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Academic careers, patents, and productivity: industry experience as scientific and technical human capital

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Abstract

We examine career patterns within the industrial, academic, and governmental sectors and their relation to the publication and patent productivity of scientists and engineers working at university-based research centers in the United States. We hypothesize that among university scientists, intersectoral changes in jobs throughout the career provide access to new social networks and scientific and technical human capital, which will result in higher productivity. For this study, the curriculum vitae of 1200 research scientists and engineers were collected and coded. In addition, patent data were collected from the U.S. Patent and Trademark Office. The overarching conclusion from our analysis is that the academic scientists' and engineers' research careers we studied are quite different than characterized in the research productivity literature that is a decade or more old. The wave of center creation activity that began in the early 1980s and continues today has resulted not only in greater ties between universities and industry, but also markedly different academic careers.
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1. Introduction

As universities ramp up to increase their technological contributions and their commercial focus, the universities' cultures inevitably change and, indeed, the very nature of the university as a social institution may undergo change. How do these changes interact with the career patterns and prerequisites of the scientists and engineers who are expected to take the lead in universities' technology-based commerce? What are the impacts of industrial "opportunities" or "contamination?" The way we approach these questions is to examine the career and attributes of university scientists and engineers who presently engage in high levels of patenting and commercial activities, especially those who have worked in industry as well as in universities. How are they different? The answer to this question may tell us much about the potential and the potential limits of universities' technology-based commerce.

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Thus, a central question of our paper is "during the course of scientists' or engineers' careers, what are the effects of changes in jobs, especially movement between universities and industry, on productivity, especially patenting?" Specifically, we not only test a model of research productivity, specifically publications and patent counts, considering the effects of diversity of job experiences, but also the interactive impacts of grant awards, early publication, and mentoring opportunities. In contrast to the existing body of literature, many of these variables can be affected by the policies of funding agencies.

Our research uses data from a U.S. Department of Energy (DOE) and National Science Foundation (NSF) funded project called the *Research Value Mapping Program*, which is headquartered at the Georgia Institute of Technology School of Public Policy. The program is studying new social and economic approaches to the valuing of publicly funded research—specifically as it is carried out in research centers. The data for our study include the curriculum vitae (CVs) of 1200 research scientists and engineers supported by DOE, the Department of Defense, and NSF research centers have been collected and coded. In addition to the CV data, patent data were collected from the U.S. Patent and Trademark Office (USPTO) database.

Our approach differs from previous approaches in that it examines the pattern of researchers' careers over time and the effect of job changes and other critical events to the rate of productivity over time. It has its intellectual roots in a scientific and technical human capital (S&T human capital) theory (Bozeman and Corley, 2004; Bozeman et al., 2001) of knowledge generation that suggests that human and social capital building experiences over time affect the formation and pattern of scientific careers, and these opportunities intersect and act in synergistic ways to affect long-term productivity. In brief, we find considerable intersectoral diversity within the careers scientists and engineers working in science and engineering research centers. And, while higher publication productivity seems to be associated with more "traditional" academic careers, patent productivity seems to be associated with less traditional, more industry oriented careers even though a substantial fraction of those who have worked in industry continue to patent in while in academia. In addition, we argue that there is potential policy benefit in removing artificial boundaries set up in the extant literature on academic and industry careers where careers are treated as if they were consistently academic or industrial in nature.

The theory implies that a diversity of job experiences will affect collaborative patterns and the exchange of human capital through the building of a wider variety of network ties and social capital. This assertion is related to Granovetter's (1973) notion that greater benefits accrue to those who are able to tap "weak ties" (e.g., a friend of friend) due to exploitation of human and social capital that is non-redundant with one's one web of human and social capital endowments[1].

2. Science and engineering careers and innovation: relevant literature

Studies of the careers of scientists originally grew out of questions as to why there seemed to be such a skewed distribution of research productivity across the population of academic scientists. As early as 1928, Alfred Lotka observed that a small minority of the population of scientists produces the vast share of published scientific work. But what explains the fact that many researchers have few publications over the lifetime, while others produce as many as 600 or more? For years, researchers in sociology, psychology, economics, and other disciplines have tried to explain why.

Two literatures, separate to a surprising degree, provide a background for thinking about the impacts of university scientists' and engineers' (hereafter, "university scientists") careers on institutional capacity for innovation and individual capacity for productivity. The management of innovation literature, anchored in economics and the business disciplines, has a long history of relevant studies of careers, typically focusing on industrial scientists. The study of productivity has chiefly been in the purview of either economics, focusing on human capital productivity, and sociology, focusing on the output of knowledge-based products.

2.1. Industrial careers and management of innovation

Traditionally, studies of scientific and technical careers have taken a single sector focus, either on the

[1] See also Burt, 1992, 1997a, 1997b.

industrial track or the academic track exclusively, mostly due to divergent interests in industrial management of innovation versus the sociological nature of academic science. Studies of academic researchers (e.g., Keith and Babchuk, 1998)—having their roots in the sociology of science—have focused principally on the publication productivity of scientists and promotion in job rank. On the other hand, studies of industrial scientific and technical careers have their historic roots in the discipline of management and the management of innovation. They tend to focus on engineers (Goldberg and Shenhav, 1984; Allen and Katz, 1992), on the dual career ladder (Shepard, 1958; Allen and Katz, 1986; Gunz, 1980, 1989), on gatekeeping behavior (Turpin and Deville, 1995), innovation (Fusfeld, 1986; Burns, 1994; Rosenberg and Nelson, 1994; Mowery, 1998), technological obsolescence (Dalton and Thompson, 1971; Pazy, 1990; Bartel and Sicherman, 1993; McCormick, 1995), and the management of technical personnel (e.g., Turpin and Deville, 1995; Debackere et al., 1997; Bowden, 1997).

In reality, however, many researchers change jobs between academia, industry, and government—sometimes changing sectors multiple times or working in multiple settings simultaneously. In the market context, economists often label this flow of knowledge from one firm to another "knowledge spillovers" (Jaffe, 1989; Griliches, 1992; Jaffe et al., 1993). In neoclassical economic thought, spillovers are considered to be inefficient to the operation of the market since creators of knowledge have difficulty capturing and containing its benefits. Yet, from a knowledge generation viewpoint, they can be viewed as often efficacious. The human and social capital that a researcher takes from one job to another (and perhaps from one job sector to another) may provide critical and ongoing knowledge inputs into new problems. The flow of people from one organization to another (such as from industry-to-academia and vice versa) is arguably key in the process of knowledge transfer, the diffusion of knowledge across organizations (Rogers, 1995), and the creation and maintenance of diverse knowledge networks over the career.

