Researchers' Industry Experience and Productivity in University–Industry Research Centers: A "Scientific and Technical Human Capital" Explanation

Min-Wei Lin[1,2]
Barry Bozeman[1,2]

ABSTRACT. We examine the impact of researchers' previous industry experience on the research outputs and outcomes of university faculty affiliated with NSF and DOE research centers. Using a dataset combining curriculum vita and surveys, our results indicate significant differences between the researchers who have previous industry experience and those who do not. Using a simple model of research productivity, we found that academic researchers who had prior industry exposure produce fewer total career publications, but they support more students. Most important, and perhaps surprising, we could not establish any difference between the two groups' publication activity when focusing on a five-year cross-section (years 1996–2000) rather than total career publications. We found statistical evidence that previous industry experience raised the annual publication productivity of junior faculty members and women researchers in our sample of research center personnel. We believe the unique blend of research center affiliation, academic post, and past industry experience gives an individual who embodies or possesses all three characteristics a diverse source of scientific and technical human capital and particular advantages over those who have no industry experience (though the "academic-only" set also has particular advantages in cumulative publishing productivity).

Key Words: technology transfer, industry-university relations, innovation.

JEL Classification: O31, O33, O38

1. Introduction

For the past two decades, the subject of university–industry relations has generated enormous interest in both higher education and science and technology policy studies (Peters and Fusfeld, 1983; Fairweather, 1988; Powers *et al.*, 1988; Slaughter and Leslie, 1997; Lee, 1998; Croissant and Restivo, 2001). Social commentaries and public reactions to closer ties between academic institutions and business sectors have ranged from outright concern and anxiety on the one side, to hype and optimism on the other, with many gradations in between. Irrespective of one's reaction to the increased intertwining of universities and industry, no one appears to question the claim that ties between academe and industry have expanded dramatically since the 1970s (Peters and Fusfeld, 1983; Geiger, 1993; Etzkowtiz *et al.*, 1998), and that these university–industry research partnerships have become more heterogeneous, intricate, visible and influential.

The literature offers several reasons why industry and universities have deliberately chosen to become more active partners and collaborators in the nation's research and development (R&D) efforts. Initially, especially during the late 1970s and early 1980s, leaders in industry viewed universities and their research resources as a possible means to reverse productivity decline and a perceived "competitiveness crisis." At the urging of government policy-makers, both the higher education and business sectors were attempting to address perceived inadequacies in the U.S. technology transfer structure. As a result, a series of federal and state programs and initiatives were introduced in the late 1970s and 1980s to promote and stimulate cooperation between universities and industry, all of which, summed together, radically altered the structural landscape of the American national innovation system (Smith, 1990; Feller, 1997).

[1]*Research Value Mapping Program,*
School of Public Policy,
Georgia Institute of Technology,
685 Cherry Street, Atlanta, GA, 30332-0345
E-mail: minwei.lin@pubpolicy.gatech.edu
[2]*Research Value Mapping Program,*
School of Public Policy,
Georgia Institute of Technology,
685 Cherry Street, Atlanta, GA, 30332-0345
E-mail: barry.bozeman@pubpolicy.gatech.edu

Journal of Technology Transfer, 31, 269–290, 2006.

Later ties seem to have been forged on the basis of the perceived effectiveness of earlier ones. Academic institutions—especially the top tier research universities—view industry ties as a means of enhancing revenues. This was an especially strong motivation during the 1980s as growth rates for federal support of university science declined. But the parties actually involved in the partnerships, the scientists and engineers working at university–industry science centers, seem to think less in terms of national policy, or university enrichment and, instead, about the resources and equipment available for their own research programs as well as the advantages of additional networks ties enabled by centers and the possibilities for diversifying their research, education and outreach portfolios (Bozeman and Boardman, 2003).

Certainly, the concept of university-based science and engineering centers is not new (Geiger, 1986; Hetzner *et al.*, 1989). Long before World War II research centers could be found in many American universities, although the majority of these early academic centers were engineering and agricultural experiment stations that were created primarily to serve the local industry and respond to the needs of local farmers (Dupree, 1957). Nevertheless, the lessons about these early centers were learned and not forgotten. Over time, university research centers have evolved to become large clusters within university campuses where many interdisciplinary and multi-sectored R&D collaborations were taking place (Geiger, 1990; Peters and Etzkowitz, 1990; Stahler and Tash, 1994). In many ways, research centers today are altogether different from those of the past: they have become increasingly formal and complex organizations, with many more linkage mechanisms, participants and stakeholders (Ikenberry and Friedman, 1972; Gray and Walters, 1998). In the past 30 years, these university–industry research centers also have grown in importance. According to one assessment (Feller, 1997, p. 20), "university–industry research centers are the primary vehicle through which industry supports academic R&D." During the 1990s, almost 70% of all industrial support for academic R&D passed through the centers (Feller, 1997).

Thus, one can think of university-based research centers as crossroads where the worlds of higher learning and commerce meet and interact. The standard assumption is that universities will supply scientific knowledge and pools of highly-skilled labor to industry, and in turn, industry will provide universities with funding, equipment, and an array of its current research needs and problems (Feller and Roessner, 1995). Two common consequences of the "research center" arrangement are that it facilitates the movement of scientific personnel across the university–industry boundary, and that it attracts those researchers who are genuinely interested in solving industry problems to affiliate themselves with the centers.

While some studies (e.g. Kleinman and Vallas, 2001) note an "asymmetric convergence" of university and industry domains, almost all observers (Powell and Owen-Smith, 1998; Hackett, 2001) agree that increased transactions between industry and universities change the institutions and their cultures. We agree. However, in this study we focus on the individual academic faculty associated with the centers rather than on the institutions and their respective organizational cultures. In particular, *we consider whether faculty who have been employed full-time in private companies (as opposed to working with industry as consultants or in research and technology development partnerships) differ from those who have spent their entire professional careers in universities*. Are former industry employees more or less productive? Are there differences in the publication rates between those with previous industrial employment and those with none? Are their differences in grants acquisitions? Does the number of graduate students and post-doctoral students supported vary between those who have only university experience and those who have some industry experience? If industry experience does have an impact, does the timing or the duration of industry experience matter? For example, do those who begin in industry different from those who begin in universities, go to industry, and then come back?

Our data set is perhaps uniquely advantageous for answering such questions. In the first place, ours is one of the few large-scale data sets that include both questionnaire data about careers and productivity and data culled from curriculum vitae (CV). Elsewhere (Dietz *et al.*, 2000) we discuss the methodological issues associated acquisition and use of CV data. In the second place, a general sample of academic scientists would not likely permit such a study simply because the percentage of university researchers who have had industry careers is so small. However, the university–industry centers, by nature of their missions and organizational culture, attract and sometimes actively recruit individuals with industry experiences. Indeed, about 40% of those in our sample have at some point had professional employment as industry researchers.

Why should one care whether employment in industry affects researchers in university centers? An obvious reason is a general concern about productivity. University research centers, and universities in general, wish to employ productive scientists and engineers. However, our chief motivation in focusing on this issue goes beyond traditional productivity concepts. Most of the scientific literature on productivity, beginning with early studies, such as Pelz and Andrews (1976) and Kornhauser (1962), and continuing to current bibliometric studies (for example, Noyons *et al.*, 1998; Butler, 2003; Ho *et al.*, 2003) have chiefly focused on the number of published scientific papers or citation impacts. We have no quarrel with the focus of these important studies, but our concern is with scientists' *capacity* to produce new knowledge and the resources for new knowledge. We use the term "scientific and technical human capital" (S&T human capital) to describe this capacity. Elsewhere (Bozeman *et al.*, 2001; Bozeman and Corley, in press) we provide an elaboration of the concept, but, in short form, S&T human capital is the sum of the scientist's technical knowledge and skills *and* ties to professionally relevant networks. The scientist's technical knowledge and skills equip her to produce knowledge and innovation and the network ties enhance the deployment of the knowledge by, for example, providing information about other researchers' work, information about employment, consulting and grants opportunities and giving insight into knowledge users' needs.

The paper is organized in the following manner. Section 2 discusses the theoretical and practical relevance of industry experience to S&T human capital. In Section 3 we describe our data sources and methodology. In Section 4, we introduce the hypotheses and variables used in the study. In Section 5, we present a detailed descriptive analysis of center-affiliated faculty with previous industry work experience—who are they, how long were they in industry, what type of industry jobs did they have.[1] Subsequently, in Section 4 we test our hypotheses with a set of regression analyses relating level of industry experience with publication productivity and student support. In Section 7, "Conclusions," we discuss the implications of our empirical findings.

2. Industry affiliation and the S&T human capital model

We expect that those researchers in university–industry research centers who have spent part of their career in industry will differ in important ways from those who have spent their entire professional career in universities. Our underlying theoretical argument is industry experience often results in different types of S&T human capital and, thus, different types of capacity. The notion of S&T human capital is especially relevant to our study inasmuch as we expect that academic researchers with industry experience will often have qualitatively different S&T human capital than those who have spent their entire career in academe. In particular, those with industry experience seem likely to preserve much of the social capital and networks ties accruing from industry work. Those who have spent their careers in academe may have stronger ties to networks composed of academic scientists and more linkages to academic scientists working in other universities. Moreover, the nature of the scientists S&T human capital may also have implications for the production of capacity and resources. Perhaps the number or type of graduate students or postdoctoral students sponsored and supervised varies as a function of industry experience. Perhaps the number, source or composition of grants varies according to industry experience. Each of these issues has important implications for S&T human capital and the productive capacity of scientists and the university–industry centers in which they work.

