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Gender differences in employment and earnings in science and engineering in the US

John W. Graham[a,*], Steven A. Smith[b]

[a]Department of Economics, Rutgers, The State University of New Jersey, 360 Martin Luther King Jr. Blvd, Newark, NJ 07102, USA
[b]Department of Management, University of New Orleans, New Orleans, LA 70148, USA

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Abstract

College-educated women are less than half as likely as men to be employed in science and engineering (S&E); and if they are, earn about 20 percent less. Using data from the 1993 National Survey of College Graduates, we estimate jointly, determinants of S&E employment and earnings in both S&E and non-S&E jobs. Taking account of gender differences in education (including S&E degrees), work experience and occupational characteristics, we can explain 60 percent of the gender differential in S&E employment and up to two-thirds of the earnings differential in S&E jobs. We find some evidence of gender earnings discrimination in S&E jobs, but less of it than in non-S&E jobs. We also show that the likelihood a worker selects S&E employment depends on her expected pay differential between S&E and non-S&E jobs, as well as on expected gender earnings discrimination in both S&E and non-S&E labor markets.

JEL classification: I21; J44; J71

Keywords: Human capital; Rate of return; Salary wage differentials

1. Introduction

It is a truth universally acknowledged that scientific advances provide the fuel for economic growth. High-technology industries have led the most recent sustained growth period in US history, resulting in an unprecedented explosion in the demand for highly skilled labor, creating intense competition for a limited pool of scientific workers. At the same time, real wages have been decreasing in science and engineering fields relative to other highly skilled occupations such as medicine, law and business (North, 1995), and the overall pool of scientists and engineers has been growing only slowly (Romer, 2000). As the demographic composition of the US labor force continues to change, in favor of women, minorities and immigrants, many of these workers are reported to hold perceptions of unfair treatment in the scientific labor market (Dix, 1987; Stossel, 1999).

This paper focuses on gender differences in aggregate employment and earnings in science and engineering (S&E) relative to other occupational fields. Our definition of S&E follows the National Science Foundation (NSF, 1999a, b) which regularly tracks the educational and employment characteristics of the college-educated

*Corresponding author. Tel.: +1-973-353-5354; fax: +1-973-353-5819.
E-mail addresses: jwgraham@andromeda.rutgers.edu (J.W. Graham), sasmith1@uno.edu (S.A. Smith).

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workforce involved in occupations that have the greatest potential to generate research and development payoffs. There were roughly 3.5 million college-educated individuals in the US in 1999 working in one of five broadly defined S&E fields—computer/math, life sciences, physical sciences, social sciences and engineering (NSF, 2003). Women were just 24 percent of all S&E workers (even though they are 46 percent of all workers) and earned on average 22 percent less than men. The main goals of this paper are to explain the causes of these gender differences in S&E employment and earnings and to assess the relationship between S&E employment and earnings. Our focus on S&E occupations as a whole rather than specific S&E jobs is consistent with a long tradition of economic analysis of the sources of gender earnings discrimination as exemplified in a recent article by O'Neill (2003).

Economist Paula Stephan (1996) has observed one reason science commands our attention is that the S&E labor market offers fertile ground for testing the human capital model which relates earnings to education, training and experience (see Becker, 1964; Mincer, 1974, among many others). To the extent S&E jobs value measurable skills and knowledge over less tangible traits such as personality or appearance (which may be more important in some non-S&E jobs such as management, sales and service), then a small set of human capital variables might be expected to capture a large portion of the variation in individual earnings and may also account for a significant portion of the gender pay gap. By contrast, sociologist Laurie Morgan (1998) offers an alternative view of S&E which emphasizes the importance of "old-boy" networks and the "glass ceiling." She argues that since S&E jobs have been traditionally male-dominated, women may find themselves at a disadvantage in terms of entry, pay and promotion. This view suggests that factors other than human capital are likely to account for much of the gender differential in pay.

In this paper, we combine these two schools of thought, arguing that a worker's decision whether or not to seek employment in an S&E occupation depends both on the earnings differential between S&E and non-S&E jobs and on perceptions of discrimination in the two fields. To model both pay and discrimination, we need unbiased estimates of what a worker could expect to earn in both S&E and non-S&E jobs. After reviewing our dataset and sketching a theory of occupational selection, we present maximum likelihood estimates of the determinants of selecting an S&E occupation and of earnings in S&E and non-S&E fields, by gender. We then offer quasi-structural equation estimates of how differences in earnings between S&E and non-S&E jobs and gender discrimination in the two fields affect the likelihood that a college-educated worker is employed in S&E.

2. An overview of the S&E labor market

The NSF sponsored the National Survey of College Graduates (NSCG) in spring 1993, a survey of 215,000 individuals under age 75 with at least a bachelor's degree at the time of the 1990 Census. The resulting database merges each individual's 1990 long-form Census data with information from the 1993 follow-up questionnaire on fields of study, level of education, occupation, earnings and other demographic information. Since the Census did not collect information in the field of study, the NSCG includes individuals, both with and without S&E backgrounds, and as such, is a nationally representative database of all college graduates. In this paper, we look at all 111,158 individuals in the survey who worked full time in 1993 and had positive earnings (or self-employment income), and we focus in particular on the 23,805 men and 5709 women working in S&E.

Table 1 provides an overview of the mean annual earnings and distribution of college-educated full-time workers by whether or not employed in an S&E occupation, by S&E educational background, and by gender. Our classification of S&E occupations and degree fields follows the guidelines established by the NSF (and is detailed in the appendix to this paper). In general, S&E occupations are those which employ a high proportion of individuals with training in an S&E educational field who are engaged in some research or development activities and whose output directly or indirectly involves the production of scientific ideas and new knowledge. Any definition of S&E necessarily involves a number of controversial and potentially arbitrary judgments about specific jobs: for example, the NSF list of S&E jobs includes postsecondary but not pre-college teachers of S&E; medical researchers but not doctors or nurses; and computer hardware and software developers but not computer programmers or technicians. Although workers in these excluded fields may have a substantial amount of scientific education and training, their primary output is not deemed to be basic research or development.

Among all college-educated full-time workers, women earned on average $40,119 per year, or 73 percent of the $55,135 mean earnings of men. About one in three men and one in seven women worked in an S&E occupation.[1] Among S&E workers, women earned on average $45,456, or 84 percent of what men did. Among non-S&E workers, the gender pay gap was much greater:

[1]NSCG respondents are more likely than college graduates as a whole to be employed in S&E. In 1993, 14.3 million male and 8.5 million female year-round, full-time workers with income had a college degree or more (US Bureau of the Census, 1995). At the NSCG rate of S&E employment, 4.8 million men and 1.2 million women would be working in S&E, about twice the number estimated by the NSF for 1997.

