AN EXAMINATION OF COMPETING EXPLANATIONS FOR THE PAY GAP AMONG SCIENTISTS AND ENGINEERS

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This article uses a nationally representative data set to determine the role of glass ceiling barriers and cohort effects on the earnings differences between women and men in an elite and growing group of professionals: Scientists and engineers. It draws on national data gathered in four surveys during the 1990s for cohorts graduating between 1955 and 1990. Results indicate a continuing pay gap net of human capital, family status, and occupational characteristics that was not fully explained by either cohort effects or the glass ceiling. The authors suggest that the gender pay gap in these fields results from several unmeasured barriers that neither worsen across the life cycle nor become less problematic for recent cohorts. Improvements will require continued attention to discriminatory barriers.

Keywords: *glass ceiling; scientists and engineers; pay gap; sex differences; discrimination*

Women's underrepresentation in the upper ranks of occupational hierarchies and their correspondingly lower earnings than men is widely acknowledged, but explanations for them vary. One possibility is a glass ceiling resulting from promotion or other barriers unlikely to dissipate without interventions. An alternative possibility is the presence in the labor force of older cohorts of women whose lower status and pay vis-à-vis men stem from barriers that have diminished with time and thus are less costly to younger cohorts. Research has supported both positions, and the

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question about the roles of cohorts and glass ceiling barriers in women's career outcomes is an open one.

Any examination of glass ceiling and cohort effects is necessarily about the role of discrimination over time, since both concepts tap into how historical change in women's opportunities plays out in the earnings arena. A finding of support for the cohort argument, outlined below, would imply that discrimination has been waning monotonically in a trajectory that will continue, barring the re-introduction of biased practices. A finding of support for the glass ceiling argument would imply ongoing discrimination that will decline only with the introduction of effective antidiscrimination remedies. A third possibility is that neither explanation is supported. This result would mean that the continued gender pay gap (net of controls for individual and family-status differences) is neither cumulative over time (as the glass ceiling would predict) nor steadily diminishing (as the cohort explanation would predict) and would require additional remedies.

Understanding the causes of women's lower pay vis-à-vis men in the sciences and engineering matters for several reasons. Most important is concern for gender equity: Because science and engineering are among the most prestigious occupations, women's poor showing in them contributes to their lower status in society (Xie and Shauman 2003, 4-5). The issue also presents an intellectual puzzle, since women should be relatively well represented in these occupations for several reasons, making it surprising that they are not. First, women's integration and equal compensation should be relatively unproblematic because of science's professed reliance on universalistic criteria for evaluation, advancement, and compensation (Xie and Shauman 2003, 4). Second, given national concerns about a scientist shortage, expanding the talent pool by admitting women and paying them equally is an obvious way to increase the supply (Xie and Shauman 2003, 5). Third, since scientific and engineering occupations have been growing and are predicted to continue increasing at a rate four times that of all occupations during the next decade (National Science Foundation 2000), women's opportunities should be expanding. Science and engineering occupations present an interesting case in this regard, since one general reason women's progress to the top has been slow in many professions is that advancement opportunities partly depend on turnover and occupational growth, which are often limited (Hargens and Long 2002). At one extreme is the occupation of Supreme Court justice, for example, which is unlikely to see rapid gains in women incumbents partly because the occupation comprises only nine positions, which, moreover, are lifetime appointments, resulting in few openings. In contrast, we should expect to see greater opportunities for women in growth occupations like science and engineering. This brings us to the final reason that this question matters: A continuing pay divergence in a growth occupation bodes poorly for future earnings parity.

The pay gap between women and men in science and engineering occupations is well documented. For example, women scientists overall earned about 11 percent less than men, net of demographic and human capital variables (Goyette and Xie 1999); among computer professionals, the pay gap ranged from 2.5 to 18 percent

(Ranson and Reeves 1996); and among engineers, it ranged from 0 to 11 percent, depending on cohort (Morgan 1998, 487-88).

This article uses a nationally representative data set to determine the role of glass ceiling barriers and cohort effects on the earnings differences between women and men scientists and engineers. By tracking six age cohorts (spanning 1955 to 1989) during a seven-year period in four scientific and engineering occupations (physical sciences, computer and math sciences, life sciences, and engineering), it expands on the work of Morgan (1998), whose data on engineers covered the years 1982 to 1992, and Maume (2004) whose analyses covered three cohorts of labor force participants between 1980 and 1992. Thus, our data set extends glass ceiling/cohort research to 1999 for a sample of more than 13,000 scientists and engineers. More important, because it addresses the link between discrimination and the wage gap over time, it offers clues about where change agents should devote their energy: Toward encouraging women to enter the scientific pipeline, toward eradicating barriers blocking their route to higher pay once in such occupations, or toward reconsidering larger social forces that work to block opportunities.

Cohort and Glass Ceiling Explanations of the Pay Gap

Research consistently has shown that the pay gap is worse for older than for younger women (Blau 1998; Maume 2004). A woman aged 55 to 64, for example, earns 64 percent of her male counterpart's earnings, compared to 82 percent for a woman 25 to 34 (for full-time, year-round workers; Padavic and Reskin 2002, 126). This disparity has given rise to two alternative general explanations: The cohort effect explanation and the glass ceiling explanation.

