SEX DIFFERENCES IN RESEARCH PRODUCTIVITY: NEW EVIDENCE ABOUT AN OLD PUZZLE*

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Numerous studies have found that female scientists publish at lower rates than male scientists. So far, explanations for this consistent pattern have failed to emerge, and sex differences in research productivity remain a puzzle. We report new empirical evidence based on a systematic and detailed analysis of data from four large, nationally representative, cross-sectional surveys of postsecondary faculty in 1969, 1973, 1988, and 1993. Our research yields two main findings. First, sex differences in research productivity declined over the time period studied, with the female-to-male ratio increasing from about 60 percent in the late 1960s to 75 to 80 percent in the late 1980s and early 1990s. Second, most of the observed sex differences in research productivity can be attributed to sex differences in personal characteristics, structural positions, and marital status. These results suggest that sex differences in research productivity stem from sex differences in structural locations and as such respond to the secular improvement of women's position in science.

Numerous studies have found that female scientists publish at lower rates than male scientists, and research efforts to explain this gender gap have been largely unsuccessful (Long and Fox 1995; Ward and Grant 1995; Zuckerman 1991). In a classic statement of the problem, Cole and Zuckerman (1984) characterize sex differences in research productivity as "the productivity puzzle":

> More than 50 studies covering various time periods and fields of science report sex differences in published productivity, more specifically, that men publish more than women, even when age and other important social attributes are taken into account. Moreover, gender differences in publication rates appear to have persisted for decades. So far, efforts to account for these differences have not been successful; their existence continues to be a puzzle. (P. 218)

From their own research on scientists who received doctorates in 1969–1970, Cole and Zuckerman (1984) estimate that "women published slightly more than half (57%) as many papers as men" (p. 217). In a more recent literature review, Zuckerman (1991) maintains that "women publish fewer papers than men of the same ages, on average, 50–60 percent as many" (p. 43).

So far, Cole and Zuckerman's provocative assertion has not been seriously challenged, and explanations for sex differences in research productivity have remained elusive. This quandary has helped propel the contin-

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ued acceptance of sex differences in research productivity as a puzzle. For example, after reviewing many explanations in the literature, Long (1992) states, "Unfortunately, none of these explanations has been very successful in accounting for sex differences in productivity. Indeed, Cole and Zuckerman (1984) aptly label these sex differences 'the productivity puzzle'" (p. 160).

We report new empirical findings from a systematic and detailed analysis of data from four large, nationally representative surveys of postsecondary faculty in 1969, 1973, 1988, and 1993. We first examine changes in observed sex differences in research productivity over the 24-year period and then apply multivariate negative binomial models in an attempt to uncover explanations for the observed sex differences.

MEASURING SEX DIFFERENCES IN RESEARCH PRODUCTIVITY

To properly assess the extent of sex differences in research productivity, we must first define the scientist population being studied and specify an appropriate measure for quantifying the sex gap in productivity.

The Scientist Population

Defining the scientist population is not a simple task (Citro and Kalton 1989). In principle, scientists can be defined according to one of three criteria (Xie 1989:29–39): (1) contribution to scientific knowledge (contribution-based definition), (2) scientific education (supply-based definition), and (3) scientific occupation (demand-based definition). In studies of sex differences in research productivity, a supply-based definition is implicit in many studies that draw samples from recipients of doctoral degrees in science (Clemente 1973; Cole and Zuckerman 1984; Long 1992; Reskin 1978). The main competing definition is a demand-based one that restricts the population of scientists to those with academic jobs in scientific fields (Blackburn, Behymer, and Hall 1978; Fox and Faver 1985). Cole's (1979) study explicitly combines the two approaches by defining scientists as recipients of science doctorates in 1957–1958 who were working in academia in 1965.

Each approach to defining scientists has advantages and disadvantages. The supply-based definition homogenizes the training credentials of scientists and theoretically permits the examination of sex differences in career trajectories; but it could suffer from an "exposure bias" well understood by Cole and Zuckerman (1984): "If unequal proportions of men and women have remained in academia, the results . . . could be biased, since academics tend to publish more than government and industrial scientists" (p. 223). In contrast, the demand-based definition homogenizes the job settings of scientists to those where publication of research results is expected and rewarded, but it foregoes the potential analysis of sex differences in the processes of entry to and exit from academia.

Hence, the supply-based and demand-based definitions have different implications for our problem: Do sex differences in research productivity result from women's lower likelihood of working in academia or from women's lower productivity within academia? If the former explanation is true, the productivity puzzle should be defined more accurately as a career puzzle (Bernard 1964:154). This proposition is plausible given Cole and Zuckerman's (1984) finding, which is also confirmed by Long (1992), that women are overrepresented among the ranks of unpublished scientists, many of whom may be "silent" because they are not employed in academic settings.

Cole and Zuckerman (1984), however, rule out differential representation in academia as a viable explanation for sex differences in research productivity by citing evidence that "women . . . tend more often than men to be employed in academic jobs" (p. 223). In an earlier work (Xie and Akin 1994, fig. 1), we showed evidence that contradicts this claim: For every scientific field, the percentage of women in a given cohort of doctoral recipients is higher than the percentage of women among the doctoral recipients with regular faculty employment in postsecondary education. Thus, it is useful to restrict the population being studied to academic scientists, because publication is generally expected, facilitated, and rewarded for scientists employed in academic settings. Following Cole (1979), we propose to combine the supply-based and demand-based criteria and define scientists as individuals with doctoral degrees who occupy faculty positions in science at academic institutions. This is a conservative strategy, as it removes a significant source of heterogeneity (job setting) between the sexes.[1]

Quantifying Sex Differences in Research Productivity

Conceptually, productivity should be measured as the amount of "research output" in a period of "exposure." The concepts of output and exposure both require some discussion. *Research output* is commonly measured by the number of publications, either reported by respondents in surveys or found in bibliographic searches. In general, the publication count is a crude measure of research output, as it does not distinguish between sole-authored and co-authored publications or between significant and insignificant publications. Most survey instruments do not separate peer-reviewed journal articles and books from other forms of publications.[2] In addition, respondents to surveys may misreport their publication counts because of recall error or social desirability pressures. Despite these problems, the count of publications is commonly used because of its simplicity. This practice is supported for the study of gender differences in productivity by the lack of evidence linking sex to the aforementioned factors that make the measure imprecise. For example, men and women scientists do not differ in their likelihood of collaboration (Cole and Zuckerman 1984; Long 1992; Sonnert 1995:135). Thus, measurement noise is commonly assumed, as it is in this study, to be innocuous with respect to the main research focus (i.e., sex differences).

Concerning *exposure*, an important distinction must be made between "cumulative" measures and "short-term" measures. Cumulative measures refer to an individual's total research output over the complete span of his/her career; short-term measures refer to research output accomplished during a relatively short interval. We contend that the use of short-term measures is preferred for studies of sex differences in research productivity. We cite three reasons for our position. First, women have only recently increased their participation in science and therefore have fewer years of experience than men on average. Hence, the use of cumulative measures works against women in any cross-sectional data set. Second, it is highly plausible that women are more likely to temporarily withdraw from active research owing to spousal or childrearing constraints. This is particularly true in earlier decades (Astin 1969:58). Third, it is difficult to incorporate explanatory variables measuring resource availability into multivariate models when the cumulative count of productivity is the outcome variable, because such explanatory variables are more likely to be endogenous rather than exogenous to one's cumulative productivity. For example, prestige and type of employing institution, and academic rank may in fact result from productivity demonstrated at various points earlier in the career. If this is the case, the causality may run opposite the direction assumed, or the explanatory and dependent variables may be jointly determined. Although the problem of reciprocal causality is not solved by the use of short-term measures, it is at least substantially mitigated.[3]

For a majority of academic scientists, research productivity is a lifelong process with a distinct life-cycle profile: It sharply increases to a peak early in life and then gradually declines (Stephan and Levin 1992). For

[1] This conservative strategy is sensible given the lack of large and informative longitudinal data sets on doctoral scientists. A comprehensive study examining both career dynamics and publication histories would require data far richer (in terms of sample size and contained information) than that currently available.

[2] For two of the data sets used in our study (NSPF-1988 and NSPF-1993), information about publication in different formats was collected. However, for consistency with the other two data sets and other comparable studies, we use the simple publication count as our output measure.

[3] Even with a short-term measure of publication rates, this research is not immune from the problem of reciprocal causality. We handle this problem in two ways: (1) through a series of hierarchical models moving from more exogenous controls to less exogenous controls, and (2) by interpreting our models as descriptive rather than as causal.

scientists at different points in their life cycles, we expect their short-term rates of productivity to be different. This problem highlights the need to control for experience. Indeed, several major studies (Cole 1979; Cole and Zuckerman 1984; Long 1992; Reskin 1978) were designed to control for experience by following a single cohort of scientists who obtained their doctoral degrees at roughly the same time. With cross-sectional data, it is necessary to statistically control for experience, and the effects of experience can be interpreted as constituting a career profile under the assumption of stationarity (i.e., no substantial changes across successive cohorts).