Table 1
Mean annual earnings of college-educated full-time workers by gender, science and engineering (S&E) field and education

	Males		Females		Difference	
	Earnings	N[a]	Earnings	N[a]	Pay gap	%[b]
All college-educated workers	$55,135 [30,280][c]	71,260 (100%)	$40,119 [21,921]	39,898 (100%)	$15,016	73
Employed in S&E field	$54,170 [21,039]	23,805 (33.4%)	$45,456 [19,386]	5709 (14.3%)	$8,714	84
Any S&E degree	$54,756 [20,432]	20,150	$46,007 [17,747]	3626	$8,749	84
No S&E degree	$50,940 [23,858]	3655	$44,497 [21,922]	2083	$6,443	87
Employed in non-S&E field	$55,619 [33,972]	47,455 (66.6%)	$39,228 [22,192]	34,189 (85.7%)	$16,391	71
Any S&E degree	$61,930 [35,353]	13,558	$45,540 [27,449]	4164	$16,390	74
No S&E degree	$53,095 [33,069]	33,897	$38,352 [21,214]	30,025	$14,743	72
Employed in S&E by field						
Engineering	$55,069	13,139 (55.2%)	$46,981	1111 (19.5%)	$8,088	85
Computer/math	$53,586	5721 (24.0%)	$46,985	2276 (39.9%)	$6,601	88
Physical sciences	$53,242	1985 (8.3%)	$43,191	465 (8.1%)	$10,206	81
Social sciences	$52,397	1169 (4.9%)	$45,544	986 (17.3%)	$6853	87
Life sciences	$51,630	1791 (7.5%)	$40,627	871 (15.3%)	$11,003	79

Note: S&E and non-S&E employment and educational fields are defined by NSF (1999a).
[a]Sample size (with percent of sample in parentheses).
[b]Female pay as a percent of male pay.
[c]SD.

women earned $39,228, or just 71 percent of what men did.

The table also displays the percentage distribution of workers and their earnings by whether or not they have any college-level degree in S&E.[2] Not all workers employed in S&E have a degree in S&E, and not all workers with an S&E degree actually work in S&E. Women employed in S&E are more likely than men *not* to have an educational background in S&E: 36 percent of women compared with 15 percent of men employed in S&E have no S&E degree. Women trained in S&E are also more likely than men *not* to be employed in S&E: 53 percent of women compared with 40 percent of men with an S&E degree work in a non-S&E occupation. Turning to earnings, male and female workers who have an S&E degree earn more in both S&E and non-S&E jobs than do workers without an S&E degree. Perhaps surprisingly, the rate of return to having an S&E degree appears to be greater in non-S&E than in S&E fields: on average, men (women) with an S&E degree earn 17 (12) percent more in non-S&E fields than those without an S&E degree, while they earn just 7 (3) percent more in S&E fields.

Table 1 also shows the distribution of workers and earnings by S&E field. More than half of all men in S&E work in engineering, compared with just 20 percent of women. Nearly 40 percent of women in S&E are found in computer/math, compared with just 24 percent of men. Social and life sciences also attract a greater fraction of female than male S&E workers, while physical sciences attract about an equal percentage. For men, earnings are highest in engineering; for women, earnings are highest in computer/math. The gender pay gap (on a percentage basis) is largest in life sciences, and smallest in computer/math.

[2]Any S&E degree includes all workers whose first, second or third most recent college degree was in an S&E educational field.

3. A theory of occupational selection and earnings

We assume individuals select their occupation to maximize utility, which in turn, depends upon expected earnings and other job-related benefits. The latter are likely to include both pecuniary aspects (such as health and pensions benefits) and non-pecuniary ones (such as overall job satisfaction). Let $Y_{\mathrm{S\&E}}$ be expected earnings from working in an S&E job, and Y_{non} be earnings in a non-S&E job. Similarly, let $B_{\mathrm{S\&E}}$ and B_{non} be other job-related benefits in the two fields. Therefore, $U(Y_{\mathrm{S\&E}}, B_{\mathrm{S\&E}}) = U_{\mathrm{S\&E}}$ is the utility from working in S&E, and $U(Y_{\mathrm{non}}, B_{\mathrm{non}}) = U_{\mathrm{non}}$ is the utility from working in non-S&E fields. Define z^* as the utility difference,

$$z^* = U_{\mathrm{S\&E}} - U_{\mathrm{non}} \tag{1}$$

and z to be a dummy variable equal to one if the individual selects S&E and zero if the individual selects a non-S&E field. The assumption of utility maximization implies that if $z^* \geqslant 0$, then $z = 1$, and if $z^* < 0$, then $z = 0$. For mathematical simplicity, we assume the utility function is log-linear and rewrite Eq. (1) as

$$z^* = a(\ln Y_{\mathrm{S\&E}} - \ln Y_{\mathrm{non}}) + b(\ln B_{\mathrm{S\&E}} - \ln B_{\mathrm{non}}), \tag{1$'$}$$

so that the likelihood of choosing an S&E job is a weighted average of the percentage differences in earnings and other benefits between jobs in S&E and non-S&E fields.

We assume the natural log of earnings in S&E and non-S&E can be described by

$$\ln Y_{\mathrm{S\&E}} = \beta_{\mathrm{S\&E}} X_Y + e_{\mathrm{S\&E}}, \tag{2a}$$

$$\ln Y_{\mathrm{non}} = \beta_{\mathrm{non}} X_Y + e_{\mathrm{non}}, \tag{2b}$$

where X_Y is a vector of socioeconomic variables, $\beta_{\mathrm{S\&E}}$ and β_{non} are coefficients and $e_{\mathrm{S\&E}}$ and e_{non} are normally distributed error terms. Similarly, other job-related benefits are determined by a set of socioeconomic variables X_B, which are likely to contain many of the same elements as in X_Y, but also some that are not (see Section 4 for details). Given these assumptions, Eq. (1′) and the selection rule can be rewritten as

$$z^* = \alpha W + u \text{ with } z = 1 \text{ if } z^* \geqslant 0 \quad \text{and} \quad z = 0 \text{ if } z^* < 0, \tag{3}$$

where W is a vector that includes all the elements of X_Y and X_B, α is a vector of their coefficients, and u is a normally distributed error term.

Estimation of the reduced form Eq. (3) is one of the main goals of this paper. A second goal is to estimate the S&E and non-S&E earnings functions, Eqs. (2a) and (2b). This task is made difficult by the presence of truncation or sample selection bias. That is, we have observations on $Y_{\mathrm{S\&E}}$ only if $z = 1$ and on Y_{non} only if $z = 0$. Therefore, estimation of Eqs. (2a) and (2b) requires we take account of the sample selection rule given by Eq. (3). To do this efficiently, we employ a full information maximum likelihood (FIML) estimation method suggested by Willis and Rosen (1979), which is often called the "mover/stayer" model.[3] In this procedure, Eqs. (2a), (2b) and (3) are estimated simultaneously, providing joint estimates of the coefficients α, $\beta_{\mathrm{S\&E}}$ and β_{non} as well as ρ, the correlation between error terms in the selection and earnings equations.