The former posits that because of the discrimination of an earlier era, older cohorts of women have experienced a greater pay gap with men throughout their careers than have more recent labor market entrants. Thus, as older cohorts retire and are replaced by younger ones, the overall pay gap would decline. If the greater pay gap at older ages were entirely due to a cohort effect (differences between cohorts but not within them) the pay gap for each cohort would remain constant throughout the life cycle. Support for the cohort explanation comes from Morgan (1998), who used data from the Survey of Natural and Social Scientists and Engineers, 1982-1989 (U.S. Department of Commerce 1990), and the 1992 Survey of Men and Women Engineers (Society of Women Engineers 1993) to show that differences in women's and men's earnings ratios over time were due to a cohort effect, not a glass ceiling. Implicit in cohort effect explanations of the pay gap is the premise that discrimination has diminished over time. If cohort effects were the sole explanation for the gender gap in pay, we could expect to see the pay gap narrow in the future, assuming trends toward lower levels of discrimination were to continue.

The cohort explanation is partly based on the notion of a pipeline that differentially channels women and men through years of schooling, early jobs, and the intermediate ranks and into top jobs. According to this reasoning, women's current underrepresentation in the upper echelons of most occupations is a result of their cumulative underrepresentation at every stage of career progress stemming from a process known as a "leaking" pipeline (for an explanation and critique, see Xie and Schauman 2003). Since women exit the pipeline at greater rates than men at each stage, it is unsurprising that their proportions in top jobs (and hence their earnings) fail to match men's. However, as women's biographies begin to match men's (as their educational credentials and experience improve) and as discrimination dissipates, one can expect more women in top jobs and a corresponding decline in the pay gap as well, according to this theory. And in fact, examinations of pay gaps in cohorts over time have tended to show successive improvements (Blau 1998; Maume 2004).

Alternatively, the glass ceiling hypothesis predicts that differential rates of access to higher-status jobs (regardless of cohort) account for women's reduced earnings relative to men. Gender-linked barriers to higher-status and higher-pay jobs ensure that as men's salaries increase, women's fail to keep pace. To return to the example of an older woman earning 64 percent and a younger woman 82 percent of their male counterparts, the first gap is largely attributable to the older woman's longer history of exposure to blocked opportunities. According to this logic, as the younger woman ages, she, too, will confront barriers, with predictable results for the pay gap. Hence, the smaller pay gap for younger cohorts would not necessarily result in an overall diminution of the pay gap over time. Support for this perspective comes from Maume (2004), who found that between 1980 and 1992, women of every cohort saw ever-greater wage inequality relative to their male counterparts. Other recent research, however, has called into question the claim that a glass ceiling is responsible for the pay gap (Baxter and Wright 2000; Morgan 1998; Wright and Baxter 2000), although this research, too, has been questioned (Britton and Williams 2000; Ferree and Purkayastha 2000).

Researchers have conceptualized the glass ceiling metaphor in several ways. Taken literally, it is a transparent barrier above which women cannot advance, although recently, researchers have offered two less literal interpretations. The first assumes progressively greater disadvantage as women move up the ranks (Baxter and Wright 2000) so that, for example, in a hierarchy where 1 is the best job and 3 is the worst, the move from 2 to 1 is more difficult than the move from 3 to 2. The second and more commonly used interpretation does not assume progressively greater disadvantage but simply assumes that the cumulative disadvantage of blocked opportunities (no matter where they occur) causes women's underrepresentation in higher ranks (Cotter et al. 2002; Ferree and Purkayastha 2000; Wright and Baxter 2000). This more general definition is the one we adopt. It implies that the glass ceiling can occur at multiple hierarchical levels and points in time.

Researchers have also used various operationalizations of the glass ceiling concept, including chances of promotion (e.g., Baxter and Wright 2000), levels of authority (e.g., Wright, Baxter, and Birkelund 1995), and increasing earnings disparity over time (e.g., Morgan 1998). We focus on the effects of glass ceiling barriers on the pay gap between women and men, and hence our references are to an earnings glass ceiling. Continued inability to leap promotion and other hurdles to successively higher-paying positions should lead to ever-wider pay gaps between women and men over time.

Some empirical evidence points to possible glass ceiling barriers for women in science and engineering occupations (Sonnert and Holton 1995a). Women make up only 11 percent of corporate officers in the computer industry, for example, but are 35 percent of the high-tech workforce (U.S. Congress, Committee on Science 1998, 1). In computer science occupations, men are nearly twice as likely as women to be managers and one-and-one-half times more likely to be supervisors (Ranson and Reeves 1996).

Hypotheses

The above considerations lead to the following predictions:

Hypothesis 1: Cohort membership affects the pay gap. Earnings differences between women and men will be greater in older cohorts than in younger ones because younger women and men entered the labor market in a period more favorable to women. We expect to observe the cohort pattern in every survey year.

Hypothesis 2: The glass ceiling affects the pay gap. Earnings differences between women and men within cohorts will grow over time. This widening occurs because the pay gap is smaller at early career stages, before women have had a chance to encounter a glass ceiling, and grows over time as men gain high-status jobs at a greater rate than do women. Given the overall decline in the pay gap during the 1990s (U.S. Department of Labor 2001), we would expect the pay gap among scientists and engineers over the 1990s to decline as well. Any evidence of an increase in the gap, net of controls, would indicate a glass ceiling effect.

