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Conflicting Logics? A Multidimensional View of Industrial and Academic Science

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A growing body of research views industrial and academic science as characterized by conflicting institutional logics. However, other scholars have long claimed that stark differences between the two sectors exist in theory but not in practice. Drawing on both views and the broader organizational literature, we develop a conceptual framework to compare and contrast industrial and academic science along four interdependent dimensions: (1) the nature of work, (2) characteristics of the workplace, (3) characteristics of workers, and (4) the disclosure of research results. We then employ detailed survey data on a sample of more than 5,000 research-active life scientists and physical scientists to examine key aspects of the framework empirically. Our results suggest that the conflicting logics view tends to overstate differences across sectors while ignoring important heterogeneity within sectors. We further advance the understanding of institutional logics by examining the relationships among dimensions of science, including the degree to which differences in the nature of work explain differences in how work is organized and results are disclosed. We discuss directions for future research on the institution of science as well as implications for managers and policy makers concerned with scientific activity within and across sectors.

Key words: industrial science; academic science; institutional logics; basic and applied research; scientist preferences; independence and pay; publishing and patenting
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1. Introduction

A growing body of work on the organization of science is based on the premise that industry and academia are characterized by conflicting institutional logics. Descriptions of the "academic logic" draw primarily on Merton's (1973) model of science, emphasizing the search for fundamental knowledge, research freedom, rewards in the form of peer recognition, and the open disclosure of research results. Industrial science, on the other hand, is seen as following a "commercial logic," focusing on applied research in a setting shaped by bureaucratic control, limited disclosure, and the private appropriation of financial returns from research (Aghion et al. 2008, Fini and Lacetera 2010, Gittelman and Kogut 2003, Lacetera 2009, Murray 2010, Vallas and Kleinman 2008).

Other scholars, however, suggest that sectoral differences are overdrawn. Historians of science, for example, provide descriptions of the coevolution of the two sectors and of nuanced, partially overlapping features (Rosenberg 1982, Shapin 2004, Stokes 1997). Research and development (R&D) managers have for decades rejected common "myths" about the organization of industrial science and about the dispositions of scientists themselves (Box and Cotgrove 1966, Copeland 2007, Nissan 1966). Finally, empirical studies of academic life paint a picture that is quite different from the Mertonian model, emphasizing that "the culture of academic science is a blend of the cultures of science and academe" (Hackett 1990, p. 245).

In our view, the continuing disagreement about similarities and differences between industrial and academic science reflects three deeper gaps in the literature. First, different streams of research focus on different aspects of institutional logics, and we lack a more comprehensive conceptual model of the various dimensions of science that can be compared across sectors. Second, little is known regarding the relationships among various institutional features and, consequently, how sectoral differences in one dimension may explain differences in others. Finally, existing empirical work tends to examine particular aspects of institutional logics within either industry or academia, yet there is little large-scale empirical research that directly contrasts industrial and academic science along multiple dimensions and uses comparable measures.

The current paper seeks to address these gaps. We first review prior work to identify key sources of tension and disconnects. Drawing on that discussion as well as the broader organizational literature, we then develop a more comprehensive and integrated framework that considers four key dimensions of science. Three of the dimensions have for a long time been central in the general organizational literature: the nature of work, characteristics of the workplace, and the characteristics of workers. The fourth dimension—the disclosure of research results—is particularly salient in the context of knowledge work and features prominently in discussions of the institution of science. In examining sectoral differences in each of the dimensions of science, our framework pays particular attention to potential relationships among the four dimensions, thus enriching the discussion of institutional logics by going beyond a simple mapping of their features.

In the empirical part of the paper, we complement the conceptual discussion by drawing on unique survey data from more than 5,000 research-active scientists working in industrial and academic science. Our analysis paints a nuanced picture. On the one hand, we find differences across sectors that are consistent with the conflicting logics perspective, including stark differences in the nature of research or in the use of patents as a disclosure mechanism. On the other hand, we also find notable similarities, such as high levels of freedom as well as significant publishing activity in both sectors. Moreover, although the institutional logics perspective emphasizes differences *across* sectors, we find significant heterogeneity *within* sectors, such as between different types of firms or between different types of academic positions.

Our empirical analysis also provides novel insights into the relationships among dimensions of science. Most notably, we find that differences in the nature of work predict differences in characteristics of the workplace and in disclosure, consistent with the view that different research agendas shape how science is done in the two sectors. However, considerable industry–academia differences in these dimensions remain even for a given type of work. Thus, organizational differences between industrial and academic science do not seem to be simply a "functional" response to different research agendas; rather, they appear to also reflect differences in more general institutional goals, missions, and value systems (Dasgupta and David 1994).

This paper makes three main contributions. First, we synthesize prior work on the institution of science as well as relevant streams of the broader organizational literature to develop a multidimensional framework of science. This framework can serve as an analytical tool for future inquiry into features of science within and across sectors. Second, we provide empirical evidence regarding similarities and differences between industrial and academic science. Broadly speaking, our results highlight the importance of distinguishing abstract models of institutional logics—such as the ideal types of "academic" and "commercial" logic—from the much more nuanced institutional realities of academic and industrial science. As such, our results speak to an ongoing debate regarding the existence and nature of differences in the institutional logics of the two sectors and have important implications for issues such as the division of labor between industry and academia (Aghion et al. 2008, Lacetera 2009), role strain and compensating wage differentials for scientists in industry (Kornhauser 1962, Stern 2004), entrepreneurial activity in the two sectors (Fini 2010), and frictions in the interactions between the sectors (Murray 2010). Finally, we begin to address both conceptually and empirically the relationships among dimensions of science. By providing initial insights into potential sources of industry–academia differences, these results also address a recent call for work on the microfoundations of institutional logics (Thornton and Ocasio 2008). Moreover, our findings regarding the relationships between the nature of work, characteristics of the workplace, and attributes of workers also inform the broader organizational literature by providing novel evidence in an important yet understudied setting.

2. A Multidimensional Framework of Industrial and Academic Science

2.1. Institutional Logics and the Study of Science

The institutional logics approach has its origins in institutional theory, where it provides a link between macro institutions and microlevel actions. Drawing on the work by Friedland and Alford (1991), Thornton and Ocasio (2008, p. 101) define institutional logics as "the socially constructed, historical patterns of material practices, assumptions, values, beliefs and rules by which individuals produce and reproduce their material subsistence." Although institutional logics are difficult to observe directly, they manifest themselves in particular organizational forms, managerial practices, and individual decisions (Fini 2010, Greenwood et al. 2010, Thornton and Ocasio 2008). Institutional logics are often conceptualized in the form of "ideal types." Such ideal types are abstract models of institutional settings that emphasize central features and facilitate comparative analysis and classification (Bradach and Eccles 1989, Thornton and Ocasio 2008, Weber 1949). For example, institutional theorists have contrasted the trustee versus performance logic in the mutual funds industry, aesthetic logic versus efficiency logic in architecture, and editorial logic versus market logic in higher-education publishing (Lounsbury 2007, Thornton and Ocasio 2008). Taking a similar approach, scholars of science increasingly distinguish between an "academic logic" and a "commercial logic" (Fini and Lacetera 2010, Murray 2010, Perkmann et al. 2011). Descriptions of the academic logic draw heavily on Merton's (1973) discussion of the institution of science, emphasizing the quest for fundamental knowledge, research freedom, rewards in the form of peer recognition, and open disclosure of research results.[1] The commercial logic, on the other hand, is thought to entail different and partially conflicting practices and norms, including bureaucratic control, restrictions on disclosure, and the private appropriation of financial returns.

Although the institutional logics of industrial and academic science are viewed as fundamentally different across the two sectors, scientists themselves are often portrayed as very similar. More specifically, it is often assumed that individuals self-select into scientific training based on a strong preexisting taste for science or are socialized into the norms of science while in school (Orth 1959, Shapin 2004, Stern 2004). As a consequence, those scientists who enter industry are thought to experience role conflict and must be paid wage differentials to compensate them for the lack of an "academic" work environment or the opportunity to publish (Aghion et al. 2008, Kornhauser 1962, Miller 1976, Stern 2004).