The final goal of the paper is to estimate Eq. (1′) directly. To do so fully, we would need not only estimates of expected earnings in S&E and non-S&E jobs (which can be obtained from fitted versions of Eqs. (2a) and (2b)), but also estimates of all other job-related benefits. Since the latter are likely to contain more dimensions than we can hope to measure, we estimate a quasi-structural form of Eq. (1′) focusing on one important aspect of job-related benefits—namely, fairness or equality of treatment, as measured by expected gender earnings discrimination. It is our thesis that workers are more likely to select an S&E occupation; the smaller is perceived discrimination in S&E jobs and the larger is perceived discrimination in non-S&E jobs. In a modification of Blinder (1973) and Oaxaca (1973), we estimate individual-specific gender earnings discrimination in S&E jobs as $(\beta^{\mathrm{m}}_{\mathrm{S\&E}} - \beta^{\mathrm{f}}_{\mathrm{S\&E}})X_{\mathrm{Yi}}$ and in non-S&E jobs as $(\beta^{\mathrm{m}}_{\mathrm{non}} - \beta^{\mathrm{f}}_{\mathrm{non}})\, X_{Yi}$, where X_{Yi} denotes the earnings-related characteristics of the ith worker.[4]

4. Selection and earnings in S&E and non-S&E occupations

According to Eq. (3), the likelihood of selecting an S&E job depends upon all of the factors that determine earnings and other job-related benefits in S&E and non-S&E occupations. Table 2 displays these determinants in three broad categories—demographic, human capital and occupation—and shows sample means by gender and by whether or not employed in S&E. Demographic variables include worker's age and number of children, and dummies to capture race, ethnicity, nativity, citizenship, marital status and location. Human capital variables include schooling, field of study, work experience, proficiency in English, and mother's education. Schooling is measured by the total number of degrees earned and by whether or not the worker has a master's (including an MBA), professional (law, medicine, dentistry or theology), or Ph.D. degree. Field of study refers to whether or not any degree (as well as the most recent degree) was earned in an S&E field.

[3] We use the 'mover/stayer' model in LIMDEP ver 7.0, following the discussion in Greene (1995, pp. 668–72).

[4] In Blinder (1973) and Oaxaca (1973), $X_{Yi}{}^{\mathrm{f}}$ is replaced by the $X_Y{}^{\mathrm{f}}$, the sample mean. These estimates of discrimination are also calculated and are shown in Table 4.

Table 2
Sample means for all college graduate full-time workers and for workers not employed and employed in science and engineering (S&E), by gender

	Males			Females		
	All males (71,260)	Employed non-S&E (47,455)	Employed S&E (23,805)	All females (39,898)	Employed non-S&E (34,189)	Employed S&E (5709)
Demographic						
Age	42.451	43.110	41.136	40.510	40.898	38.190
Married*	0.782	0.780	0.786	0.615	0.615	0.615
# of children	1.147	1.169	1.105	0.873	0.899	0.716
Asian*	0.102	0.090	0.126	0.107	0.102	0.137
Black*	0.064	0.079	0.036	0.149	0.161	0.075
Hispanic*	0.060	0.071	0.039	0.075	0.080	0.046
Native American*	0.008	0.010	0.003	0.011	0.012	0.005
Foreign-born*	0.191	0.173	0.226	0.171	0.164	0.217
Non-citizen*	0.058	0.049	0.076	0.046	0.042	0.069
Southeast*	0.168	0.169	0.167	0.181	0.180	0.187
South central*	0.139	0.139	0.139	0.143	0.145	0.128
North central*	0.213	0.215	0.207	0.203	0.205	0.191
Mountain*	0.060	0.057	0.066	0.051	0.049	0.058
Pacific*	0.200	0.197	0.207	0.190	0.189	0.200
Human capital						
Mother attended college*	0.395	0.388	0.409	0.453	0.444	0.505
# of degrees	1.558	1.537	1.600	1.507	1.478	1.682
Any S&E degree*	0.473	0.286	0.846	0.195	0.122	0.635
1st degree S&E*	0.398	0.200	0.791	0.156	0.085	0.585
Masters degree*	0.258	0.244	0.286	0.318	0.315	0.337
Professional degree*	0.092	0.133	0.011	0.047	0.053	0.013
Ph.D. degree*	0.074	0.047	0.128	0.043	0.026	0.143
Years experience	17.072	17.480	16.259	13.588	13.830	12.144
Speaks English well*	0.139	0.134	0.149	0.145	0.144	0.152
Speaks English not well*	0.039	0.035	0.046	0.037	0.036	0.046
Occupation						
Education sector*	0.149	0.168	0.112	0.360	0.385	0.207
Government sector*	0.150	0.142	0.166	0.137	0.133	0.160
Nonprofit sector*	0.049	0.059	0.029	0.090	0.096	0.056
Self-Employed*	0.127	0.170	0.043	0.066	0.069	0.051
# prof. Societies	1.347	1.427	1.189	1.242	1.253	1.180
Attended meetings*	0.605	0.624	0.567	0.639	0.646	0.599
Attended training*	0.709	0.712	0.702	0.783	0.786	0.762
Supervisor*	0.569	0.610	0.486	0.432	0.437	0.400
Observed earnings						
Annual earnings	$55,135	$55,619	$54,170	$40,119	$39,228	$45,456
Log earnings	10.784	10.762	10.830	10.485	10.458	10.645
Predicted earnings						
Expected log earnings in S&E fields	10.812	10.804	10.828	10.550	10.534	10.645
Expected log earnings in non-S&E fields	10.955	10.886	11.091	10.433	10.432	10.443
Log earnings difference (S&E minus non-S&E)	−0.143	−0.082	−0.263	0.117	0.103	0.202
Expected discrimination (−) or favoritism (+) in S&E fields	0.076	0.075	0.079	−0.072	−0.072	−0.068
Expected discrimination (−) or favoritism (+) in non-S&E fields	0.410	0.316	0.597	−0.236	−0.198	−0.466

Notes: Dummy variables (yes = 1 and no = 0) are indicated by an *, the omitted geographic region is the Northeast, the omitted language category is ‘‘speaks English fluently’’, # of children is top coded at 7, annual earnings are top coded at $150,000, 1st degree S&E is whether the most recently earned degree was in an S&E educational field.