DATA AND MEASUREMENT

Data

SESTAT is an integrated database collected through three national sample surveys supported by the National Science Foundation and includes data from the National Survey of College Graduates Science and Engineering Panel, the National Survey of Recent College Graduates, and the Survey of Doctoral Recipients. SESTAT represents recipients of bachelor's degrees or higher who have at least one degree in science or engineering or individuals holding any college degree who work in a science or engineering occupation. We use two samples from SESTAT, the National Survey of College Graduates Science and Engineering Panel, and the Survey of Doctoral Recipients. The National Survey of College Graduates Science and Engineering Panel is a nationally representative sample comprising people with science and engineering degrees and those without such degrees who work in science and engineering occupations (N = 74,462). The panel was followed up in

1995, 1997, and 1999. The Survey of Doctoral Recipients is made up of a random sample of recipients of science and engineering doctorates earned at U.S. institutions who are followed throughout their careers until age 75. Every two years, a sample of new science and engineering doctorate earners is added to the Survey of Doctoral Recipients (Kannankutty and Wilkinson 1999). Each survey asked respondents about employment information from the previous year.

For each survey year in the panel study (1993, 1995, 1997, and 1999), we selected those who worked in a science or engineering field and graduated with their most recent degree between 1955 and 1990. This resulted in four cross sections of data. Table 1 reports descriptive statistics for 1993 and 1999 survey data, broken down by gender and cohort. For other analyses, we weighted the data with the National Science Foundation–provided weights and adjusted the sample size.

Measurement

The dependent variable, earnings, is measured as annual salary in $1,000 increments, capped at $150,000 for each survey year, and is logged in the regression equations to correct for its positive skew. We use a semilog model (the dependent variable is logged, and the independent variables are not), and thus, "the slope coefficient measures the proportional change in Y for a given absolute change in the explanatory variable," which is woman in this case (Gujarati 1992, 229). Thus, the coefficient for the woman variable, once converted,[1] represents the proportional difference in earnings between women and men. Key independent variables are *woman* and *cohort*. *Woman* is a dummy variable (1 = woman). Cohorts are determined by the year respondents attained their most recent degree and are grouped as follows: 1955 to 1964, 1965 to 1969, 1970 to 1974, 1975 to 1979, 1980 to 1984, and 1985 to 1989.[2]

We control for factors previous research has found to influence our variables of interest, namely, human capital, employment, and demographic variables.[3] Human capital variables include a dummy indicator for work-related training (1 = yes), three dummy variables for highest degree (master's, Ph.D., or professional; bachelor's is the omitted category), and variables for years of full-time professional experience and years of part-time professional experience (measured in years).[4] Two dummies measure the respondent's employment sector verses all others (business = 1 and education = 1; government is the omitted category for each), and a series of dummy variables measure occupational subfield. Regarding hours of work, in most survey years, we use the natural log of hours worked per week, but because we lack these data for 1993, we use a dummy for part-time work (1 = part-time). Demographic variables include a dummy for the presence of children younger than six (1 = yes), a dummy for the interaction of the presence of children younger than six and *woman* (1 = yes; included because the effect of children on salary is likely to depend on whether the parent is a woman or a man), a dummy for country of birth (1 = United States), and a variable for age. Underrepresented minorities include African Americans and Hispanics (0 = underrepresented minority).

TABLE 1: Means and Standard Deviations for Selected Variables Used in the Analysis[a,b]

	All Cohorts			*1955-1959*[c]			*1960-1964*			*1965-1969*		
	Total	*Women*	*Men*	*Total*	*Women*	*Men*	*Total*	*Women*	*Men*	*Total*	*Women*	*Men*
1993												
n	42,553	8,349	34,204	1,082	80	1,002	2,007	208	1,799	3,635	435	3,200
Salary[d]	52,074	44,367	53,956	62,088	42,544	63,829	61,281	46,478	63,030	60,410	49,319	62,098
	(21,262)	(19,450)	(21,261)	(23,390)	(21,236)	(22,782)	(24,529)	(20,762)	(24,353)	(22,428)	(19,802)	(22,326)
Salary (ln)	10.78	10.62	10.82	10.96	10.56	11.00	10.9	10.7	11.0	10.9	10.7	11.0
	(.40)	(.41)	(.39)	(.39)	(.45)	(.36)	(.41)	(.42)	(.40)	(.39)	(.38)	(.38)
Age	42.6	40.4	43.2	61.1	60.1	61.2	57.2	54.9	57.4	52.6	51.1	52.8
	(9.0)	(8.2)	(9.1)	(3.7)	(3.7)	(3.7)	(4.2)	(4.2)	(4.1)	(4.7)	(4.3)	(4.7)
Top coded[e]	284	43	241	17	0	17	32	1	31	31	1	30
1999												
n	13,806	2,093	11,713	190	9	181	490	36	454	1,234	111	1,123
Salary[d]	73,497	64,943	75,025	73,184	68,111	73,436	72,645	58,333	73,780	77,852	70,946	78,534
	(24,962)	(23,748)	(24,866)	(36,455)	(41,855)	(36,280)	(29,658)	(21,765)	(29,922)	(27,037)	(24,364)	(27,202)
Salary (ln)	11.1	11.0	11.1	11.0	11.0	11.0	11.1	10.9	11.1	11.2	11.1	11.2
	(.45)	(.48)	(.45)	(.76)	(.62)	(.77)	(.61)	(.58)	(.61)	(.47)	(.40)	(.54)
Age	49.3	47.1	49.7	68.1	68.0	68.2	63.9	62.9	64.0	59.5	58.9	59.6
	(8.5)	(8.0)	(8.6)	(4.4)	(3.5)	(4.5)	(4.0)	(6.2)	(3.8)	(4.1)	(4.3)	(4.1)
Top coded[e]	217	22	195	9	1	8	9	0	9	27	1	26

(continued)

TABLE 1 (continued)