The institutional logics perspective focuses primarily on describing features of science and on the consequences of institutional differences across sectors. Less attention has been paid to interdependencies between dimensions of science. A particularly important question is whether differences between the logics of industrial and academic science have developed in order to accommodate different types of research, i.e., whether institutional features should be interpreted as "functional" in the sense that they ensure an efficient division of labor between the sectors. Such a functionalist perspective is implicit in economic interpretations of the institution of science, which suggest, for example, that the reputation-based reward system of science overcomes the market failures caused by the public goods nature of basic research results (Stephan 2012). Similarly, organizational and economic theory suggests that higher degrees of research freedom may be optimal for basic research where research goals and the means by which they can be achieved are difficult to specify ex ante (Donaldson 1996, Prendergast 2002). Alternatively, industrial and academic science may have developed different practices, missions, and value systems for reasons other than the efficient division of innovative labor. In their important discussion of "Science" versus "Technology," for example, Dasgupta and David (1994) suggest that the way in which results are disclosed is not a function of the basic versus applied nature of the knowledge per se. Rather, it reflects the "goals accepted as legitimate within the two communities of researchers" (Dasgupta and David 1994, p. 495), where "the community of Science is concerned with additions to the stock of public knowledge, whereas the community of Technology is concerned with adding to the stream of rents that may be derived from possession of (rights to use) private knowledge" (Dasgupta and David 1994, p. 498).

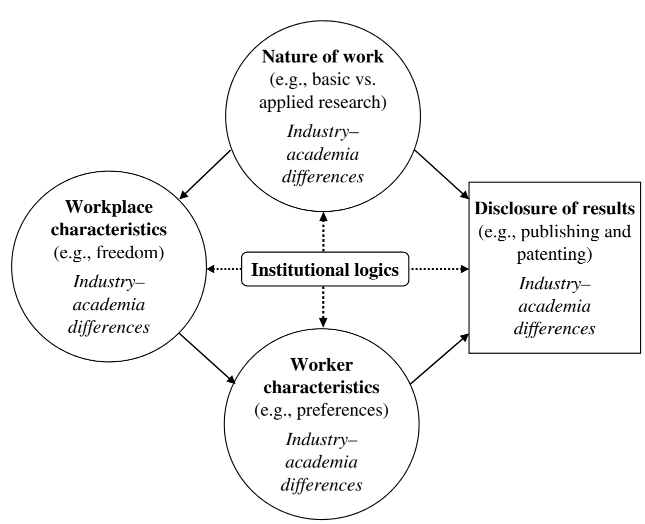
We suggest that a deeper understanding of sectoral differences can be gained with the help of a conceptual framework that identifies key dimensions of science, discusses relationships among these dimensions, and examines potential drivers of differences across sectors. In the following part of the paper, we develop such a framework, focusing on four interdependent dimensions: (1) the nature of work, (2) characteristics of the workplace, (3) characteristics of workers, and (4) the disclosure of research results. Although much of the discussion of institutional logics in science focuses on differences between industry and academia, institutional logics can also be examined at lower levels of analysis, and different logics may coexist within a given institutional realm (Nelson 2005, Perkmann et al. 2011, Thornton and Ocasio 2008). As such, we will complement our examination of sector-level differences with a selective discussion of potential heterogeneity within each sector. Given space and data limitations, our conceptual discussion will focus on selected facets within each dimension and on selected relationships between them.[2] Figure 1 summarizes the framework.

2.2. The Nature of Work

In the conflicting logics view, there is a clear division of labor between industry and academia. Firms focus on applied research with the goal of solving concrete problems valued in the market place (Aghion et al. 2008, Lacetera 2009). The research mission of academia, on the other hand, is to add to the stock of public knowledge by conducting basic research, i.e., research resulting in fundamental insights (Argyres and Liebeskind 1998, Nelson 1959). Because basic research has little direct commercial value, it must be supported by the public or by patrons (Bush 1945, David 2008, Nelson 1959).

Empirically, however, the division of labor between industry and academia is far from clear-cut. Some academic institutions were founded with an explicit charge to assist their regional economies through applied work (see Furman and MacGarvie 2007, Rosenberg and

Figure 1 Conceptual Framework



Nelson 1994), and universities may show an increasing interest in applied work as they search for new sources of funding (Rothaermel et al. 2007). Industrial firms, on the other hand, may have various reasons to engage in basic research activities. Among others, basic research may increase firms' ability to absorb external knowledge (Cockburn and Henderson 1998, Cohen and Levinthal 1990), provide a map for downstream research and development (Fleming and Sorenson 2004), or result in unexpected commercial applications (Rosenberg 1990).

Overall, it is quite clear that although there is a division of innovative labor as suggested by the conventional view of industrial and academic science, there is also some overlap. The empirical questions are how large sectoral differences are with respect to the nature of research and to what extent such differences explain differences in other dimensions of science.

2.3. Characteristics of the Workplace

A second important dimension relates to characteristics of the workplace. Perhaps the greatest attention has been paid to researchers' freedom in choosing what projects to pursue and how to approach them. In the conventional view, academic norms allow researchers to freely choose projects based on personal interest or the perceived importance for the progress of science. The commercial logic, in contrast, limits freedom and subordinates scientists' choices to the needs and requirements of their industrial employers (Aghion et al. 2008, Kornhauser 1962, Lacetera 2009, Vallas and Kleinman 2008).

Organizational and economic theory suggest that sectoral differences in freedom may to some extent result from differences in the nature of work. More specifically, contingency theory as well as agency theory suggests that higher levels of worker autonomy are beneficial in settings where there is uncertainty about the value of different problems or about the best approach to solving a given problem, where effort is hard to observe, or where supervisors lack expert knowledge (Donaldson 1996, Eisenhardt 1985, Foss and Laursen 2005, Ouchi 1979, Prendergast 2002). These criteria are more strongly associated with basic research than with applied work or development (Sauermann and Cohen 2010), suggesting that the level of researcher freedom should be higher in basic research and, thus, in academia.

Even for a given type of research, however, the academic logic may support higher levels of research freedom. In particular, if the mission of academia is to add to the stock of public knowledge, then it is of secondary importance to the university which particular piece of the "puzzle" the scientist solves, as long as the contribution is judged to be significant by the community of peers (Kuhn 1962, Polanyi 1962). Firms, on the other hand, care less about new knowledge per se but rather care about knowledge that complements existing firm assets and increases profit, likely leading them to constrain scientists' choice of projects (Aghion et al. 2008, Lacetera 2009).

A second important workplace characteristic is financial compensation. Industry may be able to pay higher wages because of its focus on applied research with higher expected returns (Aghion et al. 2008). Returns to industrial research may rise further if there are complementarities between basic and applied research (Agarwal and Ohyama 2012) or between research and other resources of the firm such as physical capital or marketing capabilities. A higher financial value of industrial research does not necessarily imply, however, that firms have to pass the value on to individual researchers in the form of higher compensation, especially if the supply of scientists is highly elastic. Thus, we need to consider more deeply how the industrial and the academic logic may differ with respect to appropriation of the value from research. In the conventional view, the academic logic prescribes that much of the knowledge is given away for free to the broader community and that scientists' primary reward from research comes from peer recognition, status in the scientific community, or the pleasure to work on interesting projects of their own choosing (Aghion et al. 2008, Merton 1973, Murray 2010). The commercial logic, in contrast, entails that firms seek to maximize financial returns from research, which typically requires that scientists limit disclosure and forgo some of the nonfinancial rewards offered by academia (Cohen et al. 2000, Sauermann and Roach 2011). To compensate for the lower levels of nonfinancial benefits, firms may have to share some of the financial returns from research with their employees, resulting in higher wages in industry than in academia (Aghion et al. 2008, Rosen 1986, Stern 2004). Consistent with this view, Agarwal and Ohyama (2012) show that Ph.D. scientists working in industry have significantly higher earnings profiles than scientists working in academia.