Yet there are even fewer empirical studies examining collaborative research between industrial and academic scientists and engineers. The most closely related in this regard is Landry et al. (1996). Although they did not address social capital directly, their study provides one of the few studies (for a focus on technology transfer offices and productivity see also Siegel et al. (2003)) seeking to relate research collaborations in the industrial setting with academic productivity. They concluded that collaborative research in any form (between academic researchers and other academic researchers or between academic researchers and researchers in government and industry) "may indeed increase" the academic researcher's productivity. They also found, however, that collaboration between academic and industry personnel had "significantly more impact" on productivity on the part of the academic researcher than did collaborations with other academics or government personnel. However, their findings need to be approached with some caution because their research is based on a survey questionnaire of academic researchers affiliated with universities only in Québec. The survey also suffered from a very low response rate (17 percent).

Zucker et al. (1998) examined geographically localized knowledge spillovers that occurred when superstar biotechnology researchers were affiliated both with universities and with firms. Through co-authorship patterns, they examined several types of social capital bonds between academic superstar researchers and scientists in local biotechnology firms, including collaborations (where there is no formal link between the two) and affiliations (where the superstars took on formal positions within the firm). What they found suggests this mixing of S&T human capital may have very real economic returns. Five articles co-authored between the academic superstars in conjunction with firm scientists corresponded to 5 more products in development, 3.5 more products on the market, and 860 more employees for the biotech firms. What role the social capital bonds and the nature of those bonds played in the increased output remains a matter for conjecture.

2.2. Academic careers and productivity

The lineage on academic research productivity begins principally in the 1950s with the notable work of Merton (1957, 1961, 1968) to explain the social stratification of science as a sociological community, and with Roe (1956, 1973) to explain the psychology of eminent scholars. But, it was not until the late 1960s and 1970s that academic productivity research blossomed with the works of Price (1963), the Coles (1967, 1970, 1973, 1979), Crane (1965, 1969, 1970, 1972), Allison (Allison and Stewart, 1974; Allison et al., 1982; Allison and Long, 1987, 1990), and a host of others (Clemente, 1973; Faia, 1975; Reskin, 1977, 1978; Friedkin, 1978; Diamond, 1984, 1986). These scholars effectively set the agenda and the intellectual milieu for what was to follow. Some of these scholars were more concerned with the reward and recognition system of science, some with social structure and stratification, some with the distribution of resources and support, and others with more internally driven, innately defined factors.

Sociologists of science have long focused on scientific productivity in their studies of the sociological structures of science (Merton, 1961). These studies dealt with how science is organized as a sociological entity, not about how scientists and engineers produce and make use of knowledge. They had a profound and lasting effect on how careers in science are conceived of today. Their inadvertent effect, however, was to mark "science" as a province of the academic enterprise within its cultural norms (Merton, 1957, 1961) governing the creation, recognition, and sharing of knowledge. Industry, or industrial jobs within a largely academic career, was not considered in these studies.

Much of the scholarly work on academic productivity reflects these norms by placing social factors in the background, favoring instead measures of institutional and personal prestige, for example (Cole and Cole, 1967; Cole, 1970; Crane, 1970; Reskin, 1977; Long, 1978; Long et al., 1979). Most of these models are essentially elite models that posit that scientific capital accrues disproportionately to those born of elite institutions with access to early advantages.

2.3. Integrative approaches

The research on scholarly productivity has proceeded along several quite different themes, largely based on assumptions about determinants of productivity. Thus, there are well developed literatures on, for example, effects of prestige (e.g., Crane, 1965; Cole and Cole, 1967; Long et al., 1993), life cycle (e.g., Levin and Stephan, 1989, 1991; Elder and Pavalko, 1993; Elder, 1994), educational endowments (e.g., Long and McGinnis, 1985; Nordhaug, 1993; Sweetland, 1996; NAS, 1999), and social network ties (e.g., Mullins, 1968; Granovetter, 1973; Burt, 1992, 1997a, 1997b; Rappa and Debackere, 1992; Hummon and Carley, 1993; Debackere and Rappa, 1994; Constant et al., 1996), to name some of the more prominent approaches. But especially relevant to our concern are the more integrative approaches that have been developed in the past decade or so.

Stephan and Levin (1992) attempted to integrate the work of several research traditions by pointing to a utility-based view of scientific productivity where scientists pursue the extrinsic rewards of recognition and prestige among peers but also the intrinsic rewards of puzzle solving. They proposed three major motivators to productivity that interact with age over scientists' careers: the puzzle (intrinsic pleasure), the ribbon (recognition), and the gold (rewards). They argued that three broad areas constitute something of a self-governing incentive system for scientists to behave in socially beneficial ways. Scientists continue investing in their own productivity until a point in the life course where further investments are unlikely to show "profitable" returns.

More recently, there has been growing recognition in policy circles of a need to place more research emphasis on the socially-embedded nature of knowledge production (e.g., Callon et al., 1991; Callon and Law, 1989; Callon, 1992; Courtial et al., 1994; Kostoff et al., 1994; Cozzens et al., 1994; Sarewitz, 1996; Katz and Martin, 1997; Caracostas and Muldur, 1998; Bozeman and Corley, 2004). In fact, as knowledge and information become more central to the functioning of the economy, they become more central to societal and social well-being and, thus, to policy. It could be argued that policymakers, in awarding grants for scientific research projects, should liken the process to putting bulbs in the ground—bulbs that grow scientific capacity over the long term even if they do not outwardly flourish in the immediate term. By favoring capacity—in the form principally of the generation of human and social capital—policymakers could be emphasizing policy-relevant variables that encompass not just knowledge outputs, economic outputs, or social outputs, but all three (Dietz, 2000). Arguably, then, public R&D evaluation should center not wholly on economic value or even improvements in state-of-the-art, but on the growth of capacity and S&T human capital (Bozeman and Rogers, 2002).