	1970-1974			*1975-1979*			*1980-1984*			*1985-1989*		
	Total	*Women*	*Men*	*Total*	*Women*	*Men*	*Total*	*Women*	*Men*	*Total*	*Women*	*Men*
1993												
n	5,812	856	4,956	7,232	1,377	5,855	9,646	2,226	7,420	13,139	3,167	9,972
Salary[d]	56,959	48,484	58,317	54,068	46,648	55,737	51,439	46,324	52,932	43,754	39,894	48,077
	(22,478)	(20,603)	(22,472)	(20,554)	(19,530)	(20,410)	(19,701)	(20,513)	(19,204)	(17,785)	(17,064)	(17,836)
Salary (ln)	10.9	10.7	10.9	10.8	10.7	10.9	10.8	10.7	10.8	10.6	10.5	10.6
	(.40)	(.40)	(.40)	(.38)	(.39)	(.37)	(.37)	(.40)	(.35)	(.38)	(.40)	(.37)
Age	48.0	46.5	48.2	43.4	43.1	43.5	38.7	38.7	38.7	35.3	35.5	35.3
	(5.3)	(5.2)	(5.3)	(5.5)	(6.0)	(5.4)	(6.0)	(6.7)	(5.8)	(5.5)	(5.9)	(5.4)
Top coded[e]	52	6	46	53	8	45	51	13	38	48	14	34
1999												
n	2,057	207	1,850	2,506	327	2,179	3,253	572	2,681	4,076	831	3,245
Salary[d]	76,523	64,599	77,857	75,862	67,364	77,138	73,745	66,346	75,323	69,116	62,561	70,795
	(26,087)	(25,845)	(25,780)	(24,784)	(24,562)	(24,571)	(23,741)	(23,044)	(23,592)	(22,775)	(22,840)	(22,456)
Salary (ln)	11.2	11.0	11.2	11.2	11.0	11.2	11.1	11.0	11.2	11.1	11.0	11.1
	(.47)	(.55)	(.46)	(.43)	(.40)	(.43)	(.41)	(.48)	(.39)	(.42)	(.45)	(.40)
Age	55.6	55.0	55.7	50.9	50.5	51.0	46.0	46.0	46.0	42.2	42.1	42.2
	(4.8)	(5.4)	(4.7)	(5.1)	(5.2)	(5.1)	(5.5)	(5.9)	(5.4)	(5.7)	(5.9)	(5.6)
Top coded[e]	40	2	38	39	5	34	51	5	46	42	8	34

NOTE: Numbers in parentheses are standard deviations.

a. Number of observations and number of top-coded observations represent actual sample; all other information is based on weighted data.

b. Cohorts are based on year of most recent degree.

c. Multivariate analyses combine the 1955-1959 and 1960-1964 cohorts.

d. Salary is based on annual salary and is top coded at $150,000.

e. Number of cases top coded at $150,000 per year.

Attrition from the sample and from the survey are potential problems because of the possibility that selection criteria correlate with earnings (Maume 2004). Selecting only paid workers in science or engineering occupations would omit people no longer in the labor force and those who moved into a nonscience or nonengineering occupation—categories in which women may be overrepresented—and would bias regression results. By adding a control variable that is the predicted probability of survival in each survey year based on 1993 data (Heckman 1979; Maume 2004), we control for post-1993 attrition. To create this control variable, we used logistic regression to predict survival for each survey year based on independent variable information from 1993. Predictors of sample inclusion were gender, cohort group, age, country of birth, presence of a child younger than six, full-time employment, minority status, degree level, employment sector, occupation, and full- and part-time experience. After estimating the logistic regression equations for each year, we used the equations to calculate the predicted probability of inclusion for each respondent and included it as a control variable in the final models.[5]

Analysis Strategy

To test for cohort and glass ceiling effects, we estimate the same regression equation for each survey year. We regress *salary* (ln) on *woman* and on control variables to obtain the effect of gender with no *cohort* controls added. We test for the different contrasts of the cohort polytomous variable using the procedures outlined by Hardy (1993):

$$(\ln)\mathit{Salary} = B_0 + B_1\,\mathit{woman} + B_2\,\mathit{cohorti} + B_3\,\mathit{woman{*}cohorti} + B_4\,\mathit{human\ capital} + B_5\,\mathit{employment} + B_6\,\mathit{demographic} + e_i,$$

where *woman* indicates respondent's gender, *cohorti* is a vector of six dummy variables signifying membership in one of the seven degree cohorts defined above, and *woman**cohort*i* is a vector of interaction between cohort groups and *woman*, on the supposition that the effect of a woman's gender on salary may depend on her cohort.

Our research design is generally based on Morgan's (1998) multicohort longitudinal design (see also Maume 2004). The above equations allow us to assess whether earnings differences increase over time after controlling for cohort membership and control variables, thus testing the cohort and glass ceiling hypotheses. Two types of results verify cohort effects. First, any significant cohort differences in earnings net of controls indicate that cohort membership affects the gender pay gap. Second, and more specifically, hypothesis 1 predicts that the effect of gender on earnings is greater for older cohorts, such that the oldest cohort (1955) would have the largest pay gap, followed in order by the 1965 cohort, 1970 cohort, 1975 cohort, 1980 cohort, and 1985 cohort.

In general, if the effect of gender within each cohort is significantly larger in 1999 than in previous survey years, then evidence of a glass ceiling is present. Such an effect means that the percentage gap in pay is greater than in earlier years, supporting hypothesis 2's claim that a glass ceiling slows women's earnings relative to men's. The criteria for determining a change in the pay gap is that the change in the coefficient *woman* between 1993 and 1999 (the first and last survey years) must be significant.

