The Impact of Research Collaboration on Scientific Productivity[Ψ]

Barry Bozeman

and

Sooho Lee

School of Public Policy
Georgia Institute of Technology

February 11, 2003

Please do not quote without the permission of the authors.

Paper prepared for presentation at the Annual Meeting of the American Association for the Advancement of Science, Denver, Colorado February, 2003.

Ψ The authors gratefully acknowledge The authors gratefully acknowledge the support of the National Science Foundation and the Office of Basic Energy Sciences, U.S. Department of Energy. This work as performed as part of the project "Assessing Economic and Social Impacts of Basic Research Sponsored by the Office of Basic Energy Sciences," under contract DE-FG02-96ER45562 and "Assessing R&D Projects' Impacts on Scientific and Technical Human Capital Development" (SBR 98-18229). The opinions expressed in the paper are the authors' and do not necessarily reflect the views of the National Science Foundation or the Department of Energy. The authors appreciate contributions to the gathering and managing of the data. We are especially grateful to Juan Rogers, James Dietz, Jongwon Park, Min-wei Lin, Monica Gaughan, and Ivan Chompalov.

The Impact of Research Collaboration on Scientific Productivity

Abstract
Scientific collaboration often is viewed as a virtue, so much so that several public policies actively encourage scientific collaboration at both the individual and institutional levels. But few studies have actually examined the impacts of collaboration and fewer still have related collaboration patterns to publishing productivity. Based on data from 443 academic scientists, our research examines the effects of collaboration on scientists' productivity, measured in terms of publications. We examine publications productivity by two measures, numbers of scientific articles and books published and "fractional count," the number adjusted by number of co-authors.

We first examine descriptive **data for publishing productivity** and find that mean number of publications (by both normal and fractional counts) grows substantially during the past three decade among all groups to 3.6 (normal) and 1.28 (fractional) in 1996, actually declining somewhat between 1996 and 1999. Fractional and normal count productivity is related to being male, tenured, married and, interestingly, being non-native. Those in the chemistry discipline have an especially high productivity rate and those in computer science publish at a much lower rate than other fields of science and engineering.

The descriptive **data for collaboration** show that the mean number of (self-defined) collaborators for one year's research work is 13.8. On average, the collaborators are 40.9% graduate students and 27.1% female (females are about 14% of the sample). On average, scientists spend about 16% of their time working alone and the remainder collaborating and more than half of the collaboration time is with those in one's own research group. We developed a "collaboration cosmopolitanism" scale to measure collaboration outside one's own work group (e.g. persons in other universities, other nations) and found that physicists tend to be the most cosmopolitan in collaboration patterns. More cosmopolitan collaboration patterns are associated with being male, being a tenured faculty member, and total number of publications since 1996 (normal count, not fractional count).

In examining the **relation between publishing productivity and collaboration** we focused on publications since 1996 because our survey data are cross-sectional and our publications data, which is based on curriculum vitae records, is longitudinal. Our approach was to test a number of regression models, alternative explanations of productivity, to determine if the explanatory power of collaboration was diminished by such factors as job satisfaction, rank and age, gender, discrimination, nationality and collaboration strategy. In each of the models, number of collaborators remains the strongest predictor of productivity, measured by both fractional and normal count.

The Impact of Research Collaboration on Scientific Productivity

1. Introduction

In the "Big Science" era, the lonely genius working alone in the laboratory is still lonelier. For decades science has been a team activity. The team basis of science has long been reflected in scientists'[1] collaboration patterns. Indeed, Big Science often requires collaboration (De Solla Price, 1963). Despite some variations among disciplines, "working with others for scientific research" has become the norm (Beaver and Rosen, 1979a). The increasingly interdisciplinary, complex, and costly characteristics of modern science seem make scientists getting involved in increasingly collaborative research activities. Various government policies[2] also facilitate active research collaboration among organizations.

Among the good reasons to focus research on scientists' collaboration is to determine the extent to which and ways in which collaboration contributes to scientific growth and productivity. Most studies of collaboration include an underlying assumption that collaborative activity increases research productivity (Lotka, 1926; Price and Beaver, 1966; Zuckerman, 1967). Surprisingly few studies have actually tested that proposition. In the next section, we briefly summarize some of the research on scientific productivity and see that only a small fraction deals in any way with collaboration.

---

[1] Our concern is with physical and natural scientists as well as engineers. For convenience, we use the term "scientists" to encompass all.

[2] A series of technology transfer policies (Bayh-Dole Act, Stevenson-Wydler Act, and Cooperative Research Act) in the 1980s enhanced interaction among researchers throughout R&D organizations. In particular, some technology programs such as Advanced Technology Program (ATP) require inter-organizational collaboration for funding and research.

Certainly, there are good reasons to think that collaboration may enhance research productivity. Many collaborations center around the joint use of expensive or unique equipment without which research would not simply be less productive, it would not be possible (Meadows and O'Connor, 1971; Meadows, 1974; Melin, 2000; Thorsteinsdottir, 2000; Beaver, 2001). With increasing interdisciplinarity, some research is arguably made much more productive by as collaborators bring special expertise and knowledge not otherwise available but crucial to research outcomes (Maanten, 1970; Goffman and Warren, 1980; Thorsteinsdottir, 2000; Beaver, 2001). Often, tacit knowledge and knowledge of technique are best conveyed through collaboration (Beaver and Rosen, 1978, 1979a, 1979b; Katz and Martin, 1997; Beaver, 2001). In many cases collaboration is they key mechanism for mentoring graduate students and postdoctoral researchers, enhancing the productivity of individual scientists in addition to discrete scientific studies (Crane, 1972; Beaver and Rosen, 1978, 1979a, 1979b; Melin, 2000; Beaver, 2001).

Despite these good reasons to expect that scientific collaboration will enhance productivity, the relationship is not patent. The fact that researchers and policy-makers *perceive* that collaboration increases productivity does not make it so. Indeed, there are some arguments as to why collaboration may undermine productivity. Most important, there are transaction costs associated with working with others (Landry and Amara, 1998). Staying in touch by various media, waiting for others to comment, respond or do their part of the research, social ingratiation—these are just some of the factors taking time and energy even in the best collaborative relationships. Not all collaborations are ideal. Most active collaborators have had projects that were never finished or that had disappointing results because one or more of the collaborators did not live up to expectations. Finally, many researchers, especially senior researchers, collaborate not so much to increase their own productivity as to mentor graduate students and postdoctoral researchers (Bozeman and Corley, forthcoming). While much such collaboration is likely to enhance the productivity of all parties, others are likely to be a drag on the productivity of the more experienced researchers, a "tithe" voluntarily given.

Another reason to examine the impact of collaboration of scientific productivity is that there may be different implications for different measures of productivity. Some of these measurement issues are simple ones. One we examine is differences between "normal count" productivity — number of authored or co-authored articles and books— and "fractional count" productivity — the number of publications divided by the number of authors. Clearly, use of the fractional count measure deflates productivity, but does it deflate productivity to the extent that there is not net publications gain from collaboration?

Other measurement and conceptual issues are much less straightforward. In particular, does one focus on the productivity increments related to particular scientific outputs, such as publications, or take a much broader view of increments to scientific capacity? And if one examines increments in the capacity to do scientific work, does one focus on the individual, the research group, or some concept of a scientific field? Elsewhere (Bozeman and Corley, forthcoming; Bozeman, Deitz and Gaughan, 2001) we have considered the impact of collaboration strategies on "scientific and technical human capital" (S&T human capital). Scientific and technical human capital (S&T human capital) is the sum of scientific and technical and social knowledge, skills and resources embodied in a particular individual (Bozeman, Dietz and Gaughan, 2001). It is both human capital endowments, such as formal education and training, and social relations and network ties that bind scientists and the users of science together "knowledge value collective" (Bozeman and Rogers, 2002). S&T human capital is the unique set of resources the individual brings to his or her own work and to collaborative efforts. S&T human capital can be understood at the level of the individual and it is possible to measure the individual scientist's training, skills and even tacit knowledge (Polanyi, 1967; 1969), as it is possible to measure individual ties to networks and transaction with those in networks. In focusing on the individual, it is often most useful to think of S&T human capital in terms of the scientist's professional life cycle (Stephan and Levin 1997).

Examining collaboration from the standpoint of multi-level S&T human capital model shows that productivity implications are part and parcel of the analytic focus. Thus, for example, any particular collaboration may be a productivity decrement for specific individuals but a productivity increment for a field, educational cohort, knowledge value collective (Rogers and Bozeman, 2001; Bozeman and Rogers, 2002).

Based on data from 443 academic scientists, our research examines the effects of collaboration on scientists' productivity, measured in terms of publications. We examine publications productivity by two measures, numbers of scientific articles and books published and "fractional count," the number adjusted by number of co-authors. We are especially interested in whether fractional count productivity is related to collaboration. Our approach is to first consider the relationship of number of collaborators to publications productivity and then to examine the relationship in a number of regression-based models that explore alternative plausible explanations of the research productivity. Do these factors, such as gender, citizenship, tenure and age, interact in such a way as to diminish the independent effects of collaboration? Is collaboration just a surrogate for these other productivity-related factors? Before developing and discussing these models, we briefly summarize relevant research on collaboration and scientific productivity.

2. Does Collaboration Affect Research Productivity?

Since Lotka (1926)'s pioneering works on the productivity of scientists, many subsequent studies have confirmed a strong relationship between collaboration and scientific productivity. Analyzing 592 scientists' publications and collaborative activities, De Solla Price and Beaver (1966) found that "there is a good correlation between the productivities and the amount of collaboration of the authors. The most prolific man is also by far the most collaborating, and three of the four next most prolific are also among the next most frequently collaborating (p.1014)." Diana Crane (1972) explained the dynamics of collaboration in terms of "invisible colleges" and argued that these institutional dynamics were responsible for the exponential growth of scientific publication.

Zuckerman's study (1967) of 41 Nobel laureates showed a strong relationship between collaboration and productivity. In general, laureates published more and were more apt to collaborate than a matched sample of scientists. Miranda Lee Pao (1982) identified a strong relationship between collaboration and productivity in musicology. Though only 15% of the literature of musicology was the result of collaborative authorship, the most collaborative musicologists were also the most productive. Applying a normalized diversity measure to study the productivity of authors, Pao found a high degree of correlation between productivity and collaboration in computational musicology.

Pravdic and Oliuic-Vukovic (1986) analyzed collaborative patterns in chemistry at both the individual and the group level. They found that scientific output as measured by publications is closely dependent on the frequency of collaboration among authors. Particular effects on productivity depend upon the type of links; while collaboration with high-productivity scientists tends to increase personal productivity, collaboration with low-productivity scientists generally decreases it. Furthermore, the most prolific authors seem to collaborate most frequently and authors at all levels of productivity tend to collaborate more with highly productive authors than less productive authors.

Do motivations for collaboration matter to productivity? Several studies have pointed out that some motivations for collaboration are highly productivity-oriented, others less so. In an early research about motives for collaboration, Beaver and Rosen (1978) identified 18 motives—access to special equipment of facilities, access to special skills, access to unique materials, access to visibility, access recognition, efficiency in use of time, efficiency of use of labor, to gain experience, to train researchers, to sponsor a protégé, to increase productivity, to multiply proficiencies, to avoid competition, to surmount intellectual isolation, need for additional confirmation of evaluation of a problem, need for stimulation of cross-fertilization, spatial propinquity, and accident or serendipity (p.70). They found that about half of the motives were related to the desire of enhancing productivity (but did not include direct observation of the relationship of the motives to productivity).