Assuming that we have a good short-term measure of productivity, how should we quantify sex *differences* in research productivity? Earlier work (Blackburn et al. 1978; Cole 1979) used the correlation coefficient. Typically, the researcher codes sex as a dummy variable and then computes the Pearson correlation coefficient (r) between sex and research productivity. The Pearson correlation involving a dummy variable for sex (X) and a continuous variable (Y) can be easily calculated from the sex-specific sample means of Y, the sex composition in the sample, and the standard deviation of Y. More specifically (Stuart and Ord 1991:995),

$$r = \sqrt{pq}\left(\bar{Y}_1 - \bar{Y}_0\right)/S_y, \qquad (1)$$

where p and q denote the proportions of female scientists and male scientists in the sample, and $\bar{Y}_1$ and $\bar{Y}_0$ represent the mean publication counts for female scientists and male scientists, respectively.

Equation 1 reveals that the correlation between X and Y is *not* invariant with respect to the sex composition in the sample. It is evident that conditional means by sex convey the most essential information on sex differences. Let the simple ratio between sex-specific means be a measure of sex differences in research productivity:

$$R = \bar{Y}_1/\bar{Y}_0. \qquad (2)$$

Given its invariance in relation to the sex composition, R is preferable to r. Indeed, this is the measure used in the studies of the gender differences in publication productivity by Cole and Zuckerman (1984) and Long (1992).[4] Easy to compute and interpret, the ratio expressed by equation 2 has been the standard measure used in the labor force literature studying sex differences in earnings (Bianchi and Spain 1986, chap. 6). It also corresponds well with a key coefficient in the multivariate regression models that are presented below.

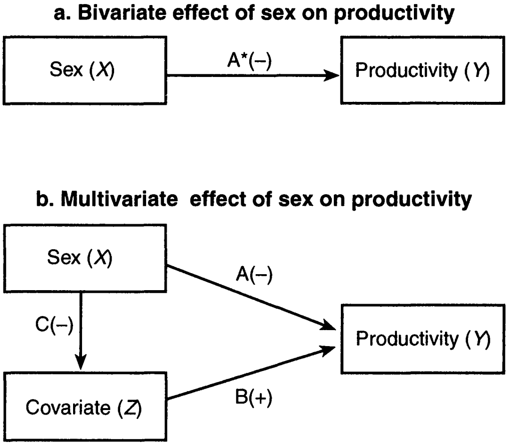

Figure 1. Illustration of Bivariate and Multivariate Models of the Relationship between Sex and Productivity

MODELING SEX DIFFERENCES IN RESEARCH PRODUCTIVITY

Why Multivariate Analysis?

It has long been recognized that sex differences in productivity are confounded by sex differences in other factors that are related to productivity. This multivariate relationship can be easily demonstrated using the language of direct, indirect, and total effects in path analysis and structural equation models (Alwin and Hauser 1975). In Figure 1 we give an unrealistically simple presentation for illustrative purposes. The bivariate effect of sex (female = 1, male = 0), shown as A* in Figure 1a, is called the total effect. In Figure 1b, this total effect of sex on research productivity is decomposed into two compo-

[4] Long's (1992) measure, based on the same idea, has a different expression:

$$\left(\bar{Y}_0 - \bar{Y}_1\right)/\bar{Y}_1$$

(i.e., the male scientists' relative advantage over female scientists).

nents: a direct effect (A) and an indirect effect through covariate Z (paths C and B).[5]

Note that sex (X) is causally prior to potential covariates (Z) so that Z represents all possible mediating variables between X and Y. In this simple setup, we are interested in the relative importance of the indirect effect of X on Y through Z. When the indirect effect constitutes a large part of the total effect of X on Y, we attain a good understanding of how the total effect of X on Y operates. In this context, we say that Z "explains" the effect of X. Covariate Z mediates sex differences in research productivity *only if* both of the following conditions are satisfied:

Condition 1: Z affects productivity in one direction.

Condition 2: Z is affected by sex in the opposite direction (with sex coded 1 for females and 0 for males).

In Figure 1b, for example, Z has a positive effect on Y and is affected negatively by X. Covariates that have a negative effect on Y but are positively affected by X also would mediate the negative total effect of X on Y.

Previous research on the productivity puzzle has considered many covariates, such as age, time between the bachelor's degree and Ph.D., prestige of Ph.D. program, institutional type, and rank (Blackburn et al. 1978; Clemente 1973; Cole 1979; Fox 1981; Fox and Faver 1985; Reskin 1978; Sonnert 1995). Despite these efforts, researchers have consistently been concerned with the inadequacy of controls for structural factors that facilitate the production of scientific knowledge but are unequally distributed between men and women scientists. For example, Cole and Zuckerman (1984:248–49) call for paying closer attention to structural determinants and specifically recommend studying the social organization of scientific laboratories and departments and the allocation of time for teaching versus research. In the report titled *Climbing the Academic Ladder*, the Committee on the Education and Employment of Women in Science and Engineering (1979) criticizes the existing literature for lacking adequate controls:

> For the specific case of science faculty, factors such as access to appropriate research facilities, division of time between undergraduate and graduate teaching responsibilities, and especially availability of graduate and other research assistants may be of far greater significance to productivity than rank or other variables which have been controlled in [previous studies]. (P. 87)

The report suggests, though it does not demonstrate, that sex differences in productivity found in earlier studies may result entirely from the omission of some important control variables.

Since the publication of *Climbing the Academic Ladder*, researchers have responded to these challenges by considering many control factors, particularly the influence of co-authorship and family status. Neither of these control factors has been found to account for gender differences in publication productivity because either condition 1 or condition 2 is not satisfied. In the case of co-authorship, condition 2 is not satisfied: Women are just as likely as men to co-author papers (Cole and Zuckerman 1984; Long 1992). In the case of marriage and motherhood, condition 1 is not true: "Women scientists who marry and have families publish as many papers per year, on the average, as single women" (Cole and Zuckerman 1987:125).

To the extent that past efforts have not located explanatory variables that mediate between sex and productivity, our confidence in the search for the mysterious other factors that will account for the gender gap in publication productivity weakens. If we exhaust plausible explanations, the unexplained differences between the sexes in productivity can be legitimately called a "puzzle." Cole and Zuckerman (1984) lament that "observed disparities in productivity between the sexes have not been eliminated by taking into account variables such as rank and institutional affiliation, although such disparities are reduced when this has been done" (p. 219). This quotation reflects Cole and Zuckerman's skepticism that the control of observed variables measuring resources will explain the observed sex differences in research productivity.[6]

[5] Because our models are not linear, the indirect effect cannot be computed as the simple product of the two direct effects C and B.

[6] Indeed, Cole's own latest attempt (Cole and Singer 1991) focuses on the compounding pro-

We argue that Cole and Zuckerman's pessimism is premature because Cole's (1979: 68) and other researchers' earlier recommendation has been only partially implemented. Thus, we set out here to incorporate into a single study of sex differences in publication output many of the individual and structural determinants suggested in the literature, including variables that capture the monetary aspect of scientific resources. In this way, we can clarify the debates, test competing hypotheses, and illuminate the puzzling question of why women scientists publish less than men scientists.

Causality

Cole (1979) remarks, "Other variables such as differences in teaching responsibilities, access to research funds, and opportunity to collaborate with other outstanding scientists might account for the differences in published productivity of men and women" (p. 68). Cole's suggestion is tantamount to the statistical control of structural and resource variables in teasing out the net effect of sex on productivity. However, are structural and resource variables such as institutional affiliation, rank, funding, and teaching hours necessarily causes of productivity?

The answer is no. For example, it is possible that type of current institution, rank, research resources, and so on are consequences as well as causes of productivity. Clearly, the causality between research productivity and resource variables is reciprocal. Without experimental data or at least longitudinal data, we cannot identify the reciprocal causality. However, we contend that it is still useful to control these variables in the recursive model depicted in Figure 1b (using available cross-sectional data) and to interpret the results descriptively. Our main rationale is that the resource variables are likely to be outcomes of cumulative productivity, whereas our measure of research productivity is short-term. This distinction in timing gives us some leverage for treating the resource variables as exogenous, because for most individuals the resource variables temporarily precede rather than succeed the current level of productivity. Consider the example of research funding. While it is reasonable to expect past productivity to affect the availability of funding, it seems much less likely that current productivity has a large influence on the current availability of funding. Still, causal inference is difficult here because current productivity may merely be a proxy for earlier productivity, where both are caused by some unobserved common factors.