Although the institutional logics view focuses on sector-level differences in workplace characteristics, there may be considerable heterogeneity *within* sectors as well. In industry, such differences may relate to firm size and age. In particular, organizational scholars have suggested that firms become more bureaucratic and formalized as they grow and mature, implying that larger and older firms may offer their employees less autonomy in their jobs (see Baron et al. 2001, Cardinal et al. 2004, Idson 1990). On the other hand, larger and older firms may offer higher wages than smaller or younger firms because of asset complementarities, differences in nonpecuniary benefits, or higher degrees of specialization (Brown and Medoff 1989, Idson and Feaster 1990, Oi and Idson 1999). With respect to potential heterogeneity within academia, tier 1 institutions have a stronger focus on research than lower-tier institutions, command higher levels of resources, and are likely to have higher expectations regarding the quantity and quality of research output. In return, they often provide their scientists with higher levels of pay and autonomy in their work. Similarly, we expect that levels of freedom and pay differ across types of academic positions, with particularly low levels for scientists in non-tenure track positions and higher levels for those scientists who are tenured or supervise large research groups (Hackett 1990).

2.4. Characteristics of Workers

The third dimension of our framework captures characteristics of workers, including scientists' preferences for certain job characteristics such as research freedom or money.[3] For many decades, scholars have held two contrasting views regarding scientists' preferences. One line of literature posits that all scientists share common preferences by virtue of their professional training in universities or their self-selection into a scientific career. In particular, scientists are assumed to share a "taste for science" and the desire for freedom in their choice of research (Aghion et al. 2008, Orth 1959, Stern 2004). As a consequence, scientists working under the (conflicting) commercial logic must be paid compensating differentials (Aghion et al. 2008), reduce their effort (Lacetera 2009), or experience role strain and dissatisfaction (Kornhauser 1962, Miller 1976).

The second view emphasizes that not all scientists are the same. Rather, there is heterogeneity in scientists' preferences, and scientists self-select into the sector that best matches their needs (Kaplan 1964, Rosen 1986, Sauermann and Roach 2011). Thus, given our earlier discussion of differences in workplace characteristics across sectors, scientists with a stronger desire for freedom should self-select into academia, whereas those with a stronger desire for financial income should prefer to work in industry (Agarwal and Ohyama 2012, Roach and Sauermann 2010). In addition, industry–academia differences in preferences may be reinforced by socialization processes (Saks and Ashforth 1997). For example, scientists who are faced with lower levels of freedom in industry may find that freedom becomes less important to them, whereas higher levels of pay may raise the salience and importance of financial rewards to the scientist (Allen and Katz 1992, Kornhauser 1962). Both mechanisms—selection and socialization—would imply that industrial scientists have stronger preferences for pay and weaker preferences for freedom than industrial scientists. As a consequence, industrial scientists may experience little role conflict and may require little extra pay, even if industry does not offer some of the workplace characteristics offered by academia (Box and Cotgrove 1966, Kaplan 1964, Sauermann and Roach 2011).

2.5. Disclosure of Research Results

The nature of work, workplace characteristics, and worker characteristics are three dimensions that play central roles in the general organizational literature. A fourth dimension is particularly important in the context of knowledge production: namely, whether and how research outputs are disclosed to the broader scientific community. Indeed, the open disclosure of research results in the form of publications is often viewed as the defining characteristic of the academic logic, whereas secrecy or disclosure in the form of patents are key aspects of the commercial logic (Dasgupta and David 1994, Murray 2010).[4]

To some extent, sectoral differences in disclosure may reflect differences in the nature of work. A functional interpretation of the publication-based reward system of academic science, for example, suggests that this system overcomes the market failures caused by the public goods nature of basic research results (Dasgupta and David 1994, Merton 1973, Stephan 2012). Downstream research, on the other hand, promises financial returns and can be regulated through the conventional market system. In particular, financial returns from downstream work can be captured through patents, which grant the inventor the right to exclude others from benefiting directly from that knowledge while still ensuring a certain level of disclosure to the general public.

Although both publications and patents constitute a form of disclosure, some downstream results may not be disclosed at all. Some results may be too incremental to pass the standards for publishing or patenting, and others may be kept secret to increase the appropriability of financial returns (Cohen et al. 2000). Similarly, Allen (1984) suggests that knowledge resulting from downstream projects is often embedded in physical objects and not codified or disclosed in written form.

The link between the nature of research and the level and form of disclosure may not be deterministic, however. Dasgupta and David (1994) as well as Nelson (2004) emphasize that basic research results can be kept secret and, at times, patented. Similarly, some downstream work may be publishable in "applied" journals. Thus, disclosure choices may also be shaped by factors other than the nature of research per se. One additional driver may be scientists' preferences for the various outcomes tied to patenting or publishing. In particular, scientists who care strongly about money may patent their research results to benefit from royalty payments that are typically shared between scientists and their employers (Intellectual Property Owners Association 2004, Lach and Schankerman 2008). Scientists with a strong desire for peer recognition may instead choose to disclose their results more widely in the form of publications.

In addition to the nature of research and scientists' preferences, patterns of disclosure may reflect broader norms and values embedded in the two sectors' institutional logics. Interestingly, these logics may be more similar with respect to publishing than with respect to patenting. Publishing is a key aspect of academic science, but it may also be valued in industry for several reasons. To some extent, norms supporting publishing may enter the industrial sector through flows of academically trained scientists (Ding 2011). Moreover, firms have been shown to value publications as a tool for various strategic purposes, e.g., to preempt patenting by competitors (Parchomovsky 1999), to signal scientific capabilities and a scientific work environment (Hicks 1995, Penin 2007), to strengthen industry–academia collaborations (Cockburn and Henderson 1998), or to position products in the marketplace (Polidoro and Theeke 2012). Differences in the logics regarding patenting are likely to be greater between the sectors. Despite increased patenting in academia, traditional norms of openness remain strong, and some academics see patenting as inappropriate even for downstream research (Argyres and Liebeskind 1998, Gans and Stern 2010, Murray 2010, Owen-Smith and Powell 2001). Moreover, academia is unlikely to value patents for the various "strategic" purposes documented for patenting in industry, including the building of fences around technologies, cross-licensing with rivals, or building reputations for toughness (e.g., Agarwal et al. 2009, Cohen et al. 2000). Thus, we expect that industry–academia differences are more pronounced with respect to patenting than with respect to publishing, especially once we account for differences in the nature of research.

3. Data and Measures

3.1. Data

We complement the conceptual discussion by providing empirical insights into key aspects of our framework. Our analysis draws on restricted-use data from the 2003 Scientists and Engineers Statistical Data System (SESTAT) provided by the National Science Foundation (NSF 2003). The data were collected in surveys whose sampling population includes all individuals living in the United States who either have a degree in a science or engineering (S&E) field or are working in a science and engineering occupation and hold a degree in a non-S&E field. The sample was drawn to be nationally representative, and we use the sampling weights provided by NSF. Response rates for the SESTAT surveys were greater than 70%. (Detailed information on the SESTAT data file is available at http://www.nsf.gov/statistics/sestat/.) For this study, we use data on Ph.D. scientists who work in either industry or academia. The "industry" subsample includes respondents whose employer is classified as a private, for-profit, noneducational entity. Included in the "academia" sample are respondents whose employer is classified as a four-year college or university or as a medical school. Given our interest in scientific work, we restrict our sample to individuals who are research-active, i.e., who report that basic research, applied research, or development is either their most important or their second-most important work activity. We exclude postdoctoral fellows because postdoctoral positions are temporary and may be followed by employment in either industry or academia.