RESULTS

Overall, the pay gap among scientists and engineers increased slightly during the 1990s. Bivariate results (not shown) of women's and men's mean earnings (in 1998 dollars) for each survey year show that the amount of the pay gap increased from $11,140 in the 1993 survey (representing 82 percent of men's earnings) to $14,932 in the 1999 survey (representing 78 percent of men's earnings). While it might be tempting to take these bivariate results as evidence of possible glass ceiling effects, findings about mean earnings are always misleading because they fail to take into account differences in human capital, particularly work experience, and other factors. They provide only a base from which to examine change. We now turn to multivariate analyses that control for human capital, occupational variables, and demographic variables.

Regression Analyses

This section reports tests of hypotheses 1 and 2 for four science and engineering occupations: Engineering, physical sciences, computer and math sciences, and the life sciences.

Engineers. For each survey year, we selected employed engineers (with earnings > 0) who obtained their most recent degree after 1954. Bivariate results show that women engineers averaged 85 percent of men's earnings in 1993, 84 percent in 1995 and 1997, and 87 percent in 1999 (results not shown).

To test for cohort and glass ceiling effects, we estimate regression equations for each survey year. Table 2 reports ordinary least squares estimates of the effects of *woman* on *salary*(ln) for each cohort of engineers, controlling for human capital, occupational variables, and demographic variables.[6] Columns represent survey years, and rows represent cohorts. Each cell contains the regression coefficient for *woman*, the standard error, and the percentage gap (converted from the coefficient) for the appropriate cohort and survey year. Five dummy variables control for engineering specialty (mechanical, chemical, civil, electrical and electronic, and "other"; postsecondary teachers was the omitted category).

Regression results for engineers lend only weak support for hypothesis 1, that cohort membership affects the pay gap such that older cohorts show greater pay gaps. While cohorts differed in the effect of gender on earnings, older cohorts did not always have larger pay gaps than younger ones. In 1993 (column 1), with some

TABLE 2: **Engineers: Coefficients, Percentage Earnings Gap, and Trends Calculated from Ordinary Least Squares Regression of the Effect of Woman on (In)Salary by Cohort and Survey Year, with Controls**

	1993 (n = 16,150)			*1995 (n = 9,244)*			*1997 (n = 7,901)*			*1999 (n = 5,489)*			
Graduated	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	*Trend*
1985-1989	–.033*	.015	–3.25	–.043	.031	–4.21	–.038	.028	–3.73	–.073	.047	–7.04	No change
1980-1984	–.049*	.020	–4.78	–.053	.038	–5.16	–.015	.030	–1.49	–.041	.051	–4.02	No change
1975-1979	–.138***	.027	–12.89	–.076	.049	–7.32	–.104*	.041	–9.88	–.079	.069	–7.60	No change
1970-1974	–.086*	.042	–8.24	–.067	.081	–6.48	–.118	.066	–11.13	–.055	.119	–5.35	No change
1965-1969	–.196***	.052	–17.80	–.474***	.086	–37.75	–.103	.072	–9.79	.001	.119	0.10	No change
1955-1964	–.341***	.056	–28.89	–.008	.154	–0.80	–.103	.072	–9.79	–.010	.142	–1.00	↓*
No cohort controls[a]	–.081***	.01	–7.78	–.018	.023	–1.78	.003	.018	0.30	.018	.029	1.82	↓***

NOTE: SE = standard error. Effects of gender by cohort are estimates of the coefficient of woman in the regression equation when the relevant Cohort and Woman × Cohort interactions are omitted. For each survey year, the equation is estimated seven times, omitting a different Cohort and Woman × Cohort interaction each time.
a. “No cohort controls” is the estimate of the coefficient of woman in equations that do not control for Cohort or Woman × Cohort interactions.
*$p < .05$. **$p < .01$. ***$p < .001$.

exceptions, older cohorts tended to have larger pay gaps than younger ones, but in all later survey years (columns 2 through 4), they did not. Indeed, the oldest cohort showed no significant pay gap at all in those survey years.

Results also fail to support hypothesis 2: No cohort of engineers showed a statistically significant increase in the gender pay gap between 1993 and 1999. In fact, the gap declined significantly for one of the six cohorts and showed no significant change in the others. The trend column summarizes the direction of change in the pay gap during the four survey years. Engineers graduating between 1955 and 1964 saw a decline in the pay gap, but those graduating later showed no significant change. Thus, we find no evidence of an earnings glass ceiling among engineers.

Physical scientists. Descriptive statistics indicate that men outearned women physical scientists: Women earned 81 percent of men's earnings in 1993, 78 percent in 1995, 79 percent in 1997, and 73 percent in 1999.

We estimate regression equations for each survey year similar to the above equation, substituting three dummy variables to control for occupation within the physical sciences (chemists, physics and astronomy scientists, and "other"; postsecondary teachers is the omitted category). Table 3 reports ordinary least squares estimates of the effects of *woman* on *salary*(ln) for each cohort of physical scientists, with controls.

Again, regression results failed to support hypothesis 1. Cohort effects did not appear in the pattern predicted. In 1993, for example, even though the oldest cohort had the largest pay gap (13.41 percent), as predicted, cohorts graduating in the 1970s had larger pay gaps than those graduating in the late 1960s, opposite the prediction. Results from the later survey years are similarly nonsupportive: In 1999, some of the relatively young cohorts—those graduating in the 1970s—showed larger gaps than those who graduated in the late 1960s.

Results also offer no support for hypothesis 2, that a glass ceiling affects the pay gap. Cohorts graduating between 1965 and 1989 showed no significant changes in the pay gap during the study period. The oldest cohort showed a shift in the pay gap, from 13.41 percent in men's favor in 1993 to 36.62 percent in women's favor in 1999, but we are cautious about interpretation because there were only 11 women in this cohort in 1999. Thus, the results failed to support hypothesis 2.