In other words, the stylized causal model depicted in Figure 1b is likely to be misspecified because it omits some unobserved characteristics that affect both Z and Y (i.e., population heterogeneity). Examples of such unobserved characteristics include "ability" or "diligence," which can underlie both past productivity and current productivity. With longitudinal data, it is possible to partial out the unobserved heterogeneity under the assumption that these characteristics are fixed (Allison and Long 1990). With cross-sectional data, unobserved heterogeneity is uncontrolled and may confound the causal relationship between the measured resource variables and productivity. When this is the case, the resource variables are proxies for underlying causes and thus serve as "proximate determinants" of productivity. It is in this sense that we wish to draw descriptive, rather than causal, inferences from our multivariate model.

Some support for tentatively treating the resource variables as exogenous is found in prior research showing the asymmetry of the reciprocal relationship between productivity and resource allocation. Despite the common wisdom that high productivity leads to appointment at prestigious universities, empirical evidence suggests a more complicated picture: Although higher productivity does not necessarily mean appointment at prestigious institutions, movement to more prestigious institutions enhances productivity (Allison and Long 1987, 1990; Long 1978; Long, Allison, and McGinnis 1979). In other words, using the notation of Figure 1b, the causal effect of Z (institutional affiliation) on Y (productivity) dominates the effect of Y on Z. Although similar asymmetric relationships may exist between productivity and other re-

cess of small differences. Despite its elegance, Cole and Singer's theory of limited differences provides only a plausible hypothesis rather than an explanation for observed differences (for a similar critique, see Reskin 1992).

source variables, we are not aware of empirical evidence that supports this conjecture.

The Model

Our model for estimating the direct effect of sex in a multivariate framework is the following loglinear model. For the ith scientist,

$$\log(\mu_i) = \log\left[E(y_i|x_i, z_i)\right] = \alpha + \beta x_i + \sum_{k=1}^{K} \gamma_{ik} z_{ik}, \qquad (3)$$

where μ is the expectation of y (research productivity) conditional on x (sex) and z (a vector of covariates), and K is the total number of covariates controlled. We use the number of publications in the past two years as our measure of y. If we further assume that μ follows an independent Poisson process for different individuals conditional on x and z, equation 3 is a standard multivariate Poisson regression estimable via maximum likelihood (Long 1997, chap. 8; Maddala 1983; McCullagh and Nelder 1983, chap. 6).

The loglinear model of equation 3 has certain attractive properties. First, publication count in the last two years is naturally modeled as a Poisson process, which can be defined as the count of repeatable events within a fixed interval (Allison and Long 1990; Long 1997:227; Maddala 1983:51–54). Second, the Poisson model allows the variance of productivity to increase with the mean of productivity, thus handling a pattern of heteroscedasticity that is apparent in the data.[7] Third, there is no need to impute a small number for individuals with zero publications as would be necessary for the least-squares estimation of equation 3 (Long 1997:227), because the Poisson model allows such occurrences. Last, the β coefficient for the sex dummy variable (with female = 1, male = 0) can be conveniently interpreted as $\log(R)$, where R is the ratio in productivity between women and men. This is true because, for two scientists with identical values of z but of different sexes:

$$\beta = \log(\mu|x = 1, z) - \log(\mu|x = 0, z) = \log(R). \qquad (4)$$

Thus, we can compare estimated Rs in a multivariate context to observed Rs in bivariate analysis. This greatly facilitates interpretation of the multivariate results.

One major drawback of the Poisson model as specified in equation 3 is that the Poisson assumption is highly restrictive. Because the mean equals the variance for a Poisson distribution, equation 3 also restricts the variance of productivity:

$$\log\left[\text{var}(y|x, z)\right] = \alpha + \beta x + \sum \gamma_k z_k.$$

In the data used in our study, the variance of productivity far exceeds the mean of productivity. This problem is called "overdispersion." Following the recommendation of McCullagh and Nelder (1983:198–200) and Long (1997:230–38), we handle overdispersion in our data by adding an additional random component ε_i to equation 3:

$$\log(\mu_i) = \log\left[E(y_i|x_i, z_i, \varepsilon_i)\right] = \alpha + \beta x_i + \sum_{k=1}^{K} \gamma_{ik} z_{ik} + \varepsilon_i. \qquad (5)$$

After further specifying the parametric assumption that $\exp(\varepsilon_i)$ follows a Gamma distribution with a mean of 1 and variance v, the model is then estimable via maximum likelihood, where $1/v$ is known as the overdispersion parameter.[8] This model is commonly known as the negative binomial model.

Our modeling strategy for each data set is to build a series of hierarchical models with the number of publications during the two years prior to the survey as the dependent variable. We first begin with the bivariate model with sex as the sole independent variable and gradually introduce other background characteristics, structural locations and resources, and finally marital status. We attempt to maintain parallel models across the four data sets, although measurement of the covariates may differ slightly due to inconsistencies among the data sets. As variables are added, the simpler model is nested within the more complicated model. With G_s^2 and G_c^2 denoting model chi-square statistics respectively for the simpler model

[7] In fact, this pattern of heteroscedasticity is also suggested by Long's (1992:166, fig. 3) data.

[8] As shown by Long (1997:233), this modification leads to $\text{var}(y) = \mu + \mu^2/v$, with $v > 0$. The larger $1/v$, the more severe the overdispersion.

and the more complicated model, the difference,

$$\Delta G^2 = G_c^2 - G_s^2,$$

follows a chi-square distribution with degrees of freedom equal to the number of additional parameters introduced in the more complicated model. Thus, we can use chi-square tests for pairs of nested models to assess the statistical significance of additional factors. At the same time, we are interested in how the net sex difference varies as relevant explanatory factors are controlled. Given the hypothesis that observed raw sex differences may result mainly from confounding factors rather than from sex per se, we are interested in whether the magnitude of the sex coefficient shrinks toward zero as we gradually introduce more controls.

DATA SOURCES

We analyze data from four sources: the National Survey of Higher Education conducted by the Carnegie Commission in 1969 (hereafter Carnegie-1969), the Teaching Faculty in Academy study sponsored by the American Council of Education in 1972–1973 (hereafter ACE-1973), the 1987–1988 National Survey of Postsecondary Faculty conducted by the National Center for Education Statistics (NCES) (hereafter NSPF-1988), and the 1992–1993 National Survey of Postsecondary Faculty also conducted by NCES (hereafter NSPF-1993). The data sets are ideal for our purpose because of their national representation of academic scientists across the complete spectrum of scientific specialties and their coverage of a variety of relevant explanatory factors. In addition, the four data sets are similar in sampling design and survey instrumentation, which allows us to replicate findings and to detect temporal changes over a span of 24 years. To make our results comparable to those from earlier research, we restrict the samples to doctoral scientists appointed as regular teaching faculty at a postsecondary institution in one of the following major fields: biological science, engineering, mathematical science, physical science, and social science. We operationalize the definition of a regular teaching faculty appointment as one responsible for teaching at least one college-level course in an academic year.[9] Our operationalization includes regularly employed lecturers/instructors but excludes graduate student instructors.

The respondents in the four data sets were drawn by essentially the same two-stage sampling design. In the first stage, a large number (more than 300) of postsecondary institutions were randomly selected with stratification based on institutional types from all two-year and four-year colleges and universities. In the second stage, faculty members employed at these selected institutions were randomly drawn. Information was collected by mail surveys only in Carnegie-1969 and ACE-1973, while telephone interviews were used for sampled individuals who failed to return mail surveys in NSPF-1988 and NSPF-1993. The overall response rates were 60 percent for Carnegie-1969, 49 percent for ACE-1973, 76 percent for NSPF-1988, and 87 percent for NSPF-1993. Using our earlier definition of scientists and restricting our sample to those with valid responses to relevant questions, we extracted information for 13,762 scientists from Carnegie-1969; 9,504 scientists from ACE-1973; 1,192 scientists from NSPF-1988; and 3,007 scientists from NSPF-1993. The differences in the number of cases across the four data sets reflect the large variation in the sample sizes of the four original studies.

The dependent variable for our analysis is the count of all publications reported by the respondent scientist for the two years prior to the date of the survey. Included in the publication count are articles published in refereed and nonrefereed journals, chapters in edited volumes, books, and monographs. Unlike the other studies, the NSPF-1988 survey instrument included "creative works" with articles and books in the publication count. This inclusion inflates the average publication count for the NSPF-1988 sample, al-

[9] This operationalization suffers from the problem of excluding permanent, doctoral-level, nonteaching researchers employed by universities. This exclusion is necessary for our study because the titles and statuses of such nonteaching researchers vary greatly across institutions. Insofar as our exclusion does not affect the relationship between sex and productivity (i.e., in the absence of three-way interaction), the exclusion does not bias our statistical results.

though it should not bias our study if the relative importance of "creative works" is not related to sex. For both the Carnegie-1969 and ACE-1973 surveys, the publication count was measured in categorical intervals through a closed-ended question. For these data sets, we use the midpoint of response categories as an approximation of publication counts.[10] The NSPF-1988 and NSPF-1993 data, in contrast, provided a detailed count of publications for each scientist.