Our sample includes 5,018 scientists; 36% are employed in industry and 64% are employed in academia; 57% work in life sciences occupations, whereas 43% work in the physical sciences.[5] Of the industrial scientists, 29% work in firms with fewer than 500 employees, whereas 35% work in firms with more than 25,000 employees. Eighty-nine percent of industrial scientists are employed in firms more than five years old. Of the academics, 43% are employed in Carnegie Research I and II institutions, 29% in medical schools, and 28% in other academic institutions (e.g., doctorate granting or comprehensive). Fifty-four percent are tenured, 21% are on the tenure track but not tenured, and 25% are not on the tenure track. The respondents who are not on the tenure track are primarily employed in tier 1 academic institutions and likely are working as staff scientists or research faculty.

3.2. Measures and Measurement Issues

Table 1 summarizes our measures, and Table 2 shows descriptive statistics.

The measure of the nature of R&D deserves further discussion. As described in Table 1, respondents indicated the type of R&D that occupied the majority of their time in a typical work week, including basic research, applied research, and development. Each of these activities was defined in the survey instrument. In contrast to prior work that uses features of patents or publications as proxies for the nature of the underlying research (e.g., Ding 2006, Narin et al. 1976, Thursby and Thursby 2010), our measure is independent of patents and publications. As such, it allows us to examine the relationship between the nature of research and disclosure empirically. Moreover, our measure captures both successful and unsuccessful research effort, providing a more complete picture of research activities. However, we cannot rule out the possibility that industrial and academic researchers apply the NSF definitions in slightly different ways, although it is difficult to sign any potential bias. Despite this limitation, our measure complements prior work based on other measures of the nature of research.

Although we have an objective measure of the salary paid by the employing organization, we rely on a measure of satisfaction as a proxy for the level of independence offered. Our rationale is that prior research has established a strong positive relationship between the actual level of a job attribute and individuals' satisfaction with that attribute, including in the R&D context (Cable and Edwards 2004, Idson 1990, Wood and LeBold 1970).[6] Because individuals' satisfaction with independence may not only reflect actual levels of independence but also their preference for independence (Cable and

Table 1 Measures

Variable	Measure description
Classification variables	
Employment sector	Dummy variable indicating whether respondent works in industry (*INDUSTRY* = 1) or academia (*INDUSTRY* = 0).
Field of occupation	Based on respondents' own classification using occupational codes provided by the NSF, we split the sample into respondents working in the life sciences and in the physical or related sciences. We also use more detailed subfield dummies to control for 10 different fields in our regression analyses (*DETAILED FIELD*). In the life sciences, these fields include agricultural and food sciences (6.5% of total), biomedical sciences including biochemistry and biophysics (40.7%), biomedical engineering (1.2%), health sciences (7.7%), and other life sciences (0.7%). In the physical sciences, these fields include physics (7.8%), chemistry (20.0%), earth sciences (6.26%), mathematics (8.5%), and other physical sciences (0.8%).
Dimensions of science	
Nature of R&D	Respondents indicated which work activities were most important and second-most important in terms of time spent. The survey instrument provided a list of work activities, including the following three R&D activities and their definitions: • "Basic research—study directed toward gaining scientific knowledge primarily for its own sake." • "Applied research—study directed toward gaining scientific knowledge to meet a recognized need." • "Development—using knowledge gained from research for the production of materials, devices." We coded three dummy variables indicating which activity was the most important R&D activity (*BASIC, APPLIED, DEVELOPMENT).*
Salary	Respondents reported the basic annual salary received at their current employer, excluding bonuses, overtime, summer support, or consulting. NSF annualized this variable (*SALARY*) on the basis of a separate question asking about the number of weeks upon which this salary was based. The NSF data also include a measure of total earnings in all jobs combined that yields qualitatively similar results. Given the difficulties in interpreting the earnings measure, we feature the measure of base salary.
Satisfaction with independence and income	Respondents rated on a 4-point scale how satisfied they were at their current employer with independence and salary. We use these measures as proxies for organizational characteristics. Given the prevalence of high ratings, we dichotomize these measures (*SAT_IND* and *SAT_SAL*) such that 1 indicates "very satisfied" and 0 indicates a rating lower than "very satisfied."
Preferences for independence and income	Respondents used a 4-point scale to rate their preferences for salary and independence in response to the following question: "When thinking about a job, how important is each of the following factors to you … ." Given the prevalence of high ratings, we dichotomize these measures (*IMP_IND* and *IMP_SAL*) such that 1 indicates "very important" and 0 indicates a rating lower than "very important."
U.S. patent applications	Each respondent reported the number of U.S. patent applications in which he or she was named as an inventor over the last five years prior to the survey. We created a dummy variable coded as 1 if the respondent had at least one patent application in the five-year period (*PATENT01*). Our empirical analysis focuses on this variable because our main interest is in whether a scientist discloses in the form of patents at all, rather than in the quantity or quality of patent output. The patent measure should capture all patents applied for by academic scientists, whether or not these patents are assigned to universities, and is thus more comprehensive than patent measures based on data provided by university administrators (see Thursby et al. 2009).
Publications	Respondents reported the number of (co)authored articles that have been accepted for publication in a refereed professional journal over the last five years. We focus our analysis on a dummy variable coded as 1 if the respondent had at least one publication in the five-year period (*PUBS01*), indicating that a scientist is willing to publish and that the employer allows the individual to publish. The data provide no information on the actual content or the quality of publications, and SESTAT users are not allowed to match the data to external publication data.
Control variables	
Experience	Years since obtaining Ph.D. degree (*YEARS_SINCE_GRAD).*
Ph.D. quality	We matched each respondent's Ph.D.-granting institution and the Ph.D. field to the National Research Council's evaluation of Ph.D. program quality (Goldberger et al. 1995) using the rating of "program effectiveness in educating research scholars and scientists." The scale ranges from 0 ("not effective") to 5 ("extremely effective"). *Ph.D. QUALITY* formally captures the quality of graduate education but may also reflect innate ability to the extent that high-ability individuals self-select or are selected into high-quality Ph.D. programs.
Number of individuals supervised	Respondents indicated how many people they supervised directly in their jobs (*PEOPLE SUPERVISED*). We interpret this (logged) measure as a proxy for managerial responsibilities and, for those scientists running their own labs, as a proxy for the size of the laboratory.

Table 1 (cont'd)

Variable	Measure description
Control variables	
Firm size	The survey asked respondents to estimate the number of employees in all locations of their employer combined, using eight size categories (<11; 11–24; 25–99; 100–499; 500–999; 1,000–4,999; 5,000–24,999; 25,000+). We constructed a continuous *FIRM SIZE* variable using the logged midpoints of these categories. Applies only to industry sample.
Firm age	Respondents indicated in a yes/no question whether their employer came into being as a new business within the past five years. We created a dummy variable *FIRM AGE* that equals 1 if the employer is older than five years and 0 otherwise. Industry sample only.
Type of academic institution	We distinguish academic institutions using the classification provided by NSF: Carnegie Research I and II institutions (*CARNEGIE*), lower-tier institutions (e.g., doctorate granting, comprehensive) (*LOWER TIER*), and medical schools (*MEDICAL*). Academic sample only.
Academic position	Dummy variables indicating whether an academic scientist is tenured (*TENURED*), on the tenure track but not tenured (*TENURE TRACK NOT TENURED*), or not on the tenure track (*NOT TENURE TRACK*). Academic sample only.
Race/Ethnicity	Dummies for white, Asian, and other (*RACE*).
Gender	*MALE* = 1 if the respondent is male.
U.S. citizen	*USCITIZEN* = 1 if the respondent is a U.S. citizen.

Edwards 2004), we estimate satisfaction models with the preference for independence as a control.

