42108.6</td>
<td>39507.6</td>
<td>39070.0</td>
<td>41959.9</td>
<td>39042.9</td>
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<td>39513.6</td>
<td>39082.0</td>
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<td>39058.9</td>
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<tr>
<td>4,835</td>
<td>4,835</td>
<td>4,835</td>
<td>4,835</td>
<td>4,835</td>
<td>4,835</td>
<td>4,835</td>
</tr>
</tbody>
</table>

NOTES: Standard errors in parentheses. Significance levels: ~ p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001.
women among majors. Whereas the time trend may have been less powerful for the women’s percentage among bachelor’s degree recipients than for their percentage among majors, the impact of the percentage of women among the faculty was stronger for the percentage of undergraduate women among degree recipients than for the percentage of undergraduate women among majors. (The coefficients were 0.36 for BACHELOR and 0.12 for MAJOR in the respective Models A, Table 2.) Moreover, all interactions were non-significant in the models for bachelor’s degrees that exclude missing values so that a simpler model emerged, containing only the main effects of year, field, and percentage of women among faculty (Model C (Table 2, Panel b)). The Carnegie classification again played no significant role in the regular approach.\(^6\)

For policy implications, a noteworthy result was that the percentages of women among majors and among bachelor’s degree recipients did not differ markedly. Comparing these percentages in the same years and departments, the women’s percentage among degree recipients was, on average, 1.4 percent lower than the percentage of women among majors. One should immediately note, however, that such a comparison is not entirely precise because it compares the graduates of one specific year to the whole population of majors, many of whom do not graduate in that year, but in a subsequent year. This distorts the findings, especially when there is—as we found—a general rising trend of women’s participation. We therefore looked at two additional difference measures, using a one-year and a two-year lagged percentage of women majors. As expected, the lagged measures indeed showed less of a difference. Using the one-year lagged percentage of women majors, the difference was only 0.5 percent; and for a two-year lag, the difference all but disappeared (−0.1 percent). The difference found above thus appears to be largely an artifact of the rising participation of women. This finding suggests that the issue at the undergraduate level is less one of women’s retention than of their recruitment.

Conclusions

What may we conclude from these findings, as they relate to institutional/structural determinants of the percentage of women among majors and among bachelor’s degree recipients in science and engineering?\(^6\)

First, time is important. Over a 16-year period of observation (1984–2000) and across departments, the percentages of women majors in the

\(^6\)An examination of the results of the multiple imputation (in italics, next to the regular results) also revealed great similarities between the two sets of models. The few observed differences were also the same that were found for the MAJOR variable. Under multiple imputation, the effect of the women’s percentage among the faculty was weaker and non-significant. The percentage of women among Bachelor degree recipients was somewhat lower at Research 1 institution departments than at other institutions (at a marginal significance).
sciences and engineering and of women recipients of bachelor degrees in these fields have risen steadily and in a remarkably linear fashion. It remains to be seen which pattern—gender equality, broadly defined, the feminization of certain scientific fields, or even a trend reversal—will emerge at the end of the linear growth phase.

Second, women’s participation in the various disciplines of the sciences and engineering has historically been uneven, with some fields containing relatively large percentages of women and others having relatively low percentages. Importantly, the trends at the undergraduate level have accentuated, rather than diminished, these differences. This study confirms that gender segregation by field is still in full force and shows no signs of abating. For policies or programs to support female undergraduates in these disciplines, it may therefore be advisable to take field differences into account and to tailor efforts and initiatives to the situation in specific fields (rather than simply targeting “women in science” or “women in science and engineering” in toto).

Third, and augmenting the previous point, what our statistical models showed to be consequential in accounting for the percentage of women among majors and (to a somewhat lesser extent) among degree recipients, was the department, rather than the institution. These results again suggest a promising locus for interventions or policies to improve the participation of women undergraduates in the sciences and engineering: the level of individual fields and departments appears to matter much more than the level of the whole institution. In other words, policy efforts should be directed toward departments (or perhaps even to smaller units, such as subfield clusters within departments).

Fourth, and more specifically regarding the effects of type of institution, women’s percentage of majors and degrees received in biological, physical, and engineering fields do not markedly differ between Research I universities and other types of institutions (though a small effect was found in the multiple-imputation approach, indicating a slightly lower percentage of women at the Research I institutions). Hence, in contrast with a persistent and strong gender segregation between fields, gender segregation within disciplinary fields by institutional type (in the sense of women’s marginalization) may occur to a small extent, but was not a major effect. Research I institutions do not appear to have a sharply lower representation of women undergraduates, compared with other types of institutions. However, Research I institutions also are clearly not “leading the way” in the percentages of undergraduate majors and degrees among women, compared with men—although, of course, large institutions (often in the Research I institution category) frequently have higher “counts” of majors and degrees among women (and men).

Fifth, the percentages of women among science/engineering majors and among bachelor degree recipients were associated (albeit in a small effect) with the percentage of women among the faculty in these fields, and the growth trajectory over time in the percentage of women among science/
engineering majors was somewhat steeper in the presence (compared to the absence) of larger percentages of women faculty. These findings, which appeared more pronounced in the standard approach than in the multiple-imputation approach, suggest that the presence of women faculty may have some impact on positive outcomes—especially in degrees received—among undergraduate women in science/engineering. These results provide at least mild encouragement to both those who believe that female “role models” (and other supporters) are beneficial for female students, and those who think that the mere presence of women in an occupation signals to young women that the occupation might be an appropriate choice for them. If anything, the fact that the percentage of women bachelor recipients appeared to be more sensitive than the percentage of women majors to the percentage of women faculty might favor the first hypothesis, suggesting that women undergraduates’ observations of female role models and actual interactions between women faculty and women students have some influence. However, our data allow no firm conclusions in this area.

Further research that investigates the specific pathways in which the presence of women faculty potentially boosts the participation of women students is needed to determine which theoretical concept (role model or occupational gender structure) is more appropriate. In any case, for initiatives to improve gender equity in undergraduate degrees received in science and engineering—which is the critical, and probably latest, stage for entry into these fields—the positive relationship between the percentages of women students and women faculty at least suggests that the presence of more female faculty may facilitate the participation of undergraduate women in science and engineering.

At the same time—and this is a caveat for deriving practices and policy measures from these results—our study does not reveal the underlying causal structure of the associations found. The questions become these: Does a stronger female presence among the faculty indeed encourage the participation and persistence of women students, as both the notions of the benefits of “role models” and of the pervasive effects of the gender composition of occupations might suggest (Astin and Sax, 1996; Hackett, Esposito, and O’Halloran, 1989; Stake and Noonan, 1985; Xie and Shuman, 1997)? Conversely, does an increase in the percentage of women students lead to the hiring of more women faculty—said to be a practice in some engineering departments in which the incentive is strong to retain women students who have excellent test scores and academic records (Fox and Stephan, 2001)? Or, might both the increases in female faculty and in female student numbers result from a third, underlying, factor, such as departmental efforts to develop more “female-friendly” climates (Camp, 1998; Rothstein, 1995)? In continuing steps in this research, we need to understand the ways in which the positive outcomes for women undergraduates and the percentages of women faculty in science and engineering unfold over time for fields—with implications for practices and policies to support sustained gender equity in science and engineering.
REFERENCES