The S&T human capital approach to scientific productivity builds most prominently on the intellectual tradition of Crane's (1969, 1972) social network approach and others (e.g., Price and Beaver, 1966) in the collaborative view of scientific productivity over the life course (Elder, 1994). The S&T human capital perspective puts more weight on the human and social assets or endowments that scientists bring to their work than do previous models. Some are obvious like the formal assets, such as educational credentials and grant awards, that scientists and engineers accumulate. Other assets are more subtle, less formal, but perhaps even more important. Each scientist and engineer can be thought of as a unique embodiment of "S&T human capital"—a walking set of knowledge, skills, technical know-how, and, just as important, a set of sustained network communications, often dense in pattern and international in scope (Dietz et al., 2000). In previous work (Dietz, 2000; Bozeman et al., 2001), we outlined an S&T human capital model as an alternative model for research evaluation, originating in response to the limitations of traditional economic, peer assessment, and case study approaches. S&T human capital includes not only the researcher's human capital (Becker, 1962), but also the social capital he or she draws upon in creating knowledge and interacting in various social and professional contexts. It includes not just the educational credentials normally recognized in traditional human capital models (Becker, 1962, 1964; Schultz, 1963, 1971) but the researchers' tacit knowledge (Polanyi, 1967, 1969), craft knowledge, and know-how. And, essential to the effective exploitation of all of these human capital endowments is the social capital (Bourdieu, 1986; Bourdieu and Wacquant, 1992; Coleman, 1988, 1990; Putnam, 1993; Burt, 1997a, 1997b) that scientists continually exercise in engaging their interests. These endowments not only make the study of scientists' and engineers' career trajectories more difficult than other professionals (e.g., less amenable to standard labor models) but also more nuanced and challenging. The movement of, and constant reshaping of S&T human capital is, arguably, a vital element of scientific discovery, technological innovation, and even economic development. As of yet, few studies have attempted to apply the concept of social capital to scientific research, some exceptions being Walker et al. (1997), Gabbay and Zuckerman (1998), Nahapiet and Ghoshal (1998), Bozeman et al. (2001) and Dietz (2000).

3. Research questions and hypotheses

Our primary research question is "what effects do job transformations[2] and career patterns have on productivity (as measured in publication and patent counts) over the career life cycle?" The central hypothesis to be tested—the "diversity" hypothesis—is derived from human and social capital theory:

Diversity Hypothesis: "Among university scientists, intersectoral changes in jobs throughout the career will provide access to new social networks, resulting in higher productivity, as measured in publications and patents."

The diversity hypothesis is taken from S&T human capital theory (Bozeman et al., 2001; Bozeman and Corley, 2004). The reasoning is straightforward. With more diversity in work experience, the scientist or engineer will develop stronger network ties, leading to increased S&T human capital, which, in turn, provides enhanced skills and access to knowledge gatekeepers. There is some suggestive empirical support. Lee and Bozeman (in press) found that job diversity was associated with increased collaboration and that collaboration led to greater productivity. However, the research literature (e.g., Reskin, 1977; Long, 1978; Long et al., 1979) provides somewhat more support for the rival hypothesis, that university researchers who remain in a university setting will, over a career span, be more productive.

We refer to the rival to the diversity hypothesis as the "homogeny," a term borrowed from biology meaning "correspondence in form or structure."

Homogeny Hypothesis: "Among university scientists and engineers, a 'traditional' career path, defined as spending one's entire post-Ph.D. career in universities, will yield higher productivity."

By this hypothesis, scientists and engineers who exhibit a career pattern of relatively uninterrupted job

[2] The word "transformations" has been used here rather than "changes" in order to remind the reader that some jobs are held concurrently. The word "changes" suggests that one has left a present position to take on a new position. Transformations means a new job either held singly or concurrently with other jobs.

sequences in academia will have higher publication productivity than those who do not, chiefly because of differences in job incentives among academia, industry, and government. It is well known that academia generally has stronger priorities for publishing productivity. However, following a non-traditional career path (i.e., a larger proportion of time spent in industry and government jobs) may result in lower overall productivity, but higher patent productivity for those with higher levels of career time in industrial jobs.

Two ancillary hypotheses are also considered here: an "education and training" hypothesis and a "precocity" hypothesis. These are stated as follows:

Education and Training Hypothesis: "Early career experiences through graduate assistantships and post-doctoral research experiences will result in higher productivity." The presumption is that these early experiences will provide opportunities to build S&T human capital.

Precocity Hypothesis: "Scientists and engineers who demonstrate early productivity by publishing before the doctorate will exhibit higher career productivity overall." The presumption is that such individuals may have greater innate talent or higher quality graduate training. This hypothesis flows from theory and research on accumulative advantages.

4. Data and methods

4.1. The data

As mentioned briefly above, our data include the curriculum vitae of 1200 research scientists and engineers supported by DOE, the Department of Defense, and NSF research centers. For each respondent, patent data were collected from the U.S. Patent and Trademark Office database.

Ours is not a general sample of university scientists and engineers, but rather academic faculty who are affiliated with research centers that were designed to have industrial ties. The sample includes sufficient number of persons with diverse job sector experience to permit the testing of a job transition model. As universities take on more of the characteristics of the private sector, when it comes to the management and diffusion of intellectual property, and as industry continues to invest more money in academic research (from 3.8 percent of the total in 1980 to 6.9 percent in 2000 (NSB, 2002; Appendix 4-07)), this issue takes on greater policy relevance

The data sources and analyses used in this study are unique. Few studies have examined aggregate CV data (Bonzi, 1992; Dietz et al., 2000; Gaughan and Bozeman, 2002; Lee and Bozeman, in press) and this is the first to incorporate patent data in the analysis of CV data.

4.2. Constructs and variables

4.2.1. Diversity of career pattern

The effect of the diversity of career pattern on productivity is measured by the following variables: the proportion of the scholar's career spent in industry and governmental jobs, the first job (industry or government) after the doctorate, and a dummy variable for those who have had at least one job in all three sectors (named "the triple helix").

4.2.2. Homogeny of career pattern

A variable "homogeny" was created to index the extent to which a career pattern more or less conforms to the norm. The data set included 5490 job transformations. All of these were examined and conditional probabilities were constructed for all possible job transformations. For example, of all respondents who held job type A, what are the relative frequencies with which they proceeded to job type B or C or D, etc.? For each respondent a string of career conditional probabilities was constructed, summed, and divided by the total number of jobs that respondent had held over the career. The result is a variable that measures how far from the norm a respondents career pattern is. The variable has a possible range of 0–100. In practice, the range of this variable was 0.35–72.47 with a mean of 14.47 and a standard deviation of 18.10. Individuals with higher values indicate more "typical" the career patterns.