Finally, a concern with self-reported preferences is that respondents might inflate ratings of preferences that they think are socially desirable and give low scores to preferences that may seem less socially desirable (Moorman and Podsakoff 1992). Any such social desirability bias that applies to both industrial and academic scientists should not affect our results regarding comparisons between the two groups. However, it is also conceivable that academic scientists think that they are expected to care more strongly about independence than industrial scientists. The latter may think it is less problematic to state a strong preference for income, potentially inflating an industry–academia gap in preferences. Any descriptive data on preferences we present should be interpreted in light of this possibility.

4. Empirical Analysis of Industry–Academia Gaps and Relationships Among Dimensions

For each of the four dimensions of science, we first compare the key measures across sectors and compute the corresponding "industry–academia gaps." These gaps are purely descriptive and may reflect a range of underlying mechanisms. We then employ regression analysis to examine relationships among the four dimensions as well as the extent to which sectoral differences in one dimension explain differences in other dimensions. Given the cross-sectional nature of the data, our ability to draw causal conclusions is limited, and our primary contribution is to examine the extent to which observed industry–academia differences are consistent with various mechanisms discussed in the conceptual part of the paper.

Our regression analysis also explores heterogeneity within sectors, e.g., across different types of firms or universities. Although not discussed in the conceptual part, we address potential differences across scientific fields (see Burton 2001, Cohen et al. 2000, Lim 2004) by analyzing data separately for the life sciences and the physical sciences and by including subfield fixed effects in our regressions.

4.1. Basic vs. Applied Nature of Research

Table 2 shows that roughly two-thirds of academics are engaged in basic research, whereas more than 90% of industrial scientists work on applied research or development. Academics in the life sciences are more likely to be engaged in applied work than are academics in the physical sciences (32% versus 21%). In industry, life scientists are more likely to be engaged in basic research than are their colleagues in the physical sciences (8% versus 4%), perhaps reflecting that firms in the biomedical sector benefit more from engaging in basic research than firms in industries that rely heavily on the physical sciences (Lim 2004). As a result of these field differences, the industry–academia gap in the nature of research is significantly smaller in the life sciences than in the physical sciences.

4.2. Characteristics of the Workplace: Freedom and Pay

Academics report significantly higher satisfaction with independence in their jobs: 78% of them are "very satisfied" compared with 51% of industrial scientists. We next employ regression analysis to examine the relationship between the nature of research and freedom as well as the degree to which the industry–academia gap in freedom is explained by differences in the nature of research. Models 1–3 in Table 3(a) use the pooled sample to estimate probit regressions of the satisfaction with independence. Consistent with our expectation, scientists involved in basic research are more likely to be

Table 2 Descriptive Statistics and Industry–Academia Gaps

			Full sample			Life sciences			Physical sciences			
Dimension	Variable	Type	Industry $N = 1{,}831$ mean	Academia $N = 3{,}187$ mean	Ind–Acad gap	Industry $N = 848$ mean	Academia $N = 1{,}993$ mean	Ind–Acad gap	Industry $N = 983$ mean	Academia $N = 1{,}194$ mean	Ind–Acad gap	Diff. in gaps life–phys
Nature of work	*BASIC*	Dummy	0.06	0.70	−0.64**	0.08	0.66	−0.59**	0.04	0.77	−0.72**	0.14**
	APPLIED	Dummy	0.58	0.28	0.30**	0.60	0.32	0.28**	0.56	0.21	0.34**	−0.06*
	DEVELOPMENT	Dummy	0.36	0.02	0.35**	0.32	0.01	0.30**	0.40	0.02	0.38**	−0.08$^{n.s.}$
Characteristics of workplace	*SALARY*	Continuous	106,081	81,326	24,755**	107,052	84,063	22,989**	105,256	76,739	28,517**	−5, 527$^{n.s.}$
	SAT_SAL	Dummy	0.41	0.26	0.15**	0.42	0.27	0.15**	0.39	0.24	0.15**	0.00$^{n.s.}$
	SAT_IND	Dummy	0.51	0.78	−0.27**	0.52	0.79	−0.27**	0.51	0.76	−0.26**	−0.01$^{n.s.}$
Characteristics of workers	*IMP_SAL*	Dummy	0.47	0.37	0.10**	0.49	0.39	0.10**	0.46	0.34	0.12**	−0.02$^{n.s.}$
	IMP_IND	Dummy	0.61	0.81	−0.20**	0.63	0.82	−0.18**	0.59	0.79	−0.20**	0.02$^{n.s.}$
Disclosure	*U.S. patent applications*	Count	2.91	0.51	2.41**	2.23	0.60	1.63**	3.50	0.35	3.14**	−1.51**
	PATENT01	Dummy	0.50	0.16	0.34**	0.43	0.19	0.24**	0.55	0.11	0.45**	−0.21**
	Publications	Count	3.49	12.00	−8.50**	3.94	12.02	−8.08**	3.10	11.95	−8.85**	0.77*
	PUBS01	Dummy	0.62	0.92	−0.30**	0.71	0.94	−0.23**	0.54	0.90	−0.36**	0.13*
Controls	*YEARS_SINCE_GRAD*	Count	15.03	17.18	−2.15**	14.33	16.79	−2.46**	15.63	17.83	−2.21**	
	Ph.D. QUALITY	Continuous	3.41	3.47	−0.06**	3.38	3.40	−0.02$^{n.s.}$	3.44	3.58	−0.15**	
	PEOPLE SUPERVISED (ln)	Continuous	0.99	1.10	−0.11**	1.07	1.26	−0.19**	0.93	0.83	0.10*	
	FIRM SIZE (ln)	Continuous	8.11			7.69			8.46			
	FIRM AGE	Dummy	0.89			0.86			0.92			
	NOT TENURE TRACK	Dummy		0.25			0.29			0.19		
	TENURE TRACK NOT TENURED	Dummy		0.21			0.22			0.20		
	TENURED	Dummy		0.54			0.49			0.61		
	CARNEGIE	Dummy		0.43			0.37			0.53		
	LOWER TIER	Dummy		0.28			0.19			0.43		
	MEDICAL	Dummy		0.29			0.44			0.04		
	MALE	Dummy	0.81	0.76	0.05**	0.75	0.71	0.04*	0.86	0.84	0.02$^{n.s.}$	
	USCITIZEN	Dummy	0.87	0.90	−0.03**	0.87	0.91	−0.05**	0.87	0.89	−0.02$^{n.s.}$	

*Significant at 5%; **significant at 1%; $^{n.s.}$not significant.

very satisfied with independence than those involved in applied research. Controlling for the nature of research leads to a reduction in the industry–academia gap in independence (change of the *INDUSTRY* coefficient), although the reduction is not statistically significant at conventional levels of confidence. Note that the coefficients on the *INDUSTRY* variable in this and subsequent analyses should not be interpreted as causal effects but rather as estimates of industry–academia differences controlling for certain observed variables.

Even though we find significantly lower levels of satisfaction with freedom in industry, levels of freedom still seem quite high in an absolute sense: the majority of industrial scientists are very satisfied with their independence. Rather than suggesting some fundamental conflict between scientists and their bureaucratic employers (Aghion et al. 2008, Kornhauser 1962), this observation supports the notion that industrial scientists enjoy considerable freedom within the broad guidelines and goals set by the organization (Copeland 2007, Shapin 2004, Vallas and Kleinman 2008). Indeed, firms may recognize that some level of autonomy is beneficial for knowledge work generally (Alvesson 2000, Drucker 1999, Lepak and Snell 2002). To gain deeper insights into potential heterogeneity in freedom within industry, Models 4 and 5 focus on the industry subsample. The results show few significant differences in satisfaction with independence between scientists working on different types of R&D. One potential interpretation is that given the heterogeneity in firms' activities (e.g., R&D, marketing, production), different types of R&D are relatively similar from the firm's perspective and are thus organized in similar ways. Consistent with prior organizational literature, we find that larger firms provide less independence. Controlling for firm size, however, physical scientists in older firms are more satisfied with their independence than those in young firms.