To highlight these issues, let us consider two different perspectives, in archetype, on academic faculty in university–industry research centers. According to the first type, what we can term the "output model," the center researcher is assessed in terms of the production of formal knowledge products—articles, patents, technical papers, algorithms—which can be made available to industry. Holding quality constant, more product equals greater effectiveness. Under this model, the center's value is that it permits the production of a greater amount and quality of product.

According to a second model, we refer to as a "capacity model," the job of the center-affiliated researcher is not just to produce formal knowledge products but to enhance the center's, the university's and perhaps the scientific field's capability for sustained contribution to knowledge. Under this model, the knowledge products are certainly important, but so are the capabilities to enrich scientific and engineering careers, to mentor and place graduate students and postdoctoral students, and to forge ties to other institutions, including industry, other universities, and agencies providing grants and other resources. If one embraces a capacity model, rather than the much simpler output model, the production of discrete knowledge products is no less important, but one also considers the ability to enhance S&T human capital.

To reiterate, the two models are archetypes. Our interviews (Rogers and Bozeman, 2001; Bozeman and Boardman, 2003) demonstrate clearly that most who work in or direct university–industry research centers have a rich, sophisticated conception of their work. But consideration of these simple archetypes is helpful for understanding the relevance of industry experience, our chief focus here. To that end, Figure 1 provides and elemental model of an "output model" for analysis of center researchers' productivity and Figure 2 provides a "capacity model."

Figure 1 recognizes that the scientist depends critically upon others for resources, scientific contributions and resources, but the model's orientation is chiefly internal. What drives the models is the creation of knowledge products. There is a recognition that utilization and impact are important, but the chief focus is not creation and, particularly, the ways in which the scientist's human capital interactions with prerequisite resources to create knowledge products. This is a functional model for the creation of discrete knowledge products but has few if any direct implications for the sustained *capacity* to create knowledge products and build fields of science and technology development.

By contrast, Figure 2 (adapted from Bozeman *et al*., 2001), focuses not only on the researcher and her immediate environment but upon the social institutions in which the researcher is embedded. The model also has a more expansive notion of productivity, focusing not only on knowledge

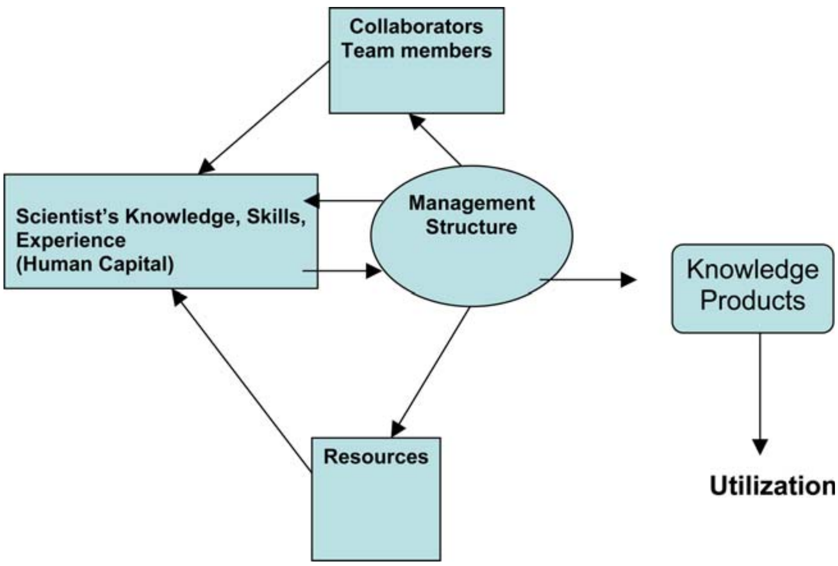

Figure 1. An output model for assessing center researchers' productivity.

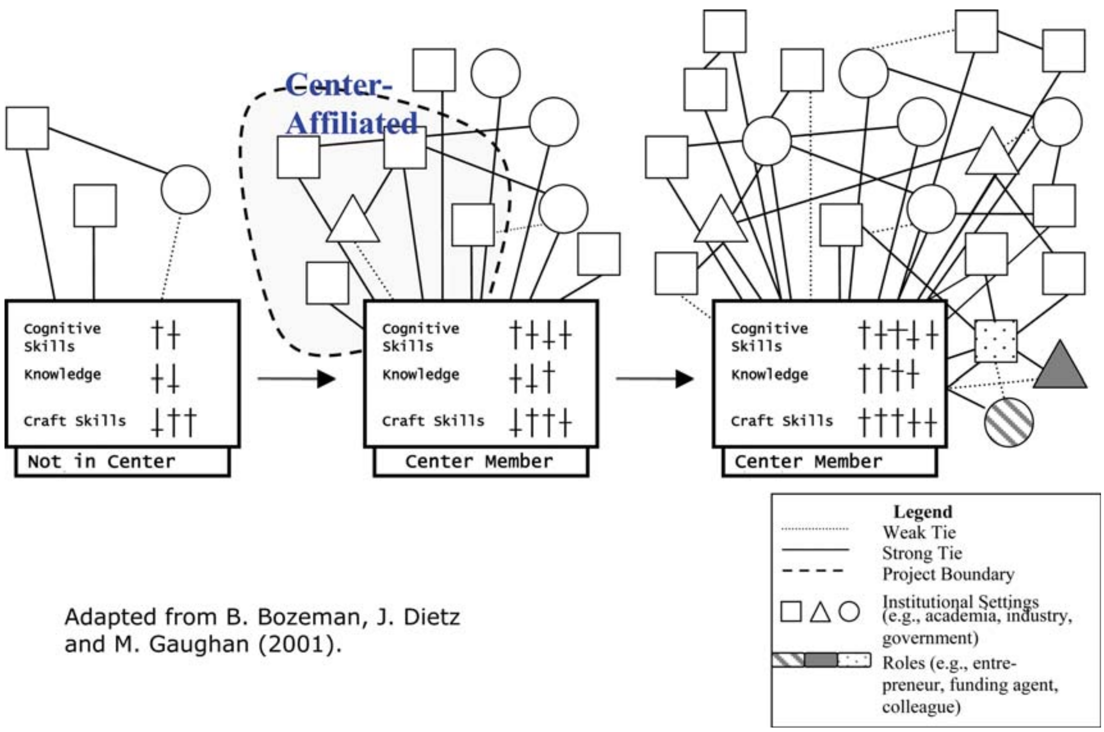

Figure 2. Model of S&T human capital: center-affiliated researchers.

products but also the creation of capacity by other means, such as educating students, contributing to others' S&T human capital, and enhancing network capabilities. Figure 2 presents a hypothetical model of the transformation of S&T human capital. The first panel shows the subject's S&T human capital prior to affiliation with the center, the second shows the hypothesized increment to S&T human capital flowing from the center affiliation, and the third panel (at time $t + 1$) shows the growth in S&T human capital as a center affiliate. The model notes that ties vary in strength and implies distinct role and distinct institutional actors. The researcher's human capital endowments are represented (formal knowledge, cognitive skills, craft skills and tacit knowledge) and the associated dimensions simply imply that these also change over time just as the network ties and social capital vary over time. The model suggests that, in general, S&T human capital increases steadily, but certain elements diminish as well (i.e. network ties decay from lack of use, craft skills become outmoded).

The importance of the S&T human capital model to the present study is its suggestiveness. If one focuses only on an output model, the potential significance of industry affiliation is its effect on producing knowledge products such as scientific articles. However, if one also considers the S&T human capital, and expands it beyond the individual case, then one considers as well both the individual's capacity to produce knowledge products and the individual's impact on others' capacity to produce and to use knowledge products. From this perspective, it is especially useful to consider impacts on students, including the support of students through mentoring, collaboration and grants support. A preliminary assumption of our paper is that industry affiliation differentiates the researcher's S&T human capital, providing a wider array (if not a larger number) of network ties and social capital and a different sort of S&T human capital than one finds with researchers who have spent their entire careers in universities. A first task, then, is to see if those with industry affiliation are different in important ways (e.g. different publications and grants support patterns) and, if so, a second task is to determine if different degrees and different timing of industry affiliation affect S&T human capital.

In Section 4 we provide more detail about our assumptions, including explicit hypotheses. However, before doing so it is useful to describe our data and methods.

3. Data and methods

The data used in this study are drawn from two primary sources: the RVM Curriculum Vitae (CV) database, and the RVM Survey of Careers of Scientists and Engineers. A brief description for each dataset is provided below.

In 2000, RVM researchers collected 1370 curriculum vitas of university professors and other personnel affiliated with NSF- and DOE-sponsored university research centers.[2] The CVs were obtained either via direct email requests, or passively through Internet searches, university department's websites, and other public means. All of the 1370 CVs were then coded into a database of more than 3000 variables that included information in the following categories: demographic information, educational background, employment record, publication data, patent data, professional affiliations, and grant/funding information. The advantages and disadvantages of CVs as a research tool are discussed elsewhere (Dietz, *et al.*, 2000).