Similarly, Fox and Faver (1984) found that division of labor is one of the main motivations of collaboration. As in business management, division of labor is expected to give mutual benefits to participants by increasing efficiency. In a recent in-depth review of research collaboration, Katz and Martin (1997) articulated several reasons why the level of research collaboration has been growing over the last 30 years: the escalating instrumentation costs of conducting fundamental science at the research frontier, the substantial fall in the cost of travel and communication, the growing importance of network and interaction, the complexity of instrumentation, the interdisciplinary research, and the political factors encouraging collaboration.

Melin (2000) surveyed 195 university professors about the major reasons for collaboration and the chief benefits of collaboration. In open-ended questions, the respondents' most often reported (41%t) motive for collaboration is that the "co-author has special competence." Other common motives included "co-author has special data or equipment (20%)," "social reasons: old friends, past collaboration (16%)," "supervisor-student relation (14%)," and "development and testing of new methods (9%)." With respect to the benefits of collaboration, the respondents pointed to "increased knowledge (38%)," "higher scientific quality (30%)," "contact and connections for future work (25%)," and "generation of new ideas (17%)." Based on the data, Melin concluded that scientists collaborate on the basis of strong pragmatic reasons. Melin's "pragmatic reasons" are largely consistent with the productivity-oriented collaboration.

3. Measuring Productivity

It is rarely easy to develop consensus about productivity measures, either in science or in other occupations. A management definition of productivity is "the ratio of output to input" (Swiss, 1991). A valid measure of productivity can be calculated if one can identify all input and output factors. But this is rarely possible due to the notorious difficulty in identifying all input and output factors, much less the exact causal mechanisms between the two.

Three issues are especially crucial in measuring scientific productivity: (1) What kind of input and output should be measured? (2) How should we weigh the quality of publications? Does an article in a prestigious journal have the same credit as an article in a lower prestigious journal? How do articles equate with books? (3) How should credit be distributed among the multiple authors?

Previous studies have used several proxies and correlates of productivity, including expenditures, number of researchers, person-hours and so forth as inputs. The most commonly examined outputs include journal articles, patents, books, book chapters, prizes, comments, abstracts, book reviews, invention-disclosures, licenses, lectures, conference papers, proceedings and technical reports (Gaston, 1970; Fox, 1992b; Jaffe, 1998). But most studies do not examine input factors, rather they use the output and make assumptions about input. When input measures are employed, the most common ones are time and the number of co-authors. Thus, productivity is sometimes measured by average publication rate for individuals (the total number of publication divided by the number of years) or a per capita publication rate for group (the total number of publications divided by the total number of authors).

The most common output measure is published articles, but few authors provide an explicit rationale for this measure. An exception is Wanner and colleagues (1981) who argued that the most important results of research in the sciences are reported in the refereed journals and that compared to the journal articles, books, and other outputs are less often used by scientists to actually advance science.

The weighting of publications is an important issue in measuring productivity. Several studies rely on essentially arbitrary scales of quality. For example, Clemente (1973) used Glenn-Villemez Comprehensive Index (GVCI) which gives scores 10 for any article in American Sociological Review and American Journal of Sociology, 8 for Social Forces and Sociometry, 7 for Social Problems, 5 for Sociology of Education, 30 for books received by American Sociological Review. Generally, weighting the publications is possible only in the study of the same discipline; cross-disciplinary comparisons are difficult to justify.

In cases of multi-authored publications, how much credit should be given to each co-author? There are three kinds of counting found in the research literature. First, Cole and Cole (1972) proposed to use "straight count," which takes no account of multiple authorship; the articles are allocated to only the first authors. The great advantage of this procedure is that the exact number of papers is completely preserved. Cole and Cole (1973) claim that "the omission of collaborative citations to papers on which the author was not the first among collaborators does not affect substantive conclusions." They therefore recommend such omission. This strategy has two results. First, it solves the problem of distributing credit for multiple-authored work by disregarding all but the first author who receives all the credit. Second, it greatly reduces the work required to collect data on any sample of scientists. Straight count assumes that the name order of authors listed on a given paper reflects the level of their contributions, with the greatest contributor listed first, and so on in descending order. But a problem with a straight count is that it may discriminate against those scientists whose name appears late in an alphabetic listing. Rudd (1977) found a greater percentage of first authors among those with last names beginning with A to F compared with G to M, and with G to M compared with N to Z (the percentage of first authors in the three groups were 56.8, 29.9, and 13.3 respectively).

The second counting method is "adjusted count," which gives data on fractional authorship. This approach has some of the same advantages as the straight count. Each item in a multiple-authored paper is divided by the number of authors and then summed to one (Pravdic and Oluic-Vukovic, 1986). Narin (1976) claimed that there does not seem to be any reasonable way to deal with the attribution problem, except to attribute a fraction of a publication to each of the authors. Lindsey (1980) vindicated the advantage of adjusted count, pointing out that it can control for the bias in overestimating production when the full value of a co-authored paper is awarded to all contributors. But the main weakness is that the procedure is tedious.

The third one is "normal count," which is most frequently applied. It gives full credit to all contributors. In other words, it allows equal treatment for each author which results in giving a full credit to each of them regardless of who happens to be the first or the last author. The correct number of papers in a given sample cannot be expressed by summing up the authors' data. The inaccessibility of the actual number of papers is the major drawback of the normal count procedure (Pravdic and Oluic-Vukovic, 1986). Another problem is that in most cases there is no reason to expect that co-authors contributed equally. Hagstrom (1965) found evidence that some publications listed authors for purely social reasons. More recently, LaFollette (1992) showed that the practice of making colleagues "honorary co-authors" has become quite common.

4. Models of Collaboration's Effects on Productivity

Policy-makers apparently assume that collaboration has positive effects on research productivity, otherwise one would be hard pressed to account for the diverse programs that in one way or another either encourage or mandate research collaboration. Similarly, researchers themselves seem to have accepted the idea that collaboration results in greater productivity (Beaver and Rosen, 1978). There are many good reasons to believe that collaboration has salutary effects on research productivity. Research in many fields is more complex and requires more specialized knowledge, more than single individuals can expect to have. Collaboration permits individuals to play to their strong suits, contributing their strongest skills and deepest knowledge, relying on others to contribute other skills and knowledge. Research groups sometimes seem to be more than the sum of their parts, contributing a synergy.

Despite many good reasons to expect collaboration to lead to increased productivity, the relationship is not patent. On balance, we are more impressed with the arguments for a positive effect of collaboration on research productivity and we hypothesize that collaboration tends to have positive effects on research productivity. We test this core hypothesis. Specifically, we examine the effects on number of research collaborators on the average number of refereed articles and books published, considering productivity in terms of not only the number of publications but also a "fractional count" (divided by number of co-authors). (Details of measures are provided in section 6.0 below).

Even if collaboration does have an effect on productivity, it is possible that many factors moderate the relationship between collaboration and productivity. Thus, is any observed relationship between collaboration and productivity a direct one, or perhaps a function of interactions with other variables correlated with both collaboration and productivity?

4.1 Age, Rank and Status

Is the effect of collaboration on productivity chiefly a function of the scientists' age? Arguably, older scientists, or at least ones who have had longer careers, have had more time to develop S&T human capital and to build up their professional networks and, possibly, any productivity increment from collaboration could be confounded with age.

In the sociological study of productivity, age has long been a focus. No doubt the convenience of its measurement is part of the attraction. H.C. Lehman (1953) argued that scientists' major contributions occur in their late 30s or early 40s, and thereafter decline. He also emphasized that the age peak occurred earlier in abstract and theoretical disciplines such as theoretical physics and later in more empirically based fields such as biology. Similarly, Pelz and Andrews (1976) found a productivity peak in scientists' late 30s and early 40s. But they also observed a second peak ten to fifteen years later at age 50. Similarly, Bayer and Dutton (1977) identified a bi-modal productivity curve, with the first peak at about the tenth year of career-age, followed by a second productivity peak as the scientists near retirement age. Stephen Cole (1976), on the other hand, reported a slightly curvilinear relationship between age and quality of publications for a cross-section of academics in six scientific fields. His data showed that the productivity does not differ significantly with age.

Why would one expect the productivity to decline with age? Pelz and Andrews (1976) provided four hypotheses. First, intellectual functioning of scientists may atrophy with age. Second, able scientists may be drawn off into non-research activities, particularly administration. Third, scientists may relax their zeal and motivation to achieve. And fourth, as scientists specialize and, through increased specialization, may lose the broader viewpoint needed for breakthroughs. Pelz and Andrews found support for only the third and fourth hypotheses.

Hammel (1980), however, presented a quite different finding that productivity increases strongly with age and decreases weakly with the square of age, so that the pattern is one of "gradually decelerating increase." In a more recent study of age and productivity, Levin and Stephan (1991) found that life cycle effects are present in a fully specified model of publishing productivity that, among other things, controls for individual fixed effects such as motivation and ability. Using the data of 903 natural scientists, they argued that there is evidence that, on average, scientists become less productive as they age and that the age effect is attributed to age per se and not to the possibility that older scientists in the sample have different attributes, values, or access to resources than younger members of the sample.

Possibly, the relationship between collaboration and productivity could be explained by one's rank or tenure. It seems reasonable to expect that collaboration might be a different experience for a senior tenured and research group leaders than for untenured faculty, postdocs or graduate students. The specter of exploitation is always in the background when there are status differences among collaborators. At the same time, a collaboration that is quite productive for an experienced junior researcher may prove "inefficient" for the mentor. Finally, there are important learning effects that may make collaboration more productive for more senior scholars. They not only have time to acquire greater knowledge and scientific and technical human capital (Bozeman, Dietz and Gaughan, 2001), but they also have more experience with the collaboration process itself and, all else equal, may have more productive returns from collaboration.

4.2 Research Grants and Contracts

Both collaboration and productivity may be wrapped up in grants and contracts success. In the first place, most grants are for teams of researchers and those who are working on grants often have commitments to devoting a certain percentage of their time to collaborative or team-based goals, projects and publications. Second, if one is the principal investigator (PI) in the grant, it is often the case that one has an extended set of collaborations not only because of formal contractual commitments but also due to norms of crediting the PI in publication when the PI's data or experimental apparatus are used. In general, we expect those with grants and larger grants (in funding dollar terms) to collaborate more and to have more publications. We do not expect that the dollar amount of the grant will be nearly so important as simply having been awarded grants or contracts. In the first place, dollar amounts are often related to field- and discipline-specific dynamics, such as the expense of equipment, and, in the second place, earlier research has shown that research productivity is not monotonic in its relationship to magnitude of funding (Kingsley, Bozeman and Coker, 1996).

We consider not only grants funding but also the scientist's "batting average": the percentage of submitted proposals that are actually funded. This is a rough quality indicator (though a messy one given the many confounding factors related to one's funding agency, institution, and discipline) and, perhaps, an indication of greater cumulative advantage (Merton, 1968).

4.3 Gender and Family Relations

One of the most consistent findings in the literature on research productivity is that women tend to have somewhat lower publication rates than men. This could be in part because women have less developed collaboration networks and collaborate less than men. Or it could be due to systematic discrimination. It is also possible that women collaborate less and produce fewer scientific papers because, compared to men, women are less likely to have a full time homemaking spouse, more likely to have a prominent role in child rearing. Marital status also seems to interact with gender and productivity with married males being most productive and unmarried females the least. We anticipate that the relationship of collaboration and productivity will be moderated by these issues of gender, family and marital status. The research literature provides ample support for this expectation.

The lesser productivity of females has been established in dozens of studies covering diverse fields, spanning decades, and using myriad measures (Cole & Zuckerman, 1984; Fox, 1983; Long, 1987). As Long (1992) pointed out, obligations of family and children may differentially affect the careers of males and females. Also, sex discrimination may make it more difficult for females to obtain resources and this may, in turn, limit their ability to publish. But he argues that 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 as the “productivity puzzle.”