Is the scientist's self-reported number of publications a valid measure of productivity? To our knowledge, the accuracy of self-reported publication counts has not been systematically examined. This stands in contrast to productivity measures based on bibliographic sources, which Allison's (1980) study verifies to be highly reliable. Unfortunately, productivity measures based on bibliographic databases are not available in our data sets. There are good reasons, however, to rely on the self-reported publication count as the dependent measure for this analysis. First, publication is a salient part of a scientist's work activities, and correct accounting of this information should be no less reliable than that for many other types of information (such as job history, cohabitation history, and voting behavior) commonly collected in social surveys and widely used in sociological research. Furthermore, the mean level of productivity is roughly comparable (around three to four publications in two years) across these surveys and between the surveys and other studies that rely on bibliographic searches (Allison 1980; Allison and Long 1990; Cole and Zuckerman 1984; Long 1990; Stephan and Levin 1992). This apparent comparability in means is no proof of the validity of the self-reported measure, but nonetheless it is reassuring. Finally, although self-reported counts are likely to be contaminated by measurement error, it is not clear why the measurement error should be related to sex, our primary independent variable of interest. In fact, our bivariate result on sex differences in productivity from Carnegie-1969 and ACE-1973 closely replicates those from earlier studies. In sum, while we acknowledge potential inaccuracies in the self-reported measure of publication count, we are reassured by its apparent consistency across multiple surveys and its congruity with studies based on bibliographic searches.

Although the control variables we include in our analysis are not strictly parallel across the data sets, they are similar. We include a measure of the *quality of employing institution* at the time of the survey for all four data sets. The institutional quality ratings in the Carnegie-1969 data, based on the Gourman Report of 1967 (Trow 1975), were contained in the data file made available for public use. In the ACE-1973 data file, institutions were rated according to the Carnegie Classification scheme (shown in Appendix Table B). In NSPF-1988 and NSPF-1993, institutions were rated according to a modified Carnegie Classification comparable to that used for the ACE-1973. *Time between the undergraduate and the doctorate degrees* is defined as the difference between the year of graduation with a B.S. or B.A. and the year the scientist received his or her Ph.D. We also include measures of *research resources* in the multivariate analysis, as all of the surveys asked questions about research funding and access to research assistance. Information about the receipt of funding by five types of sources (federal, state, private, industrial, and own institution) is coded as dummy variables that are not mutually exclusive. The research assistance variable is coded as a single dummy indicating access to graduate research assistants. The other variables used in the analysis are self-explanatory.

RESULTS

Descriptive Results

Table 1 presents summary statistics of two productivity measures, one cumulative and one short-term, by sex and data source. The cumulative measure is the total number of publications in a scientist's entire career (denoted T); the short-term measure is a scientist's total number of publications in the two years prior to the survey date (denoted Y). Severe overdispersion is apparent, as the standard deviations rather than the variances of T and Y are close to the means of T and Y.

[10] The following coding scheme was used: none = 0, 1 to 2 = 1.5, 3 to 4 = 3.5, 5 to 10 = 7.5, more than 10 = 12.5.

Table 1. Observed Sex Differences in Self-Reported Measures of Research Productivity in Four National Surveys of Postsecondary Faculty

Survey/Total Publications	Sex	Mean	S.D.	N	r	R
National Survey of Higher Education, Carnegie Commission, 1969 (Carnegie-1969)						
Total publications in career (T)	Male	15.96	15.99	13,126	−.093	.560
	Female	8.94	12.01	636		
Total publications in last 2 years (Y)	Male	3.65	3.27	13,126	−.086	.634
	Female	2.32	2.61	636		
Teaching Faculty in Academy, American Council of Education, 1973 (ACE-1973)						
Total publications in career (T)	Male	21.46	22.45	9,025	−.095	.549
	Female	11.79	16.06	479		
Total publications in last 2 years (Y)	Male	3.72	3.38	9,025	−.079	.675
	Female	2.51	2.87	479		
National Survey of Postsecondary Faculty, National Center for Education Statistics, 1988 (NSPF-1988)						
Total publications in career (T)	Male	29.10	43.47	1,013	−.122	.515
	Female	14.98	23.25	179		
Total publications in last 2 years (Y)	Male	4.65	5.97	1,013	−.062	.785
	Female	3.65	4.38	179		
National Survey of Postsecondary Faculty, National Center for Education Statistics, 1993 (NSPF-1993)						
Total publications in career (T)	Male	24.27	35.06	2,276	−.153	.520
	Female	12.63	21.06	731		
Total publications in last 2 years (Y)	Male	4.02	5.45	2,276	−.079	.759
	Female	3.05	4.46	731		

Both the correlation (r) and the ratio (R) measures for sex differences are presented. As measured by both r and R, sex differences are greater for the cumulative counts of publications than for the counts of publications in the last two years, which supports our earlier statement that the cumulative count is biased against women scientists.

According to the short-term measure of productivity (Y), the gender gap in productivity rate has appreciably narrowed over the 24-year period. In 1969, women's productivity rate was only 63 percent that of men's. It increased to 68 percent in 1973, and to 79 percent in 1988. In 1993, the sex ratio in productivity was 76 percent. While the Carnegie-1969 data confirm Zuckerman's (1991:43) statement that women publish at "50–60 percent" of men's rate, our results from the more recent surveys point to much smaller gender gaps. Instead of the "50–60 percent" range in earlier times, data from NSPF-1988 and NSPF-1993 suggest that the female-to-male productivity ratio now hovers around 75 to 80 percent.[11] Our result is consistent with the observation of Bentley and Blackburn (1992) that "two-year publication differences between men and women have narrowed considerably since 1969" (p. 702). This finding represents a radical departure from the historically persistent pattern observed by Cole (1979:242) and suggests that sex differences in productivity are not immune to social change.

One of the most dramatic social changes in the United States since the 1960s is women's greater involvement and improved status in the labor force. As shown by Spain and Bianchi (1996:82), among women of prime working ages (25 to 54), women's la-

[11] Testing for statistical significance of the changes in sex differences is tantamount to testing for the interaction effects between sex and period in a regression analysis with pooled data. For the baseline negative binomial model without other covariates, the chi-square statistic for the interaction is 11.34 for 3 degrees of freedom, and is significant at the $p < .01$ level.

bor force participation rate increased significantly from 42.9 percent in 1960 to 75.3 percent in 1994. This greater involvement of women in the labor force has been accompanied by declines in occupational sex segregation and the gender gap in earnings (Spain and Bianchi 1996:94, 113). In scientific academia, the changes are equally dramatic (Bentley and Blackburn 1992; Fox 1995). We observe the trend toward equal representation of women among science faculty in our own data. From the sex-specific sample sizes reported in Table 1, it is easy to see that the percentage of women scientists increased from 5 percent in 1969–1973 to 15 percent in 1988 and 24 percent in 1993.

Along with increasing representation, the relative status of women science faculty also improved during the study period (Bentley and Blackburn 1992). This pattern is evident in the descriptive statistics presented in Appendix Tables A through D. Consistent with earlier findings (Fox 1995:212; Long and Fox 1995; Rosenfeld 1991), our data indicate that women scientists are more concentrated in teaching colleges and are less likely to be found in research universities than their male counterparts.[12] For the Carnegie-1969 data, for example, women are about twice as likely as men to be employed in four-year colleges (17, 12, and 9 percent for women, compared to 9, 6, and 3 percent for men, in high-, medium-, and low-quality four-year colleges, respectively). In contrast, only 20 percent of women, compared to 25 percent of men, are employed in high-quality universities. While this pattern of sex differences in institutional affiliation persists throughout the study period, the trend appears to be toward convergence. Let us measure the extent of sex segregation by institution type using the index of dissimilarity, which represents the minimum proportion of scientists who would have to change institution type in order to achieve equity between men and women. The indices of dissimilarity for the four different surveys point to a sharp decline between the early 1970s and the late 1980s: .201 for Carnegie-1969, .212 for ACE-1973, .073 for NSPF-1988, and .068 for NSPF-1993.

It is also clear from our data that sex differences in teaching load have substantially narrowed over the period. With roughly the same five-category classification of teaching hours, the index of dissimilarity between the sexes is .152 for Carnegie-1969, .141 for ACE-1973, .042 for NSPF-1988, and .033 for NSPF-1993, respectively.[13] This suggests that the average teaching loads of male and female scientists have become more equitable. Similarly, sex differences in research funding appear to have decreased. The female-to-male ratio of funding from federal sources, for example, is .610 in Carnegie-1969, .653 in ACE-1973, .770 in NSPF-1988, and .784 in NSPF-1993.