In order to gain deeper knowledge on the collaboration habits and the research environment of the university personnel working at these NSF and DOE centers, RVM researchers followed up the CV collection with a mailed questionnaire survey conducted between October of 2001 and March of 2002. The survey—the RVM Survey of Careers of Scientists and Engineers—targeted the 997 full-time academic faculty and postdoctoral researchers that were in the RVM CV database. In other words, 373 (1370 minus 997) researchers were excluded from the survey population because they didn't fit into our respondent criteria: they were graduate students, part-time/adjunct professors, retired/emeritus scholars, or industry and government scientists. We received 443 usable returns after two mailings, a 44% response rate. In the mailed questionnaire, we asked the respondents to provide more detail about their research collaboration patterns, grants and contracts, job selection criteria, current work environment, and other demographic data. All the survey responses were coded and later combined with the CV data. In summary we have in our extended database the CVs and individual survey responses from 443 full-time university faculty members who are affiliated with either NSF or DOE research centers.[3]

4. Hypotheses and variables

While Figure 2 provides a general S&T human capital model, Figure 3 presents the model that we can actually examine with our data. As depicted in Figure 3, our productivity focus is on two factors—publications and students supported. We feel the latter is especially relevant to S&T human

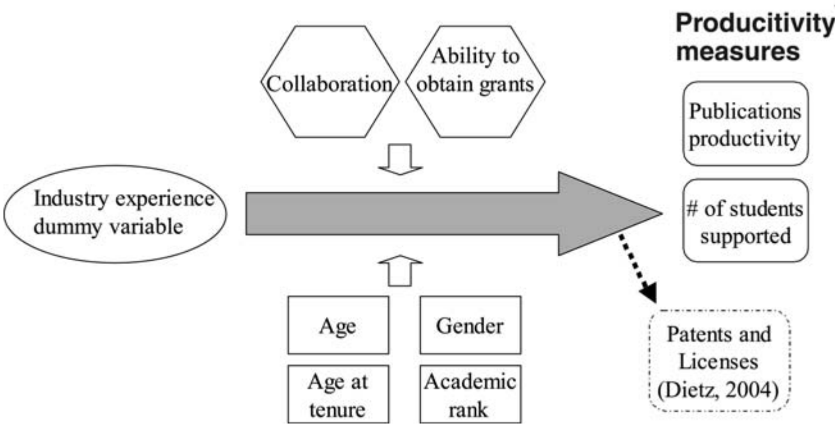

Figure 3. Hypothesized impact of industry affiliation.

capital concerns. We also examine grants acquisition, an important resource in S&T human capital development, but we consider this resource as enabling S&T human capital rather than a direct manifestation. We hypothesize that grants acquisition, as well as collaboration patterns, affect productivity, and that collaboration and grants acquisition vary as a function of industry experience, as attenuated by four control variables, age, age at tenure, gender and academic rank. Finally, we show production of patents and licenses as a function of the same model, but the linkage is not examined here (hence the broken lines), but is considered in detail elsewhere (Dietz, 2004).

Following the conceptual framework described in the previous section, we test the following two hypotheses regarding level of previous industry experience and research outcomes:

H1. (Controlling for collaboration patterns, grants acquisition, age, age at tenure, gender and academic rank) Previous industry job experience decreases researcher's (a) total career publications, and (b) total publications between the years 1996 and 2000.

H2. (Controlling for collaboration patterns, grants acquisition, age, age at tenure, gender and academic rank) Researchers with previous industry experience support more graduate students (a) throughout their careers and (b) currently.

With respect to publications, we anticipate that those who have spent their entire career in universities will have had both more opportunity to publish and stronger pressures for publication. Research (Allen, 1977; Godin, 1995) comparing industry and university researchers shows that university researchers spend more time on publishing-directed activities and, in general, publish more public domain research. Most of the industry-affiliated researchers were affiliated with universities during the period 1996–2000. Nonetheless, we expect that many of the same factors will result in their having fewer publications than those who have not worked in industry. That is, the industry-affiliated faculty will not have such strong social network ties and their S&T human capital will be in large measure geared to industry needs. We should note, however, that there is some hazard to hypothesizing based on more general studies of industry researchers. The set of industry-affiliated researchers in our sample are quite different from the population of industry researchers because (1) almost all have doctoral degrees; (2) they choose to work in universities and have the credentials to do so; (3) many have been strongly recruited by universities.

With respect to our second hypothesis, we expect that researchers with industry experience will support more graduate students during their career and at any particular time, *ceteris paribus*. Our expectations are not derived from previous research literature (there is virtually no systematic, comparative research on this topic) but from RVM program case studies (Bozeman and Klein, 1999; Rogers and Bozeman, 2001). In visiting more than forty industry–university research centers, RVM researchers have noted that a surprising number of center graduate students seem to be supported by individuals who have industry experience, often via industry or industrially oriented contracts and grants. This hypothesis provides a systematic means of testing our case-based impressions.

Independent variables

To determine the influence of industry experience on productivity and other work patterns of our respondents, we define *IND_EXPERIENCE* as a dummy variable that indicates whether or not the respondent has (previously) worked in industry.[4] The source of this information comes from examining the career employment or career history section of the respondents' curriculum vitas.

A second variable, *TOT_IND_JOBS*, sums all the industry positions the respondent has had in her career up to the year 2001, one year after we stopped collecting center personnel's CVs. A third variable, *TOT_IND_YEARS*, indicates the total number of years, added serially, that the respondent has worked in an industry setting during the course of her career. If a faculty member has worked or consulted for two different companies during the 1997–1998 academic year, his subtotal *TOT_IND_YEARS* for that year would be two, not one.

Finally, we created a variable that indicated the timing of the researcher's first job with industry. The variable *IND_JOB_TIMING* is coded 1 if the industry job before the respondent's Ph.D. granting year, and 2 if the employment occurred after the respondent has earned her Ph.D. Those with no industry work experience take the value of zero.

Dependent variables

Publication productivity

The publication counts for each university faculty member were obtained from their respective CVs. Each publication listed in the CV is classified by type (article, book or book chapter, and conference papers or proceedings), and by the order in which the author is listed (single author, first author, or one of multiple authors). For junior scientists and beginning academics, one or two pages often suffice to catalog all their scientific contributions. For seasoned scholars, a complete list of their publications can sometimes be more than 20 pages long.

There is no consensus in the research literature about measuring scientific productivity or even publishing (e.g. Clemente, 1973; Fox, 1983; Babu and Singh, 1998). In this study, we made three decisions that affected the method in which we tally publications. First, we do not distinguish published articles by the quality of the journals in which they have appeared, nor do we give more (less) weight to authored books or book chapters. There are two principal reasons for not doing so. One, the weighting of publications is ultimately subjective, and two, weighting the publications is more suited for single-discipline studies. The decision to refrain from distinguishing among articles, books, and book chapters is perhaps not momentous inasmuch as the vast majority of publications reported in this sample are journal articles. We omit conference papers and presentations. After empirical investigation, we decided to count each publication, even co-authored publications, as "1" rather than adjusting for co-authorship.[5]

We scrutinize a researcher's publication productivity from two different perspectives: (1) total career publications by normal count*(TOT_PUBS_CAREER)*, and (2) total publications between 1996 and 2000[6] by normal count*(TOT_PUBS_96–00)*.

TOT_PUBS_CAREER was deliberately chosen to contrast with TOT_PUBS_96-00, the study's other publication productivity variable. TOT_PUBS_CAREER can be seen as an overall count of "long-term" productivity (as corrected by age and other controls), while TOT_PUBS_96-00 can be interpreted as an indicator of a researcher's "recent" or short-term productivity. There is no *a priori* reason to use total career publications for one of our dependent variables. However, given the longitudinal nature of the CV data, we feel that the appeal of utilizing an overall career productivity measure lies in its simplicity and straightforwardness.

Number of students supported

Our measure of student support is a total number of students (at both master and doctoral levels) supported by the academic faculty. Similar to the publication productivity variables, we also distinguish career totals from current totals. Thus, the two dependent variables for students supported are

(a) total number of graduate students supported throughout researcher's career (*TOT_STUDENTS*);
(b) total number of graduate students supported currently (*CUR_STUDENTS*).

The number of students supported by the researcher—currently as well as over the length of the research career—can be a clear indication that these academic scientists are actively involved in educating, advising/mentoring and, with respect to the S&T human capital model, raising the capacity levels of the next generation of scientists and engineers. These variables are limited in the sense that they are inherently biased against junior faculty and those who have only recently started their academic careers. It is not unreasonable to expect the ability to support students and other research personnel to be a function of career time. Another limitation is that this set of variables may be too stringently defined by monetary research support. A faculty can educate, mentor and raise the capacity of her students by means other than financial support such as teaching classes, giving research talks, and sitting in dissertation committees.

The data on the number of students supported were obtained from the RVM questionnaire.

Control variables

We include four control variables in our analysis: age, age at tenure, gender and academic rank. Past studies on scientific productivity have consistently regarded age effects to be important (see for example Stephan and Levin, 1992). We expect the researchers with industry experience—assuming that they took some time away from a straight academic career path—to be somewhat older than those without industry experience at comparable career milestones (i.e. age at Ph.D. graduation or age at tenure). Thus, in order to make any group comparisons accurately, we need to consider the relationship between age and productivity. We can also test whether industry researchers become more (less) productive over time compared with the rest of the sample by multiplying *IND_EXPERIENCE* with age; such variable will give us age–industry experience interaction effects. The "age at tenure" variable can be interpreted as the interaction term between age and rank status.

Another control is gender. Female scientists have been consistently found to be less productive than male scientists, but the reasons which explain the gender gap—also labeled as "the productivity puzzle" by Cole and Zuckerman (1984, pp. 217–218)—are still not well understood (Zuckerman, 1991, p. 45). In a recent effort to solve the puzzle Xie and Shauman (1998) concluded that gender has very little direct effect on research productivity, but that women scientists publish fewer papers than men because women are less likely than men to have the "personal characteristics, structural positions, and facilitating resources that are conducive to publication" (p. 863). We do not anticipate gender to be a significant factor in explaining differences in publication activity between the industry researchers and those who are not, but only that it may play an indirect role in affecting research productivity through the choices of collaborators.