Contrary to the stereotype that women are less productive, Clemente (1973) argued that sex differences in publication productivity are negligible. He used a sample of 1899 male and 306 female sociologists and examined types of publications. Similary, Wanner and colleagues (1981) found evidence that gender does not affect productivity in terms of articles published. They used a sample of 17,399 university faculty members from almost all fields and disciplines.

In a more recent study, using the longitudinal productivity data of 556 male and 603 female biochemists, Long (1992) found that sex differences in the number of publications and citations increase during the first decade of the career but are reversed later in the career. He also found that papers by females on average receive more citations than those by males. As revealed in Long's study, lifetime productivity might be negligible or small but the difference in the early stage of careers seems more visible. Xie and Shauman (1998) again confirmed a decline in the effects of gender on scientific productivity, attributing this in part to the increasing ratio of females in scientific jobs.

4.4 Citizenship

With increasing numbers of foreign nationals working in U.S. research institutions, factors related to nationality, culture and language likely affect collaboration and, in turn, productivity. Since most researchers prefer to work with someone fluent in their own language (Bozeman and Corley, forthcoming), those who are not fluent in English are likely to have their collaborator "demand" reduced, but perhaps, might be even more strongly motivated to collaborate than those fluent in English. We expect that nationality factors will not have a direct effect on productivity but will have and effect on collaboration and perhaps through that effect and indirect effect on productivity.

4.5 Job Satisfaction

Few group behaviors are immune from influence by individuals' sense of personal esteem and job or life satisfaction. We expect that personal and job satisfaction, including satisfaction with pay and with colleagues' perceptions of research contributions will relate to both collaboration and productivity. But the relationship is surely a complicated one. Invitations to collaborate are both an indication of the respect and esteem of colleagues, but it is often also a sober calculation of past contributions. If past contributions have been disappointing, these will condition not only potential collaborators' "rational calculations" but also one's sense of esteem and job satisfaction. Thus, any relation to productivity is necessarily a complicated one. We hypothesize that job satisfaction and a sense of having colleagues' respect will be an important factor in collaboration but will be more an effect of research productivity than a cause.

4.6 Perceived Discrimination

A special and extreme case of job dissatisfaction is perceived discrimination. One who perceives discrimination on the basis of sex, religion or national origin (or probably any basis) is likely to be less active in seeking collaborators, at least local ones, and may well have negative effects on productivity. We anticipate those who perceive discrimination will be less productive and have fewer collaborators and that perceived discrimination will have direct effects on collaboration and productivity.

4.7 Collaboration Strategies

As we noted above, any calculation of the apparent productivity costs and benefits of collaboration should consider the motive for collaboration. One collaborating as a mentor to an inexperienced student may well be thought of as having a service motive. One collaborating on the basis of the other parties' reputation may have either a quality motive or a social capital motive. These are just a few of the possibilities. Some choose collaborators for their business-like demeanor, others just because collaborations are fun or entertaining. One of the most powerful predictors, of course, is proximity.

We anticipate that the relationship between collaboration and productivity will be moderated by the researchers' strategies for collaboration with those seeking collaborators with complementary skills or strong scientific reputations having the greatest productivity gains from collaboration and those seeking primarily to help students or junior colleagues having fewer productivity gains.

5. Data and Variables

5.1 Data

The data are based on the RVM[3] CV (Curriculum Vitae) data and RVM Survey of Careers of Scientists and Engineers. The RVM CV data has 1370 random samples from university professors and researchers who are affiliated with NSF and DOE centers in the US universities. The CV data include 3000 variables of demographic data, degree data, job data, publication data, patent data, professional affiliation data, and grant award data. The CVs were collected in 2000.

The RVM Survey of Careers of Scientists and Engineers was conducted from October 2001 to March 2002. The survey was sent to the 997 university faculty members from the RVM CV data who are not a retired professor and an industrial researcher. The response rate was 44%, which means 443 returns. The survey includes questions about research collaboration, Grants and Contracts, Job selection and work environment, and demographic information. Among the respondents, a 41% (181) is engineering

[3] RVM stands for Research Value Mapping, a research project supported by NSF and DOE. It is located in School of Public Policy, Georgia Tech.

professors; a 15% (66) is bioscience professors; a 5.6% (25) is computer science professors; a 10.61% (47) is chemistry professors; a 9.7% (43) is physics professors; and the rest of 12.9% (57) are other science field professors. By the group, tenured faculty is 62.8% (278); not-tenured faculty 37.2% (165); male 86.5% (383); female 13.1% (58); native scientists 68.4% (303); and immigrants 31.4% (139). The average age of the sample is 46 in the year of 2000. In particular, the gender ratio and native/immigrant ratio in this sample is very close to the national level.

6. Findings for Descriptive Analysis

6.1 Productivity

This section presents descriptive data pertaining to the productivity of the researchers in our study. It is important to remember that we are measuring productivity in two different ways and that the difference will sometimes be significant. When we refer to "normal count" productivity, the measure is total publication of refereed scientific articles and books. When we refer to "fractional count" we divide by the number of authors.

The explosion of publications first noted by De Solla Price (1963) is underscored by **Table 1**. While there are relatively few 1950's era Ph.D.s in the sample, there are several from the 1960's era. If we examine by cohort the data show that the publication rate is much greater for later years and, starting with during the 1980's the difference between fractional count and normal count sharpened, perhaps indicating effects of norms encouraging collaboration or perhaps due to the increased complexity and interdisciplinarity of scientific work.

Table 2 provides the mean number of publications after researchers have received their doctoral degree, with the lower line representing fractional count and the upper line normal count. A "0" means that less than one year has passed since receiving the degree and a "44" means that 44 years have passed since the individual received the doctoral degree. Thus, the table gives insight into productivity levels during the life course of a researcher's career.

The normal count data show that productivity peaks between the 23rd and 28th year, averaging nearly five publications per year during that period (discerned from more detailed tables than provided here). After that period the researcher four publications for about five years or so and then the average drops to a little more than two by after forty years. Interestingly, the average is less than three publications for the first eight years, the time during which many researchers are struggling to be awarded tenure. Naturally there are some cohort effects after six to eight years due to "drop outs" among persons who did not receive tenure. That is, the 0-8 cohorts presumably include some people who will not receive tenure and the cohorts after eight probably include very few people who did not receive tenure.

With respect to fractional count, **Table 2** shows that there are fewer peaks and the curve is somewhat smoother. The effect of using a fractional count is to make the data more closely approximate a normal distribution, perhaps indicating that later years' productivity is related to the scientific and technical human capital and the collaborative arrangements that develop. As before, the early years and the later years are less productive, but there is less of a sharp peak from years 8 to 40, though the most productive years appear to be from about 19 to 29 years after the doctoral degree.

Table 3-1 and 3-2 shows that there are considerable disciplinary differences in numbers of publications during the researchers' life course. Chemistry is the highest producing discipline and computer science has the fewest publications. The data also indicate that whereas chemistry researchers peak between 28 and 30 years after the dissertation, physics researchers peak at 37 years after the degree, much later than one might expect. Productivity by gender is examined in **Table 4-1 and 4-2.** The table indicates that males' level of normal count productivity is higher than females until the 18^{th} year at which time females have a somewhat higher productivity rate. The data must be treated with caution as the relatively small percentage of females (13.1%, n=58) in the sample makes the trend data highly subject to individual cases and small cohorts. **Table 5** shows productivity by rank for both fractional and normal count. In order to make figures comparable, the measure is median publications 1996-2000, dropping individuals who did not have doctoral degrees by 1996. By normal count, the discrepancy between full professors, associate and assistant is considerable with more than five per year for full professors and less than three for assistants. A similar pattern holds for fractional count, with the numbers for full professor being twice that for assistants.

Using the same indicator— productivity since 1996— we find that two other demographic factors are importantly related to productivity. As **Tables 6, 7, and 8** show, married researchers, non-native researchers, and male are more productive in terms of both fractional and normal count. Using t-tests of significance, rank, gender, native status and marital status are all significantly associated (<.05) with both productivity measures. Other variables (not reported in these tables, but more details are available from the authors) positively and significantly associated with both normal count and fractional count productivity include total number of doctoral students currently supported, self-reported job satisfaction, and a perception that department colleagues appreciate one's work.

6.2 Collaboration

While we have elsewhere (Bozeman and Corley, forthcoming) provided findings for collaboration patterns and, particularly, collaboration strategies, it is nonetheless useful to consider her basic findings about number of collaborators and who collaborates with whom. Our questionnaire asked each respondent to indicate the number of persons with whom they had "research collaborations" within the past twelve months, by category. The categories included male university faculty, male graduate students, male researchers who are not university faculty or students, female university faculty, female graduate students, and female researchers who are not university faculty or students. We focused on research collaborations rather than publications because (1) we wished to include important collaborations that did not involve publication (including research that had not yet been submitted for publication); (2) we wished to exclude co-authors who achieved that status not by virtue of collaboration but because of position (e.g. head of a laboratory or project). We focused on just the past twelve months because we expected that a limited time frame would both improve recall and reduce the response difficulty.

Table 9 presents data for total number of collaborations for a single year. The table presents the distribution of numbers of collaborators, with the mean being 13.82 and the median being 12.0. Among this average of 13.8 collaborators, the averages by category are 10.2 male (3.6 female), 5.7 faculty, 5.9 graduate students. Only 2.2 percent of collaborators were neither university faculty nor students. In sum, the data seem to show active collaboration, chiefly with other academics, with males being a much higher percentage of collaborators and with faculty and graduate students having about equal likelihood of being chosen as collaborators.

One might expect considerable difference in disciplines' collaboration patterns (reference citation of previous work showing disciplinary differences). **Table 10** bears this out. The table shows that electrical engineers are the most active collaborators whereas biology and life sciences researchers as well as civil engineers are well below the mean.

Another of our questionnaire items sought to determine the breadth of researchers reach in collaboration, that is, whether they tended to work with persons geographically close or far away. We asked respondents to indicate the percentage of research time spent working: alone, with researchers in the immediate work group or laboratory, with researchers in one's university but not in the immediate work group, with researchers in other U.S. universities, with researchers in other nations' universities, with researchers in industry and researchers in government laboratories. **Table 11** provides the results. The table shows that more than half (51.1%) of research time is spent with colleagues in the immediate work group, with the next largest amount of time (16.3%) devoted to working alone. Thus, only about one-third of research time is spent collaborating with persons who are not immediately proximate and only about one-quarter of research time is spent with those outside one's university.[4]

[4] We expect that these numbers are higher than the average for all university researchers because the respondents are affiliated with centers, many of which were established with a collaboration mandate or strategy.

We created a "collaboration cosmopolitanism scale[5]," seeking to indicate the extent to which researchers tended to be "more cosmopolitan" (collaborating with those outside the proximate work environment) or less so. The scale ranged from 0 to 5 with 0 being the least cosmopolitan and 5 the most. **Table 12** shows that there is no great variance among the disciplines with respect to collaboration cosmopolitanism. Physicists have the highest cosmopolitanism scale, chiefly because they are somewhat more likely to collaborate with researchers in other nations. Mechanical engineers and biologists are less likely to be cosmopolitan in their collaborations. But the most important point is that there is relatively little difference among disciplines.

Among the various demographic variables, a few are associated with greater collaboration cosmopolitanism. Significant correlates include gender (>.03) (males score higher), tenure (>.01) (tenured score higher), status as a principal investigator (>.001), and total dollar amount of current grants and contracts (>.001).