4.2.3. Education and training and precocity

The education and training and precocity hypotheses are relatively straightforward in terms of variables and measurement. Under the education and training hypothesis those individuals who have had a graduate assistantship and/or postdoctoral position are expected to have higher overall career productivity than those who have not. Likewise, those who publish the year of the doctorate or earlier are also expected to have higher overall career productivity.

4.3. Analytical approaches

With respect to analytical approach, the research uses descriptive statistics, Tobit models, and Poisson models, which are appropriate due to the skewness and censoring of productivity data.

The basic statistical models to be estimated are as follows:

$$\begin{aligned} Y = {} & \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \\ & + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} \\ & + \beta_{11} X_{11} + \beta_{12} X_{12} + \beta_{13} X_{13} + \beta_{14} X_{14} \\ & + \beta_{15} X_{15} + \beta_{16} X_{16} + \beta_{17} X_{17} + \beta_{18} X_{18} \\ & + \beta_{19} X_{19} + \beta_{20} X_{20} + \beta_{21} X_{21} + \beta_{22} X_{22} \\ & + \beta_V \mathbf{X_V} + \varepsilon \end{aligned}$$

where,

X_1 = job homogeny (index of career pattern conformity);
X_2 = precocity (cumulative number of publications at the doctorate year);
X_3 = had graduate assistantship (1 = Yes, 0 = No);
X_4 = held postdoctoral position (1 = Yes, 0 = No);
X_5 = triple helix (had one or more jobs in all three sectors);
X_6 = first job was industry job? (1 = Yes, 0 = No);
X_7 = first job was government job;
X_8 = years in industry jobs/total job years;
X_9 = years in government jobs/total job years;
X_{10} = total grants/career length;
X_{11} = industry grants/total grants;
X_{12} = federal grants/total grants;
X_{13} = years in all jobs/career length;
X_{14} = square of above job variable;
X_{15} = doctorate granted before 1972? (1 = Yes, 0 = No);
X_{16} = doctorate granted 1972–1980;
X_{17} = doctorate granted 1981–1987;
X_{18} = doctorate granted 1988–1993;
X_{19} = doctorate in biological science? (1 = Yes, 0 = No);
X_{20} = doctoral field in computer science;
X_{21} = doctoral field in engineering;
X_{22} = doctorate field in physical sciences;
$\mathbf{X_V}$ = a vector of dummy variables for each research center;
Y = either the patent rate (number of patents per career year) or the publication rate (number of publications per career year starting the year after the doctorate).

5. Findings

The findings are presented in three sections, first descriptive analysis, then the Tobit models and, finally, the Poisson models.

5.1. Descriptive results for job transformations

Table 1 gives the descriptive information for the 5490 job transformations made by the scientists and engineers over the course of their careers (ending when RVM data were collected in 2000). The average is approximately 5.7 transformations per respondent.

The majority of transitions are academic-to-academic; these accounted for 62.5 percent of all job transformations. Academic-to-industry job transformations accounted for 4.8 percent of all job transformations. Academic-to-government transformations represented 2.9 percent of all transformations. For any given researcher in an academic position, the likelihood that the following position will be in academia is 0.85, that it will be in industry is 0.07, and that the position will be in government is 0.04. The remaining 0.04 represents the frequency of following an academic position within a consulting position.

Industry-to-industry job transformations accounted for 4.5 percent of all job transformations. Industry-to-academic job transformations accounted for 8.1 percent of all job transformations. Government-to-government job transformations accounted for 1.6 percent of all job transformations. Government-to-academic job transformations accounted for 3.8 percent of all job transformations. Government-to-industry

Table 1
Job transformations across and within sectors (frequencies)

From job (job sector)	To job					
	Academic	Industry	Government	Consulting	Medical	Totals
Academic	3429	265	158	163	14	4029
Industry	447	249	39	26	2	763
Government	211	53	86	10	1	361
Consulting	150	16	5	105	0	276
Medical	28	3	2	0	28	61
Total						
	4265	586	290	304	45	5490

transformations represented just 1 percent of all transformations.

5.2. Tobit model results

The basic statistical model estimated in our Tobit model is described above. We present results in terms of, first, publication productivity and, then, patent productivity.

5.3. Publication productivity

Several factors are associated with higher publication productivity as seen in Table 2. First, publication precocity and career homogeny were associated with higher publication rates. For each paper published by the year of the doctorate, the publication rate after the doctorate increased by 0.12, holding all else constant.[3] The effect of career homogeny on publication rate is low (i.e., the coefficient is 0.05), suggesting a slightly positive association between career pattern homogeny and publication productivity.

Among the variables that had statistically significant coefficient estimates, the strongest effects were field differences (with physical and mathematical scientists and engineers having higher publication productivity),[4] cohort differences (where earlier Ph.D. age cohorts exhibited higher productivity than the most recent cohort possibly due to the fact that larger proportion of their peak productivity years was captured in the dataset), and center affiliation differences (where the scientists and engineers in some centers tended to be more productive than in other centers). Precocity and homogeny both had a weak, positive, relationship with publication rates (Table 3).

The coefficients on the education variables were neither statistically significant, nor were the coefficients on the variables associated with diversity of job patterns or grant patterns. Finally, the overall model was statistically significant (Wald Chi-square statistic of 179 and *P*-value of 0.00).

5.4. Patent productivity

Patent productivity seems to be affected by the proportion of total job years spent in industry, and by field and cohort differences. The coefficient estimate on precocity was positive but small. For each paper published by the year of the doctorate the patent rate increased by 0.02, holding all else constant (see Table 4).

The proportion of job years spent in industry had a strong positive relationship to patent productivity. As the number of years a researcher spent in industry as a proportion of his or her total career years increased by one percent, the model estimates that the average number of patents per year increases by 0.83, holding all else constant.

Those who earned their doctorates before 1980 seem to patent at higher rates than more recent cohorts. Like publication rate, this may be due to the likelihood that scientists and engineers in earlier Ph.D. cohorts have experienced their prime productivity years whereas those in more recent cohorts may not yet have reached their productivity peak.

[3] Unless specified, all results discussed yielded variable coefficients with *P*-values of 0.05 or below.