Finally, we wish to rule out academic rank as a rival explanation for our model. Presumably, the higher up one is on the academic ladder, the better indication that one has shown capacity to publish and to attract resources. Rank is sometimes confounded with age (since obtaining tenure takes time, and tenured faculty is normally older), and possibly related to other forces such as cumulative advantage (Merton, 1968; Stephan and Levin, 1992). Rank may also be related to industry experience, especially for those individuals actively recruited from industry.

Intervening variables

In addition to the four controls above, we also consider two intervening variables. The first is the pattern of a scientist's collaborative activities, and the second is related to the researcher's ability to obtain grants. Since the ground-breaking work of Lotka (1926) on the productivity of scientists, most ensuing studies suggest a strong, positive correlation between collaboration and productivity. The famous assessment of de Solla Price and Beaver (1966)—"the most prolific [person] is also the most collaborating"—and Diana Crane's (1972) powerful demonstration of the existence of "invisible colleges" in science more than three decades ago, still represent the orthodox thinking on this issue.

We expect industry work experience to be positively associated with the number of collaborators because industry emphasizes intra-firm teamwork more than on the individual efforts and breakthroughs (Peters and Fusfeld, 1983). Since research centers are, by design, a breeding ground for new collaborative activities between university and industry, we speculate that these center-affiliated researchers have more collaborators and opportunities for collaboration than non-center-affiliated scientists. To correctly specify a research productivity model for center faculty, we include a collaboration variable. This variable is defined as "the total number of collaborators with whom the respondent has collaborated over the past 12 months."[7] Focusing on individual *collaborators* rather than on *collaborated* publications gives us the added benefit to a wide variety of types of research collaboration, including types that do not result in co-authorship (Bozeman and Corley, in press).

Our second intervening variable is acquisition of external research grants and contracts. We expect those who are more successful in obtaining a research grant or contract to have more publications and to support more students. However, the inter-relationship between funding (measured in dollars) and productivity seems not to be linear (Kingsley *et al.*, 1996). We use the ‘‘grant batting average’’ (the ratio of number of proposals awarded to number of proposals submitted) as a proxy for the ability to obtain grants and contracts.

5. Results—descriptive statistics

In this section, we explore in detail the characteristics of center-affiliated university faculty who have previous industry work experience. We begin by answering basic questions such as how many researchers with industrial work experience are in the sample, how many jobs and what type of jobs did they have, how many years and when were they in industry. We will also give information about their current rank, disciplinary background, gender and citizenship status. We then attempt to determine whether or not differences exist between researchers with industry experience and others with respect to productivity, student support and collaborative behavior. Table I presents the key variables and simple descriptive statistics.

Industry researchers—basic characteristics

Figure 4 shows that 178 researchers—40% of the sample—list at least one previous industry work experience in their curriculum vita. Of the 178 faculty members who listed industry work experience, 98 had more than one industry work experience.

Among those with industry experience, our data show that 41.6% of industry researchers spend less than 3 years in the private sector, 28.7% between 3 and 9 years, and the remaining 29.8% stay for more than 9 years. The average is 8.75 years of industry experience for each person. The average duration for any particular industry job is 3.65 years.

With respect to the timing of industry experience, nearly three-fifths (62.4%, 111) had their first industry job before obtaining their doctoral degree. About one-third (32.6%, 58) were employed by industry only after they completed their doctoral studies (but before they received tenure). About 1 in 20 (5.1%, 9) had their first industry work experience after receiving tenure.

Figure 5 shows the characteristics of those with industry experience. In our sample, 42% of the male scientists and engineers have had previous industry work experience, compared to 29.3% of the women. Compared to the population of academic researchers, the percentages of organisms our centers sample with industry experience (both men and women) are likely more than double (Andrews, 1979). The percentage of native-born

Table I
Variable summary and descriptive statistics

Variable names	*N*	Minimum	Maximum	Mean	Std. deviation
Respondent’s age	418	27	75	46.66	10.00
Respondent’s age at tenure	251	29	66	37.81	5.54
Gender (1 = male; 0 = female)	441	0	1	0.87	0.33
Academic rank (1 = assistant; 2 = associate; 3 = full)	361	1	3	2.14	0.88
Total number of collaborators	360	0	85	13.82	9.97
Grants batting average (GBA)	379	0	1	0.56	0.22
Industry experience (1 = Yes, 0 = No) [IND_EXPERIENCE]	443	0	1	0.40	0.49
Total number of industry jobs [TOT_IND_JOBS]	443	0	21	0.97	1.88
Total number of years in industry [TOT_IND_YEARS]	443	0	57	3.52	7.74
Industry job timing (0 = never; 1 = before Ph.D.; 2 = after Ph.D.) [IND_JOB_TIMING]	443	0	2	0.55	0.74
Total career publications (articles, books, and book chapters) [TOT_PUBS_CAREER]	443	0	555	60.89	77.46
Total publications between 1996 and 2000 [TOT_PUBS_96-00]	443	0	121	17.11	18.40
Total students supported (Career) [TOT_STUDENTS]	425	0	200	21.32	26.40
Total students supported (Currently) [CUR_STUDENTS]	405	0	50	3.98	4.54
Age–industry experience interaction term	434	0	73	18.74	24.08

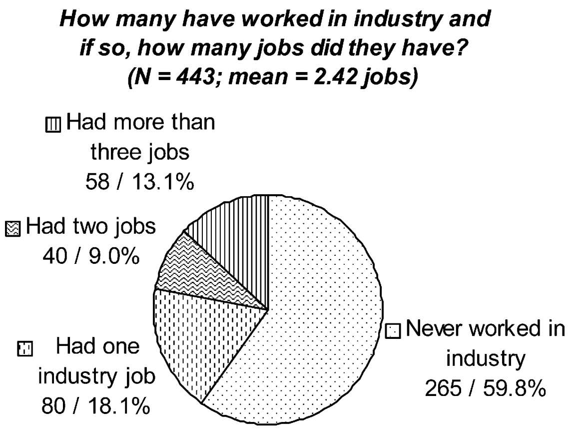

Figure 4. Center researchers and industry experience.

US citizens who have prior industry experience (42.9%) is greater than that of foreign/immigrant scientists (34.5%). Among the industry researchers, more have been principal investigators (PI) of a research contract or grant (41.3%) than not (32.6%). Lastly, in terms of the researcher's current academic rank status, 37.6 % of assistant professors, 44% of associate professors, and 40.2% of full professors have previous industry experience.

Table II shows industry experience according to the researcher's discipline. As expected, a clear majority of the industry researchers (100 out of 172, or 58.2%) work in engineering or applied research (chemical, civil, electrical, mechanical, and other engineering). Physical and natural sciences (biology, chemistry, physics, computer science, and other natural sciences) are next in housing 69 (40.1%) industry researchers.

Collaboration patterns

With whom do they collaborate and what kind of collaboration patterns do they have?

An examination of the research collaboration variables in our questionnaire indicates that faculty with first-hand industry working experience have, by most accounts, greater numbers of collaborators in the past 12 months than those without. From Table III the difference between the two groups can be seen in the total number of collaborators (ρ, number of male collaborators ($\rho < 0.001$), number of collaborators who are other academic faculty (ρ, and most significant of all, number of collaborators who are graduate students (ρ. The difference in the number of female collaborators between the two groups is barely significant ($\rho < 0.10$).

In terms of scientific publications (refereed articles, books, and book chapters), the industry-affiliated researchers—despite having more overall collaborators—have on average fourteen fewer publications *in aggregate*. The implications of having prior industry experience on the researchers' collaboration patterns are thus somewhat counter-intuitive, if not contradictory. There are several possible reasons why those with industry experience have more collaborators and fewer publications.

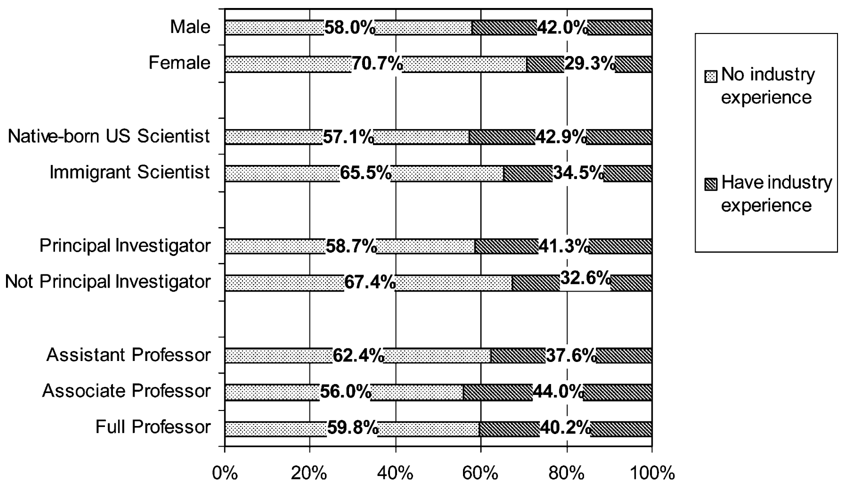

Figure 5. Industry experience vs. gender, citizenship, PI status, and academic rank.