Computer and math scientists. Descriptive statistics indicate that men outearned women computer and math scientists. Women earned 85 percent of men's earnings in 1993, 82 percent in 1995, 84 percent in 1997, and 83 percent in 1999.

As before, we estimate regression equations for each survey year, substituting a dummy variable for occupational subfields, which in this case are only postsecondary teachers and all others. Table 4 reports ordinary least squares estimates of the effects of *woman* on *salary*(ln) for each cohort of computer and math scientists, with controls.

As with the other occupations examined thus far, *cohort* had an inconsistent effect on the pay gap and thus fails to lend support to hypothesis 1. In the early to

TABLE 3: Physical Scientists: Coefficients, Percentage Earnings Gap, and Trends Calculated from Ordinary Least Squares Regression of the Effect of Woman on (ln)Salary by Cohort and Survey Year, with Controls

	1993 (n = *5,266*)			*1995* (n = *3,556*)			*1997* (n = *3,169*)			*1999* (n = *2,510*)			
Graduated	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	*Trend*
1985-1989	–.006	.023	–0.60	.076	.040	7.90	.042	.038	4.29	.059	.056	6.08	No change
1980-1984	–.043	.027	–4.21	.024	.043	2.43	–.058	.038	–5.64	–.085	.049	–8.1	No change
1975-1979	–.095**	.030	–9.06	–.045	.044	–4.40	–.069	.038	–6.67	–.114*	.052	–10.77	No change
1970-1974	–.092*	.039	–8.79	.084	.055	8.76	–.005	.044	–0.50	–.155*	.062	–14.36	No change
1965-1969	.000	.043	0.00	.051	.061	5.23	.092	.057	9.64	.061	.076	6.29	No change
1955-1964	–.144**	.049	–13.41	–.744***	.081	–52.48	–.007	.075	–0.70	.312**	.090	36.62	↓***
No cohort controls[a]	–.047**	.014	–4.59	–.001	.024	–0.10	.023	.020	2.33	–.009	.026	–0.90	↓***

NOTE: SE = standard error. Effects of gender by cohort are estimates of the coefficient of woman in the regression equation when the relevant Cohort and Woman × Cohort interactions are omitted. For each survey year, the equation is estimated seven times, omitting a different Cohort and Woman × Cohort interaction each time.

a. "No cohort controls" is the estimate of the coefficient of woman in equations that do not control for Cohort or Woman × Cohort interactions.

$*p < .05$. $**p < .01$. $***p < .001$.

TABLE 4: Computer and Math Scientists: Coefficients, Percentage Earnings Gap, and Trends Calculated from Ordinary Least Squares Regression of the Effect of Woman on (ln)Salary by Cohort and Survey Year, with Controls

	1993 (n = *9,203*)			*1995* (n = *4,760*)			*1997* (n = *4,116*)			*1999* (n = *3,185*)			
Graduated	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	*Trend*
1985-1989	–.070***	.015	–6.76	–.117***	.028	–11.04	–.113***	.027	–10.68	–.094*	.039	–8.97	No change
1980-1984	–.082***	.017	–7.87	–.086**	.031	–8.24	–.118***	.029	–11.13	–.102*	.040	–9.70	No change
1975-1979	–.112***	.020	–10.60	–.128***	.034	–12.01	–.127***	.033	–11.93	–.113*	.046	–10.68	No change
1970-1974	–.104***	.022	–9.88	–.205***	.037	–18.54	–.114**	.034	–10.77	–.252***	.052	–22.28	↑**
1965-1969	–.129***	.031	–12.10	–.166**	.049	–15.30	–.154**	.047	–14.27	–.004	.066	–0.40	No change
1955-1964	–.169**	.039	–15.55	–.091	.068	–8.70	.049	.076	5.02	–.047	.130	–4.59	No change
No cohort controls[a]	–.092***	.009	–8.79	–.063**	.018	–6.11	–.063***	.016	–6.11	–.077***	.021	–7.41	No change

NOTE: SE = standard error. Effects of gender by cohort are estimates of the coefficient of woman in the regression equation when the relevant Cohort and Woman × Cohort interactions are omitted. For each survey year, the equation is estimated seven times, omitting a different Cohort and Woman × Cohort interaction each time.

a. "No cohort controls" is the estimate of the coefficient of gender in equations that do not control for Cohort or Woman × Cohort interactions.

*$p < .05$. **$p < .01$. ***$p < .001$.

mid 1990s, the gap was larger for older cohorts, but for later years, the pay gap in older cohorts disappeared. In fact, after 1995, the gap was higher in the 1985-1989 cohort (the most recent graduates) than in two of the older cohorts. Thus, we fail to see the gradual decreases in the pay gap for each successive cohort that hypothesis 1 predicted.

The trends in the pay gap indicated very little support for hypothesis 2. Only the 1970-1974 cohort, for whom the pay gap increased from 9.88 percent to 22.28 percent during the period, showed evidence of a glass ceiling effect on earnings. This is the first evidence of a pay glass ceiling in these analyses. It is weak support, however, as the remaining cohorts experienced no significant change.

Life scientists. As with the other occupations, descriptive statistics indicate that men outearned women and that the size of the gap fluctuated during the seven-year survey period. Women life scientists earned 79 percent of men's earnings in 1993, 73 percent in 1995, 75 percent in 1997, and 82 percent in 1999.