[4] See Table 3 for publication and patent rate means for specific fields.

Table 2
Tobit model of publication rate (number of publications after the year of the doctorate as a proportion of career length in years)

Independent variables	Estimated coefficients	Standard error	Asymptotic *T*-ratio	*P*-value	Normalized coefficient
Career homogeny index[a]	0.049	0.005	3.522	*0.000	0.017
Precocity[b]	0.120	0.008	5.270	*0.000	0.042
Held postdoctoral position[c]	−0.309	0.085	−1.265	0.206	−0.107
Triple helix[d]	0.277	0.109	0.877	0.380	0.096
First job was industry job[c]	−0.038	0.097	−0.134	0.894	−0.013
First job was government job[c]	−0.548	0.130	−1.464	0.143	−0.190
Years in industry jobs/total job years	−0.640	0.231	−0.960	0.337	−0.222
Years in government jobs/total job years	1.154	0.328	1.220	0.222	0.400
Number of job institutions/career length	−1.333	0.265	−1.747	0.081	−0.462
Square of above job variable	0.051	0.088	0.200	0.842	0.018
Total grants/career length	0.138	0.043	1.110	0.267	0.048
Industry grants/total grants	0.170	0.304	0.194	0.846	0.059
Federal grants/total grants	0.664	0.130	1.776	0.076	0.230
Doctorate granted before 1972[c]	1.842	0.135	4.723	*0.000	0.638
Doctorate granted 1981–1987[c]	1.537	0.127	4.182	*0.000	0.533
Doctorate granted 1972–1980[c]	2.096	0.131	5.559	*0.000	0.727
Doctorate granted 1988–1993[c]	0.909	0.109	2.885	*0.004	0.315
Doctorate in biology[c]	0.013	0.164	0.027	0.979	0.004
Doctorate in computer science[c]	0.543	0.213	0.886	0.376	0.188
Doctorate in engineering[c]	1.037	0.134	2.681	*0.007	0.359
Doctorate in physical sciences[c]	1.380	0.143	3.336	*0.001	0.478
Constant	0.038	0.225	0.059	0.100	0.013

Wald chi-square statistic = 179.38 with 21 d.f., *P*-value = 0.00. Findings about coefficients for individual Center effects are available from the authors (these findings are not included here due to space constraints, but these coefficients have affected the results reported here).

[a] Homogeny is an index of career patterns over time. It is the sum of conditional job probabilities of moving from one job to another corrected for total number of jobs. A high value means the career path is tending toward a common one. A low value means that few others in the data set made such job transformations.

[b] Precocity is the number of publications during or before the year the doctorate was granted.

[c] This is a dummy variable where 1 = Yes and 0 = No.

[d] Triple helix is a dummy variable taking on the value of 1 when the respondent has had at least one job in all three sectors (academia, industry, and government) otherwise the value is 0.

* Indicates *P*-value < 0.05.

Unlike the model of publication rate, career homogeny did not have a statistically significant relationship with patent productivity and the coefficient is 0.

In summary, among the variables that had statistically significant coefficient estimates, the strongest effects were field differences (in particular, physical and mathematical scientists and engineers had higher patent rates), cohort differences (where earlier Ph.D. age cohorts exhibited higher productivity), and center affiliation differences (where the scientists and engineers in some centers tended to be more or less productive than in other centers). Unlike publication productivity, patent productivity seems to be positively related to the proportion of total job years spent in industry. In general, it appears that chemists, electrical engineers, chemical engineers, and physicist had the highest patent rates. Among engineers, civil engineers have lower patent rates. Among scientists, biologists appear to have lower patent rates (see Table 3).

Higher levels of funding from industry sources tended to have a strong positive association with higher overall patent rate ($P < 0.10$). Like the model of publication rate, precocity had weak positive effects on patent rates. However, unlike publication rate, the coefficient on career homogeny was not statistically significant.

Finally, the overall model was statistically significant (Wald Chi-Square statistic of 110 and *P*-value of 0.00). The squared correlation between the observed and expected values of the dependent variable was 0.20.

Table 3
Mean publication and patent rate, by disciplinary fields

Disciplinary field	Number of respondents	Mean publication rate	Mean patent rate
Agricultural sciences	11	2.913	0.040
Biology			
Physiology/pharmacology	13	4.153	0.024
General biology	50	2.859	0.023
Cell/molecular biology	5	4.082	0.020
Genetics	3	3.522	0.033
Business	9	1.848	0.000
Social sciences/humanities	24	3.063	0.002
Computer sciences	44	3.999	0.121
Engineering			
Aerospace engineering	9	2.088	0.030
Bioengineering	7	4.592	0.252
Chemical engineering	68	4.387	0.195
Civil engineering	38	2.964	0.019
Electrical/electrical engineering and computer science	153	4.197	0.267
General engineering	9	3.547	0.035
Environmental engineering	9	2.591	0.021
Industrial engineering	23	2.441	0.006
Materials engineering	38	5.135	0.170
Mechanical engineering	54	3.840	0.137
Engineering, other	40	2.756	0.116
Medicine/health sciences	22	5.497	0.041
Mathematical sciences	18	2.714	0.008
Physical sciences			
Physics	101	4.590	0.180
Geosciences	10	1.965	0.000
Astronomy/astrophysics	6	6.458	0.013
Chemistry	85	4.793	0.278
Physical sciences, other	43	5.099	0.118
Psychology	21	3.946	0.016

5.5. *The Poisson model of patent rate*

As seen in Table 5, there were seven variables for which the coefficient estimates were statistically significant—precocity, the number of years working in industry jobs as a proportion of total job years, the number of industry grants as a proportion of total grants, a doctorate granted between 1972 and 1980, a doctorate in the physical and mathematical sciences, a doctorate in engineering, and a doctorate in computer science. All signs on these variable coefficients are positive; each is associated with higher patent rates.

Among the strongest statistically significant relationships to patent productivity rate is the number of job years the researcher worked in industry as a proportion of total job years. The model estimates that increasing this proportion by 1 percent increases the patent rate by a factor of 5.8, holding all else constant. Similarly, increasing the number of industry grants as a proportion of all grants by 1 percent increases the patent rate by a factor of 3.7.