1. Industry researchers are more likely to be engineers (see Table II), and engineers in general collaborate more than scientists do and publish less.
2. Industry-related or industry-sponsored projects do not always put a premium on publications.
3. Their industry experience can also drive them towards other entrepreneurial activities (such as patenting, consulting, fund-raising, and administrating) that do not necessarily translate into more publications
4. Previous studies (e.g. Andrews, 1979) show psychological differences between scientists and engineers, with the latter being more gregarious and the former having low-intensity personal relationships.
5. Those with industry affiliation and more collaborators appear to have more publications than those with industry affiliation and fewer collaborators.

Figure 6 displays a step-wise pattern between job timing and the number of collaborators. The data show that he later one begins an industry job, the higher the number of other faculty, graduate student and total collaborators. This is not surprising. People who enter industry jobs later tend to have already earned doctoral degrees and to have developed academic social capital.

Scientific productivity

Figure 7 shows the difference in the career productivity levels of researchers with and without industry experience, in terms of normal count publications. The horizontal axis indicates the

Table II
Industry experience vs. discipline cross-tabulation

Degree field	Have industry experience	No industry experience	Total
Chemical engineering	24	21	45
Civil engineering	10	8	18
Electrical engineering	31	19	50
Mechanical engineering	10	15	25
Other engineering	25	18	43
Biological/life sciences	11	55	66
Chemistry	19	28	47
Computer science	11	14	25
Physics	13	30	43
Other natural sciences	15	42	57
Social sciences	3	9	12
Total	172	259	431

Note: Discipline background for 12 respondents couldn't be determined from the data.

Table III
Means comparisons (*T*-tests) between collaboration measures and industry experience

Category	Valid *N*	Have industry experience [A] Mean (median)	No industry experience [B] Mean (median)	Difference [A – B] and significance
Total number of collaborators	360	15.92 (14)	12.44 (11)	3.48**
Total female collaborators	361	3.85 (3)	3.42 (3)	0.43†
Total male collaborators	363	12.08 (10)	9.02 (8)	3.05***
Total faculty collaborators	365	6.50 (5)	5.17 (4)	1.34*
Total graduate student collaborators	365	7.12 (7)	5.11 (4)	2.01***
Collaborated publications (articles, books, and book chapters)	443	46.34 (26.5)	60.31 (30)	−13.96*
Ratio of collaborated publications/total publications	428	0.87 (0.93)	0.90 (0.95)	−0.03*

†$\rho < 0.10$; *$\rho < 0.05$; **$\rho < 0.01$; ***$\rho < 0.001$.

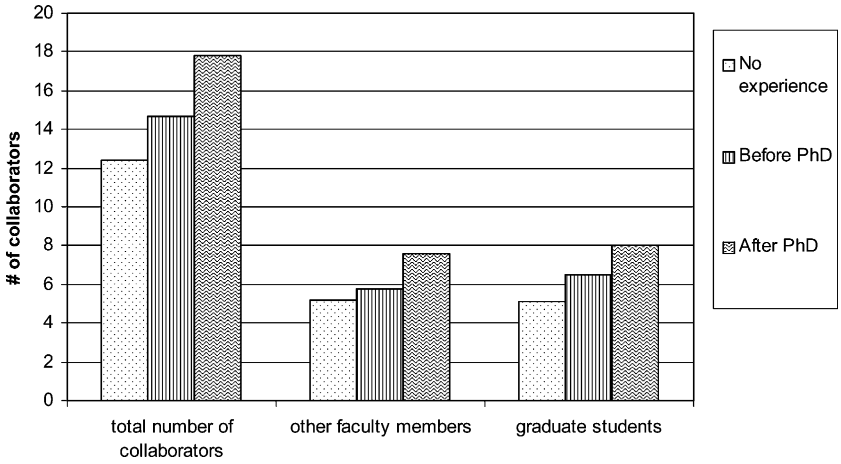

Figure 6. Mean number of collaborators as grouped by timing of researcher's first industry experience.

number of years elapsed since the researcher received her doctoral degree. Although we have publication data for all researchers from 0 to 45 years after receiving the degree, the data become increasingly unreliable 40 years after Ph.D. due to small cohorts. The average age of our respondents is about 45 in 2001, and we believe that few of our respondents are still publishing 40 years after Ph.D.

The data show that productivity levels (measured by "normal count") remains virtually identical for both industry-affiliated and not-industry-affiliated scientists up to the first decade after the Ph.D. was granted. It is only after the tenth year, during which the average hovers around three publications per year for both groups, that their productivity levels begin to diverge noticeably. For the next two decades, the non-industry researchers continue to extend their upward productivity climb to average to more than six publications annually. Their career productivity peak is reached in the 27th year. After that period their publication rate oscillates around five yearly publications for the next 15 years, before dropping to fewer than three publications after 45 years.

Industry researchers, on the other hand, continue to produce three publications per year between the 11th and 15th year, and will not average four publications per year until the 19th year or so. After that period, the industry

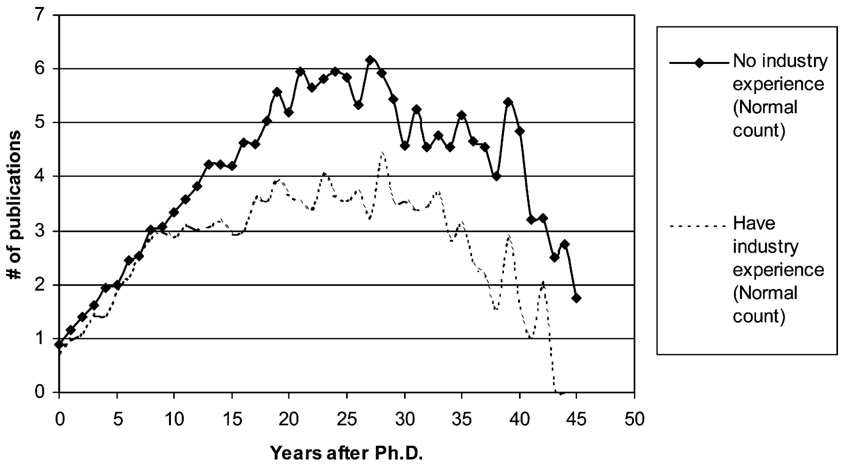

Figure 7. Difference in the mean number of publications over career: industry experience vs. no industry experience.

researcher goes through a series of productivity highs (runs) and lows (slumps), before achieving a career maximum (4.4 publications) in their 28th year. After reaching the peak, their productivity drops nearly every year to average fewer than two annual publications after some forty-odd years.

In sum, researchers with industry labor experience appear to publish fewer articles in any given year than those without any industry experience, but this result is not evident until a decade or so has passed since the individual graduated with her doctoral degree. The publication rate dissimilarity between the two groups, in other words, is a "delayed" effect.[8]

Table IV presents productivity differences between industry researchers and non-industry researchers by gender, citizenship, PI status, and academic rank. Using annual average publications between 1996 and 2000 as the comparable measure, we find that among men, those who had prior industry experience produced 0.63 fewer publications than those who did not ($\rho < 0.10$). Among women faculty members, the publication gap between the two is actually in the other direction: those who had previous industry experience averaged one *more* publication than those who did not have the experience, but this means difference is not statistically significant. A productivity gap between men and women scientists is not observed within the group of industry researchers (3.59 and 3.45 publications respectively). However, confirming the results of prior studies, a gender gap is observed in university faculty who did not have any industry experience (4.22 publications for men and 2.48 publications for women, $\rho < 0.001$).

Productivity differences are not much accentuated by rank. For each level of academic rank status, we do not find significant differences in the annual productivity between the industry researchers and those who are not. Assistant professors with industry experience produced one more publication than those without, but full professors with industry experience produced one less publication ($\rho < 0.10$). No difference in annual productivity was found for the associate professors. The more substantial divergence occurs in the within-group productivity differences. Within the group of faculty researchers with no industry experience, the discrepancy in the publication rates among the full professors, associate professors and assistant professors is considerable.

Number of students supported

With respect to the number of students supported, we find that faculty with prior work experience in the private sector (a) support more Ph.D. and Masters students throughout their careers, and (b) are supporting more Ph.D. and Masters students presently, than their academic colleagues with no industry experience. Table V shows that researchers who have worked in industry are able to support additionally six masters ($\rho < 0.001$) and more than three doctoral ($\rho < 0.05$) students over

Table IV
Means comparisons of annual average publications between 1996 and 2000 by gender, citizenship, PI status, academic rank, and industry experience

Annual average publications between 1996 and 2000 (articles, books, and book chapters)		Valid N	Have industry experience [A] Mean (median)	No industry experience [B] Mean (median)	Difference [A – B] and significance
Gender	Male	356	3.59 (2.60)	4.22 (3.00)	−0.63†
	Female	53	3.45 (2.60)	2.48 (2.20)	0.97
Citizenship	Native-born US Scientist	280	3.32 (2.40)	3.72 (2.40)	−0.40
	Immigrant Scientist	130	4.28 (3.40)	4.37 (3.10)	−0.08
PI status	PI	372	3.71 (2.60)	4.11 (2.80)	−0.39
	Not PI	34	2.04 (1.40)	2.39 (1.80)	−0.35
Academic rank	Assistant Professor	114	3.44 (2.20)	2.44 (2.00)	1.00†
	Associate Professor	72	3.09 (2.60)	3.38 (3.00)	−0.29
	Full Professor	168	4.50 (3.40)	5.57 (4.20)	−1.07†

†$\rho < 0.10$; $^{*}\rho < 0.05$; $^{**}\rho < 0.01$; $^{***}\rho < 0.001$.