Although academics generally enjoy higher levels of freedom than industrial scientists do, our results show that not all academics are satisfied with their independence. Exploring heterogeneity within academia (Models 6–9), we find that physical scientists involved in basic research report higher freedom than those working in applied research or development, perhaps reflecting that downstream work in academia is often tied to funding from industry or other agencies that may constrain project choice. We do not find differences across types of work in the academic life sciences. In both fields, however, the satisfaction with freedom depends on the scientist's position. More specifically, scientists not on the tenure track report significantly less freedom, perhaps because they work in research groups led by other principal investigators or because they have less access to resources and thus to choice of research topics. This finding is also consistent with the notion that (non-tenure track) "unfaculty" experience poorer working conditions than regular faculty (Hackett 1990). In the academic life sciences, satisfaction with independence further increases with the number of people supervised, especially when we drop the controls for tenure status (Model 7). Interestingly, we find no such relationship in industry or in the academic physical sciences, suggesting that the highly competitive academic life sciences may be special in that the path to research freedom leads through running a large (and well-resourced) lab.

Turning to salary as the second important workplace characteristic, we find that industry wages are higher by an average of approximately US$25,000 (see Table 2). In Table 3(b), we again use regression analysis to examine the degree to which this gap is explained by differences in the nature of research. Model 10 uses the pooled sample and shows as expected that applied researchers are paid more than basic researchers. Including the nature of research (Model 11) only slightly reduces the industry–academia gap in pay.[7] Model 12 includes additional controls and shows that the salary gap is not explained by differences in scientists' ability or experience—indeed, the gap increases once we take into account that academic scientists tend to have been trained at higher-quality institutions, have more work experience, and supervise more people.[8]

Although a comprehensive analysis of wage determinants is beyond the scope of this paper, we explore potential sources of heterogeneity within industry using Models 13 and 14. We find no pay differences across types of research in the life sciences, perhaps reflecting that basic and applied research are complements, resulting in a sharing of rents between researchers (Agarwal and Ohyama 2012). However, we make the interesting observation that physical scientists working in basic research in industry earn slightly more than their colleagues working in applied research. Given the very small share of industrial scientists who classify their work as "basic" (see Table 2), we are cautious about interpreting this result. However, it may reflect that the complementarities between basic and applied research are less pronounced in the physical sciences (see Lim 2004) and that the small number of basic physical scientists in industry may play a unique (and valuable) role for the firms who employ them.

Within academia (Models 15–18), we find that academic physical scientists engaged in applied research earn significantly more than those engaged in basic research. Recall that the salary measure captures only base salary, and any unobserved consulting income or patent royalties would likely further increase the pay difference. As expected, we also observe higher pay at tier 1 institutions and at medical schools. Non-tenure track academic scientists earn significantly less than those who are on the tenure track or tenured—in addition to enjoying lower levels of freedom. Across all sectors and fields, managerial responsibilities are associated with significantly higher pay.

Table 3(a) Characteristics of the Workplace: Independence (Probit Regressions)

				Industry		Academia			
	Full			Life	Physical	Life		Physical	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
INDUSTRY	−0.627**	−0.565**	−0.496**						
	[0.042]	[0.056]	[0.061]						
BASIC		0.109*	0.153**	−0.112	0.201	0.037	0.058	0.226*	0.265*
		[0.053]	[0.057]	[0.187]	[0.223]	[0.084]	[0.084]	[0.112]	[0.110]
DEVELOPMENT		0.020	0.005	−0.167	0.234*	−0.394	−0.413	−0.344	−0.363
		[0.063]	[0.064]	[0.102]	[0.092]	[0.237]	[0.246]	[0.289]	[0.290]
DETAILED FIELD			incl.	incl.	incl.	incl.	incl.	incl.	incl.
YEARS_SINCE_GRAD			0.001	0.006	−0.006	0.009	0.008	0.000	−0.003
			[0.003]	[0.006]	[0.006]	[0.005]	[0.005]	[0.007]	[0.005]
$(YEARS\_SINCE\_GRAD)^2$			0.001**	0.000	0.002**	0.001	0.001	0.000	0.000
			[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ph.D. QUALITY			0.022	−0.042	0.060	0.004	0.005	0.002	0.013
			[0.029]	[0.073]	[0.058]	[0.051]	[0.051]	[0.064]	[0.063]
PEOPLE SUPERVISED			0.096**	0.064	0.088	0.098*	0.117**	0.062	0.072
			[0.025]	[0.064]	[0.054]	[0.046]	[0.046]	[0.052]	[0.052]
FIRM SIZE				−0.052**	−0.047*				
				[0.018]	[0.019]				
FIRM AGE				−0.049	0.466**				
				[0.154]	[0.181]				
NOT TENURE TRACK						−0.380**		−0.408**	
						[0.102]		[0.154]	
TENURED						−0.128		−0.178	
						[0.113]		[0.157]	
LOWER TIER						−0.280**	−0.222*	−0.127	−0.063
						[0.102]	[0.101]	[0.105]	[0.103]
MEDICAL						−0.039	−0.073	0.184	0.105
						[0.088]	[0.086]	[0.227]	[0.226]
MALE			−0.067	−0.250*	−0.024	−0.071	−0.037	0.011	0.002
			[0.051]	[0.111]	[0.129]	[0.078]	[0.077]	[0.117]	[0.116]
USCITIZEN			0.137	−0.101	0.074	0.207	0.194	0.364*	0.362*
			[0.075]	[0.164]	[0.164]	[0.130]	[0.131]	[0.142]	[0.141]
RACE			incl.	incl.	incl.	incl.	incl.	incl.	incl.
IMP_IND	0.712**	0.710**	0.682**	0.447**	0.735**	0.688**	0.737**	0.758**	0.771**
	[0.045]	[0.045]	[0.046]	[0.097]	[0.089]	[0.084]	[0.082]	[0.103]	[0.102]
Constant	0.220**	0.145*	−0.025	0.883*	−0.523	0.021	−0.213	0.090	−0.219
	[0.044]	[0.057]	[0.154]	[0.386]	[0.431]	[0.254]	[0.246]	[0.505]	[0.485]
Observations	5,018	5,018	5,018	848	983	1,993	1,993	1,194	1,194
χ^2	567.57	570.729	648.244	58.147	109.179	170.984	160.622	121.383	115.651
df	2	4	21	17	17	19	17	19	17

Notes. The dependent variable is *SAT_IND*. Robust standard errors are in brackets. Omitted categories are *APPLIED, TENURE TRACK BUT NOT TENURED*, and *CARNEGIE*.

*Significant at 5%; **significant at 1%.

4.3. Characteristics of Workers: Scientists' Preferences

Table 2 shows that industrial scientists express a stronger preference for pay than academics (47% versus 37% "very important" ratings), consistent with significantly higher pay levels in industry. Similarly, 81% of academics rate independence as very important, whereas only 61% of industrial scientists do so. The regressions reported in Table 4 provide further insights regarding the relationships between workplace characteristics and scientists' preferences. Models 1–3 show the expected positive relationship between levels of independence and preference for independence. Moreover, including the measures of organizational characteristics in the regression significantly reduces the industry–academia gap in the preference for independence. Models 4–7 show separate regressions for industrial and academic scientists. We find a positive relationship between the levels of independence and the preference for independence in both sectors, suggesting that selection and socialization may occur not only across the two sectors but also across organizations within sectors.