The finding that the proportion of total job years spent working in industry jobs is associated with an increase in the patent rate is particularly noteworthy when we consider that starting one's career in industry may be detrimental to patent productivity. One possibility is that there are selection effects operating in one's starting a career in industry (e.g., unable to find a suitable academic job) but that movement back and

Table 4
Tobit model of patent rate (number of patents as a proportion of career length in years)

Independent variables	Estimated coefficient	Standard error	Asymptotic *T*-ratio	*P*-value	Normalized coefficient
Career homogeny index[a]	−0.001	0.006	−0.270	0.787	−0.002
Precocity[b]	0.016	0.009	2.917	0.004*	0.027
Held postdoctoral position[c]	−0.056	0.104	−0.900	0.368	−0.094
Triple helix[d]	0.055	0.131	0.704	0.482	0.092
First job was industry job[c]	−0.011	0.115	−0.165	0.869	−0.019
First job was government job[c]	−0.104	0.163	−1.079	0.281	−0.175
Years in industry jobs/total job years	0.828	0.268	5.188	0.000*	1.390
Years in government jobs/total job years	−0.242	0.439	−0.924	0.356	−0.406
Number of job institutions/career length	−0.184	0.350	−0.883	0.378	−0.309
Square of above job variable	0.043	0.118	0.609	0.543	0.072
Total grants/career length	−0.006	0.072	−0.140	0.889	−0.010
Industry grants/total grants	0.415	0.379	1.837	0.066	0.696
Federal grants/total grants	−0.060	0.173	−0.585	0.559	−0.101
Doctorate granted before 1972[c]	0.306	0.168	3.068	0.002*	0.514
Doctorate granted 1972–1980[c]	0.327	0.163	3.362	0.001*	0.549
Doctorate granted 1981–1987[c]	0.166	0.158	1.757	0.079	0.278
Doctorate granted 1988–1993[c]	0.037	0.143	0.431	0.667	0.061
Doctorate in biology[c]	0.305	0.230	2.229	0.026*	0.512
Doctorate in computer science[c]	0.457	0.283	2.712	0.007*	0.767
Doctorate in engineering[c]	0.525	0.192	4.581	0.000*	0.881
Doctorate in physical sciences[c]	0.527	0.201	4.405	0.000*	0.885
Constant	−0.900	0.302	−4.996	0.000*	−1.511

Wald chi-square statistic = 110.99 with 21 d.f., *P*-value = 0.00. Findings about coefficients for individual Center effects are available from the authors (these findings are not included here due to space constraints, but these coefficients have affected the results reported here).

[a] Homogeny is an index of career patterns over time. It is the sum of conditional job probabilities of moving from one job to another corrected for total number of jobs. A high value means the career path is tending toward a common one. A low value means that few others in the data set made such job transformations.

[b] Precocity is the number of publications during or before the year the doctorate was granted.

[c] This is a dummy variable where 1 = Yes and 0 = No.

[d] Triple helix is a dummy variable taking on the value of 1 when the respondent has had at least one job in all three sectors (academia, industry, and government) otherwise the value is 0.

* Indicates *P*-value < 0.05.

forth between industries represents a completely different phenomenon, perhaps indicting attractiveness to multiple sectors.

5.6. Productivity changes in job transformations to and from industry

To test the assertion that intersectoral changes in jobs affect overall productivity, all of the transformations from academic-to-industrial jobs and vice versa were identified and the mean number of publications was calculated for the 5 years before and after the transformation. These means were then summed and averaged over all job transformations made by all scientists and engineers between academia-to-industry. As seen in Table 6, the mean number of publications for the 5-year period preceding a job transformation *from industry-to-academia* (for all scientists and engineers who made this transition) was 1.5 publications per year. For the 5-year period after the transformational move to academia, the mean was 2.6 publications—a 1.1 increase in the mean number (and a statistically significant difference at the 0.05 level). Thus, the average productivity of scientists and engineers increased after a job transformation from industry-to-academia.

A similar analysis was performed for all job transformations made by the scientists and engineers *from academia-to-industry*. For the 5-year period preceding the move, the mean number of publications overall was

Table 5
Poisson model of patent rate (patent count divided by career length in years)

Independent variables	Estimated coefficient	Standard error	*T*-ratio	*P*-value	Standardized coefficient	Experimental coefficient
Career homogeny index[a]	−0.002	0.013	−0.144	0.886	−0.038	0.998
Precocity[b]	0.037	0.015	2.448	0.014*	0.447	1.038
Held postdoctoral position[c]	−0.160	0.228	−0.704	0.481	−0.190	0.852
Triple helix[d]	−0.199	0.293	−0.680	0.496	−0.182	0.819
First job was industry job?[c]	−0.093	0.236	−0.395	0.693	−0.112	0.911
First job was government job[c]	−0.167	0.372	−0.449	0.653	−0.152	0.846
Years in industry jobs/total job years	1.759	0.433	4.066	0.000*	0.893	5.808
Years in government jobs/total job years	−0.679	1.110	−0.612	0.541	−0.234	0.507
Number of job institutions/career length	0.259	0.694	0.373	0.709	0.266	1.295
Square of above job variable	−0.066	0.241	−0.273	0.785	−0.188	0.936
Total grants/career length	0.003	0.126	0.023	0.982	0.007	1.003
Industry grants/total grants	1.311	0.593	2.211	0.027*	0.429	3.708
Federal grants/total grants	−0.702	0.442	−1.587	0.113	−0.548	0.496
Doctorate granted before 1972[c]	0.318	0.363	0.877	0.380	0.326	1.374
Doctorate granted 1972–1980[c]	0.677	0.344	1.970	0.049*	0.682	1.968
Doctorate granted 1981–1987[c]	0.271	0.350	0.775	0.438	0.258	1.312
Doctorate granted 1988–1993[c]	0.133	0.311	0.428	0.669	0.142	1.142
Doctorate in biology[c]	0.852	0.742	1.148	0.251	0.675	2.344
Doctorate in computer science[c]	1.514	0.736	2.057	0.040*	0.821	4.546
Doctorate in engineering[c]	1.768	0.603	2.933	0.003*	2.277	5.860
Doctorate in physical sciences[c]	1.758	0.608	2.893	0.004*	2.050	5.800
Constant	−4.118	0.715	−5.756	0.000*	0.000	0.016

Wald chi-square statistic = 112.68 with 21 d.f., *P*-value = 0.00. Findings about coefficients for individual Center effects are available from the authors (these findings are not included here due to space constraints, but these coefficients have affected the results reported here).