Table V
Means comparisons (*T*-tests) between student support variables and industry experience

Category	Valid *N*	Have industry experience [A] Mean (median)	No industry experience [B] Mean (median)	Difference [A – B] and significance
Total masters students supported (career)	426	14.22 (8)	8.00 (3)	6.22***
Total Ph.D. students supported (career)	437	12.79 (8)	9.30 (5)	3.50**
Current masters students supported	407	1.67 (1)	0.73 (0)	0.94***
Current Ph.D. students supported	428	358 (3)	2.41 (2)	1.17***

†$\rho < 0.10$;* $\rho < 0.05$;** $\rho < 0.01$;*** $\rho < 0.001$.

their careers (one masters and one Ph.D. student currently) than those who did not have any industry experience.

Research grants and resources

Turning now to research grants we find in Table VI that industry researchers submit six more research grant and contract proposals ($\rho < 0.10$), and in turn, are awarded with nearly four more grants and contracts ($\rho < 0.05$) than those who did not have any industry experience. The fact that industry researchers have more research grants and contracts partially explains why and how they support more students. Their overall grant success rate (defined as number of proposals awarded divided by number of proposals submitted) is not statistically better than those did not have industry experience, however. In terms of dollars, industry researchers have much higher amount of research grants than the rest of the sample.

6. Results—OLS findings

With these descriptive findings as a backdrop, we examine results from ordinary least squares (OLS) regression for our four different dependent variables: (1) total career publications, (2) total publications between 1996 and 2000, (3) total number of students supported throughout the researcher's career, and (4) total number of students supported currently.

OLS regression was used in the study mainly because we did not suspect missing data to be a major problem. Neither the publication nor the student support information is heavily censored from below as to introduce a significant level of bias in the regression coefficients. Moreover, a tobit model was used to determine differences in results with OLS (results are available from the authors). The tobit estimates and standard errors were found to be very similar to those reported in OLS.

We model each dependent variable we model the regressions three different ways, resulting in a total of four regressions of increasing relative complexity. In Model 1—the Basic Model—only the control and intervening variables are included in the regression. In Model 2, or the Full Model, we add the independent variable—whether or not one has previous industry experience—to the regression equation. In Model 3, the Interaction Model, we check for possible interaction effects

Table VI
Means comparisons (*T*-tests) between research resources variables and industry experience

Category	Valid *N*	Have industry experience [A] Mean (median)	No industry experience [B] Mean (median)	Difference [A – B] and significance
Grant proposals submitted	381	35.47 (25)	29.45 (20)	6.02†
Grant proposals awarded	382	19.40 (12)	15.53 (10)	3.88*
Grants batting average	379	0.56 (0.57)	0.55 (0.50)	0.01
Total dollar amount of current grant (in millions)	339	3.634 (0.450)	1.248 (0.450)	2.386*

†$\rho < 0.10$;* $\rho < 0.05$;** $\rho < 0.01$;*** $\rho < 0.001$.

between age and industry experience by inserting into the regression equation the product of those two terms.

Total career publications

Table VII shows, as expected, age is the strongest predictor of a scientist's total number of publications. The table also indicates that industry experience has a negative and significant effect on total career publications (at the minimum of 0.05 level). Holding all other variables constant, faculty with industry experience publish 35 fewer articles. This finding can be observed in Model 2, the Full Model, and offers some statistical evidence to our casual observation during descriptive statistics that industry researchers publish fewer articles over their careers than the rest of the sample. In all three models neither the total number of collaborators nor the researcher's ability to obtain grants is a significant predictor of total career publications. None of the other control variables—age at tenure, gender and rank—is significant. The R^2 ranges from 0.237 to 0.300.

The negative and significant coefficient on the age-industry experience interaction term indicates that the expected total career publications decreases more rapidly over the course of one's career for the industry researchers than for the rest of the sample.

Total publications between 1996 and 2000

Regression results for total publications for the 5 years between 1996 and 2000 are provided in Table VIII.[9] The statistical performance of the industry experience dummy on the dependent variable in the Full Model is not significant at the 0.05 level, although the coefficient remains in the negative direction (as in Table VII).

Unlike the analysis for career publications, age plays no significant role in predicting total number of publications for this five-year period, nor do age at tenure and gender. In general, both the researcher's rank and total number of collaborators positively affect the number of publications.

As with total career publications, the analysis for the five year period shows negative age–industry experience interaction effects ($\rho < 0.05$) in the researcher's five-year publication counts (Interaction Model). Industry researchers decrease their annual publication outputs (about 0.7

Table VII
OLS regression results for total career publications

Dependent variable: total career publications (TOT_PUBS_CAREER)	Model 1: Basic model	Model 2: Full model	Model 3: Full model + interaction term
Control variables			
Age	3.827^{***} (3.970)	3.820^{***} (4.047)	5.513^{***} (5.094)
Age at tenure	−0.197 (−0.166)	0.056 (0.048)	−0.050 (−0.044)
Gender	27.606 (1.408)	32.769† (1.699)	25.142 (1.322)
Academic rank	7.005 (0.656)	6.998 (0.669)	8.358 (0.817)
Industry experience variable			
Industry job experience dummy		-35.251^{**} (−2.897)	168.037^{*} (2.437)
Age * industry experience interaction			-4.045^{**} (−2.994)
Intervening variable: collaboration			
Total number of collaborators	0.773 (1.274)	1.038† (1.726)	0.806 (1.358)
Intervening variable: resources			
Grant batting average (GBA)	61.954† (1.966)	57.047† (1.980)	40.925 (1.333)
Constant	-187.25^{**} (−3.647)	-187.77^{***} (−3.735)	-252.68^{***} (−4.703)
Adjusted R^2	0.237	0.268	0.300
Model fit (F)	10.252^{***}	10.362^{***}	10.606^{***}

Note: All figures are unstandardized coefficients (t-statistics in parentheses).

†$\rho < 0.10$; $^{*}\rho < 0.05$; $^{**}\rho < 0.01$; $^{***}\rho < 0.001$.

Table VIII
OLS regression results for total publications between 1996 and 2000

Dependent variable: total publications between 1996 and 2000 (TOT_PUBS_96-00)	Model 1: Basic model	Model 2: Full model	Model 3: Full model + interaction term
Control variables			
Age	−0.272 (−1.229)	−0.273 (−1.238)	0.004 (0.017)
Age at tenure	0.152 (0.556)	0.184 (0.676)	0.166 (0.617)
Gender	6.519 (1.447)	7.179 (1.593)	5.929 (1.316)
Academic rank	4.897^{*} (1.996)	4.896^{*} (2.004)	5.119^{*} (2.114)
Industry experience variable			
Industry job experience dummy		−4.508 (−1.585)	28.823† (1.766)
Age * industry experience interaction			-0.663^{*} (−2.073)
Intervening variable: collaboration			
Total number of collaborators	0.336^{*} (2.405)	0.369^{**} (2.628)	0.331^{*} (2.359)
Intervening variable: resources			
Grant batting average (GBA)	12.568† (1.735)	11.940 (1.653)	9.297 (1.279)
Constant	−0.040 (−0.003)	−0.106 (−0.009)	−10.749 (−0.845)
Adjusted R^2	0.068	0.076	0.093
Model fit (F)	3.170^{*}	3.100^{**}	3.302^{**}

Note: All figures are unstandardized coefficients (t-statistics in parentheses).

$\dagger\rho < 0.10;^{*}\ \rho < 0.05;^{**}\ \rho < 0.01;^{***}\ \rho < 0.001.$

publications) in 1996–2000 with each passing year more so than the no-industry-experience researchers.

Combining the statistical evidence from Table-s VII and VIII we tentatively conclude that industry experience:

(a) significantly decreases a researcher's total career publications, even after controlling for respondent's age → H1a confirmed
(b) does not have a significant effect on the faculty's publications between 1996 and 2000 → H1b rejected

Total number of students supported throughout the researcher's career

Turning now to the number of students supported, we find in Table IX, the Full Model, that previous industry work experience does significantly predict the total number of graduate students faculty members support throughout their career. On average, those with industry experience support 8 more students over the course of their academic career.

Since the dependent variable is a career count of the number of students supported, its relationship with age is positive, as expected. With respect to other variables in the framework, total number of collaborators is a significant and positive determinant of total number of students supported in one's career. We do not find any such impact from the researcher's age at tenure, gender, academic rank, or the researcher's grant batting average. Lastly, we find in the Model 3 that the interaction term between age and industry experience is statistically insignificant.

Total number of students supported currently

In Table X we examine the factors that predict the number of graduate students a faculty researcher is currently supporting. We find that the impact of industry experience on number of current students is strongly predicted by the industry experience dummy variable (Model 2). Having previous industry work experience increases one's number of graduate students supported. This result is consistently robust even after controlling for the total number of collaborators and researcher's grants batting average, which are all positive and significant estimators of the dependent variable. However, in Model 3, industry experience is not a significant predictor once the age–industry interaction term is introduced. The coefficient on the interaction term is positive (but not significant),

Table IX
OLS regression results for total number of students supported throughout researcher's career

Dependent variable: total number of students supported throughout researcher's career (TOT_STUDENTS)	Model 1: Basic model	Model 2: Full model	Model 3: Full model + interaction term
Control variables			
Age	1.312^{***} (4.144)	1.302^{***} (4.154)	1.101^{**} (2.959)
Age at tenure	−0.317 (−0.826)	−0.365 (−0.958)	−0.349 (−0.915)
Gender	9.601 (1.440)	8.696 (1.314)	9.741 (1.454)
Academic rank	2.397 (0.688)	2.462 (0.714)	2.298 (0.666)
Industry experience variable			
Industry job experience dummy		8.385^{*} (2.093)	−14.656 (−0.629)
Age * industry experience interaction			0.459 (1.003)
Intervening variable: collaboration			
Total number of collaborators	0.698^{**} (3.503)	0.632^{**} (3.164)	0.662^{**} (3.277)
Intervening variable: resources			
Grant batting average (GBA)	4.870 (0.474)	6.649 (0.634)	8.276 (0.799)
Constant	-50.362^{**} (−3.028)	-50.818^{**} (−3.086)	-43.338^{*} (−2.398)
Adjusted R^2	0.254	0.268	0.268
Model fit (F)	10.796^{***}	10.067^{***}	8.935^{***}

Note: All figures are unstandardized coefficients (t-statistics in parentheses).
$\dagger\rho < 0.10$; $^{*}\rho < 0.05$; $^{**}\rho < 0.01$; $^{***}\rho < 0.001$.

and we take this to mean that industry researchers are shown to support more current students than the rest of the sample for every passing year of age.