7. Correlation and Regression Results for Impacts of Collaboration on Productivity

---

[5] The cosmopolitan scale is a measure of how close or far away a participant's collaborators are (i.e., a participant with more collaborators in foreign countries would rank higher on the cosmopolitan scale than a participant with collaborators only in the U.S.). This is not, of course, a true physical distance scale since, for example, a collaborator foreign country may be closer than a collaborator in another part of the US. The scale was calculated by multiplying the fraction of their time each participant spent working with a type of collaborator by the cosmopolitan rank of that variable (measured on a 1 to 5 scale). "Research time spent working alone" is given a value of 0 on the cosmopolitan scale. Similarly, "research time spent working with members of the same work group" is assigned a 1 and "time spent working with others in the same university, but a different work group" is assigned a value of 2. "Working with researchers at a different university" counts as a 3 on the cosmopolitan scale and "working with others in industry or government laboratories" are both assigned a value of 4. Lastly, "working with researchers in other nations" counts as a 5 on the cosmopolitan scale. For instance, if I work alone 10% of the time, within my own work group 20% of the time, with scholars at other universities 30% of the time, with industry 10% of the time, government 10% of the time and with scholars at other nations 20% of the time, my cosmopolitan score would be 2.6 (i.e., 0.1(0) + 0.2(1) + 0.3(2) + 0.1(4) + 0.1(4) + 0.2(5)).

We hypothesize that collaboration is positively and significantly productivity, measured by both normal count and fractional count publication. Our suggestion of a possible correlation between collaboration and productivity is certainly not original. If one did not expect collaboration to have a bearing on productivity there would be little reason for policies encouraging collaboration and productivity. If researchers did not expect collaboration to enhance their productivity it seems unlikely that the practice would be so widespread. If we assume collaboration and productivity are correlated (an assumption tested below), the more interesting questions are these:

- Even if collaboration is correlated with normal count productivity, is there a positive correlation once the number of co-authors is factored in (i.e. fractional count)?
- If collaboration and productivity are correlated, is the correlation really any more than an statistical artifact of other variables intercorrelated with both collaboration and productivity (e.g. grants or number of graduate student supervised)? To put it another way, does the relationship hold with a properly specified model? We address this issue by first considering the relationship between collaboration and productivity and then determining if the relationship vanishes with alternative specifications of the model.
- Most difficult, what is the causal direction of any observed relation between collaboration and productivity? Does collaboration cause productivity? Does productivity increase collaboration opportunities or "demand"? Are effects reciprocal? While our data are not sufficient to fully address these questions, we consider them and provide some relevant evidence.

7.1 Zero Order Correlations for Collaboration and Productivity

Table 13 gives the zero order correlations between selected collaboration variables and both normal count and fractional count productivity. As one would expect, the correlation between normal count and fractional count productivity is quite strong (.928). Since normal count is the numerator for the fractional count recoded variable, one would expect a strong correlation but not necessarily as strong as .9.

Table 13 shows that there is a significant positive relationship between total number of collaborators and both normal count (.209 p=<.000) and fractional count (.147, p=<.006). While these correlations seem not to explain a great deal of variation between collaboration and productivity, one would expect from the literature that collaboration would be only one factor determining productivity. Studies have shown that research productivity is a complex phenomenon determined by a wide variety of variables at both the individual and group level of analysis (Long and McGinnis, 1981; Cole and Zuckerman, 1984).

Furthermore, we examine only one type of productivity, publications of articles and books. We argue elsewhere for multiple measures of research productivity (see Bozeman, Dietz and Gaughan, 2001; Bozeman and Rogers, 2002; Crow and Bozeman, 1998), but many desirable measures cannot be obtained from the type of instruments used in this study.

Table 13 indicates that it is not only the number of collaborators that relates to productivity, choice of collaborators makes a difference. The cosmopolitanism of collaboration scale is significantly correlated (.107, p. <.05) with normal count publications productivity (but not fractional count). An examination of the raw data revealed that those researchers who spend a larger percentage of their work time collaborating with researchers in other nations are especially more productive. The direction of effect is in all likelihood productivity to collaboration. More productive senior scholars generally have more opportunity to collaborate internationally.

Finally, **Table 13** indicates those who spend a higher percentage of their time working alone are less likely to be productive, at least in terms of normal count productivity (-.156, p. <.002). Time working alone can be viewed as a different dimension of collaboration. Number of collaborators is not the same percentage of time collaborating. One could spend an enormous amount of time collaborating with a single person or a small amount of time collaborating with several. The fact that these are somewhat different measures of collaboration seems to be born out by the fact that the correlation between total collaborators and percentage of time working alone is significant but not enormous (-.206, p <.000).

7.2 Regression Models

The central questions for our study is: “Does research collaboration affect researchers’ publishing productivity or is any observed relationship an artifact of co-variation with other related factors?” We see in the above section that total number of collaborators correlates with both fractional count and normal count publications. But there are alternative plausible hypotheses tested in models presented here. The objective, then, is to see if the relationship is altered with various specifications of the model. Alternative models, each having some justification in the literature on scientific productivity, include: (1) grants and research proposals; (2) gender and family circumstance; (3) status as either a foreign national or U.S. citizen; (4) academic rank; (5)

cohort effects and field effects; (5) satisfaction with colleagues and work environment. We begin with cohort (age and career age) and field effects in order to determine whether it is necessary to include these factors as controls in the other models we examine.

7.2.1 Age, Rank and Collaboration as Research Productivity Factors

As **Table 14** shows, the age-rank-status model does not greatly diminish the relationship of total collaborators to normal count productivity ($\beta = .236$, $p<.000$). Even if we account for effects of age and rank, the relationship remains strong and in the expected direction. The only other variable that is significant is tenure ($\beta = .177$, $p<.004$). This is certainly not surprising inasmuch as the tenure process at most universities is, in part, a means of selecting on the basis of research productivity. **Table 14** shows us that the results for the relationship of total collaborators and fractional count productivity is quite similar but with reduced magnitude ($\beta = .167$, $p<.002$) and, similarly, tenure is significant in this model as well ($\beta = .218$, $p<.000$). The effect of using a fraction-based productivity measure is to switch the magnitude of influence between tenure and number of collaborators. It is interesting that age plays no independent role in research productivity, as least by our measures, but if is, of course, strongly correlated with tenure.

7.2.2 Research Grants and Collaboration as Research Productivity Factors

Since one of the chief purposes of research grants and contracts is to enhance research productivity, we might expect a strong, independent relationship between grants and productivity. But our measures, the connection is a weak one and it has little effect in diminishing the important of total number of collaborators to research productivity. With respect to normal count productivity, **Table 15** tells us that only total collaborators is significant ($\beta = .208$, $p< .001$). Neither the size of the current grant nor the "batting average," (percentage of submissions funded) has clear independent effects of research productivity, though the "batting average coefficient is in the expected direction and is significant at the .10 level. The batting average variable has stronger effects with respect to fractional count productivity (β =.117, p<.05. In this equation as well, total collaborators remains the strongest predictor of research productivity (β= .140, p. <.02).

The seeming irrelevance of the grants variable is not as surprising as it may seem. The variable examines the dollar size of the current grant. Other research has indicated that the magnitude of grants often has little correspondence to research productivity (Kingsley, Bozeman and Coker, 1996). It is the fact of having a grant. But in this dataset almost 90% of the respondents in this sample have research grants, making the grant-no grant hypothesis impossible to test validly due to insufficient variance.

7.2.3 Gender, Family Relations and Collaboration as Research Productivity Factors

There is considerable research on the impacts of gender on scientists research productivity (e.g. Fox, 1991, 1985), most finding that women are not as productive, at least in terms of publications measures, and that they face barriers not often encountered by men (e.g. Centra, 1974; Holmstrom and Holmstrom, 1974; Kjerulff and Blood, 1973). In this model we examine not only gender itself but also to variables presumed to be closely related, number of children and whether the spouse is a full time homemaker or family care giver. **Table 16** shows that the effects of total number of collaborators remains strong (for normal count β= .258, p<,000, for fractional count β= .177, p<.001). For both normal count and fractional count productivity, only the variable relating to spouse as a full time homemaker is significant (normal count β= .123, p<.038, fractional count β= .136, p>,025. In neither equation is gender significant at the .05 level or greater, nor is marital status. Both these variables have been found as important in some previous research. In both the normal count and fractional count cases the signs of the coefficients are in the expected direction.

There are several possible explanations for why gender and marital status have been found to be more important in other studies. In the first place, our sample is of scientists working in science centers, institutions set up to promote collaboration, and it may be that results would be different from persons working in more traditional settings. Second, few of the previous studies of gender and marital status effects have taken into account the impacts of either total number of collaborators or whether spouse is a fulltime homemaker. Finally, the collaboration variable may not be the most important one for differences based on gender. Previous research has shown that women tend to collaborate as often as men but with fewer persons (Fox, 1991).

7.2.4 Citizenship and Collaboration as Research Productivity Factors

One might reasonably expect citizenship to interact with collaboration, but perhaps with productivity as well. **Table 17** provides the results for regression models examining the effects of citizenship and collaboration variables on, respectively, normal count and fractional count productivity. In both models, total number of collaborators remains a significant predictor of scientific productivity (normal count, $\beta = .203$, $p < .000$, fractional count, $\beta = .143$, $p < .007$). While the variable native born is not significant in either model, the impact of the naturalized citizen variable is noteworthy. Naturalized citizens are actually more productive than others in the sample (normal count, $\beta = .178$, $p < .007$; fractional count, $\beta = .153$, $p < .021$). Quite likely, naturalized citizen respondents resemble the tenured cohort in one respect. Like tenured researchers, the naturalized citizens have been selected for productivity. Had the not been more productive than average, their likelihood of remaining employed in the U.S. as scientists and, thus, become naturalized citizens would be sharply reduced.

7.2.5 Job Satisfaction and Collaboration as Research Productivity Factors

The relationships between job satisfaction and productivity have been investigated in a wide variety of settings, ranging from factory workers to submarine teams to sports teams. The results of these studies vary greatly, with some finding that job satisfaction causes greater productivity, others that productivity causes satisfaction, others that there is not relation between the two. Some studies have examined the reciprocal effects between satisfaction and productivity while others have examined threshold effects. It is, perhaps, not surprising that the findings are so unstable. In addition to the usual problems of inconsistent measures applied inconsistently, it seems plausible that these highly varied work settings may have such an important bearing as to govern the relationship between satisfaction and productivity.

The preponderance of studies of job satisfaction and productivity in R&D organizations suggests a positive relationship between the two. Our results, displayed in **Table 18**, show that job satisfaction, using a variety of measures, seems to have little impact on scientists' productivity, at least holding constant the impact of total number of collaboration. Only one satisfaction variable is significant among the zero order correlations, satisfaction with one's personal life and only for normal count productivity. Total number of collaborators remains significant for both normal count productivity (β= .183, $p<.001$) and fractional count (β= .117, $p<.036$).

7.2.6 Discrimination and Collaboration as Research Productivity Factors

Perhaps related to job satisfaction, but a pathological manifestation, is discrimination. In this model we ask the extent to which perceived discrimination interactions with productivity, as attenuated by number of collaborators. The results for this analysis appear in **Table 19**. The results indicate that perceived discrimination on the basis of sex does negatively affect productivity, with little difference between normal count (β= -.123, $p<.054$) and fractional count (β= -.122, $p<.054$). Discrimination does not seem much interrelated with total number of collaborators as the zero order correlation and the partial correlation are virtually the same. For both productivity measures, total number of collaborators is significant (normal count, β= .210, $p<.000$; fractional count, β= .146, $p<.007$).

It is worth noting that perceived discrimination by race, ethnicity, religion or national origin does not appear to be strongly related to research productivity. It is probably even more important to note that the findings must be taken with care because there is relatively little variance in the two discrimination variables. Only 4.7% of the sample perceive that they are discriminated against by race, ethnicity, religion or national origin. Only 5.4% of the respondents reported perceiving discrimination on the basis of sex (24 individuals, 14 females and 10 males).