[a] Homogeny is an index of career patterns over time. It is the sum of conditional job probabilities of moving from one job to another corrected for total number of jobs. A high value means the career path is tending toward a common one. A low value means that few others in the data set made such job transformations.

[b] Precocity is the number of publications during or before the year the doctorate was granted.

[c] This is a dummy variable where 1 = Yes and 0 = No.

[d] Triple helix is a dummy variable taking on the value of 1 when the respondent has had at least one job in all three sectors (academia, industry, and government) otherwise the value is 0.

* Indicates *P*-value < 0.05

1.8; for the 5-year time interval following the transformational move to industry, the mean was 2.6—an increase of 0.8 publications per year (also a statistically significant difference). Thus, the mean number of publications for the 5-year period of time following a move from academia-to-industry also increased.

Table 6
Mean number of publications for 5 years before and after a job transformation from and to industry (standard deviation, 95% Confidence intervals)

From industry	Mean	S.D.	Confidence intervals
Mean before	1.50	2.84	(1.23, 1.77)
Mean after	2.60	3.55	(2.27, 2.93)
To industry			
Mean before	1.81	3.01	(1.44, 2.18)
Mean after	2.57	3.12	(2.19, 2.95)

These results may suggest that making a job transformation has important effects on productivity. However, an alternative interpretation is that making a job change is correlated when productivity rates are naturally increasing. For example, it may be the case that researchers in the early stages of their careers are more likely to make job transformations than those in later stages and that this is precisely the same time period when researchers' productivity is on the rise. Another possibility is that transitions are themselves quality indicators (those transitioning are by definition in demand) and higher productivity correlates with this quality indicator.

6. Summary of evidence about hypotheses

6.1. Similarities and differences in publication and patent productivity analyses

Taken as a whole, the analyses of publication and patent productivity reveal some consistent findings. First, physical and mathematical scientists and engineers have higher productivity rates than researchers in other fields. Second, publication precocity seems to have little effect except in cases of extremely high levels of precocity. All of these education and human resource variables taken together suggest long-term, or career, productivity rates are not affected by these variables as measured.

Third, although not statistically significant, we note that, consistently across all of the models, having had a postdoctoral research position is negatively related to career productivity rates at least for those scientists and engineers in our dataset. Fourth, there is some evidence that researchers who made relatively high numbers of institutional job changes have lower productivity than those with fewer.

The major differences in publication and patent productivity involve job and grant related variables. There is some evidence that patent productivity is positively related to closer connections to industry and negatively related to closer connections with government. Higher proportions of the career spent in industrial settings and higher proportions of research funding from industry sources seem to be related to higher patent productivity.

In contrast, a higher proportion of the career spent in industry seems to be negatively related to publication productivity. Finally, the source of the support (industry or federal) is unrelated to publication productivity, while a higher proportional level of industry support is positively related to patent productivity.

6.2. Evidence in support or opposition to hypotheses

6.2.1. Precocity hypothesis

This hypothesis states: “Scientists and engineers who demonstrate early productivity by publishing before the doctorate will exhibit higher career productivity overall (due either to innate talent, working with highly productive scholars, higher quality graduate training, or other factors).”

There is evidence to support this hypothesis, although the relationship between precocity and future productivity appears to be weak and perhaps influenced by several cases of extreme precocity outliers.

The Tobit models estimate that for each additional predoctoral publication, the publication and patent rate increase by 0.12 and 0.02, respectively, holding all else constant. To put this in context, the mean publication rate was approximately four publications per year and the mean patent rate was 0.14 for all scientists and engineers in the RVM dataset. Proportionate to their means then, the effect of precocity on patent rate was actually estimated to be higher. The Poisson model provides consistent results.

6.2.2. Education and training hypothesis

This hypothesis states: “Early career experiences through postdoctoral research experiences will result in higher productivity (because they provide educational and human resources (i.e., human capital) building opportunities).” Across both the Tobit and Poisson models there may be evidence to support the notion that postdoctoral research positions may inhibit longer-term productivity. The Tobit and Poisson model coefficient estimates were negative and moderate in size. In sum, this hypothesis is not supported.

6.2.3. Homogeny hypothesis

This was the main rival hypothesis to the diversity hypothesis. It states: “Following the ‘traditional’ career path will yield higher productivity. Scientists and engineers who exhibit a career pattern of relatively uninterrupted job sequences in academia will have higher publication productivity than those who do not. Likewise, those with higher levels of career time in industrial jobs will have higher patent productivity (due to the differences in job incentives between academia, industry, and government).”

The Tobit model of publication rate estimates that the coefficient of the career homogeny index is positive and statistically significant although small in size (0.05). This means that as the homogeny index increases one point, holding all else constant, the estimated publication rate increases by 0.05. In contrast, for patent rate, the Tobit and Poisson models estimate a coefficient of zero (not statistically significant).

Both models estimate a negative relationship between starting one's career in industry or government and productivity (both for publication and patent rate). For publication rate, the Tobit model estimates a negative relationship with the proportion of career years worked in industry jobs, which suggests a more traditional academic career path results in higher publication rates. Likewise, both models showed a strong positive relationship between proportion of career spent in industry jobs and patent rates, which would be expected under the homogeny hypothesis. Finally, publication productivity is associated with more grants in general, although the source of the grant (federal versus industry) does not seem to matter. Again, this is expected in environments where publication productivity is prized. Overall, there is sufficient evidence to suggest that the homogeny hypothesis is plausibly supported by the data.

6.2.4. Diversity hypothesis

The diversity hypothesis—the central hypothesis of this paper—states: "Inter and intrasectoral changes in jobs throughout the career will result in higher research productivity (due to the opportunity provided to build S&T human capital)." The primary evidence for this hypothesis (and thus against the homogeny hypothesis) is from the descriptive statistics. Higher patent rates were associated with careers proportionally higher in industry jobs and job years in industry. Thus, both publication and patent productivity are associated with some degree of career diversity.

The patent rate was also associated with proportionally higher levels of funding from industry. Thus, the diversity hypothesis may be more relevant in explaining patent productivity as compared to publication productivity.

Although the career homogeny hypothesis may be better supported by the data analysis two important findings are drawn from examining the data through the lens of the diversity hypothesis. First, there seems to be substantial intersectoral diversity among researchers in the RVM dataset, perhaps more than would typically be expected. And, second, the diversity hypothesis is more plausible in explaining patent productivity than it is in explaining publication productivity.