Multivariate Results

The main findings from our multivariate analysis are summarized in Table 2. Parallel results are presented from each data set. Four model specifications are presented in hierarchical order for each data set, with a lower-numbered specification nested within a higher-numbered specification. Definitions and descriptive statistics of the covariate variables used in the multivariate analysis are presented in Appendix Tables A through D. The simplest specification is Model 1, which includes only the effect of sex. The exponential function of the estimated coefficient for sex (i.e., $\exp[\beta_{\text{sex}}]$) yields the observed female-to-male ratio of mean productivity (R). Model 2 adds controls for the following individual background variables: field, time lag between bachelor and doctoral degrees, and years of experience beyond the doctoral degree. The introduction of these control variables significantly improves the explanatory power of the model. In the Carnegie-1969 data set, for example, the change in G^2 is 1,183 for 11 degrees freedom. Improvement in the goodness-of-fit of Model 2 over Model 1 is smaller but highly

[12] Although Zuckerman (1991:35–36) maintains that women are no less likely to be located in prestigious research institutions than men, Long and Fox (1995:51) clearly reject Zuckerman's claim.

[13] Because of limitations in the original format of the ACE-1973 data, teaching hours are coded with one less category than the coding for the other three surveys. This coding difference could produce a conservative bias, as fewer categories usually lead to smaller indexes of dissimilarity.

Table 2. Estimated Parameters for the Effect of Sex on Research Productivity, and Model Fit Statistics for Four Negative Binomial Models: Four National Surveys of Postsecondary Faculty

Survey/Statistic	Model 1	Model 2	Model 3	Model 4
Carnegie-1969 (N = 13,762)				
β_{sex}	$-.456^{***}$	$-.379^{***}$	$-.095^{**}$	−.070
	(.040)	(.039)	(.037)	(.038)
Exp(β_{sex})	.634	.685	.909	.933
Model χ^2 (G^2)	123.22	1,306.68	4,640.45	4,649.39
Degrees of freedom	1	12	31	32
Pseudo-R^2 (percent)	.93	9.48	29.78	29.83
ACE-1973 (N = 9,504)				
β_{sex}	$-.393^{***}$	$-.293^{***}$	−.044	−.018
	(.048)	(.047)	(.043)	(.044)
Exp(β_{sex})	.675	.746	.957	.982
Model χ^2 (G^2)	64.84	966.21	3,392.63	3,399.16
Degrees of freedom	1	12	32	33
Pseudo-R^2 (percent)	.72	1.15	31.33	31.38
NSPF-1988 (N = 1,192)				
β_{sex}	$-.242^{**}$	−.094	−.062	−.058
	(.104)	(.104)	(.087)	(.088)
Exp(β_{sex})	.785	.911	.940	.944
Model χ^2 (G^2)	5.22	119.85	543.37	543.49
Degrees of freedom	1	12	32	33
Pseudo-R^2 (percent)	.51	11.16	41.51	41.52
NSPF-1993 (N = 3,007)				
β_{sex}	$-.276^{***}$	$-.171^{**}$	−.096	−.082
	(.058)	(.059)	(.051)	(.052)
Exp(β_{sex})	.759	.843	.908	.921
Model χ^2 (G^2)	22.09	190.33	1,071.01	1,073.65
Degrees of freedom	1	12	32	33
Pseudo-R^2 (percent)	.97	8.02	37.54	37.61

Note: Numbers in parentheses are standard errors. Model 1 includes sex only. Model 2 includes sex, field, time between B.A./B.S. and Ph.D., and years of experience beyond the doctoral degree. Model 3 adds to Model 2 type of current institution, academic rank, teaching hours, research funding, and research assistance. Model 4 adds marital status to Model 3.

$^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$ (two-tailed tests)

significant for the other three data sets (901 for ACE-1973, 115 for NSPF-1988, and 168 for NSPF-1993, all with 11 degrees of freedom). The significant improvement in goodness-of-fit is also indicated by much higher values of pseudo-R^2 in Model 2 than in Model 1, with pseudo-R^2 defined as

$$1 - \exp(G^2/N),$$

where N denotes the sample size (Long 1997:105).

In Model 3, we add the variables measuring type of current institution, academic rank, teaching hours, research funding, and research assistance. While the background variables included in Model 2 are clearly exogenous to the dependent variable measuring productivity, the resource variables introduced in Model 3 are potentially contaminated by reciprocal causality with respect to productivity. Again, we observe that the covariates strongly affect the two-year publication count, with a significant improvement in goodness-of-fit over Model 2. In Carnegie-1969, the change in G^2 between Models 3 and 2 is 3,334 for 19 degrees of freedom; the change is, respectively, 2,426, 424, and 881 in ACE-1973, NSPF-1988 and NSPF-1993, all with 20 degrees of freedom. The increase in pseudo-R^2 from Model 2 to Model 3 is similarly impressive. Finally, we include a dummy variable denoting a scientist's marital status in Model 4.[14] By the ΔG^2 criterion, marital status is a significant predictor for two of the four data sets, with the exceptions being NSPF-1988 and NSPF-1993. All parameter estimates and their asymptotic standard errors for the final model are reported in the last two columns of Appendix Tables A through D.

For all four data sets, the introduction of the control variables significantly reduces the net sex difference in productivity. Although these control variables are rather crude, their unequal distribution by sex helps explain the estimated gender gap in productivity. For the first two data sets, the coefficient for sex drops precipitously with the inclusion of these controls: for Carnegie-1969, from –.456 in Model 1 to –.379 in Model 2 and –.095 in Model 3; for ACE-1973, from –.393 in Model 1 to –.293 in Model 2 and –.044 in Model 3. In the case of ACE-1973, the coefficient for sex is no longer significantly different from zero at the $\alpha = .05$ level in Model 3. For NSPF-1988, the coefficient for sex is reduced to a statistically nonsignificant –.094 in Model 2.[15] For NSPF-1993, the sex coefficient decreases from –.276 in Model 1 to –.171 in Model 2 and –.096 in Model 3.

Between the two earlier surveys and the two later surveys, there is a notable decrease in the power of the resource variables introduced in Model 3 to explain sex differences in productivity. The reason for this trend is *not* a decline in the importance of these resource variables for determining productivity, for there is evidence that their importance has increased over time (Bentley and Blackburn 1992).[16] Rather, this trend is a result of the fact that these resources have become more equally distributed between men and women. That is, in the language of our stylized causal model (Figure 1b), path C has weakened over time.

Model 4 includes marital status as an explanatory variable. Although previous research has found childbearing to negatively affect productivity for both men and women scientists (Hargens, McCann, and Reskin 1978), there is reason to hypothesize that marriage is a personal asset. A scientist's work may benefit from marriage because of the additional economic resources and emotional support contributed by a spouse. In addition, a spouse also may provide domestic help that may free up time for the scientist's research. For three of the data sets (Carnegie-1969, ACE-1973, and NSPF-1993), we found married scientists to have significantly higher (about 7 to 11 percent higher) rates of productivity than unmarried scientists, controlling for other factors included in the model. Given that women scientists are less likely than men scientists to be married (Marwell, Rosenfeld, and Spilerman 1979; Shauman and Xie 1996), women scientists, on average, are less likely to benefit from marriage. Thus, controlling for marital status reduces the estimated sex difference in publication productivity. Indeed, the coefficient for sex is not significantly different from zero in Model 4 for all four data sets.

Given the prevalence of within-family gender inequality (Hochschild 1989), it seems probable that men scientists benefit more from marriage than women scientists. To test this hypothesis, we add an interaction effect between marriage and sex to Model 4.[17] To our surprise, this interaction is not

[14] NSPF-1988 and NSPF-1993 did not collect information on parenthood status. When we added a dummy variable measuring the presence of children to the full model for the other two data sets, it was significantly different from zero but unexpectedly positive only for the Carnegie-1969 data. We found no interaction effect on research productivity of presence of children × sex.

[15] Of course, part of the reason for the nonsignificance is the relatively small sample size for NSPF-1988.

[16] In our data, for example, the productivity penalty paid for a heavy teaching load (11 or more hours per week) has increased from about 20 percent in 1969-1971 to 30 to 40 percent in 1988-1993. Similar results hold for other resource variables.

[17] The effect of the rank × sex interaction on productivity will be reported later. Although we

statistically significant (ΔG^2 = .01, .03, 2.44, and .45 respectively for the four data sets, all with 1 degree of freedom). That is, we find that men and women scientists benefit *equally* from marriage. One possible interpretation of this finding is that although women scientists may not gain relief from the domestic demands of marriage, they benefit from the high human capital of their spouses, who tend to be highly educated professionals (Marwell et al. 1979; Shauman and Xie 1996).