In none of the models does gender, age at tenure, or rank have an impact on the number of students currently supported. The effect of age can be observed in Models 2 and 3, and it is in the expected negative direction: older faculty fund fewer students. The results from Tables IX and X indicate that the impact of industry experience is a

Table X
OLS regression results for total number of students supported currently

Dependent variable: total number of students supported currently (CUR_STUDENTS)	Model 1: Basic model	Model 2: Full model	Model 3: Full model + interaction term
Control variables			
Age	−0.096† (−1.917)	-0.097^{*} (−2.019)	-0.130^{*} (−2.285)
Age at tenure	−0.008 (−0.128)	−0.022 (−0.366)	−0.020 (−0.333)
Gender	1.427 (1.325)	1.244 (1.197)	1.349 (1.293)
Academic rank	0.208 (0.376)	0.214 (0.400)	0.191 (0.357)
Industry experience variable			
Industry job experience dummy		2.275^{***} (3.633)	−1.518 (−0.426)
Age * Industry experience interaction			0.075 (1.080)
Intervening variable: collaboration			
Total number of collaborators	0.176^{***} (5.512)	0.157^{***} (5.014)	0.162^{***} (5.120)
Intervening variable: resources			
Grant batting average (GBA)	4.707^{**} (2.783)	5.237^{**} (3.200)	5.503^{**} (3.327)
Constant	2.977 (1.104)	2.737 (1.053)	4.044 (1.411)
Adjusted R^2	0.205	0.261	0.262
Model fit (F)	8.082^{***}	9.345^{***}	8.331^{***}

Note: All figures are unstandardized coefficients (t-statistics in parentheses).
$\dagger\rho < 0.10$; $^{*}\rho < 0.05$; $^{**}\rho < 0.01$; $^{***}\rho < 0.001$.

significant predictor of the total number of students supported over the faculty member's career and in the near term (see the respective Full Models from each table). We therefore cannot reject H2.

7. Discussion & conclusions

Using a unique database combining questionnaire data and curriculum vita data, we examined the impact of previous industry experience on the research outputs and outcomes of university faculty who are affiliated with NSF and DOE research centers, a sample with an unusually high percentage of university researchers with industry experience. Our results show quantitative differences between academic researchers with industry experience and those with no industry experience. Using a simple model of research productivity, we found that, controlling for age, gender, rank, collaboration and resources, industry researchers have fewer total career publications but support more students, both in terms of students currently supported and the number supported over the course of a career. Contrary to expectations, we could not establish significant differences in recent publication activity (from 1996 to 2000). We also found some statistical evidence that previous industry experience actually *raised* the annual publication productivity of junior faculty members and women researchers in our sample of research centers personnel.

We feel these findings are potentially relevant to both theory and policy. With respect to theoretical implications, the S&T human capital model suggests focuses on researchers' capacity to produce knowledge and, just as important, contributions to others' capacity to produce knowledge. From the standpoint of the S&T human capital model, the fact that those with industry experience are more active in supporting graduate students suggests that the distinctive career experiences of industry researchers joining academe are beneficial in the production of S&T human capital. While we have not with our data ruled out all other explanations (especially selection effects), the findings seem sufficiently interesting to warrant exploration of other S&T human capital contributions of those with industry experience, including placement of students in jobs and brokering linkages to industry. Quite possibly, the S&T human capital repertoire of many of those endowed with industry experience typically differs from those whose entire career is spent in academia. We expected that those with exclusively academic careers would have substantial advantage in publication as a result of the more specialized S&T human capital built up over the years. However, our results showed little difference in publications productivity. This may be an artifact of the types of industry-experienced individuals recruited to university centers and, thus, the finding may have little or no generalizability to the population of academic scientists. Nonetheless, the results are interesting for those who feel that the research culture of universities is fundamentally altered by increasing the number of individuals with an industrial orientation.

The implications of our findings for public policy are not altogether straightforward. One's interpretation depends in large measure upon one's views about the roles of university–industry research centers. In our judgment, our findings are an endorsement of the centers policies that originated more than 25 years ago. If the objective change university faculties, especially engineering faculties (over-represented in our sample) to increase an industrial orientation but, the same time, at little or no diminution of traditional research productivity, then the policy seems to have worked well. The persons who populate university–industry centers publish at rates comparable to those with more traditional academic career trajectories but appear to bring added value in terms of larger grants and more student support as well as, in our judgment, a different sort of S&T human capital.

There are other limitations to the study. In addition to possible selection effects, the results may be biased from misspecification due to omitted variables. More specifically, we have not included in our model any psychological effects or other individual differences in ability and motivation that may set the industry researchers apart from the purely academic scientists. We do not have data permitting such analysis. While the curriculum vita data has many advantages, these data tell us how someone's career trajectory unfolds, but not why it unfolded the way it did.

While we feel that our findings add to knowledge about industry–university career trajectories and their S&T human capital consequences, ours is only a first step. Our model will achieve a higher level of generalizability if we expand our population sample to include all university faculty members, not just those affiliated with centers. Second, we would hope to broaden the idea of industry experience to give more attention to particular types of experience and to periodicity effects that we have only begun to address. We feel that the placement of students may be extremely important to an S&T human capital model, as well as more explicit analysis of industry ties and how these ties interact with other S&T human capital concerns.

Despite these limitations, the study begins to shed some empirical light on issues that have long been in the realm of conjecture or case-by-case analysis. Most important, using the S&T human capital model as a point of departure accompanied by career-long data seems to us to lead to different focus and different research directions than do cross-sectional studies aimed at assessing productivity via discrete output. In future work, we hope to further develop the S&T human capital model and include additional direct indicators for the model.

Acknowledgments

Funding for this study comes in part from the project "Assessing Economic and Social Impacts of Basic Research Sponsored by the Office of Basic Energy Sciences" (contract DE-FG02-96ER45562), and in part from the National Science Foundation-sponsored project "Assessing R&D Projects' Impacts on Scientific and Technical Human Capital Development" (SBR 98-18229). The authors gratefully acknowledge the support of the Office of Basic Energy Sciences, U.S. Department of Energy, and the National Science Foundation. The opinions, findings, and conclusions contained in the paper are those of the authors and do not represent the views of the Department of Energy or the National Science Foundation. We are especially grateful to Sooho Lee for his extensive work on the dataset. We thank Juan Rogers, Monica Gaughan, and Craig Boardman for their contributions to the larger projects as well as their comments on this paper. We are also indebted to Stuart Bretschneider and Albert Link for their valuable comments and suggestions.

Notes

1. We shall also refer them as "industry researchers" in our discussions.
2. For a more complete description of the methodology used in this study, see Gaughan and Bozeman (2002).
3. To determine possible selection bias, we compared attributes of those responding to the survey with those for whom we had CV data, but no survey response. Examining differences of means, there were three variables for whom *t*-tests were significant at the 0.05 level or greater. These included age, age at tenure time, and academic rank, but not our main independent variable, whether or not the respondent has industry job experience. For both age and age at tenure, the differences were modest (e.g. 47 years vs. 50 years of age between respondents and non-respondents). The most significant difference comes from the respondent's rank: we have a higher percentage of survey-responding assistant professors (32%) than the non-responding assistant professors (18%). Conversely, a lower percentage of full professors responded to our survey (47%) than the non-responding set (60%). For associate professors, the percentage of those responding to the survey is similar to that of the non-responding group (21% vs. 22%). Given this distribution of academic rank, our dataset reflects a younger—and presumably less academically established—group of university professors. It is theoretically possible that because of the lower overall rank of the respondents, the productivity estimates are underestimated (inclined towards zero), holding all other variables constant. However, using another *t*-test we did not find a statistically significant means difference in the career publication productivity between survey respondents and non-respondents ($\rho = 0.382$).
4. We provide no differentiation among the various types of industry positions that are listed in an individual's curriculum vitae. All possible job categories, ranging from "industry scientist or researcher without any other title" to "vice-president of research," to "researchers" were included. The vast majority of those with industry experience listed "researcher" or "research manager." We excluded internships and external paid consultants. About 6% of those who reported any industry experience report *only* consulting experience. Difference of means tests showed that the sample with consulting experience only was almost identical to the sample reporting no industry experience. Receiving a research grant or contract from industrial sources, but not directly or explicitly being hired by the private sector, is not coded as industry experience.
5. Following previous work with this sample (Bozeman and Lee, 2003), we had considered measuring productivity in two ways: normal count and fractional count. In normal count full credit is allocated to all the contributors in the publication; in fractional count, publication credit is divided among the number of authors and then sum to one. Such a distinction between productivity measures is useful to shed light on the impact of

collaboration on productivity—which is Bozeman and Lee's main research question—it was found that the correlation between normal and fractional count is 0.928. Given such a strong correlation between normal count and fractional count, to simplify matters we decided to use the normal count measures only.