7. Conclusions and policy implications

If there is any single, overarching conclusion from our analysis it is that academic scientists' and engineers' research careers are quite different than characterized in the research productivity literature that is a decade or more old. This is particularly the case for the researchers we studied, all of whom are affiliated with university researcher centers. The wave of center creation activity that began in the early 1980s and continues today has resulted in markedly different academic careers and greater ties between universities and industry.

One of the individuals most responsible for launching the wave of university researcher centers in the U.S. is Erich Bloch, former National Science Foundation Director and Presidential Science Advisor. In a recent interview (Bozeman and Boardman, 2004a,b), Bloch described the motivations behind the creation of the NSF Engineering Research Centers program, a program that has served as a template for the more than 300 present-day NSF university centers as well as centers developed by other government agencies and in other nations:

> The idea (of multidisciplinary collaborative research) needed to penetrate the whole engineering community. I thought 12 (engineering research centers) would send a message. When I looked at NSF it was the paymaster for principal investigators. I thought this was dead wrong. The idea was that the NSF should be concerned about competitiveness and look for new avenues to tie together industry and government and universities.

At least within the domain of university research centers, there does, indeed, seem to be considerable ties and these are reflected not only in more passive ways but also through changes in careers. It is fair to say that there is now a revolving door between industry and university research jobs. Our data provide some preliminary evidence of the rate at which the door revolves. On average, nearly one in six of our respondents' total jobs positions were industry jobs and one in eight of their career years were spent in industry jobs. Approximately half had one or more jobs in industry. One-quarter had worked for government. And, nearly half began their careers in non-academic jobs—for 33 percent the first job was in industry and for 15 percent the first job was government. An average of 24 percent of the grants awarded to researchers in the RVM dataset came from industry. While our data are representative of university centers, not all of academe, it is still surprising to us that academic and industry careers have melded to such a large extent.

One finding that is particularly at odds with the conventional ivory tower model is 20 percent of our respondents took their first academic job 5 or more years into their career. In the past, the conventional wisdom was that a first job in industry all but foreclosed an academic career. Perhaps what has changed, however, is the nature of “an academic career,” with increasing emphasis on industry relations, applications and technology development in addition to the conventional formula of publish-for-tenure.

If, indeed, academic careers have changed fundamentally, in university centers and perhaps elsewhere, it is doubly important to understand that the formula for publication productivity may be quite different from the one for patenting productivity. Not surprisingly, those scientists who have spent a substantial percentage of their career in industry jobs have more funding from industry and a higher rate of patent productivity. This may be due, at least in part, to the trust and social capital required for commercial activity (Daellenbach and Davenport, 2004). In contrast, a higher proportion of the career spent in industry is negatively related to publication productivity. Just as important, and especially policy relevant, the source of grants affects the type of productivity. Those with government grants have higher publications productivity but government grants are actually negative for patenting. Similarly, those with industry grants have higher patenting rates but lower publications rates. The fact that basic grant and contract sources do not complement one another may be a significant policy issue.

Some public policies promote movement back and forth between industry and universities and others promote active collaboration or personnel exchange, such as the NSF Grant Opportunities for Academic Liaison with Industry (GOALI) program. From a policy perspective, it is often assumed that the job exchanges and transitions are useful. But most of the literature on research productivity either assumes or demonstrates negative effects on productivity. Moreover, many institutional barriers remain to university scientists’ working effectively with industry (Hall et al., 2001). But as policymakers seek to encourage flexible scientific careers and university–industry ties, it is crucial to sort out the effects of collaborative work and career transitions on productivity. Our results suggest that the impacts of intersectoral career transitions are complex. As discussed above, job transformations lead to publications productivity boosts not only when the transformation is from industry-to-academia but also from academic-to-industry. Why? It is easy to see why moving from an industry position to an academic one would increase publications, but why does a move from academia, generally publications-dominated, to industry has the same positive effect? We advanced many possibilities, including various methodological artifacts such as selection effects and time lag effects. Nevertheless, this is worth further explanation and, moreover, seems to support the nature of accumulating S&T human capital in multiple settings.

Regarding S&T human capital and public policy, perhaps our most disturbing finding is the negative impact of postdoctoral positions on productivity. This is worrisome not only because of the proliferation of postdoctoral positions, including serial postdocs, but also because some public policies actively promote postdocs through traineeships and other programs. Our findings show that those with no postdoctoral job had a patent rate more than five times those who had postdoctoral jobs. Regarding publications, those with no postdoctoral job averaged 3.6 publications per year compared to 3.2 publications per year for those with one postdoc and 2.7 for those with more than one postdoctoral job.

It is not easy to sort out either the causality or the policy implications of these findings. Among the many possibilities: (1) postdoctoral positions really have become exploitative and are chiefly a low wage means of advancing senior scientists’ agendas; (2) one postdoc position may be useful but the point of diminishing return occurs before a second one; (3) the most talented researchers are the ones who immediately receive and take offers from permanent or tenure track positions; (4) there may be a correlation between having a postdocs and discrimination against women and foreign nationals; (5) the general finding may mask very important field effects (though a level of aggregation below that we examined here). The basic point is that the negative relation in the RVM dataset of both publications and patenting productivity to having a postdoctoral position is worrisome, especially so because the percentage of persons entering postdocs continues to increase. For example, in 1973 only 27 percent of the people earning biomedical Ph.D.'s went into postdoctoral positions, but by 1995 the proportion had risen to 63 percent (Monastersky, 2004). Now that in some fields most researchers have a postdoctoral research position in their careers it seems imperative to know more about why that experience seems to dampen productivity.

Finally, if government policy chooses to focus on the commercial productivity of academic institutions, as seems to be the policy trend, then there is reason to believe that the solution may be human capital in nature. The hiring of researchers with industrial job experience and, perhaps, visiting positions and exchanges with industry may be a productive means of boosting the commercially relevant innovation of universities. The GOALI program, to encourage academic researchers to take sabbaticals in industrial research jobs and vice versa, and similar programs that can be found at Department of Energy and the Department of Commerce agencies, warrant evaluation in relation to the career diversity findings we present.

The question implicit in the title to our paper is "What are the S&T human capital implications of academic careers that include industry working experience?" Our results suggest important effects, sometimes profound ones. The revolutions of the revolving career door warrant close watching.

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