7.2.7 Collaboration Strategies and Number of Collaborators as Research Productivity Factors

Previous studies have shown that scientists' have coherent strategies guiding their collaboration choices (Bozeman and Corley, forthcoming), strategies based on a wide variety of motives. The most commonly cited motives for research collaboration include:

1. access to expertise (Katz and Martin, 1997; Melin, 2000; Thorsteinsdottir, 2000; Beaver, 2001), access to equipment or resources one (Meadows and O'Connor, 1971; Meadows, 1974; Melin, 2000; Thorsteinsdottir, 2000; Beaver, 2001),
2. to improve likelihood of research funding or to share funds (Smith, 1958; Clarke, 1967; Heffner, 1981; Beaver, 2001),
3. to obtain prestige or visibility (Crane, 1972; Beaver and Rosen, 1978, 1979a, 1979b; Katz and Martin, 1997; Beaver, 2001),
4. to obtain specialized knowledge about a technique (Beaver and Rosen, 1978, 1979a, 1979b; Katz and Martin, 1997; Beaver, 2001),
5. to pool knowledge for tackling large and complex problems (Maanten, 1970; Goffman and Warren, 1980; Thorsteinsdottir, 2000; Beaver, 2001),
6. to enhance productivity(Thorsteinsdottir, 2000; Beaver, 2001), for fun and pleasure (Katz and Martin, 1997; Melin, 2000; Thorsteinsdottir, 2000; Beaver, 2001), and,
7. to educate or mentor students and junior colleagues (Crane, 1972; Beaver and Rosen, 1978, 1979a, 1979b; Melin, 2000; Beaver, 2001).

Our concern in this model was to determine if the particular motives for collaboration were actually more important than the total number of collaborators in affecting scientists' research productivity. As shown in **Table 20**, the total number of collaborators seems to be a more important determinant of research productivity than the particular motives for collaboration. Total number of collaborators is significant for both normal count productivity ($\beta = .166$, $p<.004$) and fractional count productivity ($\beta = .129$, p<.027). Among the collaboration motive variables, only the motive of choosing a collaborator who sticks to a schedule is significant at the .05 level (β= -.112). Given the negative sign of the coefficient, it appears that less productive scientists emphasize this particular collaborator choice criterion. This variable is significant only with respect to normal count productivity. It is perhaps worth noting that the two collaboration motive variables having the largest zero order correlations are "help junior colleagues" (r .102) and "help graduate students" (r .114). While these are relatively modest correlations, they drop most precipitously in the partial correlation, perhaps indicting a confluence with number of collaborators.

8. Summary and Conclusions

Our research question is, on its face, a simple one: "To what extent, if any, do scientists' collaboration patterns affect their publishing productivity?" Phrased this way, the question is important for a number of reasons. In the first place, many public policy-makers, and apparently most scientists, assume that scientific collaboration has positive effects on scientific productivity. The collaboration-as-synergy assumption affects not only particular awards of research grants and contracts but also entire programs of research policy. The assumption even affects the move toward interdisciplinary science centers, institutions built in part to promote collaboration, interdisciplinary work and inter-sectoral cooperation (Behrens and Gray, 2000; National Academy of Engineering, 1983).

A second reason for examining the impact of collaboration on scientific productivity is that there may be spillovers beyond the publication of papers. Elsewhere (Bozeman and Corley, in press) we have argued that collaboration seems to be a major factor in promoting and transmitting "scientific and technical human capital"- the set of scientists' skills, knowledge and social ties that affect the capacity to do scientific work and to apply it. While we do not directly examine this connection in the current paper there may be implications.

Finally, examining the collaboration-productivity relationship is interesting because anything more than the most superficial model requires one to examine a host of alternative explanations of the relationship. Our focus, then, has been on examining collaboration's effects on productivity but also seeking to understand the way that a host of other potentially relevant factors mitigate the relationship. Perhaps our most important finding is that the positive relationship between collaboration and productivity is remarkably robust. The relationship is not simply an artifact of rank or status, or of gender, or grants or even the "cosmopolitanism" of collaboration. We examined fractional count publications productivity, taking into account the obvious notion that more authors may lead to more publications for all, and found that the impacts of collaboration on publishing productivity cannot be explained away by this measurement issue. Scientists choose to collaborate and in most instances those choices seem to enhance productivity, even if we consider the transactions costs involved (which are endogenous in our model). Can a prescription recommended by thousands of scientists be wrong? Perhaps, but the collaboration prescription seems to work.

Our research suggests to us several questions we feel deserve more attention. Our focus is on the number of collaborators. We have no measures of quality of collaboration and it is certainly the case that not all collaborations are equally fruitful. Related, the number of collaborators is not the same as the number of collaborations. If one collaborates ten times with one person how does that differ, in productivity effects, from collaborating ten times with ten different persons?

Another question we pondered during our analysis was the nature of the collaboration seeking dynamics. Our data are about collaborations and we do not address (and neither does any other large scale study of which we are aware) the dynamics of collaboration seeking. Who seeks whom? For example, do collaboration dynamics mimic communications dynamics with lower status individuals seeking to collaborate with higher status individual? Or do such dynamics get supplanted by mentoring motivations or, more mundanely, the power of proximity?

Related, it seems sensible to us to think of collaboration as a sort of market. One has skills one wishes to match with others but no all skills are equal and, thus, the skills and the scientists have different "demand," with some scientists perhaps have much more demand than could ever be met and others having almost no demand. What is the relationship between the supply of certain skills and the demand and how are those relationships mediated? How can the "market" be more efficient? Our study suggests that most people collaborate with those in their immediate environment. This seems sensible in many ways. This approach may reduce transactions costs and may promote work that could not easily be done by remote communications. And people are not drawn together entirely by accident. People work in the same setting because, among other factors, they share similar interests or at least compatible ones. But it seems highly unlikely that a system that is so much dictated by proximity (with more than half of collaborators being in one's work group) is the most efficient "collaboration market."

References

Bayer, Alan E. and Jeffrey E. Dutton (1977) Career Age and Research Professional Activities of Academic Scientists, Journal of Higher Eudcation. Vol 48, 259-282.

Beaver, D and Rosen, R (1978) Studies in scientific collaboration: Part I-The professional origins of scientific co-authorship, Scientometrics 1, 65-84.

Beaver, D and Rosen, R (1979a) Studies in scientific collaboration: Part II-Scientific co-authorship, research productivity and visibility in the French scientific elite, 1799-1830, Scientometrics 1, 133-149.

Beaver, D and Rosen, R (1979b) Studies in scientific collaboration: Part III-Professionalization and the natural history of modern scientific co-authorship, Scientometrics 1, 231-245.

Beaver, D (2001). Reflections on Scientific Collaboration (and its study): Past, Present, and Future. Feature Report. Scientometrics. Vol 52, No 3. 365-377.

Behrens, T.R. and Gray, D.O. (2000). Unintended consequences of cooperative research: Impact of industry sponsorship on the climate for academic freedom and other graduate student outcomes. Research Policy, 30, 179-199.

Bozeman, B., Dietz, J.,Gaughan., M., 2001. Scientific and technical human capital: an alternative model for research evaluation. International Journal of Technology Management 22 (7/8), 636-655.

Bozeman, Barry and Elizabeth Corley (Forthcoming) Research collaboration strategies among scientists and engineers. Research Policy.

Bozeman, B., Rogers, J., 2002. A churn model of scientific knowledge value: internet researchers as a knowledge value collective. Research Policy 31, 769-794.

Centra, John A. 1974. Women, Men and the Doctorate. Princeton: Educational Testing Service.

Clarke, B.L., 1967. Communication patterns of biomedical scientists. Federation Proceedings 26, 1288-1292.

Clemente, Frank (1973) Early Career Determinants of Research Productivity. American Journal of Sociology. Vol 79. 409-419.

Cole, J.R. and S. Cole (1972) The Ortega Hypothesis, Science. 178. 368.

Cole, J.R. and S. Cole (1973) Social Stratification in Science. The University of Chicago Press.

Cole, Stephen (1976) Age and Scientific Performance. American Journal of Sociology. Vol 84. 958-977.

Cole, Jonathan R. and Harriet Zuckerman. (1984) The Productivity Puzzle. In Advances in Motivation and Achievement, Martin L. Maehr and Marjorie W. Steinkamp (eds). JAI Press. 217-258.

Crane, D (1972) Invisible Colleges. University of Chicago Press, Chicago.

Crow, M. and Bozeman, B. (1998) Limited by design: R&D laboratories in the U.S. national innovation system. New York, Columbia University Press.

De Solla Price, D (1963) Little Science Big Science. Columbia University Press. New York and London.

De Solla Price, D and Beaver D (1966) Collaboration in an invisible college. American Psychologist 21, 1011-1018.

Fox, Mary Frank (1983) Publication Productivity Among Scientists: A Critical Review. Social Studies of Science 13: 285-305.

Fox, Mary Frank. 1991. "Gender, Environmental Milieu, and Productivity". In The Outer Circle, Eds., Harriet Zuckerman, Jonathon Cole, and John Bruer, 188-204. New York: W.W. Norton and Company.

Fox, Mary Frank and Catherine A. Faver (1984) Independence and Cooperation in Research: The Motivations and Costs of Collaboration. Journal of Higher Education. Vol 55, 347-359.

Fox, Mary Frank and Catherine A. Faver (1985) Men, women, and publication productivity: patterns among social work academics. The Sociological Quarterly v. 26, 537-49

Fox, Mary Frank and Glenn Firebaugh (1992a). Confidence in science: the gender gap. Social Science Quarterly v. 73, 101-13.

Fox, Mary Frank (1992b) Research, Teaching, and Publication Productivity: Mutuality Versus Competition in Academia. Sociology of Education. Vol 65, Issue 4. 293-305

Gaston, Jerry (1970) The Reward System in British Science. American Sociological Review. vol 35, Issue 4. 718-732.

Goffman, W., Warren, K.S., 1980. Scientific Information Systems and the Principle of Selectivity. Praeger, New York.

Hagstrom, W.O., 1965. The Scientific Community. Basic Books, New York.

Hammel, Eugene (1980) Report of the Task Force on Faculty Renewal. Population Research. University of California, Berkeley.

Heffner, A.G., 1981. Funded research, multiple authorship, and subauthorship collaboration in four disciplines. Scientometrics 3, 5-12.

Holmstrom, E. I., & Holmstrom, R. W. (1974). The plight of the woman doctoral student. American Educational Research Journal, 11, 1-17.

Jaffe, Adams B. (1998). Measurement Issue in Investing in Innovation. L.M.Branscomb and J. Keller. Eds. MIT Press. pp 64-84.

Katz, Sylvan J and Martin, Ben R (1997) What is research collaboration? Research Policy. 26, 1-18.

Kjerulff, K. H., & Blood, M. R. (1973). A comparison of communication patterns in male and female graduate students. Journal of Higher Education, 44, 623-632.

Kingsley, G., Bozeman, B., and Coker, K (1996) Technology Transfer and Absorption: an 'R&D Value-Mapping' Approach to Evaluation. Research Policy 25, 967-995

La Follette, M.C., 1992. Stealing into Print. University of California Press, Berkeley, CA.

Landry, R., Amara, N., 1998. The impact of transaction costs on the institutional structuration of collaborative academic research. Research Policy 27, 901 –913.

Lehman, H.C. (1953) Age and Achievement. Princeton University Press.

Levin, Sharon and Paula E. Stephan (1991) Research Productivity over the life cycle: evidence for academic scientists. American Economic Review. Vol 81. 114-132.

Lindsey, Duncan (1980) Production and Citation Measures in the Sociology of Science: TheProblems of Multiple Authorship. Socila Studies of Science. vol 10. 145-162.

Long, J. Scott (1987) Problems and Prospects for Research on Sex Differences in the Scientific Career. In Women: Their Underrepresentation and Career Differentials in Science and Engineering, L.S. Dix (Eds). National Academy Press. 157-169.