Table 3(b) Characteristics of the Workplace: Salary (Ordinary Least Squares Regressions)

				Industry		Academia				
	Full			Life	Physical	Life		Physical		Full
	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
INDUSTRY	0.266**	0.233**	0.319**							0.329**
	[0.020]	[0.026]	[0.025]							[0.026]
BASIC		−0.048*	−0.069**	−0.108	0.128*	−0.059	−0.045	−0.100**	−0.076*	−0.072**
		[0.024]	[0.023]	[0.090]	[0.053]	[0.034]	[0.035]	[0.037]	[0.036]	[0.023]
DEVELOPMENT		0.003	−0.045	−0.077	−0.025	0.119	0.096	0.012	−0.001	−0.045
		[0.033]	[0.031]	[0.051]	[0.046]	[0.065]	[0.059]	[0.094]	[0.096]	[0.031]
DETAILED FIELD			incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
YEARS_SINCE_GRAD			0.022**	0.023**	0.024**	0.018**	0.020**	0.017**	0.019**	0.022**
			[0.001]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]
(*YEARS_SINCE_GRAD*)^2			−0.000**	−0.000*	−0.001**	0.000	−0.000*	0.000	0.000	−0.000**
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ph.D. QUALITY			0.050**	0.060	0.019	0.028	0.031	0.035	0.042	0.050**
			[0.012]	[0.038]	[0.031]	[0.019]	[0.020]	[0.022]	[0.022]	[0.012]
PEOPLE SUPERVISED			0.139**	0.157**	0.088**	0.132**	0.148**	0.110**	0.119**	0.137**
			[0.010]	[0.032]	[0.022]	[0.014]	[0.014]	[0.020]	[0.019]	[0.010]
FIRM SIZE				0.016*	0.011					
				[0.008]	[0.010]					
FIRM AGE				−0.052	0.002					
				[0.067]	[0.113]					
NOT TENURE TRACK						−0.184**		−0.143**		
						[0.036]		[0.053]		
TENURED						0.024		0.037		
						[0.037]		[0.043]		
LOWER TIER						−0.170**	−0.138**	−0.156**	−0.127**	
						[0.038]	[0.038]	[0.043]	[0.042]	
MEDICAL						0.143**	0.113**	0.272**	0.230**	
						[0.031]	[0.032]	[0.056]	[0.054]	
SAT_IND										0.049*
										[0.021]
MALE		0.066**	−0.03	0.035	0.116**	0.133**	0.018	0.016	0.067**	
		[0.023]	[0.043]	[0.080]	[0.035]	[0.035]	[0.034]	[0.034]	[0.023]	
USCITIZEN		0.014	0.024	0.006	0.094	0.085	−0.067	−0.06	0.012	
		[0.037]	[0.077]	[0.099]	[0.070]	[0.072]	[0.043]	[0.044]	[0.036]	
RACE		incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	
Constant	11.165**	11.199**	10.364**	10.571**	10.713**	10.415**	10.326**	10.840**	10.726**	10.332**
	[0.012]	[0.021]	[0.068]	[0.156]	[0.237]	[0.107]	[0.108]	[0.116]	[0.117]	[0.067]
Observations	5,018	5,018	5,018	848	983	1,993	1,993	1,194	1,194	5,018
df	1	4	21	17	17	19	17	19	17	22
R-squared	0.038	0.039	0.192	0.155	0.13	0.24	0.223	0.195	0.185	0.193

Notes. The dependent variable is ln(*SALARY*). Robust standard errors are in brackets. Omitted categories are *APPLIED, TENURE TRACK BUT NOT TENURED*, and *CARNEGIE*.

*Significant at 5%; **significant at 1%.

Models 8–14 show results for the preference for salary. We observe a strong positive relationship between actual pay and the preference for pay, and the industry–academia gap is reduced by more than half when measures of organizational characteristics and the nature of research are included.

Although cross-sectional data do not allow us to conclusively distinguish between selection and socialization mechanisms as drivers of the industry–academia gaps in preferences, we conduct two exploratory analyses. First, given that socialization would occur over time, we examine the relationships between preferences and time since graduation. Although the time since graduation has a positive relationship with the preference for independence among academic physical scientists (Model 7), the coefficients for other subsamples and for the preference for money provide little support for a socialization mechanism. Note, however, that the interpretation of these results is complicated since we cannot disentangle age and cohort effects (Levin and Stephan 1991). Second, we compute the industry–academia gap in preferences for scientists who graduated within the prior three years,

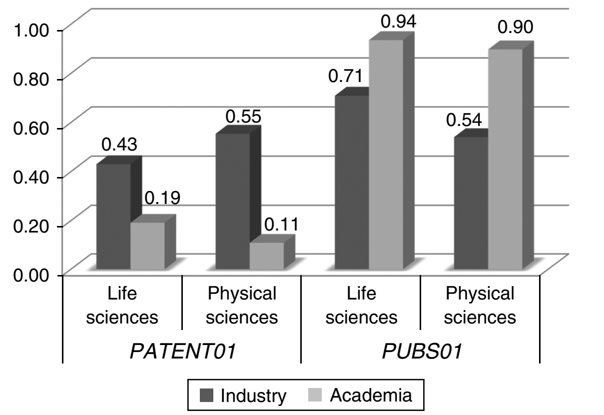
Table 4 Characteristics of Workers: Preferences for Independence and Salary (Probit Regressions)

				Industry		Academia					Industry		Academia	
				Life	Physical	Life	Physical				Life	Physical	Life	Physical
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
INDUSTRY	−0.592**	−0.403**	−0.330**					0.259**	0.124*	0.164**				
	[0.041]	[0.060]	[0.065]					[0.039]	[0.054]	[0.059]				
BASIC		0.056	0.045	−0.23	−0.127	0.049	0.005		−0.116*	−0.094	−0.281	−0.008	−0.11	−0.054
		[0.057]	[0.061]	[0.180]	[0.224]	[0.088]	[0.124]		[0.049]	[0.052]	[0.183]	[0.210]	[0.074]	[0.107]
DEVELOPMENT		−0.054	−0.059	0.122	−0.217*	−0.011	−0.213		0.015	0.009	0.097	0.083	−0.725**	−0.391
		[0.063]	[0.064]	[0.104]	[0.093]	[0.259]	[0.306]		[0.061]	[0.062]	[0.101]	[0.090]	[0.280]	[0.321]
SAT_IND		0.691**	0.674**	0.448**	0.729**	0.676**	0.750**		−0.061	−0.043	0.1	0.024	−0.128	−0.13
		[0.044]	[0.045]	[0.095]	[0.088]	[0.082]	[0.101]		[0.042]	[0.043]	[0.094]	[0.086]	[0.076]	[0.097]
SALARY (ln)		0.103**	0.038	0.056	0.073	0.011	−0.021		0.151**	0.139**	0.219**	0.113	0.131*	0.102
		[0.030]	[0.033]	[0.075]	[0.062]	[0.061]	[0.077]		[0.032]	[0.035]	[0.079]	[0.064]	[0.062]	[0.079]
DETAILED FIELD			incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.	incl.
YEARS_SINCE_GRAD			0.008**	0.007	0.004	0.001	0.016**			0.002	−0.013*	−0.007	−0.002	0.013**
			[0.002]	[0.006]	[0.005]	[0.005]	[0.005]			[0.002]	[0.006]	[0.005]	[0.004]	[0.005]
Ph.D. QUALITY			0.051	−0.029	0.003	0.137*	0.053			−0.082**	−0.121	0.002	−0.161**	−0.038
			[0.030]	[0.072]	[0.058]	[0.057]	[0.066]			[0.027]	[0.072]	[0.058]	[0.047]	[0.056]
PEOPLE SUPERVISED			0.110**	0.117	0.153**	0.102*	0.050			0.052*	0.015	0.111*	−0.001	0.059
			[0.026]	[0.065]	[0.055]	[0.045]	[0.054]			[0.023]	[0.063]	[0.053]	[0.039]	[0.048]
FIRM SIZE				0.024	−0.027						0.002	0.045*		
				[0.018]	[0.019]						[0.018]	[0.018]		
FIRM AGE				−0.398*	0.282						0.029	−0.216		
				[0.163]	[0.180]						[0.153]	[0.183]		
NOT TENURE TRACK						−0.470**	−0.184						0.015	0.100
						[0.104]	[0.149]						[0.090]	[0.142]
TENURED						0.071	−0.036						0.186*	0.101
						[0.117]	[0.135]						[0.094]	[0.128]
LOWER TIER						−0.121	0.006						−0.112	0.079
						[0.108]	[0.105]						[0.093]	[0.096]
MEDICAL						−0.118	−0.215						0.135	−0.030
						[0.092]	[0.222]						[0.075]	[0.222]
MALE			−0.088	−0.057	−0.272*	−0.224**	0.102			0.110*	0.250*	0.093	0.092	0.007
			[0.052]	[0.114]	[0.127]	[0.084]	[0.116]			[0.047]	[0.109]	[0.125]	[0.069]	[0.108]
USCITIZEN			−0.071	0.176	−0.209	−0.13	−0.108			−0.179*	−0.238	−0.079	−0.199	−0.194
			[0.077]	[0.160]	[0.159]	[0.154]	[0.152]			[0.070]	[0.163]	[0.153]	[0.125]	[0.141]
RACE			incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.	incl.
Constant	0.872**	−0.812*	−0.452	−0.528	−1.184	−0.162	−0.203	−0.325**	−1.886**	−1.617**	−2.241*	−1.568*	−1.071	−2.092*
	[0.027]	[0.339]	[0.370]	[0.885]	[0.770]	[0.688]	[0.965]	[0.024]	[0.362]	[0.392]	[0.917]	[0.784]	[0.682]	[1.010]
Observations	5,018	5,018	5,018	848	983	1,993	1,194	5,018	5,018	5,018	848	983	1,993	1,194
χ^2	204.109	459.172	492.797	50.15	103.01	179.298	85.84	44.086	73.967	150.008	34.155	23.318	65.534	58.181
df	1	5	21	17	17	19	19	1	5	21	17	17	19	19