We estimated regression equations as above, this time adding two dummy variables to control for occupational subfields (biological and medical scientists and "other"; postsecondary teachers was the omitted category). Table 5 reports ordinary least squares estimates of the effects of *woman* on *salary*(ln) for each cohort of life scientists after controlling for human capital, occupational variables, and demographic variables.

Regression results again failed to support hypothesis 1, that cohort membership affects the pay gap, because the gap was not always greater for older cohorts. While in the first three survey years, the oldest cohorts showed some of the largest pay gaps, in the 1993 survey year, cohorts graduating in the 1980s showed larger pay gaps than 1970s cohorts, opposite the prediction. Similarly, in 1995, the 1970s cohorts showed larger pay gaps than those from the late 1960s. The pattern for the 1997 survey year was similar.

The changes in the pay gap also offered no support for hypothesis 2: No cohort of life scientists showed an increasing pay gap, and two showed declining gaps. The gap declined for the 1975-1979 cohort (from 4.4 percent to no significant gap) and for the oldest cohort (from nearly 25 percent to no significant gap).

In sum, results showed that neither glass ceiling nor cohort effects were able to account for the pay gap in this group of scientists and engineers. Younger cohorts sometimes showed larger pay gaps than older ones, indicating that more recent labor market entrants did not always fare better than earlier ones, and in only 1 cohort-occupation group out of 24 did we observe possible glass ceiling effects.

DISCUSSION

We ended up rejecting two common explanations for women scientists' lower earnings. Not only did we find no evidence of a glass ceiling effect; we also found no evidence that older cohorts exhibited consistently larger gender pay gaps than

TABLE 5: Life Scientists: Coefficients, Percentage Earnings Gap, and Trends Calculated from Ordinary Least Squares Regression of the Effect of Woman on (ln)Salary by Cohort and Survey Year, with Controls

	1993 (n = *7,612*)			*1995* (n = *4,673*)			*1997* (n = *4,079*)			*1999* (n = *2,622*)			
Graduated	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	B	*SE*	*Percentage Gap*	*Trend*
1985-1989	–.071***	.017	–6.85	–.087**	.032	–8.33	–.086**	.030	–8.24	–.014	.045	–1.39	No change
1980-1984	–.156***	.020	–14.44	–.054	.036	–5.26	–.116**	.030	–10.95	–.083	.049	–7.96	No change
1975-1979	–.045*	.022	–4.40	–.106**	.036	–10.06	–.097**	.031	–9.24	.063	.051	6.50	↓*
1970-1974	–.061*	.029	–5.92	–.120*	.051	–11.31	–.066	.038	–6.39	–.126*	.061	–11.84	No change
1965-1969	–.074*	.037	–7.13	–.073	.060	–7.04	–.024	.056	–2.37	–.002	.093	–0.20	No change
1955-1964	–.282***	.040	–24.57	–.242***	.065	–21.49	–.185***	.052	–16.89	.157	.098	17.00	↓**
No cohort controls[a]	–.099***	.011	–9.43	–.051*	.021	–4.97	–.037*	.016	–3.63	.065*	.027	6.72	↓***

NOTE: SE = standard error. Effects of gender by cohort are estimates of the coefficient of woman in the regression equation when the relevant Cohort and Woman × Cohort interactions are omitted. For each survey year, the equation is estimated seven times, omitting a different Cohort and Woman × Cohort interaction each time.

a. "No cohort controls" is the estimate of the coefficient of gender in equations that do not control for Cohort or Woman × Cohort interactions.

*$p < .05$. **$p < .01$. ***$p < .001$.

did younger ones during the 1990s. Instead, we found evidence of continued earnings disparities that stemmed neither from women's attributes (e.g., experience or education) nor from glass ceiling barriers. We concur with Xie and Shauman (2003, 207-208)—who similarly found little support for a different set of influential hypotheses and claims—that the explanations of gender differences in outcomes among scientists and engineers are complex.

Why No Glass Ceiling Effect?

Our results fail to corroborate Maume's (2004) finding of glass ceiling effects among the general population of workers and are consistent with previous research (Morgan 1998) demonstrating the lack of a glass ceiling among engineers. Several explanations for this lack of effect are possible. The top coding of annual salary at $150,000 potentially could have masked glass ceiling effects; however, maximum likelihood regression results showed that this is not the case. Another possibility is that glass ceiling barriers simply may not exist in these four scientific and engineering occupations, despite their prevalence in the labor force more generally. Alternatively, a seven-year time frame may be insufficient to gauge what may be a more gradual trend.

The glass ceiling explanation centers on one narrow, but measurable, form of discrimination when in fact other forms might be more pertinent to the pay gap. Our findings indicate that discrimination (indicated by the finding of a gender pay gap despite controls for human capital) is ongoing but unrelated to the barriers captured by the glass ceiling concept. Locating discrimination is always a difficult project empirically, which is why researchers (including us) often resort to attributing it to the unexplained variance in regression equations (see also Maume 2004). Even though the glass ceiling has the advantage of being measurable, making it useful for testing theories of discrimination, it is not the only discriminatory barrier women face, and the pay gap in sciences and engineering may be due to discrimination that manifests itself in ways not captured by the glass ceiling concept.

One such possibility is that employers pay women and men in the same job differently, in violation of the Equal Pay Act. Another possibility is that segregation at the job level (which we cannot measure) gives rise to unequal pay. This would be the case, for example, if women were concentrated in lower-paid lab technician jobs and men in higher-paid lab supervisor jobs, although both shared an occupational title. Segregation at the establishment level would work similarly: Men would outearn women if women worked in lower-paying establishments than did men (Petersen and Morgan 1995), although our data would not pick this up.