Parameter estimates for the last model are presented in Appendix Tables A through D. Inspection of the results reveals that the estimated effects for all the remaining covariates included in the multivariate analysis are in the expected direction. Because our main focus is on sex differences in research productivity, we make only two brief observations based on other regression coefficients from the final model. First, the estimated pattern of experience agrees with Levin and Stephan's (1991; Stephan and Levin 1992) finding that scientists' productivity peaks early in their careers and then decreases with experience. Second, time between a bachelor's degree and the Ph.D. has a negative effect on productivity. For example, those who took more than 10 years between their bachelor's degree and Ph.D. are 30 to 40 percent less productive than those who completed their Ph.D. within 4 years. Because women are 40 to 80 percent more likely than men to take 11 or more years between a bachelor's degree and a Ph.D., the negative effect of time to Ph.D. contributes to women scientists' lower rates of productivity relative to men's.

Decomposition of Explanatory Power

As shown in equation 4, the ratio measure (R) of sex differences in productivity can be obtained from multivariate models as $\exp(\beta_{\text{sex}})$. Thus, the difference in β_{sex} between a particular model and the baseline model (Model 1) yields a sensible measure of the extent to which explanatory variables included in a model "explain" the raw bivariate sex difference. While this method gauges the explanatory power of a model, it cannot decompose the explanatory power to the individual factors that are included in the model. The reason for this is that the explanatory factors are correlated with each other. How much the coefficient of sex (β_{sex}) is changed by the inclusion of a particular factor depends on what other variables are included in the model.

The models presented in Table 2 form a particular series of hierarchical models so that a higher-numbered model necessarily includes the variables present in a lower-numbered model. While this is an effective way to examine the *additional* explanatory power of the variables being added in a higher-numbered model and their influence on the sex coefficient, this strategy does not allow the decomposition of the explanatory power of individual factors. That is, we know the collective explanatory power of the control variables included in Model 3 and Model 4 in explaining sex differences in productivity, but we do not know their relative importance. It is desirable to decompose the total explanatory power to components uniquely due to the different factors.

While it is not possible to establish the "pure" explanatory power of the individual factors, it is illustrative to demonstrate how the inclusion or exclusion of an individual factor affects the sex coefficient (β_{sex}) under certain conditions. We focus on the changes in β_{sex} under two starkly different situations and use the changes to measure the explanatory power of the individual factor. The first measure of explanatory power is based on the *decrease* in β_{sex} after an explanatory factor is taken out of the full model (Model 4). Define D_1 as (omitting the subscript for sex):

$$D_1 = \exp(\beta^4) - \exp(\beta^{4-k}), \tag{6}$$

where β^4 denotes the sex coefficient for Model 4, and β^{4-k} denotes the sex coefficient for the model in which the kth factor is excluded from Model 4. If a particular factor contributes additional explanatory power in the presence of all other variables, we expect D_1 to be greater than 0. A negative D_1 means

also tested other interactions, none was significant except for teaching hours × sex for the NSPF-1993 data (χ^2 = 21.28 for 4 degrees of freedom). The direction of the interaction effect favors women at long teaching hours. Interested readers may request computer output from the authors.

Table 3. Attribution of Explanatory Power to Individual Explanatory Factors (in Percentages)

Explanatory Factor	Carnegie-1969 "Low" (D_1)	Carnegie-1969 "High" (D_2)	ACE-1973 "Low" (D_1)	ACE-1973 "High" (D_2)	NSPF-1988 "Low" (D_1)	NSPF-1988 "High" (D_2)	NSPF-1993 "Low" (D_1)	NSPF-1993 "High" (D_2)
Field	–2.46	.53	–.46	3.45	–1.28	4.07	–.90	5.24
Time between B.A./B.S. and Ph.D.	3.95	4.52	3.06	3.54	1.65	10.35	.52	5.45
Years of experience	2.50	.57	2.95	1.42	–2.27	2.24	–3.27	1.60
Type of current institution	2.57	7.21	7.75	14.59	.45	7.38	.67	10.03
Rank	5.49	4.05	4.67	3.76	4.22	11.85	.52	4.04
Teaching hours	.92	5.96	.29	4.04	–1.32	2.74	–.22	5.32
Research funding	1.83	12.61	1.06	10.75	–1.19	10.16	1.85	11.66
Research assistance	1.53	12.21	–.17	5.50	.21	2.91	.29	2.03
Marital status	2.37	5.87	2.47	4.38	.38	2.01	1.25	2.73
All factors $\exp(\beta^4) - \exp(\beta^1)$	29.85		30.73		15.85		16.17	

Note: The entries represent the amount of sex differences in research productivity that is explained by each factor. Two methods are used. The first method, labeled "low" (D_1), is based on the *decrease* in the coefficient of sex after an explanatory factor is taken out of the full model (Model 4 of Table 2). The second method, labeled "high" (D_2), is based on the *increase* in the coefficient of sex after an explanatory factor is added to the baseline model (Model 1 of Table 2). In general, the "low" method tends to be too conservative whereas the "high" method tends to be too liberal. The last row, defined as the difference in the sex coefficient between the full model and the baseline model, gives the upper limit of the explanatory power. All calculations ignore sampling error.

that a particular factor does not appear to explain the sex difference in the presence of other control variables. If the explanatory power of Model 4 were entirely due to this factor, β^{4-k} would be the same as β^1, the sex coefficient for the bivariate model (Model 1), and D_1 would be $[\exp(\beta^4) - \exp(\beta^1)]$.

Our second measure is based on the *increase* in β_{sex} after an explanatory factor is added to the bivariate baseline model (again omitting the subscript for sex):

$$D_2 = \exp(\beta^{1+k}) - \exp(\beta^1). \quad (7)$$

In our data, β^{1+k} is estimated to be greater than β^1 but less than β^4. This means that D_2 varies between zero and $[\exp(\beta^4) - \exp(\beta^1)]$, with zero meaning no explanatory power and $[\exp(\beta^4) - \exp(\beta^1)]$ being the maximum explanatory power.

Hence, for a well-behaved explanatory factor k, both $D_1$and D_2 should vary somewhere between 0 and $[\exp(\beta^4)–\exp(\beta^1)]$. In general, the D_1 measure tends to be conservative whereas the D_2 measure tends to be liberal. For this reason, we also call D_1 the "low" method, and D_2 the "high" method. The results are presented in Table 3. All entries in this table ignore sampling error.

Several findings emerge from an examination of Table 3. First, the range between the low and the high estimates is fairly large for most of the explanatory factors. In fact, the low estimates of several explanatory factors are negative. Again, this reflects the joint explanatory power among different factors and makes the task of decomposing explanatory power difficult. Second, the high estimates of institution type and research funding are consistently large across the surveys (around 7 to 13 percent). In contrast, the high estimates of field, experience, rank, teaching hours, and research assistance are moderate (less than 6 percent), with the exception of rank in 1988 and research assistance in 1969. This suggests the potentially central role played by institution type and research funding in generating sex differences in productivity. Third, although moderate in size, the low estimates for time to Ph.D. and marital status are consistently positive across the surveys. This last finding reaffirms the inde-

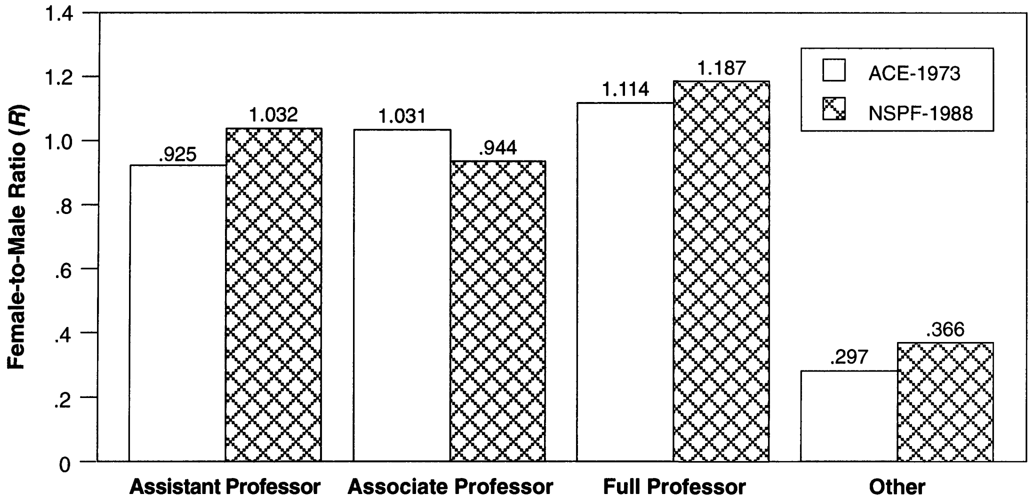

Figure 2. Net Sex Differences in Productivity by Academic Rank

pendent explanatory power of personal attributes in explaining sex differences in productivity beyond measures of resources conducive to research.