Occupation variables are: membership in professional societies; employment in education, government or the non-profit sectors; self employment; supervision of others; and recent attendance at professional meetings or training. Like demographic and human capital factors, occupation variables are assumed to represent ex ante information about the productivity of workers themselves, rather than their jobs. In analyses of earnings by race or gender, Anderson and Shapiro (1996) and Kidd and Shannon (1996) have maintained similar assumptions.

Table 3 presents FIML estimates of how these factors affect the likelihood of selecting an S&E occupation and how they affect earnings in S&E and non-S&E fields. Although model identification can be achieved on the basis of nonlinearity, it is preferable to exclude at least one variable from the earnings regressions. The most likely candidate for exclusion is some family background variable that influences occupational preferences (and hence selection into S&E) but not current earnings per se. In our case, this is the mother's education (measured as whether or not she attended college).[5] Theory and prior evidence support the hypothesis that parents' education directly impacts children's educational and career choices, but only indirectly affects their earnings (Haveman & Wolfe, 1995).

4.1. Determinants of the likelihood of selecting an S&E occupation

The first and fourth columns in Table 3 give probit coefficients and *T*-values for men and women, respectively, showing the impact of demographic, occupation and human capital variables on the likelihood of selecting an S&E occupation.[6] All else equal, non-Hispanic whites are more likely than other ethnic or racial groups to be employed in S&E. Younger workers and those who have fewer children are more likely to be in S&E. Men who are married or were born outside of the US are more likely to be in S&E, but neither of these factors has an influence among women. Self-employed individuals and those who work in the education or nonprofit sector are less likely than those in the for-profit sector to have an S&E job. Men who work in government are more likely to have S&E jobs, while women are less likely to. Workers who attended a job-training program in the past year are more likely to be in S&E; workers who supervise others are less likely to hold S&E jobs.

As might be expected, human capital variables are strongly related to employment. Workers with an MA or Ph.D. degree are more likely to work in S&E while workers with a professional degree are less likely to. Years of full-time work experience and proficiency in English have positive impacts on S&E employment. For women only, having additional degrees or having a father with more education increases the likelihood of being in an S&E job. But by far the strongest determinant of S&E employment is field of study: all else equal, men (women) whose most recent degree was in an S&E educational field are 52 (24) percentage points more likely than those without any S&E degree to be employed in S&E.[7] Even if the most recent degree was not in an S&E field, having a prior S&E degree raises the likelihood of S&E employment by 22 percent for men and 8 percent for women.

In our sample, 33.4 percent of men and 14.3 percent of women were employed in an S&E occupation. Taking account of average gender differences in all demographic, human capital and occupational characteristics, and the impact of these characteristics on S&E employment, how much of the 19.1 percentage point differential in S&E employment between men and women can be explained? Using a Blinder–Oaxaca type decomposition, we find we can explain from 55 to 64 percent of the total, depending upon whether female or male coefficients are used to evaluate gender differences in characteristics.[8] Moreover, even though many individual demographic, human capital and occupation characteristics are significant determinants of the likelihood of S&E employment, it turns out that the entire explained differential can be accounted for by gender differences in S&E educational backgrounds.[9] Men are 28 percentage points more likely than women to have any S&E degree and 24 points more likely to have their most recent degree in S&E (see Table 2). Taken together,

[5]Father's education is also known, but was excluded from the final estimation since mother's and father's educational attainments were highly collinear.

[6]Marginal effects which can be interpreted as partial derivatives are found by multiplying the male (female) probit coefficients by 0.329 (0.161), the standard normal density evaluated at the male (female) means.

[7]This is found by summing the probit coefficients on "Any S&E Degree" and "1st Degree S&E" and then multiplying by the adjustment factors in footnote 5.

[8]The actual Blinder-Oaxaca decomposition assumes linear regressions, but since probits are nonlinear, this decomposition is only an approximation. The results reported in the text are based on differences in predicted rather than actual probabilities: evaluated at sample means, 26.7 percent of men versus 8.9 percent of women were predicted to be in S&E, for a total differential of 17.8 points. Using male probit coefficients and female means, 15.4 percent of women are predicted to be in S&E, for an explained differential of 11.3 points. Thus, $\frac{11.3}{17.8}$ is the 63 percent reported in the text. A similar analysis is used for the female coefficients.

[9]If women had all the same characteristics as men except for "Any S&E Degree" and "1st Degree S&E," then based on male probit coefficients, we would expect an 11.5 point differential in S&E employment, which is 102 percent (i.e., $\frac{11.5}{11.3}$) of the explained difference.

Table 3
Full-information maximum likelihood estimates of the probability of employment in S&E and of log-earnings in S&E and non-S&E among college graduates by gender