Long, J. Scott (1992) Measure of Sex Differences in Scientific Productivity. Social Forces. 71(1) 159-178.

Long, J. Scott and R. McGinnis (1981) "Organizational context and scientific productivity," American Sociological Review, 46: 422-442.

Lotka, A. J (1926) The frequency distribution of scientific productivity, Journal of the Washington Academy of Science, 16. 317-323.

Maanten, A.A., 1970. Statistical analysis of a scientific discipline: palynology. Earth Science Reviews, 181 – 218.

Meadows, A.J., 1974. Communication in Science. Butterworths, London.

Meadows, A.J., O'Connor, J.G., 1971. Bibliographic statistics as a guide to growth points in science. Science Studies 1, 95-99.

Melin, G and Persson, O (1996) Studying research collaboration using co-authorships. Scientometrics. 36(3), 363-377

Melin, G (2000) Pragmatism and self-organization Research collaboration on the individual level. Research Policy. 29, 31-40

Merton, R.K., 1965. The Ambivalence of Scientists. In N. Kaplan (ed.), Science and Society. Rand McNally Press: Chicago, 112-132.

Merton, R.K. 1968. The Matthew effect in science. Science. 159 (3870), 56-63.

Merton, R.K., 1973. The Sociology of Science. The University of Chicago Press: Chicago.

National Academy of Engineering (1983). *Guidelines for Engineering Research Centers*. Washington, D.C.: National Academy Press.

Narin, Francis (1976). Evaluative Bibliometrics: The Use of Publication and Citation Analysis in the Evaluation of Scientifc Activity. Computer Horizons, Cherry Hill, NJ.

Pao, Miranda Lee (1982) Collaboration in computational musicology. Journal of the American Society for Information Science. 33(1) 38-43.

Pelz, Donald and Frank M. Andrews (eds) (1976) Scientists in organizations: productive climate for research and development. Institute for Social Research, Michigan. Ann Arbor.

Polanyi, M., 1967. The Tacit Dimension. London, Cox & Wyman.

Polanyi, M., 1969. The Logic of Tacit Inference. Knowing and being. London, Routledge & Kegan Paul.

Pravdic, N and Oluic-Vukovic, V (1986) Dual approach to multiple authorship in the study of collaborator / scientific output relationship. Scientometrics 10, 259-280.

Rogers, J.D., Bozeman, B., 2001. Knowledge value alliances: an alternative to R&D project evaluation. Science, Technology and Human Values 26 (1), 23-55.

Rudd, Ernest (1977) The Effect of Alphabetic Order of Author Listing on the Careers of Scientists. Social Studies of Science. vol 7. 268-269/

Smith, M., 1958. The trend toward multiple authorship in psychology. American Psychologist 13, 596-599.

Stephan, P.E., and Levin, S.G., 1997. The critical importance of careers in collaborative scientific research. Revue d'Economie Industrielle 79, 45-61.

Swiss, James E (1991) Public Management Systems: Monitoring and Managing Government Performance. Prentice Hall. NJ.

Thorsteinsdottir, O., 2000. External research collaboration in two small science systems. Scientometrics 49, 145-160.

Wanner, Richard A. Lionel S. Lewis, David I. Gregorio (1981) Research Productivity in Academia: A comparative study of the sciences, social sciences, and humanities. Sociology of Education. Vol 54, 238-253/

Xie, Yu and Kimerlee A. Shauman (1998) Sex differences in research productivity: new evidence about an old puzzle. American Sociological Review. vol 63, 847-870.

Zuckerman, Harriet (1967) Nobel laureates in science: patterns of productivity, collaboration, and authorship. American Sociological Review, vol 32, 3, 391-403

Table 1. Mean number of publications between 1960 and 2000

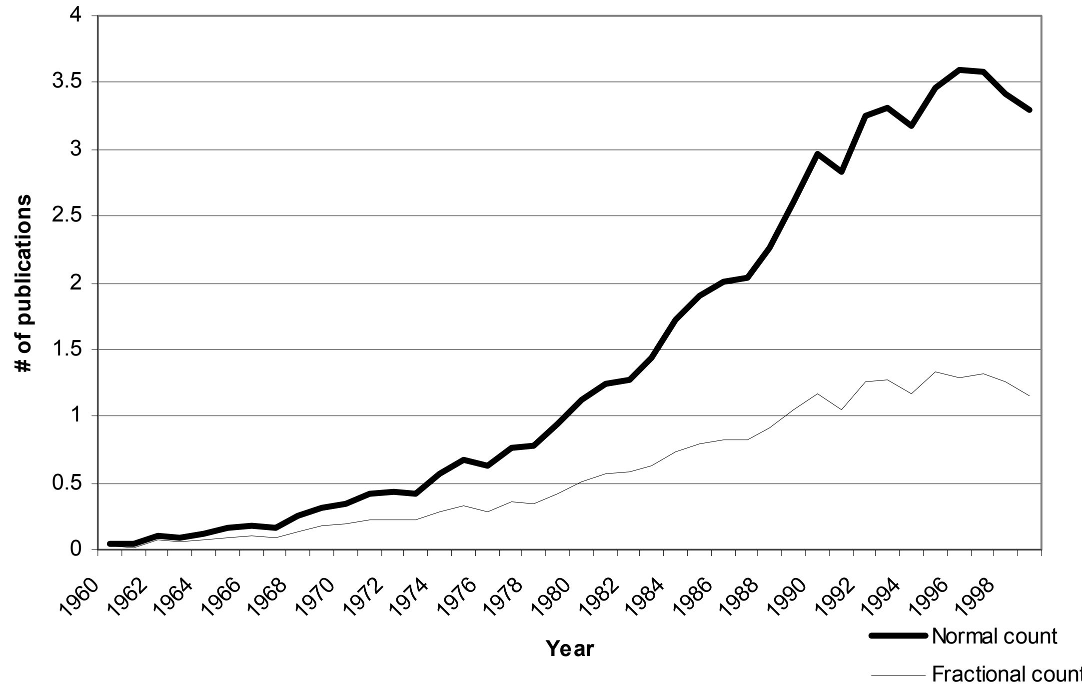

Table 2. Difference of Normal and Fractional count in the mean number of publications

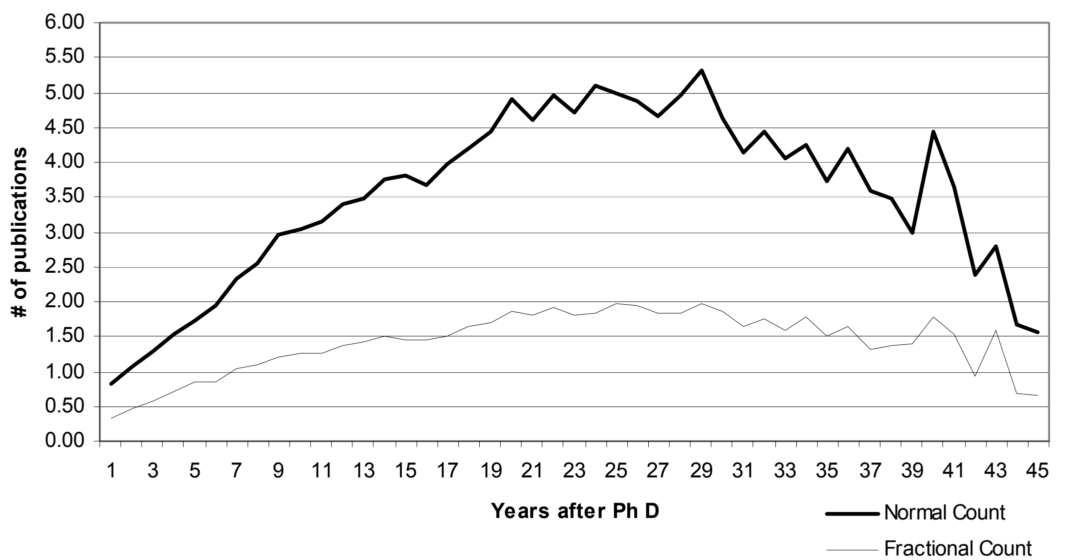

Table 3-1. Disciplinary Difference of Median Number of Publications (Normal count)

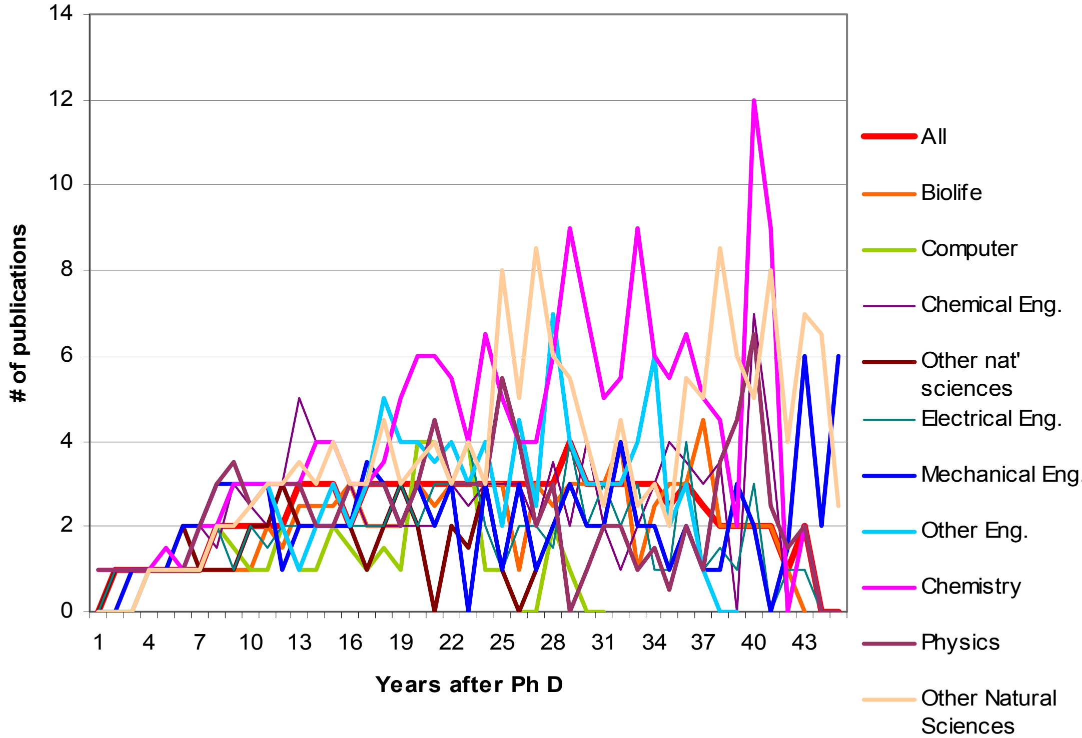

Table 3-2. Disciplinary Difference of Median Number of Publications (Fractional count)