Selectivity Issue

A clear finding of our analysis is that net sex differences in productivity are small once other personal characteristics, structural settings, and facilitating resources are taken into account. As mentioned earlier, however, interpretation of this result is less clear. The covariates we use may be the effects, rather than the causes, of research productivity, or they may be jointly determined by other unobserved variables such as motivation and ability. For example, men scientists may score favorably on variables measuring structural locations and resources conducive to research because such structural locations and resources are rewards for high productivity. For example, consider academic rank, which is highly dependent on productivity (Long et al. 1993). As can be calculated from Appendix Tables A through D, full professors are about 20 to 40 percent more productive than associate professors, and associate professors are in turn 10 to 20 percent more productive than assistant professors. From the first two columns of the Appendix tables, we observe that women scientists are more likely to be found at lower ranks than men (also see Ahern and Scott 1981:34–39).

Because promotion depends on productivity, promotion is always selective. Unproductive scientists are either kept at the entry (or a relatively low) rank or encouraged to leave academia. With productivity as an important criterion for promotion, women scientists should be promoted more slowly if they indeed publish less than men. According to this reasoning, we then would expect sex differences in productivity to be smaller at high ranks than at lower ranks. Lacking the necessary longitudinal information, we cannot depict the career trajectory of sex differences in productivity as is done by Cole and Zuckerman (1984) and Long (1992).[18] However, we can gain some insights into the career pattern of sex differences in productivity by examining the interaction effects between sex and rank. For only two of the four data sets, the interaction proves to be significant: ΔG^2 is 22.67 for the ACE-1973 data and 9.10 for the NSPF-1988 data, with 3 degrees of freedom. For the Carnegie-1969 data and the NSPF-1993 data, ΔG^2 is marginally nonsignificant at 5.99 and 6.47 respectively, also with 3 degrees of freedom.

[18] At first glance, it seems that we can retrospectively trace the trajectory from the scientist's year of Ph.D. degree. However, this would not be correct, as only "survivors" from any given Ph.D. cohort are retained in our samples. In short, we are faced with the selectivity problem discussed earlier.

In Figure 2, we present the estimated variation (ignoring sampling error) in terms of female-to-male ratios, from ACE-1973 and NSPF-1988. From this figure it is easy to see the following pattern: Sex disparity in productivity narrows or even reverses as rank rises. Note that the "other" rank refers to lecturers and instructors, a temporary status lower in rank than that of assistant professor. Because the "other" category is numerically small and operationally amorphous, it is not too surprising that the estimated sex differences for this category are not stable across the four data sources.

The pattern revealed in Figure 2 supports the notion that selectivity in promotion is at work: Women scientists' disadvantage disappears or reverses at high ranks. This seems to contradict Cole and Zuckerman's (1984) and Long's (1992) finding that sex differences in productivity generally increase for a given cohort, at least over the first nine career years. This apparent contradiction can be explained by the fact that scientists in our study are by definition academic scientists. If selectivity works to keep more women scientists than men out of high academic ranks, the observed disparity in productivity between men and women scientists should narrow rather than widen. If one follows a cohort of scientists, as Cole and Zuckerman (1984) and Long (1992) do, however, the selectivity could also mean that the average publication rate for women falls further with time, with an increasingly larger proportion of women dropping out of academia.

Although selectivity seems to be at work, it appears to be of relatively minor importance. We can support this claim by comparing sex differences in productivity depicted in Figure 2 at the three ranks of professorship. If the estimated net sex difference in productivity at the associate and full professor ranks are contaminated by selectivity, there is reason to suspect that the estimate at the assistant professor rank is relatively free from such a problem, for assistant professorship is an entry-level title of an academic career. Here again, the estimated net sex difference is small, with R being .925 from the ACE-1973 data and 1.032 from the NSPF-1988 data. We thus conclude that selectivity may weaken, but does not qualitatively alter, our results.

CONCLUSION

Have we solved "the productivity puzzle"? The answer is both yes and no. The answer is yes in the sense that we have, for the first time, successfully identified differences between men and women scientists in personal characteristics, structural positions, and facilitating resources that account for women's lower research productivity. That is, we have found that women scientists publish fewer papers than men because women are less likely than men to have the personal characteristics, structural positions, and facilitating resources that are conducive to publication. There is very little *direct* effect of sex on research productivity. However, we still do not know *why* men and women scientists differ systematically in these important dimensions, and in this sense the puzzle remains unsolved. As a friendly *ASR* reviewer points out, this research replaces "the old puzzle of productivity differences with a new puzzle involving differences in personal and structural characteristics." In fact, this "new" puzzle is closely related to a long-standing interest in differences in career trajectories between men and women scientists (Bernard 1964; Rossi 1972; Zuckerman 1991).

Another important finding of this research is that overall sex differences in research productivity among academic scientists have declined in the recent years. With the number of publications in the last two years as the measure of productivity, we find that the female-to-male ratio in productivity increased from 60 to 65 percent in 1969 and 1973 to 75 to 80 percent in 1988 and 1993. A major reason for this trend is that the distribution of resources and structural positions, albeit still unfavorable to women, has become more equitable over the observed time period.

The empirical evidence presented in our analysis is significant in its own right, even if theoretical interpretations of it may remain inconclusive for the time being. Some of the debates in the literature are of an empirical nature and can be settled with better data or better data analysis. Our results suggest that the notion of sex differences in research productivity as "the productivity puzzle" may be misleading for three reasons. First, when properly defined and operationalized, the magnitude of raw sex differences in research productivity is smaller than previously claimed.[19] Second, to the extent that sex differences can be explained by personal characteristics, employment positions, and access to resources, sex differences in research productivity have structural causes that can be further investigated. Calling it a puzzle, therefore, mystifies an observed pattern. Finally, as a manifestation of deeper social processes, sex differences in research productivity have declined in response to the secular improvement of women's role in science, while the notion of a puzzle suggests an inherently static and persistent nature of the phenomenon.

Taken as a whole, the available evidence points out that men and women scientists often pursue somewhat different career tracks. It has long been recognized that values and career ambitions differ between the sexes (Bernard 1964; Davis 1964, 1965; Turner 1964). Much of the source of this difference is sex-typed socialization (Marini and Brinton 1984). However, a nontrivial part of the difference can also be traced to women's extra family responsibility associated with childbearing (Shauman and Xie 1996). In this study, we reaffirm the importance of structural sources of gender inequality in science: Women and men scientists are located in different academic structures with differential access to valuable resources. Our study confirms the pattern found in other studies (Fox 1995; Zuckerman 1991)—that men generally have positions superior to those of women, although structural differences by gender have appreciably declined over time. Once sex differences in such positions and resources are taken into account, as in this study, net differences between men and women in research productivity are nil or negligible.

[19] In fact, this finding is not new. Blackburn et al. (1978), Fox and Faver (1985), and Reskin (1978) all report smaller sex differences than the generalization of Cole and Zuckerman (1984) that women publish at 50 to 60 percent of the rate of men.

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Appendix Table A. Sex-Specific Means for Explanatory Variables and Their Estimated Coefficients in the Final Negative Binomial Model of Research Productivity: Carnegie-1969

	Sample Means		Parameter Estimates	
Variable	Males	Females	β	S.E.
Constant	—	—	1.009	(.038)
Female	.000	1.000	–.070	(.038)
Field				
Biological science	.231	.297	—	—
Engineering	.173	.013	–.178	(.023)
Mathematical science	.104	.110	–.212	(.029)
Physical science	.226	.143	–.028	(.020)
Social science	.266	.437	–.024	(.020)

(Appendix Table A continued on next page)

(Appendix Table A continued)

Variable	Sample Means		Parameter Estimates	
	Males	Females	β	S.E.
Time between B.A./B.S. and Ph.D.				
1 to 4 years	.258	.167	—	—
5 to 7 years	.407	.385	–.154	(.017)
8 to 10 years	.189	.186	–.259	(.021)
11 years and above	.145	.263	–.387	(.024)
Years of Experience				
0 to 5	.380	.401	—	—
6 to 10	.236	.231	–.009	(.022)
11 to 20	.288	.269	–.197	(.027)
21 to 30	.079	.096	–.275	(.035)
31 and above	.016	.003	–.226	(.058)
Type of Current Institution				
High quality university	.253	.204	—	—
Medium quality university	.314	.211	–.105	(.018)
Low quality university	.255	.206	–.278	(.019)
High four-year college	.092	.173	–.322	(.027)
Medium four-year college	.055	.118	–.578	(.039)
Low four-year college	.029	.085	–.771	(.055)
Junior college	.002	.003	–.630	(.225)
Rank				
Assistant professor	.336	.461	—	—
Associate professor	.292	.256	.238	(.022)
Full professor	.347	.201	.461	(.028)
Other	.026	.082	.095	(.044)
Teaching Hours				
1 to 4 hours	.321	.222	—	—
5 to 6 hours	.285	.242	–.057	(.017)
7 to 8 hours	.155	.146	–.078	(.021)
9 to 10 hours	.120	.156	–.176	(.025)
11 hours and above	.119	.234	–.231	(.026)
Research Funding				
Federal (dummy)	.529	.322	.374	(.016)
State/local (dummy)	.100	.039	.061	(.023)
Industrial (dummy)	.086	.014	.197	(.024)
Private foundation (dummy)	.109	.096	.230	(.021)
Own institution (dummy)	.535	.392	.144	(.014)
Research Assistance				
Graduate assistant (dummy)	.577	.278	.219	(.017)
Marital Status				
Married (dummy)	.915	.525	.073	(.025)
Overdispersion Parameter				
$\ln(1/v)$	—	—	–1.188	(.025)
$1/v$	—	—	.305	