	Males ($N = 71,260$)			Females ($N = 39,898$)		
	Probit for S&E	Log-earnings in		Probit for S&E	Log-earnings in	
		S&E	Non-S&E		S&E	Non-S&E
Demographic						
Age	−0.0129	−0.0013	−0.0011	−0.0108	−0.0005	−0.0021
	(10.87)	(2.45)	(2.88)	(7.10)	(0.58)	(6.69)
Asian	−0.0553	−0.0166	−0.0170	−0.1173	0.0346	0.0411
	(2.34)	(1.98)	(1.79)	(3.16)	(1.86)	(4.69)
Black	−0.2990	−0.0762	−0.1372	−0.3300	−0.0585	0.0066
	(11.27)	(5.59)	(14.67)	(10.60)	(2.37)	(0.96)
Hispanic	−0.2531	−0.0406	−0.0563	−0.2189	0.0147	0.0183
	(8.94)	(3.21)	(5.51)	(5.02)	(0.60)	(1.93)
Native American	−0.3870	−0.0883	−0.1761	−0.3156	−0.1687	−0.0129
	(4.87)	(2.52)	(7.20)	(2.90)	(2.63)	(0.68)
Foreign-born	0.0288	0.0415	0.0306	−0.0223	0.0191	0.0199
	(1.36)	(5.17)	(3.77)	(0.63)	(1.04)	(2.50)
Non-citizen	−0.0205	−0.0385	−0.0157	0.0406	−0.0279	−0.0647
	(0.75)	(4.36)	(1.60)	(0.88)	(1.38)	(5.90)
Married	0.0442	0.0402	0.0816	−0.0039	0.0357	0.0328
	(2.87)	(6.97)	(13.29)	(0.19)	(3.48)	(6.73)
# of children	−0.0125	0.0106	0.0178	−0.0441	−0.0023	−0.0089
	(2.34)	(5.11)	(8.61)	(4.44)	(0.40)	(4.07)
Southeast	0.0200	−0.0163	−0.0679	0.0577	−0.0529	−0.1321
	(1.10)	(2.36)	(9.43)	(2.01)	(3.52)	(18.95)
South central	0.0139	−0.0401	−0.1330	0.0075	−0.1099	−0.1984
	(0.71)	(5.63)	(17.23)	(0.24)	(6.84)	(26.12)
North central	0.0061	−0.0768	−0.1135	0.0168	−0.1017	−0.1324
	(0.35)	(11.87)	(16.64)	(0.60)	(6.83)	(19.71)
Mountain	0.0822	−0.0515	−0.1308	0.0778	−0.1062	−0.1806
	(3.14)	(5.24)	(12.17)	(1.70)	(5.04)	(16.45)
Pacific	0.0176	0.0459	0.0096	0.0307	0.0180	0.0080
	(1.00)	(7.29)	(1.38)	(1.08)	(1.26)	(1.16)
Human capital						
Mother attended	0.0172	—	—	0.0357	—	—
College	(1.55)			(1.92)		
# of degrees	−0.0234	−0.0027	−0.0299	0.0891	0.0005	−0.0007
	(1.72)	(0.56)	(5.72)	(3.86)	(0.05)	(0.11)
Any S&E degree	0.6812	0.1006	0.1966	0.5115	0.0794	0.0866
	(28.29)	(4.22)	(22.39)	(11.74)	(2.21)	(7.75)
1st degree S&E	0.9023	0.0059	0.1804	0.9901	0.0082	−0.0935
	(37.55)	(0.24)	(17.30)	(21.64)	(0.17)	(6.18)
Masters degree	0.2811	0.0884	0.1866	0.3712	0.0844	0.1308
	(14.13)	(9.26)	(23.25)	(11.47)	(3.85)	(15.83)
Professional degree	−0.5167	0.4034	0.5033	−0.3159	0.3862	0.5303
	(13.75)	(16.33)	(55.82)	(5.23)	(8.71)	(52.29)
Ph.D. degree	0.8696	0.2598	0.4631	1.3548	0.2354	0.2061
	(26.31)	(11.52)	(31.99)	(23.52)	(3.94)	(10.56)
Years experience	0.0113	0.0311	0.0336	0.0215	0.0335	0.0322
	(5.05)	(37.07)	(43.04)	(5.60)	(15.63)	(42.19)
Exp-squared	−0.0001	−0.0004	−0.0006	−0.0006	−0.0006	−0.0005
	(2.73)	(24.85)	(31.23)	(5.73)	(9.66)	(25.71)
Speaks English	0.0141	−0.0242	−0.0401	−0.0396	−0.0521	0.0035
Well	(0.64)	(2.98)	(4.72)	(1.10)	(3.00)	(0.43)
Speaks English	−0.0992	−0.1012	−0.1755	−0.1081	−0.1061	−0.0952

Table 3 (*continued*)

	Males ($N = 71,260$)			Females ($N = 39,898$)		
	Probit for S&E	Log-earnings in		Probit for S&E	Log-earnings in	
		S&E	Non-S&E		S&E	Non-S&E
not well	(2.89)	(8.66)	(13.43)	(1.96)	(4.01)	(7.77)
Occupation						
Education	−0.2441	−0.3090	−0.3560	−0.5601	−0.3709	−0.1608
	(12.35)	(34.19)	(43.70)	(21.21)	(13.53)	(24.98)
Government	0.0629	−0.1276	−0.1518	−0.0593	−0.0896	−0.0681
	(3.71)	(18.58)	(18.09)	(2.07)	(5.54)	(8.45)
Nonprofit	−0.3086	−0.0756	−0.3367	−0.3711	−0.1573	−0.1165
	(10.76)	(5.44)	(35.04)	(10.47)	(6.05)	(13.58)
Self-employed	−0.6342	0.0269	−0.1376	−0.2964	0.0390	0.0035
	(29.58)	(1.51)	(22.95)	(7.28)	(1.97)	(0.52)
# prof. Societies	0.0002	0.0217	0.0351	−0.0245	0.0068	0.0283
	(0.05)	(16.67)	(26.75)	(3.49)	(2.05)	(18.55)
Attended meetings	0.0162	0.0015	0.0830	0.0035	0.0242	0.0612
	(1.23)	(0.31)	(15.02)	(0.16)	(2.15)	(11.31)
Attended training	0.0723	0.0253	0.0597	0.0922	0.0419	0.0630
	(5.59)	(5.14)	(11.46)	(3.96)	(3.55)	(11.57)
Supervisor	−0.3388	0.0613	0.1295	−0.1777	0.0662	0.1144
	(28.63)	(6.63)	(26.78)	(9.25)	(5.26)	(24.79)
Constant	−0.6935	10.3527	10.2957	−1.209	10.301	10.1126
	(15.45)	(181.4)	(627.3)	(18.54)	(92.53)	(676.4)
Rho		0.0099	−0.6798		0.0007	0.3535
		(0.08)	(71.36)		(0.01)	(9.57)

Note: *T*-values shown in parentheses. ρ is the correlation coefficient between the error terms in the probit and earnings equations.

these two facts account for 102 percent of the explained difference in S&E employment. In other words, we conclude that one needs to look for answers about gender differences in S&E employment in gender differences in S&E educational backgrounds. A recent study by Turner and Bowen (1999) finds that gender differences in college majors are persistent and the reasons for them remain largely a puzzle.

4.2. Determinants of earnings in S&E and non-S&E occupations

FIML estimates of how demographic, occupation and human capital factors affect log-earnings in S&E and non-S&E also appear in Table 3. The ceteris paribus effects of race and ethnicity differ by gender: among males, Blacks, Native Americans and Hispanics earn less in both S&E and non-S&E jobs; among females, Asians earn more while Blacks and Native Americans earn less, but only in S&E jobs and Hispanics earn more, but only in non-S&E jobs. Workers in the Northeast and Pacific states tend to earn more than workers in other regions. The payoff to being married is about the same for men and women in S&E, but is twice as high for men in non-S&E jobs. The impact of having children varies by gender: for men, each child *raises* earnings 1–2 percent; for women, each child *lowers* earnings up to 1 percent in non-S&E jobs but has no significant impact in S&E jobs.

Men and women employed in the for-profit sector earn significantly more than those employed in education, government or the non-profit sector. For men, the earnings sacrifice from working outside the for-profit sector is greater in non-S&E jobs, while for women it is greater in S&E jobs. Self employed women in S&E jobs earn 4 percent more and self employed men in non-S&E jobs earn 14 percent less than otherwise similar workers.[10] Belonging to more professional societies, attending professional meetings, having recently attended a training program or supervising others are all occupational activities that are positively associated with earnings. The payoffs to these activities are similar for men and women, but are generally stronger in non-S&E than in S&E jobs.