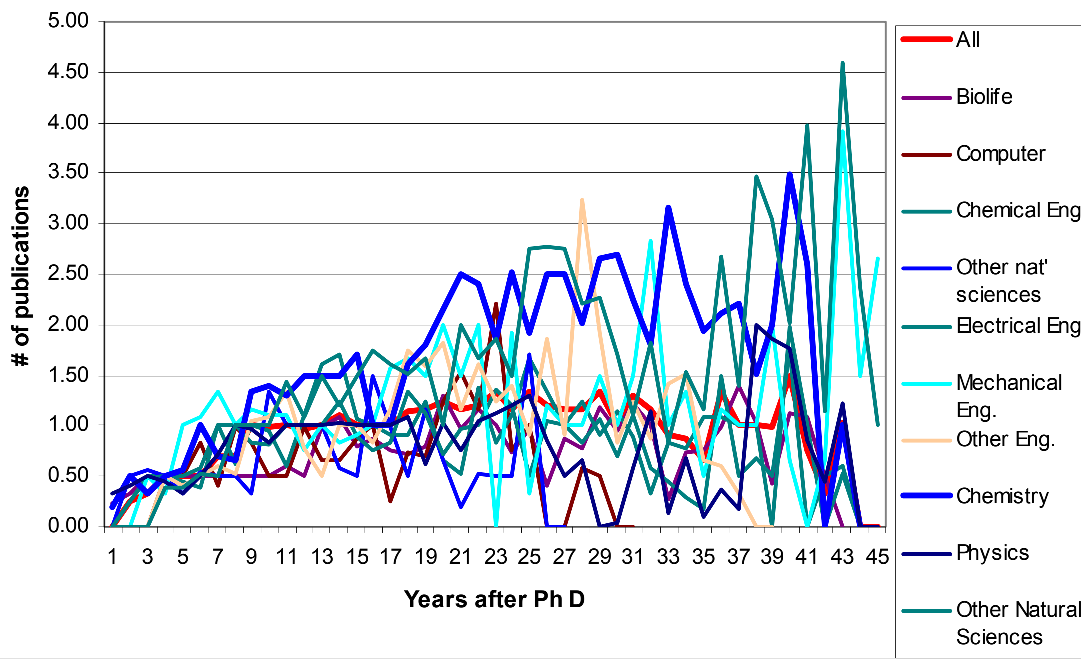

Table 4-1. Gender difference in the mean number of publication

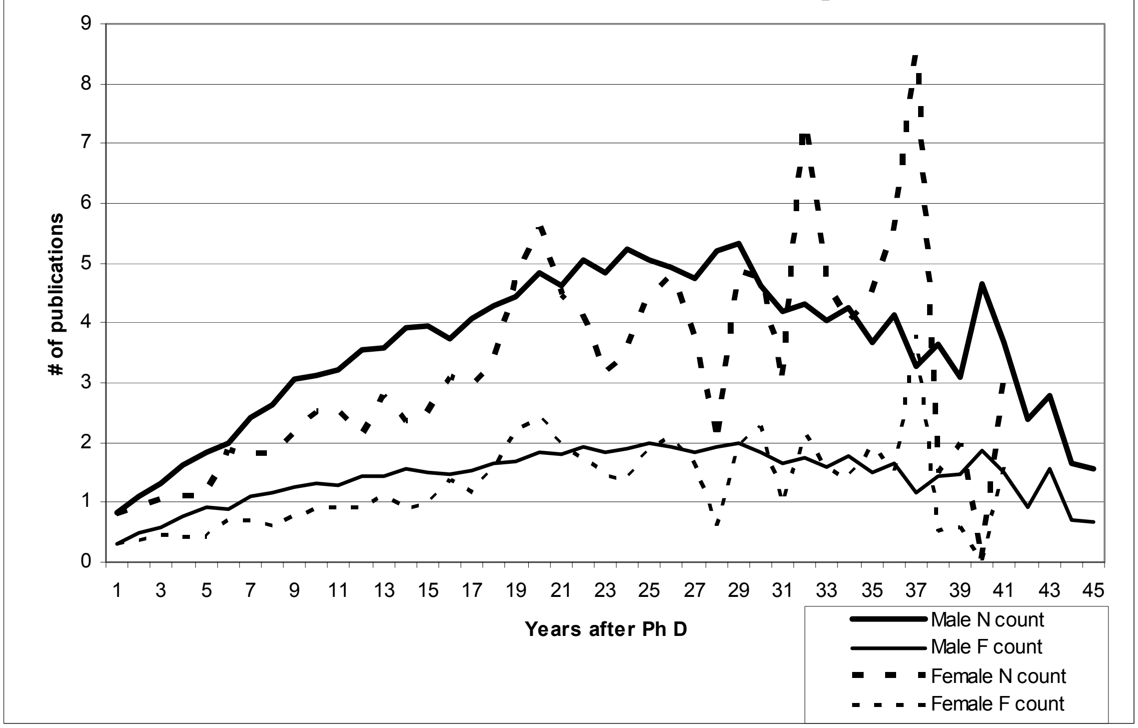

Table 4-2. Gender difference in the median number of publication

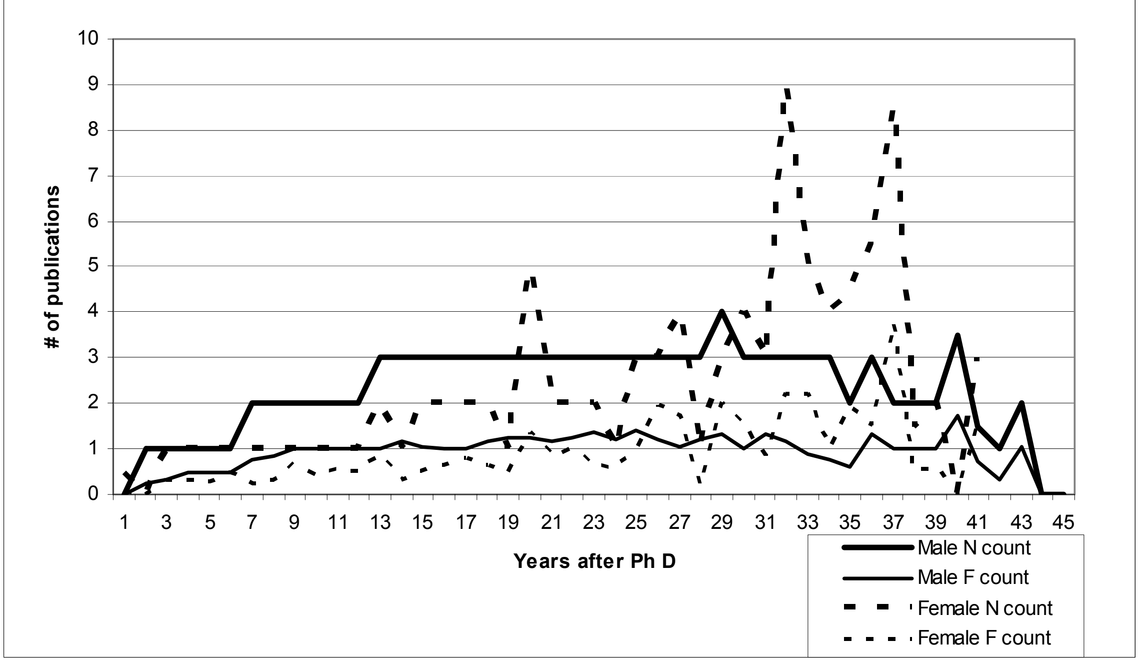

Table 5. Productivity by Rank

Count		Full professor (Valid N:168)	Associate (valid N: 72)	Assistant (Valid N: 114)
Normal Count	Mean	5.15	3.25	2.82
	Median	3.9	2.60	2.20
Fractional Count	Mean	1.87	1.22	1.04
	Median	1.51	.99	.78

Table 6. Productivity by Marital Status

Count		Married (Valid N:371)	Single (valid N: 36)	Difference
Normal Count	Mean	3.91	2.59	Sig; <.01
	Median	(2.60)	(2.30)	
Fractional Count	Mean	1.41	.97	Sig; <.05
	Median	(1.44)	(1.00)	

Table 7. Productivity by Citizenship

Count		Native (Valid N:280)	Non-native (valid N: 130)	Difference
Normal Count	Mean	3.55	4.34	Sig; <.05
	Median	(2.40)	(3.20)	
Fractional Count	Mean	1.29	1.55	Sig; <.05
	Median	(.93)	(1.26)	

Table 8. Productivity by Gender

Count		Male (Valid N:356)	Female (valid N: 53)	Difference
Normal Count	Mean	3.96	2.75	Sig; <.01
	Median	(2.60)	(2.40)	
Fractional Count	Mean	1.42	1.08	Sig; <.05
	Median	(1.06)	(.89)	

Table 9. Total number of collaborators

(Mean: 13.82; Median:12.00; Valid N=360)

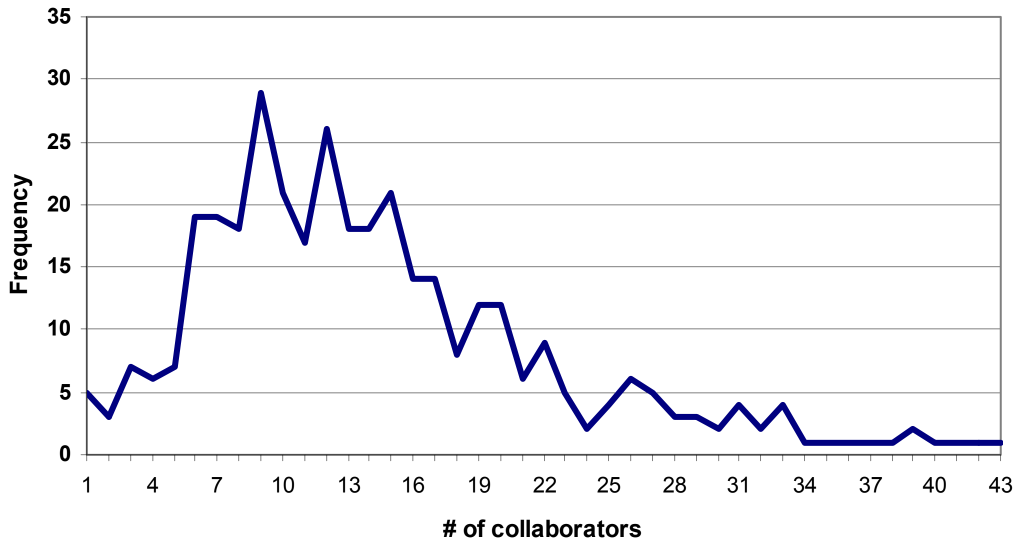

Table 10. Disciplinary difference in the number of collaborators

Field	Valid N	mean	median	std
Total	360	13.82	12	9.97
Chemical engineering	39	14.77	13	7.58
Civil engineering	14	11.21	12	6.33
Electrical engineering	41	17.34	14	13.83
Mechanical engineering	19	14.42	11	10.69
Other engineering	41	17.31	14	10.13
Biological/Life Sciences	58	9.74	8	7.08
Computer sciences	18	14.78	15	3.80
Chemistry	39	14.95	13	14.89
Physics	35	12.74	10	8.95
Other natural sciences	39	13.28	11	7.14

Table 11. Research Time

Work Setting	N	Mean percentage of Research time	Std. Deviation
Research time working alone	420	16.38%	20.336
Research time working with researchers and graduate students in my immediate work group	434	51.07%	24.006
Research time working with researchers in my university, but outside my immediate work group	407	12.21%	12.632
Research time working with researchers who reside in nations other than the U.S.	391	5.71%	8.074
Research time working with researchers in U.S. universities other than my own	403	9.11%	10.901
Research time working with researchers in U.S. industry	393	5.96%	8.455
Research time working with researchers in U.S. government laboratories	380	3.35%	6.715