6. Faculty researchers who were not employed in academia (or were still students) between 1996 and 2000 are excluded for this part of the analysis.

7. According to an earlier study of the same data, "total number of collaborators" is the strongest predictor of researcher productivity (Bozeman and Lee, 2003).

8. Similar interpretation can be drawn from the fractional count data as well.

9. The analysis drops out those who were not employed in universities between 1995 and 2000.

References

Allen, T., 1977, *Managing the Flow of Technology: Technology Transfer and the Dissemination of Technological Information within the R&D Organization*, Cambridge, MA: MIT Press.

Andrews, F., 1979, *Scientific Productivity: The Effectiveness of Research Groups in Six Countries*, Cambridge: New York University Press.

Babu, A.R. and Y.P. Singh, 1998, 'Determinants of Research Productivity,' *Scientometrics* **43** (3), 309–329.

Bozeman, B. and C. Boardman, 2003, *Managing the New Multipurpose, Multidiscipline University Research Center: Institutional Innovation in the Academic Community*, Washington, DC: IBM Endowment for the Business of Government.

Bozeman, B. and Corley, E., 2004, 'Scientists Collaboration Strategies,' *Research Policy* **33** (4), 599–616.

Bozeman, B., J. Dietz, and M. Gaughan, 2001, 'Scientific and Technical Human Capital: An Alternative Model for Research Evaluation,' *International Journal of Technology Management* **22** (7/8), 716–740.

Bozeman, B. and H. Klein, 1999, 'The Case Study as Research Heuristic: Lessons from the R&D Value Mapping Project,' *Evaluation and Program Planning* **22** (1), 91–103.

Bozeman, B. and S. Lee, 2003, 'The Impact of Research Collaboration on Scientific Productivity'. Annual Meeting of the American Association for the Advancement of Science. Denver, CO. Manuscript available at http://www.rvm.gatech.edu.

Butler, L., 2003, 'Explaining Australia's Increased Share of ISI Publications—The Effects of a Funding Formula based on Publication Counts,' *Research Policy* **32**, 143–155.

Clemente, F., 1973, 'Early Career Determinants of Research Productivity,' *American Journal of Sociology* **79**, 409–419.

Cole, J. and H. Zuckerman, 1984, 'The Productivity Puzzle: Persistence and Change in Patterns of Publication of Men and Women Scientists,' in M. Steinkamp and M. Maehr (eds.), *Advances in Motivation and Achievement*, 2 Greenwich, CT: Jai Press, pp. 217–258.

Crane, D., 1972, *Invisible Colleges*, Chicago: University of Chicago Press.

J. CroissantS. Restivo(.), 2001, *Degrees of Compromise: Industrial Interests and Academic Values*, Albany, NY: State University of New York Press.

Dietz, J., 2004, *Scientists and Engineers in Academic Research Centers—An Examination of Career Patterns and Productivity. Doctoral Dissertation*, Atlanta, GA: Georgia Institute of Technology.

Dietz, J., I. Chompalov, B. Bozeman, E. Lane, and J. Park, 2000, 'Using the Curriculum Vita to Study the Careers of Scientists and Engineers: An Explanatory Assessment,' *Scientometrics* **49** (3), 419–442.

Dupree, H., 1957, *Science in the Federal Government: A History of Policies and Activities to 1940*, Cambridge, MA: Belknap Press of Harvard University Press.

Etzkowitz, H., A. Webster, and P. Healey, 1998, *Capitalizing Knowledge: New Intersections of Industry and Academia*, Albany, NY: SUNY Press.

Fairweather, J., 1988, *Entrepreneurship and Higher Education: Lessons for Colleges, Universities, and Industry*, Washington, DC: ASHE.

Feller, I., 1997, 'Technology Transfer from Universities,' in J. Smart (ed.), *Handbook of Higher Education*, XII New York: Agathon Press, pp. 1–42.

Feller, I. and Roessner, D, 1995, 'What does Industry Expect from University Partnerships?' *Issues in Science and Technology*, Fall, 80–84.

Fox, M.F., 1983, 'Publication Productivity Among Scientists: A Critical Review,' *Social Studies of Science* **13**, 285–305.

Gaughan, M. and B. Bozeman, 2002, 'Using Curriculum Vitae to Compare Some Impacts of NSF Research Grants with Research Center Funding,' *Research Evaluation* **11** (1), 17–26.

Geiger, R., 1986, *To Advance Knowledge: The Growth of American Research Universities 1900–1940*, New York: Oxford University Press.

Geiger, R., 1990, 'Organized Research Units—Their Role in the Development of University Research,' *Journal of Higher Education* **61** (1), 1–19.

Geiger, R., 1993, *Research and Relevant Knowledge: American Research Universities Since World War II*, New York: Oxford University Press.

Godin, B., 1995, 'Research and the Practice of Publication in Industries,' *Research Policy* **25**, 587–606.

Gray, D. and S.G. Walters, 1998, *Managing Industry/University Cooperative Research Center: A Guide for Directors and Other Stakeholders*, Columbus, OH: Battelle Press.

Hackett, E., 2001, 'Organizational Perspectives on University–Industry Research Relations,' in J. Croissant and S. Restivo (eds.), *Degrees of Compromise: Industrial Interests and Academic Values*, Albany, NY: SUNY Press, pp. 1–21.

Hetzner, W., T. Gidley, and D. Gray, 1989, 'Cooperative Research and Rising Expectations: Lessons from NSF's Industry/University Cooperative Research Centers,' *Technology in Society* **11**, 335–345.

Ho, Y., C. Chiu, T. Tseng, and W. Chiu, 2003, 'Assessing Stem Cell Research Productivity,' *Scientometrics* **57** (3), 369–376.

Ikenberry, S. and R. Friedman, 1972, *Beyond Academic Departments*, San Francisco: Jossey-Bass Publishers.

Kingsley, G., B. Bozeman, and K. Coker, 1996, 'Technology Transfer and Adsorption: An R&D Value Mapping Approach to Evaluation,' *Research Policy* **25**, 967–995.

Kornhauser, W., 1962, *Scientists in Industry: Conflict and Accommodation*, Berkeley, CA: University of California Press.

Kleinman, D. and S. Vallas, 2001, 'Science, Capitalism, and the Rise of the 'Knowledge Worker': The Changing Structure of Knowledge Production in the United States,' *Theory and Society* **30** (4), 451–492.

Lee, Y.S., 1998, 'University–Industry Collaboration on Technology Transfer: Views from the Ivory Tower,' *Policy Studies Journal* **26** (1), 69–84.

Lotka, A.J., 1926, 'The Frequency Distribution of Scientific Productivity,' *Journal of the Washington Academy of Science* **16**, 317–323.

Merton, M., 1968, 'The Matthew Effect in Science,' *Science* **159**, 56–63.

Noyons, E.C.M., M. Luwel, and H.F. Moed, 1998, 'Assessment of Flemish R&D in the Field of Information Technology: A Bibliometric Evaluation based on Publication and Patent Data, Combined with OECD Research Input Statistics,' *Research Policy* **27**, 285–300.

Pelz, D. and F. Andrews, 1976, *Scientists in Organizations: Productive Climates for Research and Development, Revised Edition*, Ann Arbor, MI: Institute for Social Research, University of Michigan.

Peters, L. and H. Etzkowitz, 1990, 'University–Industry Connections and Academic Values,' *Technology in Society* **12**, 427–440.

Peters, L. and Fusfeld, H., 1983, "Current U.S. University–Industry Research Connections", in *University–Industry Research Relationships*. National Science Board. National Science Foundation, Washington, DC.

Powell, W. and J. Owen-Smith, 1998, 'Universities and the Market for Intellectual Property in the Life Sciences,' *Journal of Policy Analysis and Management* **17** (2), 253–277.

Powers, D., M. Powers, F. Betz, and C. Aslanian, 1988, *Higher Education in Partnership with Industry: Opportunities and Strategies for Training, Research, and Economic Development*, San Francisco: Jossey-Bass Publishers.

Price, D. and D. Beaver, 1966, 'Collaboration in an Invisible College,' *American Psychologist* **21**, 1011–1018.

Rogers, J.D. and B. Bozeman, 2001, 'Knowledge Value Alliances: An Alternative to the R&D Project Focus in Evaluation,' *Science, Technology & Human Values* **26** (1), 23–55.

Slaughter, S. and L. Leslie, 1997, *Academic Capitalism: Politics, Policies, and the Entrepreneurial University*, Baltimore: The Johns Hopkins University Press.

Smith, B., 1990, *American Science Policy Since World War II*, Washington, DC: The Brookings Institution.

Stahler, G.J. and W.R. Tash, 1994, 'Centers and Institutes in the Research University: Issues, Problems, and Prospects,' *Journal of Higher Education* **65** (5), 540–554.

Stephan, P. and S. Levin, 1992, *Striking the Mother Lode in Science: The Importance of Age, Place, and Time*, New York: Oxford University Press.

Xie, Y. and K. Shauman, 1998, 'Sex Differences in Research Productivity: New Evidence About an old Puzzle,' *American Sociological Review* **63** (6), 847–870.

Zuckerman, H., 1991, 'The Careers of Men and Women Scientists: A Review of Current Research,' in H. Zuckerman, J. Cole and J. Bruer (eds.), *The Outer Circle: Women in the Scientific Community*, New Haven: Yale University Press, pp. 27–56.