Not surprisingly, it is the human capital variables that tend to be the strongest and most consistently are the

[10]The analysis has also been performed excluding the self-employed. Results are qualitatively similar to those reported in this paper. The full set of results is available from the first author.

significant determinants of earnings. Workers with advanced degrees earn significantly more than those with only 4 years of college, with professional degrees yielding the highest rate of return in both S&E and non-S&E jobs. In S&E jobs, the rate of return to schooling is similar for men and women; in non-S&E jobs, the return to having an MA or Ph.D. degree is higher for men than women. For both men and women, years of full-time work experience has a positive but nonlinear effect on earnings: an additional year of experience (measured at the mean) raises earnings by 2 percent. Holding constant schooling and experience, age has a small negative impact on earnings, suggesting more time away from work reduces earnings. Finally, proficiency in English is associated with higher earnings, although men experience a greater payoff than women in non-S&E jobs.

Our most interesting and novel findings about human capital concern on the impact of having an S&E degree. For both men and women employed in S&E, the payoff to an S&E degree is roughly the same: having *any* S&E degree raises earnings 10 percent for men and 8 percent for women, and there is no additional payoff if it was the most recent degree that was in S&E. The gender pattern of returns to S&E degrees in non-S&E jobs is quite different: men whose most recent degree was in an S&E field earn 38 percent more than those without any S&E degree, and men with a prior S&E degree earn 20 percent more; women whose most recent degree was in an S&E field earn about the same as women without any S&E degree, while women with a prior S&E degree earn 9 percent more.

These findings raise a number of questions. One question is why for both sexes, but especially for men, the payoff to having an S&E degree appears to be higher in non-S&E than in S&E jobs. Suppose both S&E educational degrees and S&E jobs attract a fairly homogeneous group of workers (with unobservable but presumably high quantitative and analytical skills) while non-S&E degrees and non-S&E jobs attract a more heterogeneous workforce. Suppose further that these quantitative/analytical skills are highly rewarded in both S&E and non-S&E jobs. Then, it will appear that having an S&E degree pays higher rates of return in non-S&E jobs since almost all workers with S&E jobs have these skills, while many with non-S&E jobs do not. A second question raised by these findings is why the rate of return in non-S&E jobs to having a recently earned S&E degree appears to be positive for men but near zero for women. The answer to this may hinge on occupational segregation and earnings among some jobs considered by the NSF classification to be non-S&E occupations—for example, medical doctors and nurses. Both doctors (predominantly male) and nurses (predominantly female) are likely to have their most recent degrees in an S&E field, but while the earnings of doctors tend to be well above average, the earnings of nurses are only about average that of other non-S&E workers without S&E degrees.[11]

Table 3 also reports estimates of ρ, the correlation coefficient between the error terms in the selection and earnings equations. For both sexes, ρ is insignificant in S&E, which indicates that unobserved determinants of S&E selection are uncorrelated with the unobserved determinants of S&E earnings. In other words, workers who unexpectedly (on the basis of their characteristics) take S&E jobs do not tend to earn either more or less in these jobs than would be expected. By contrast, ρ is statistically significant in both the male and female non-S&E earnings regressions, but with opposite signs—negative for men and positive for women. This means that men who unexpectedly take non-S&E jobs tend to earn more than would be expected, while women tend to earn less. We have seen that whether or not a worker has a degree in S&E is by far the strongest predictor of S&E employment. So, the sign of ρ might be interpreted this way: men and women with educational backgrounds in S&E who take non-S&E jobs do so for very different reasons: men do it for the money; women do it for other reasons. These other reasons may include a preference for some other benefits associated with non-S&E jobs or a dislike for S&E jobs resulting from an unpleasant prior S&E employment or educational experience.

5. Accounting for gender differences in earnings in S&E and non-S&E occupations

On average, men employed in S&E occupations earn \$8714 more than women in S&E, and men in non-S&E occupations earn \$16,391 more than women in non-S&E jobs. In the two panels of Table 4, we decompose the gender gaps in mean log-earnings—0.185 in S&E and 0.304 in non-S&E fields—into explained and unexplained portions. In turn, the explained portion is subdivided into portions accounted for by demographic, human capital and occupational variables. These decompositions can be performed using either male or female earnings coefficients to weight gender differences in average characteristics. As we will see, it is possible to explain more of the gender earnings gap in S&E than in non-S&E occupations, and more on the basis of male than female coefficients.

Taking account of gender differences in average characteristics, we can account for 63 percent of the gender earnings gap in S&E when characteristics are evaluated with male coefficients, and slightly less (57 percent) using female coefficients. In both cases, human

[11] In our sample, 18 percent of men and 28 percent of women who work in non-S&E jobs and have S&E degrees are health professionals. Of these, 84 percent of the men are doctors; 65 percent of the women are nurses or other health technicians.

Table 4
Accounting for male-female differences in mean annual log-earnings among full-time workers in S&E and non-S&E occupations

	Based on male coefficients	Based on female coefficients
S&E occupations		
Log-earnings difference[a]	0.185 (100%)	0.185 (100%)
Explained difference[b]	0.117 (63.1%)	0.105 (56.8%)
Unexplained difference[c]	0.068 (36.9%)	0.080 (43.2%)
Percent explained by:		
Demographic factors	5.1%	1.7%
Human capital factors	39.3%	32.7%
Experience	32.1%	27.4%
S&E education	12.3%	10.1%
Other	−5.1%	−4.8%
Occupation factors	18.7%	22.4%
Sector	16.7%	21.2%
Other	2.0%	1.2%
Non-S&E occupations		
Log-earnings difference	0.304 (100%)	0.304 (100%)
Explained difference	0.172 (56.5%)	0.092 (30.4%)
Unexplained difference	0.132 (43.5%)	0.212 (69.6%)
Percent explained by		
Demographic factors	6.1%	−0.6%
Human capital factors	29.0%	18.3%
Experience	9.4%	9.2%
S&E education	11.7%	0.8%
Other	7.9%	8.3%
Occupation factors	21.4%	12.7%
Sector	19.5%	8.5%
Other	1.9%	4.2%

[a]Male minus female mean of log-earnings.

[b]Explained by gender differences in means of the explanatory variables evaluated at the male (or female) coefficients.

[c]Total minus explained difference, or gender differences in coefficients evaluated at the female (or male) means of explanatory variables.

capital variables account for the largest portion (39 percent based on male coefficients) and demographic variables account for the smallest (at most 5 percent). Among all human capital factors, gender differences in years of full-time work experience (on average, men have 4 more years) are by far the most important. This is consistent with recent findings by Blau and Kahn (1997) and O'Neill (2003). Our study is the first to document that gender differences in S&E education matter too, accounting for 10–12 percent of the total pay gap. Occupational variables also account for a sizeable portion (19–22 percent) of the earnings gap, with sector of employment (education, government or nonprofit versus for-profit) accounting for most of it. But, even after taking account of all these factors, we find that women employed in S&E jobs still earn 6.8–8 percent less than men.