Table 12. Cosmopolitan scale: Disciplines

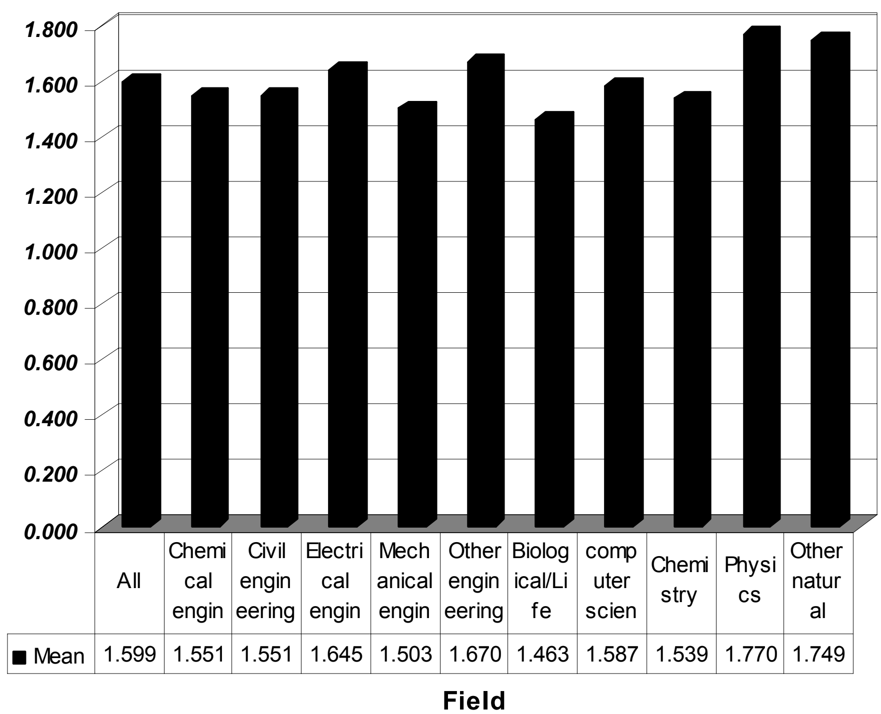

Table 13. Correlations among collaborators, research time, and cosmopolitan scale

		Normal count	Fractional count	total number of collaborators	Research time working alone	cosmopolitan scale
Normal count	Pearson Correlation	1	.928**	.209**	-.156**	.107*
	Sig. (2-tailed)	.	.000	.000	.002	.047
	N	417	417	336	395	345
Fractional count	Pearson Correlation	.928**	1	.147**	-.069	.022
	Sig. (2-tailed)	.000	.	.006	.167	.682
	N	417	426	345	404	352
total number of collaborators	Pearson Correlation	.209**	.147**	1	-.206**	.299**
	Sig. (2-tailed)	.000	.006	.	.000	.000
	N	336	345	365	352	308
Research time working alone	Pearson Correlation	-.156**	-.069	-.206**	1	-.532**
	Sig. (2-tailed)	.002	.167	.000	.	.000
	N	395	404	352	427	371
cosmopolitan scale	Pearson Correlation	.107*	.022	.299**	-.532**	1
	Sig. (2-tailed)	.047	.682	.000	.000	.
	N	345	352	308	371	372

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 14. Age, Rank, and Status Model

DV	Independent Variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	56.613	45.544		1.243	0.215			F=7.52 Sig=.000 R^2=.109
	Ttotal number of collaborators	0.097	0.023	0.236	4.308	0.000	0.251	0.238	
	Tenured faculty	1.431	0.489	0.177	2.925	0.004	0.227	0.164	
	Postdoctoral researcher	0.359	1.357	0.015	0.265	0.792	-0.062	0.015	
	Research group leader	0.029	0.979	0.002	0.030	0.976	0.035	0.002	
	Year born	-0.028	0.023	-0.072	-1.213	0.226	-0.142	-0.069	
Fractional count	(Constant)	17.425	15.122		1.152	0.250			F=6.77 Sig=.000 R^2=.097
	Ttotal number of collaborators	0.023	0.007	0.167	3.085	0.002	0.185	0.171	
	Tenured faculty	0.586	0.161	0.218	3.646	0.000	0.258	0.201	
	Postdoctoral researcher	0.066	0.456	0.008	0.145	0.885	-0.067	0.008	
	Research group leader	-0.073	0.329	-0.012	-0.222	0.824	0.012	-0.012	
	Year born	-0.009	0.008	-0.066	-1.112	0.267	-0.154	-0.062	

* Dependent variable: Annual average publication between 1996 and 2000

Table 15. Research Grants and Collaboration Model

DV	Independent variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	1.629	0.748		2.176	0.030			F=5.66 Sig=.001 R^2=.061
	Total number of collaborators	0.085	0.025	0.208	3.388	0.001	0.215	0.205	
	Total dollar amount of current grant or contract as PI	0.000	0.000	0.062	1.003	0.317	0.113	0.062	
	Number of proposals awarded/number of proposals submitted	1.777	1.075	0.100	1.653	0.099	0.093	0.102	
Fractional count	(Constant)	0.725	0.248		2.921	0.004			F=3.21 Sig=.023 R^2=.035
	Total number of collaborators	0.019	0.008	0.140	2.275	0.024	0.139	0.138	
	Total dollar amount of current grant or contract as PI	0.000	0.000	0.031	0.495	0.621	0.069	0.030	
	Number of proposals awarded/number of proposals submitted	0.693	0.356	0.117	1.944	0.053	0.112	0.118	

* Dependent variable: Annual average publication between 1996 and 2000

Table 16. Gender, Family Relations and Collaboration Model

DV	Independent variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	0.422	0.914		0.462	0.644			F=7.33 Sig=.000 R^2=.108
	Total number of collaborators	0.104	0.022	0.258	4.710	0.000	0.275	0.262	
	Gender	0.809	0.617	0.073	1.311	0.191	0.121	0.075	
	Marital status	1.158	0.754	0.087	1.535	0.126	0.096	0.088	
	Spouse is full time homemaker or family caregiver	1.009	0.485	0.124	2.081	0.038	0.165	0.119	
	Number of children	-0.204	0.195	-0.061	-1.047	0.296	0.007	-0.060	
Fractional count	(Constant)	0.415	0.307		1.354	0.177			F=4.80 Sig=.000 R^2=.072
	Total number of collaborators	0.023	0.007	0.177	3.207	0.001	0.195	0.179	
	Gender	0.222	0.210	0.059	1.058	0.291	0.103	0.060	
	Marital status	0.395	0.252	0.089	1.567	0.118	0.098	0.089	
	Spouse is full time homemaker or family caregiver	0.369	0.163	0.136	2.259	0.025	0.158	0.127	
	Number of children	-0.093	0.065	-0.084	-1.420	0.157	-0.011	-0.080	

* Dependent variable: Annual average publication between 1996 and 2000

Table 17. Citizenship and Collaboration Model

DV	Independent variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	2.529	0.546		4.628	0.000			F=9.58 Sig=.000 R^2=.081
	Total number of collaborators	0.077	0.020	0.203	3.829	0.000	0.210	0.207	
	I am a native born US citizen	-0.175	0.541	-0.021	-0.324	0.746	-0.123	-0.018	
	I am a naturalized US citizen	1.986	0.734	0.178	2.705	0.007	0.199	0.148	
Fractional count	(Constant)	1.072	0.184		5.829	0.000			F=6.31 Sig=.000 R^2=.053
	Total number of collaborators	0.018	0.007	0.143	2.698	0.007	0.148	0.145	
	I am a native born US citizen	-0.100	0.182	-0.036	-0.550	0.582	-0.124	-0.030	
	I am a naturalized US citizen	0.571	0.247	0.153	2.315	0.021	0.180	0.125	

* Dependent variable: Annual average publication between 1996 and 2000

Table 18. Job Satisfaction and Collaboration Model

DV	Independent variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	-0.919	1.344		-0.684	0.495			F=4.70 Sig=.000 R^2=.069
	Total number of collaborators	0.070	0.021	0.183	3.310	0.001	0.207	0.183	
	My colleagues in this department appreciate my research contributions	0.505	0.326	0.095	1.548	0.123	0.170	0.087	
	I am satisfied with my job	0.413	0.360	0.077	1.148	0.252	0.151	0.064	
	I am satisfied with my personal life (everything other than my job)	0.123	0.315	0.023	0.390	0.697	0.081	0.022	
	I think I am paid about what I am worth in the academic market	0.118	0.268	0.025	0.442	0.659	0.065	0.025	
Fractional count	(Constant)	-0.021	0.442		-0.047	0.962			F=3.07 Sig=.01 R^2=.045
	Total number of collaborators	0.015	0.007	0.117	2.104	0.036	0.143	0.116	
	My colleagues in this department appreciate my research contributions	0.158	0.110	0.090	1.445	0.149	0.154	0.080	
	I am satisfied with my job	0.142	0.121	0.079	1.170	0.243	0.145	0.065	
	I am satisfied with my personal life (everything other than my job)	0.069	0.105	0.040	0.657	0.511	0.091	0.036	
	I think I am paid about what I am worth in the academic market	-0.017	0.089	-0.011	-0.191	0.849	0.038	-0.011	

* Dependent variable: Annual average publication between 1996 and 2000

Table 19. Discrimination and Collaboration Model

DV	Independent variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	3.215	0.640		5.021	0.000			F=6.33 Sig=.000 R^2=.056
	Total number of collaborators	0.080	0.021	0.210	3.877	0.000	0.211	0.212	
	At my current institution, I am discriminated against on the basis of my sex	-0.824	0.425	-0.123	-1.936	0.054	-0.103	-0.107	
	At my current institution, I am discriminated against on the basis of my race, ethnicity, religion or national origin	0.339	0.451	0.048	0.752	0.453	-0.025	0.042	
Fractional count	(Constant)	1.224	0.215		5.701	0.000			F=3.73 Sig=.012 R^2=.033
	Total number of collaborators	0.018	0.007	0.146	2.700	0.007	0.148	0.147	
	At my current institution, I am discriminated against on the basis of my sex	-0.276	0.143	-0.122	-1.936	0.054	-0.095	-0.106	
	At my current institution, I am discriminated against on the basis of my race, ethnicity, religion or national origin	0.152	0.151	0.063	1.001	0.318	-0.007	0.055	

* Dependent variable: Annual average publication between 1996 and 2000

Table 20. Collaboration Strategies and Number of Collaborators Model

DV	Independent variables	Unstandardized Coefficients		Std. Coefficient	t	Sig.	Correlations		Model Fit
		B	Std. Error	Beta			Zero-order	Partial	
Normal count	(Constant)	1.643	2.664		0.617	0.538			F=2.83 Sig=.003 R^2=.076
	total number of collaborators	0.063	0.022	0.166	2.894	0.004	0.206	0.162	
	Time known person	-0.147	0.310	-0.026	-0.475	0.635	-0.030	-0.027	
	Help jr. colleagues	0.312	0.275	0.069	1.133	0.258	0.102	0.064	
	Strong sci. rep	-0.138	0.302	-0.026	-0.455	0.649	0.025	-0.026	
	Complementary skills	0.211	0.479	0.025	0.440	0.660	0.052	0.025	
	Quality other collab	0.665	0.399	0.095	1.669	0.096	0.101	0.094	
	Help grad students	0.461	0.315	0.090	1.466	0.144	0.114	0.083	
	Fun or entertaining	-0.442	0.272	-0.091	-1.624	0.105	-0.067	-0.092	
	Sticks to schedule	-0.711	0.366	-0.112	-1.942	0.053	-0.064	-0.110	
Fractional count	(Constant)	0.578	0.889		0.650	0.516			F=1.91 Sig=.049 R^2=.052
	total number of collaborators	0.016	0.007	0.129	2.225	0.027	0.166	0.124	
	Time known person	-0.013	0.104	-0.007	-0.126	0.899	-0.011	-0.007	
	Help jr. colleagues	0.066	0.092	0.044	0.716	0.474	0.077	0.040	
	Strong sci. rep	-0.026	0.100	-0.015	-0.261	0.794	0.022	-0.015	
	Complementary skills	0.055	0.161	0.019	0.340	0.734	0.047	0.019	
	Quality other collab	0.183	0.133	0.078	1.372	0.171	0.084	0.077	
	Help grad students	0.157	0.104	0.092	1.513	0.131	0.114	0.085	
	Fun or entertaining	-0.159	0.091	-0.098	-1.737	0.083	-0.075	-0.097	
	Sticks to schedule	-0.143	0.122	-0.068	-1.175	0.241	-0.027	-0.066	

* Dependent variable: Annual average publication between 1996 and 2000