Other impediments that perpetuate the pay gap without working via a glass ceiling stem from organizational processes. In contrast to the overtly discriminatory practices of an earlier era, contemporary, "second generation" discrimination (Sturm 2001) is subtle, often entrenched and unnoticed in organizational structures and practices. The much-publicized report on women scientists' unequal treatment at MIT, for example, reported inequitable distributions of lab space, salary compensation from grants, teaching assignments, honors and awards, and exclusion from important departmental and nondepartmental committees (Committee on the Status of Women Faculty 1999, 8; see also Science and Technology Recruiting to Improve Diversity and Excellence Committee 2004; Sonnert and Holton 1995b), which hamper women scientists' chances to attain salaries commensurate with men's. Unintended cognitive biases, including stereotypes and in-group favoritism (what the MIT report called cronyism) also can perpetuate the pay gap if they lead employers to consider gender in distributing tasks, jobs, and rewards (see Heilman 1995; Padavic and Reskin 2002; Reskin 2002). The glass ceiling concept cannot capture these subtle barriers, but they nevertheless have ramifications for the pay gap.

Why No Cohort Effect?

We also failed to find cohort effects in the pattern that we expected, in which the pay gap would be smaller for younger cohorts. Instead we found that younger cohorts did not always show smaller pay gaps than older ones during the 1990s. Since research on the 1980s and earlier has confirmed the cohort pattern fairly consistently, it raises the question of why we did not find it. This unexpected finding can be explained by reference to older or younger cohorts, and we address each possibility in turn.

The deviation from the expected pattern on the part of the oldest cohort (1955-1964) is probably due to women's small numbers in each cohort (only 45 women across four occupations). It is also possible that the earliest cohort of women scientists in some fields, such as engineering, were the "crème de la crème," since the only women hired at all were supremely qualified ones. As institutions began to accept a broader array of women engineers, their quality and their financial compensation would not be as high as that of the select group that preceded them.

For the younger cohorts, we cannot determine with certainty the cause of differences in pay gaps across cohorts (some in the expected direction, others not). Historical periods, career cycles, and family cycles are elements of timing that are hard to disentangle, making the task of empirically pinpointing when and why women experience career blockage difficult. This confounding hinders our ability to interpret the meaning behind our unexpected pattern of cohort effects, and we can only point to the importance of timing issues in understanding cohort effects.

Historical events are captured in the notion of "period effects." Much of women's success depends on characteristics of the period: Political, legislative, judicial, and enforcement environments and the willingness of aggrieved parties to press for change (Reskin and Padavic 1994, 99). Some periods are characterized by greater opportunities for women, but these periods need not necessarily be the most recent. Hence, younger women are not necessarily more likely than older ones to be the beneficiaries of enlightened public policy. The Carter years, for example, were better for Equal Employment Opportunity enforcement of antidiscrimination laws than the Reagan years that followed (Reskin 2001).

Since career progress and family formation occur in distinct historical periods, it is difficult to unravel the independent effects of period from the effects of cohorts and of glass ceilings. If all factors were perfectly aligned, a scientist at a career stage ripe for a pay raise will also have her or his family responsibilities at a low-maintenance point and be living in an era marked by a social commitment to gender equality. Since in reality, there is much room for imperfection in this alignment, it is difficult to empirically model the time-related causes of the gender pay gap. In short, the problem with verifying a cohort effect is that researchers cannot completely untangle period and cohort effects. Because we did not see consistent improvement in more recent cohorts, it means that improvements in the pay gap are contingent on other factors, most likely attributes of the period in which women are forging their careers and families.

This consideration of period effects is important because it has implications for the breadth of the remedies used to combat discrimination. We found that gender inequity was not solely the result of problems with women's attributes (e.g., their education or experience), their family lives (e.g., the presence of preschoolers), or with the pay glass ceiling. If problems with gender equity tend to be larger than individual careers and family stages, then it is necessary to go beyond remedies that center on individuals' life cycles and to consider the role played by other actors—enforcement agencies, courts, elected officials, and employers.

In conclusion, we found that the pay gap for scientists and engineers scarcely abated throughout the 1990s but that it has less to do with an earnings glass ceiling barrier than with the likely presence of other, unmeasured, types of discrimination. The finding that career and family issues do not fully explain age differences in the gender pay gap means that attention to larger social and historical factors is warranted. Incoming cohorts will not automatically continue to show improvement in the pay gap without a focus on all the factors that influence earnings inequality.

NOTES

1. The conversion from effect of woman to earnings differential percentage is as follows: Earnings differential % = ($\exp B_{sex}$ – 1) * 100% (Allison 1999).

2. All cohorts are grouped in five-year increments except the oldest one, which includes more years because of the small number of women graduating between 1955 and 1964.

3. The data set does not include a measure of marital status. Not all research supports the power of women's marital status to affect earnings. Maume (1999) found that married workers faced no earnings penalty once other factors were controlled, and Xie and Shauman (2003, 149-50) found no evidence of a marriage penalty for women scientists.

4. Years of work experience was available only for the 1993 survey year. We computed the values for later survey years by adding respondents' years of experience in 1993 to their employment status in subsequent survey years, imputing values for missing years (1994, 1996, and 1998) based on their employment status in the previous year.

5. The addition of the control for attrition failed to substantially affect results or the pattern of results. We do not present the results of the logistic regression because our focus is on wage disparity.

6. Using weighted least squares for these and subsequent equations did not change results, nor did the addition of controls for job tasks affect results.

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