The gender gap in earnings in non-S&E occupations is larger, and we can account for less of it: using male coefficients we explain 57 percent; with female coefficients we explain only 30 percent. Again, human capital variables account for the largest portion of the explanation, and demographic variables the smallest. Among human capital variables, no single determinant looms as large as years of experience did in accounting for the S&E earnings gap.[12] Using male coefficients, gender differences in S&E education are still important, accounting for 12 percent of the earnings gap, but using female coefficients they account for almost nothing (given the negative rate of return to recent S&E degrees among women with non-S&E jobs). Sector of employment remains the single largest explanatory factor among occupation variables. After taking account of all of these factors, we find that women in non-S&E jobs still earn 13.2–21.2 percent than men.

What accounts for the unexplained gender earnings gap in both S&E and non-S&E fields? Of course, the unexplained is simply the total minus the explained gap, but it can be shown (see Blinder, 1973 or Oaxaca, 1973) the unexplained gap is also equal to the gender difference in coefficients evaluated at the sample mean (of male or female) characteristics. In other words, if earnings coefficients are thought to represent how the labor market treats specific characteristics, then the unexplained represents differences in treatment (holding characteristics constant). As such, the unexplained gap is often equated with labor market discrimination, although this remains controversial. The unexplained gap will overstate discrimination if any productivity-related characteristic by which men and women differ has been omitted from the earnings equation (in our study, perhaps quantitative/analytical ability); it understates discrimination if gender differences in the mean of any characteristic included in the equations (in our study, perhaps the percent of workers with S&E degrees) is itself the result of anticipated discrimination. Despite these cautions, the unexplained pay gap remains the most often cited single measure of earnings discrimination. And on this basis, gender pay discrimination appears to be less in the S&E labor market than elsewhere.

We also propose a second measure of discrimination, based not on average but on individual characteristics. To do so, we estimate earnings two ways for each worker in our sample—first by evaluating an individual's characteristics on the basis of the earnings

[12]Experience accounts for less because gender differences in mean years of experience are smaller in non-S&E than in S&E jobs and because the overall gender gap in earnings is larger among non-S&E workers.

coefficients for one's own gender (in either S&E or non-S&E jobs) and then on the basis of the earnings coefficients for the other gender. The difference between these two estimates represents an individual-specific measure of gender-based inequality in treatment. We call this "expected discrimination or favoritism in S&E (or non-S&E) fields" and display sample means (by gender and whether or not employed in S&E) in the last two rows of Table 2.[13] For women, the average value of expected discrimination in S&E is 7.2 percent, an amount that varies little depending upon whether or not a woman actually holds an S&E job. And consistent with our earlier decomposition analysis, the average value of expected discrimination in non-S&E jobs is much greater—23.6 percent. This value does vary across the sample: it averages 19.8 percent for women not in S&E and 46.6 percent for those in S&E jobs. Table 2 also shows estimates for men of expected favoritism in S&E and non-S&E fields. These estimates suggest that on average men expect to earn 7.6 percent more in S&E than if they were treated like women, and 41.0 percent more in non-S&E jobs.

6. Structural estimates of selection into S&E occupations

Our final goal is to estimate how expected differences in earnings and other job-related benefits between S&E and non-S&E jobs affect the likelihood that a worker will select an S&E job—that is, estimating Eq. (1′) directly. Knowing the parameters of this equation would be important for policymakers who may be interested in ways of increasing employment in S&E in general, and among women in particular.

Table 5 shows quasi-structural probit estimates of Eq. (1′) by gender. The first determinant of S&E selection is the expected log-earnings difference between S&E and non-S&E jobs, which is calculated on the basis of a worker's own characteristics evaluated by the gender-specific earnings coefficients in Table 3. The second determinant are other job-related benefits, which are captured in part by the individual-specific measures of expected discrimination or favoritism in S&E and non-S&E jobs discussed in the previous section. But since job-related benefits are likely to include many other factors as well, we also include additional control variables in the selection equation. In the first set of probit estimates, these controls are limited to the mother's education (the variable excluded from the earnings regressions) and three measures of educational background (any S&E degree, 1st degree S&E and # of degrees). In the second set of probits, the list of control variable is expanded to include all demographic, human capital and occupation variables that were statistically significant at the 1-percent level in the original selection equations.[14]

Among all women in our sample, the average expected log-earnings difference between S&E and non-S&E jobs is 0.117 (see Table 2). Among women who are employed in S&E jobs, the expected log-earnings difference is 0.202; and among women who are employed in non-S&E jobs, it is only 0.102. Among men in our sample, average expected log-earnings differences are all negative, indicating that men, unlike women, expect to earn more in non-S&E jobs than in S&E jobs. Using these data, the probit results in Table 5 show how earnings differences affect the likelihood of being employed in an S&E job, holding other factors constant. The results provide strong and consistent evidence that the greater is the expected earnings difference between S&E and non-S&E jobs, the more likely a worker is to be employed in an S&E occupation. Based on the marginal effects corresponding to the probit coefficients, we can say that, all else equal, a 10-point increase in the earnings difference between S&E and non-S&E jobs would raise the likelihood of S&E employment by 0.5 (col. 2) to 1.5 (col. 1) percentage points for men and by 0.9 (col. 4) to 1.3 (col. 3) percentage points for women.[15] In other words, men and women exhibit similar modest but positive employment responses to increases in S&E earnings.

Our results also offer evidence that workers base part of their decision about whether or not to seek employment in an S&E field on how they expect to be treated (i.e., paid) relative to similar workers of the opposite sex. As we have seen, this expected earnings inequality takes the form of discrimination against women and favoritism of men (Table 2). The results in Table 5 suggest that smaller the expected gender inequality in S&E jobs and the greater the expected gender inequality in non-S&E jobs, the more likely a worker is to be employed in an S&E job. Consider the evidence for women first: a 10-point *decrease* in expected S&E earnings discrimination increases the likelihood of S&E employment by 1.0 (col. 4) to 2.3 (col. 3) percentage points; meanwhile a 10 point *increase* in non-S&E earnings discrimination increases S&E employment by 0.2 (col. 4) to 2.9 (col. 3) points. Perhaps surprisingly, men also appear responsive to gender inequality—reacting negatively to favoritism. Unfortunately, these effects are estimated somewhat imprecisely: a 10 point increase in expected favoritism in S&E jobs either decreases a man's likelihood of taking an S&E job by 4.8 (col. 1) percentage points or by an insignificant amount (col. 2); a 10 point increase in

[13] Discrimination is represented by a negative number; favoritism by a positive number.