Appendix Table B. Sex-Specific Means for Explanatory Variables and Their Estimated Coefficients in the Final Negative Binomial Model of Research Productivity: ACE-1973

Variable	Sample Means		Parameter Estimates	
	Males	Females	β	S.E.
Constant	—	—	1.001	(.049)
Female	.000	1.000	–.018	(.044)
Field				
Biological science	.229	.271	—	—
Engineering	.163	.006	–.151	(.027)
Mathematical science	.124	.100	–.147	(.033)
Physical science	.231	.123	.020	(.025)
Social science	.253	.499	–.063	(.026)
Time between B.A./B.S. and Ph.D.				
1 to 4 years	.227	.161	—	—
5 to 7 years	.427	.443	–.153	(.021)
8 to 10 years	.195	.150	–.281	(.026)
11 years and above	.152	.246	–.483	(.030)
Years of Experience				
0 to 5	.239	.328	—	—
6 to 10	.296	.278	.070	(.029)
11 to 20	.320	.267	–.158	(.036)
21 to 30	.123	.106	–.275	(.043)
31 and above	.025	.022	–.273	(.066)
Type of Current Institution				
Research I	.410	.307	—	—
Research II	.203	.161	–.052	(.022)
Doctoral I	.138	.094	–.188	(.026)
Doctoral II	.071	.048	–.203	(.035)
Comprehensive I	.082	.106	–.524	(.039)
Comprehensive II	.014	.038	–.780	(.092)
Liberal arts I	.061	.163	–.698	(.044)
Liberal arts II	.019	.077	–1.002	(.084)
Two-year colleges	.003	.006	–.502	(.222)
Rank				
Assistant professor	.250	.349	—	—
Associate professor	.321	.403	.140	(.028)
Full professor	.419	.205	.368	(.035)
Other	.011	.044	–.135	(.093)
Teaching Hours				
1 to 4 hours	.224	.184	—	—
5 to 8 hours	.420	.319	.001	(.021)
9–12 hours	.254	.353	–.085	(.025)
13–16 hours	.102	.144	–.207	(.035)
Research Funding				
Federal (dummy)	.527	.344	.384	(.020)
State/local (dummy)	.117	.058	.037	(.026)
Industrial (dummy)	.090	.031	.091	(.029)
Private foundation (dummy)	.107	.094	.235	(.026)
Own institution (dummy)	.328	.313	.103	(.018)
Research Assistance				
Graduate assistant (dummy)	.536	.386	.286	(.019)
Marital Status				
Married (dummy)	.924	.574	.080	(.031)
Overdispersion Parameter				
$\ln(1/\nu)$	—	—	–1.080	(.030)
$1/\nu$	—	—	.340	

Appendix Table C. Sex-Specific Means for Explanatory Variables and Their Estimated Coefficients in the Final Negative Binomial Model of Research Productivity: NSPF-1988

	Sample Means		Parameter Estimates	
Variable	Males	Females	β	S.E.
Constant	—	—	1.420	(.172)
Female	.000	1.000	–.058	(.088)
Field				
Biological science	.230	.263	—	—
Engineering	.140	.034	.044	(.104)
Mathematical science	.140	.106	–.313	(.107)
Physical science	.216	.145	.156	(.088)
Social science	.273	.453	.113	(.088)
Time between B.A./B.S. and Ph.D.				
1 to 4 years	.142	.112	—	—
5 to 7 years	.435	.307	–.267	(.088)
8 to 10 years	.218	.218	–.303	(.103)
11 years and above	.204	.363	–.377	(.106)
Years of Experience				
0 to 5	.151	.274	—	—
6 to 10	.168	.257	.163	(.113)
11 to 20	.420	.374	.034	(.124)
21 to 30	.237	.073	–.320	(.142)
31 and above	.025	.022	–.031	(.224)
Type of Current Institution				
Public research	.294	.291	—	—
Private research	.103	.101	.101	(.098)
Public doctoral granting	.136	.078	–.193	(.095)
Private doctoral granting	.038	.045	–.103	(.154)
Public comprehensive	.204	.196	–.583	(.097)
Private comprehensive	.110	.145	–.536	(.119)
Liberal arts	.071	.073	–.909	(.148)
Public two-year	.044	.073	–1.185	(.205)
Rank				
Assistant professor	.205	.391	—	—
Associate professor	.272	.307	.085	(.106)
Full professor	.478	.184	.355	(.118)
Other	.044	.117	–.258	(.172)
Teaching Hours				
1 to 4 hours	.269	.246	—	—
5 to 6 hours	.210	.235	–.020	(.084)
7 to 8 hours	.109	.095	–.118	(.104)
9 to 10 hours	.134	.128	–.238	(.106)
11 hours and above	.278	.296	–.441	(.094)
Research Funding				
Federal (dummy)	.283	.218	.450	(.075)
State/local (dummy)	.082	.045	.240	(.107)
Industrial (dummy)	.099	.056	.358	(.099)
Private foundation (dummy)	.091	.101	.217	(.098)
Own institution (dummy)	.112	.145	.119	(.091)
Research Assistance				
Graduate assistant (dummy)	.734	.704	.216	(.077)
Marital Status				
Married (dummy)	.847	.637	.028	(.079)
Overdispersion Parameter				
$\ln(1/v)$	—	—	–.417	(.068)
$1/v$	—	—	.659	

Appendix Table D. Sex-Specific Means for Explanatory Variables and Their Estimated Coefficients in the Final Negative Binomial Model of Research Productivity: NSPF-1993

	Sample Means		Parameter Estimates	
Variable	Males	Females	β	S.E.
Constant	—	—	1.426	(.134)
Female	.000	1.000	–.082	(.052)
Field				
Biological science	.187	.224	—	—
Engineering	.131	.047	.009	(.078)
Mathematical science	.171	.116	–.098	(.075)
Physical science	.181	.093	–.021	(.070)
Social science	.330	.520	.016	(.062)
Time between B.A./B.S. and Ph.D.				
1 to 4 years	.094	.057	—	—
5 to 7 years	.417	.361	–.186	(.077)
8 to 10 years	.237	.233	–.293	(.083)
11 years and above	.251	.349	–.334	(.085)
Years of Experience				
0 to 5	.199	.358	—	—
6 to 10	.169	.233	.000	(.069)
11 to 20	.348	.304	–.291	(.077)
21 to 30	.261	.101	–.540	(.092)
31 and above	.023	.004	–.885	(.173)
Type of Current Institution				
Public research	.159	.108	—	—
Private research	.049	.047	.117	(.097)
Public doctoral granting	.158	.153	–.152	(.070)
Private doctoral granting	.095	.090	–.112	(.080)
Public comprehensive	.263	.259	–.658	(.071)
Private comprehensive	.084	.094	–.755	(.095)
Liberal arts	.103	.157	–.677	(.087)
Public two-year	.088	.092	–1.026	(.113)
Rank				
Assistant professor	.246	.435	—	—
Associate professor	.268	.274	.157	(.069)
Full professor	.411	.204	.570	(.079)
Other	.075	.088	–.143	(.104)
Teaching Hours				
1 to 4 hours	.206	.178	—	—
5 to 6 hours	.205	.226	.025	(.062)
7 to 8 hours	.093	.088	–.160	(.081)
9 to 10 hours	.188	.189	–.128	(.069)
11 hours and above	.308	.320	–.311	(.067)
Research Funding				
Federal (dummy)	.231	.181	.364	(.054)
State/local (dummy)	.075	.062	.260	(.077)
Industrial (dummy)	.087	.036	.284	(.077)
Private foundation (dummy)	.122	.104	.333	(.062)
Own institution (dummy)	.156	.163	.282	(.056)
Research Assistance				
Graduate assistant (dummy)	.744	.711	.273	(.055)
Marital Status				
Married (dummy)	.833	.628	.085	(.052)
Overdispersion Parameter				
$\ln(1/v)$	—	—	–.143	(.041)
$1/v$	—	—	.866	

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