[14] It is not possible to include all control variables since they would be collinear with expected earnings.

[15] Marginal effects are obtained as outlined by the procedure in footnote 6.

Table 5
Quasi-structural probit estimates of the likelihood of employment in S&E among male and female college graduates employed full-time

	Men ($N = 71,260$)		Women ($N = 39,898$)	
	(1)	(2)[a]	(3)	(4)[a]
Expected log-earnings difference				
Between S&E and non-S&E	0.444	0.138	0.764	0.565
	(7.27)	(1.28)	(7.94)	(3.16)
Expected discrimination	−1.416	0.047	1.379	0.606
Or favoritism in S&E	(13.69)	(0.22)	(7.98)	(1.83)
Expected discrimination	1.877	0.125	−1.715	−0.114
Or favoritism in non-S&E	(30.58)	(0.94)	(18.78)	(0.57)
Mother attended college	0.060	0.044	0.076	0.052
	(5.25)	(3.63)	(4.17)	(2.79)
# of degrees	0.188	−0.007	0.357	0.072
	(21.71)	(0.45)	(25.14)	(3.09)
Any S&E degree	0.373	0.706	0.272	0.530
	(16.45)	(25.93)	(6.48)	(11.14)
1st degree S&E	0.720	0.893	0.566	0.876
	(26.69)	(22.43)	(11.41)	(12.69)
Constant	−1.963	−0.729	−2.425	−1.328
	(88.74)	(14.09)	(73.83)	(17.86)
Log-likelihood	−32172	−30630	−11941	−11599
Likelihood ratio index	.2913	.3252	.2710	.2918
% cases predicted	79.81	80.64	88.15	88.66

Note: *T*-values are shown in parentheses.
[a]Also controls for Age, Black, Hispanic, Native American, Masters degree, Professional degree, Ph.D. degree, years of experience, experience-squared, nonprofit sector, education sector, self-employed, attended training, supervisor.

expected favoritism in non-S&E jobs increases his likelihood of an S&E job by 6.3 (col. 1) percentage points or by an insignificant amount (col. 2).

6. Summary and conclusions

Recognizing the ever-critical need for scientists and engineers, together with the continuing demographic shift in the college-educated labor force in favor of women and minorities, policy makers and others have voiced concern about current and future equity and efficiency in S&E labor markets. Women represent just slightly more than one-fifth of the total S&E workforce, and on average, earn about 20 percent less than men. The main goal of this paper has been to identify factors responsible for the disproportionate selection of women away from S&E and for gender inequality in pay. It is our thesis that S&E selection and pay are related and need to be analyzed simultaneously.

We find that about 60 percent of the gender differential in the likelihood that a college-educated worker selects an S&E job can be explained, and all of it on the basis of gender differences in S&E educational backgrounds. Men are much more likely than women to have a degree in an S&E field, a factor which greatly increases their chances of selecting an S&E job. From a policy viewpoint, encouraging more women to major in science or engineering in college remains the single most important way to increase the representation of women in S&E occupations. But not all students who major in S&E fields go on to work in S&E jobs, and attrition away from S&E is greater among women than men. We offer evidence (on the basis of the correlation between the error terms in the selection and earning equations) that men with S&E degrees who unexpectedly select non-S&E jobs tend to do so for reasons of higher expected earnings while women do so reasons other than higher earnings. Future research needs to identify these reasons as a prelude to reducing the high rate of attrition of S&E-trained women away from S&E employment.

We find that almost two-thirds of the gender pay gap in S&E occupations can be explained. Consistent with Paula Stephan's (1996) view of the S&E labor market as one in which monetary rewards depend largely upon measurable skills, the explained pay gap can be attributed to a standard set of demographic, human capital and occupation-related variables. We also find some support for Laurie Morgan's view on the gender differences in treatment, since one-third of the S&E pay gap remains unexplained. But, compared with S&E occupations, there appears to be even greater pay inequity in the non-S&E labor market: as much as 70 percent of the pay gap in non-S&E jobs remains unexplained.

Finally, we showed that the likelihood of selecting an S&E occupation depends positively upon the expected earnings difference between S&E and non-S&E jobs as well as on expected gender earnings inequality (i.e., discrimination against women or favoritism of men) in both the S&E and non-S&E labor markets. For men and women, participation in S&E is negatively related to expected gender earnings inequality in S&E and positively related to expected inequality in the non-S&E labor market. No one would advocate increasing gender inequality in non-S&E jobs as a means to boosting S&E employment, but our findings do suggest two positive approaches to raising S&E employment in general and among women in particular. First, we need to increase S&E pay generally, perhaps through government subsidies or spending to boost the demand for and pay of S&E workers. Second, we need to target federal EEOC antidiscrimination enforcement and affirmative action policies toward reducing gender earnings discrimination in S&E jobs.

Appendix A

NSF definitions of S&E and non-S&E occupations and educational degree fields

S&E occupational fields

1. Computer and mathematical scientists (computer and information scientists, mathematical scientists, post-secondary teachers of computer and mathematical sciences).
2. Life scientists (agricultural and food scientists, biological scientists, environmental life scientists including forestry, post-secondary teachers of life sciences).
3. Physical scientists (chemists, earth scientists, geologists, oceanographers, physicists, astronomers, other physical scientists, postsecondary teachers of physical sciences).
4. Social scientists (economists, political scientists, psychologists, sociologists, anthropologists, other social scientists, post-secondary teachers of social sciences).
5. Engineers (aerospace, chemical, civil, electrical, industrial, mechanical, other engineers, post-secondary teachers of engineering).

Non-S&E occupational fields

1. Managers and administrators.
2. Health-related (doctors and other health practitioners, nurses, pharmacists, therapists, health technologists and technicians).
3. Pre-college teachers.
4. Postsecondary teachers in non-S&E fields.
5. Social service (clergy, counselors, social workers).
6. Technologists and technicians (computer programmers, technicians in S&E fields).
7. Sales and marketing.
8. Artists and other humanities (artists, editors, entertainers, writers, historians).
9. All other non-S&E occupations.

S&E educational degree fields

1. Computer and mathematical sciences.
2. Life sciences (agricultural, food, biological, medical and environmental, health fields at the doctoral level).
3. Physical sciences (chemistry, earth science, geology, oceanography, physics, astronomy).
4. Social sciences (economics, political science, psychology, sociology, anthropology).
5. Engineering.

Non-S&E educational degree fields

1. Business administration.
2. Business and managerial economics.
3. Health fields, at the bachelor's and master's level.
4. Education fields.
5. Social services (social work, philosophy, religion, theology).
6. Technologies (computer programming, data processing, engineering technologies).
7. Sales and marketing.
8. Art and humanities.

Source: Adapted from NSF (1999a).

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