Notes. In Models 1–7, the dependent variable is *IMP_IND*; in Models 8–14, the dependent variable is *IMP_SAL*. Robust standard errors are in brackets. Omitted categories are *APPLIED, TENURE TRACK BUT NOT TENURED*, and *CARNEGIE*.

*Significant at 5%; **significant at 1%.

Figure 2 Probability of Patenting and Publishing by Field and Sector



thus limiting the analysis to scientists who are in a similar cohort and who had less exposure to socialization processes within their current employment sector. We find significant gaps in the preference for independence for this early career group (0.60 in industry versus 0.74 in academia) and for salary (0.54 in industry versus 0.38 in academia), suggesting that selection plays an important role in explaining industry–academia differences in scientists' preferences.

4.4. Disclosure of Research Results

4.4.1. Main Analyses. Fifty percent of industrial scientists have at least one patent application in a five-year span compared with only 16% of academics who report at least one patent application. In contrast, 92% of academics have at least one publication in five years, compared with 62% of publishing scientists in industry. Figure 2 shows the likelihood of patenting by sector and field. We see that the industry–academia gap in patenting is smaller in the life sciences than in the physical sciences, both because life scientists in academia are more likely to patent than physical scientists in academia and because life scientists in industry are less likely to patent than physical scientists in industry.[9] The industry–academia gap in publishing is smaller in the life sciences primarily because life scientists in industry are more likely to publish than are physical scientists in industry (71% versus 54%).

Regressions using the pooled sample show that scientists engaged in development are less likely to have a patent application than are those in applied research (see Model 2 in Table 5). Regressions by sector and field (Models 4–7) show that the negative coefficient on development is significant only among industrial life scientists, perhaps reflecting that inventions in the life sciences are typically patented before they enter the development stage. In the physical sciences, academics engaged in basic research are much less likely to patent than are those engaged in applied work, likely reflecting that their research results do not meet the criteria for patentability.

We also observe other important sources of heterogeneity in patenting within sectors. For example, physical scientists in young firms are more likely to have a patent than those in older firms. This finding may reflect that young firms have an advantage in attracting highly productive employees, that employees are more productive when working in young firms, or that young firms are more likely to use patents as a signal of scientific capability (see Hsu and Ziedonis 2008, Sauermann and Cohen 2012). Moreover, the likelihood that an industrial scientist has a patent increases with the ranking of her Ph.D.-granting institution, possibly reflecting an effect of ability on the quality of research. In academia, scientists in lower-tier institutions are less likely to have patents than those in Carnegie I/II institutions and medical schools, perhaps reflecting otherwise unobserved differences in the commercial value of results or in the resources devoted to technology transfer activities (see Belenzon and Schankerman 2009).

Models 8–14 examine the probability of publishing. In the pooled sample, we find no significant difference in publishing between scientists working in basic versus applied research, but scientists engaged in development are much less likely to publish. Once we control for the nature of research, the industry–academia gap in publishing decreases significantly, suggesting that publishing is less common among industrial scientists in part because they are more likely to be engaged in work that is less likely to result in a publication.

Our split-sample regressions show that the likelihood of publishing decreases with time since graduation in both sectors; i.e., younger scientists are more likely to have published in a five-year span than older scientists. In industry, this result may reflect that firms have recently shifted toward open science by hiring more "academic" types of scientists (see Lacetera et al. 2004) or that freshly minted Ph.D.'s publish their dissertation research after entering industry. To examine the latter possibility, we dropped those industrial scientists who graduated within the last five years from the sample but find that the effect of time since graduation remains highly significant.

4.4.2. Disclosure by a "Standardized Individual." The regressions using the pooled sample showed that significant industry–academia gaps in publishing and especially patenting remain, even after controlling for the nature of R&D and various other factors (see Table 5). To determine more precisely the magnitude of these gaps, we estimate regressions separately by sector for two large subfields and use the results to predict the probability that a "standardized individual" engaged in a particular type of work patents or publishes when working in industry versus in academia. For the most part, we use the median or mean values of variables to

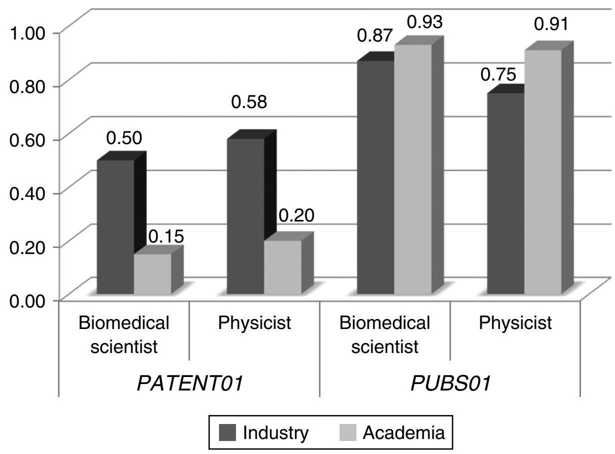
Table 5 Disclosure: Patenting and Publishing (Probit Regressions)

				Industry		Academia					Industry		Academia	
				Life	Physical	Life	Physical				Life	Physical	Life	Physical
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	probit 13	Model 14
INDUSTRY	0.986**	1.017**	0.922**					−1.113**	−0.845**	−0.871**				
	[0.042]	[0.058]	[0.066]					[0.047]	[0.062]	[0.073]				
BASIC		−0.044	−0.102	0.039	0.004	0.100	−0.490**		0.087	0.035	0.346	0.332	0.122	0.001
		[0.056]	[0.063]	[0.187]	[0.229]	[0.090]	[0.141]		[0.064]	[0.072]	[0.249]	[0.237]	[0.122]	[0.142]
DEVELOPMENT		−0.173**	−0.240**	−0.318**	−0.154	−0.265	−0.019		−0.599**	−0.515**	−0.417**	−0.554**	−0.534	−0.155
		[0.062]	[0.066]	[0.106]	[0.093]	[0.342]	[0.364]		[0.063]	[0.065]	[0.106]	[0.094]	[0.294]	[0.383]
IMP_SAL			0.044	−0.096	−0.019	0.082	0.256*			−0.084	−0.203*	−0.117	−0.078	−0.02
			[0.045]	[0.096]	[0.090]	[0.073]	[0.121]			[0.049]	[0.103]	[0.090]	[0.098]	[0.121]
IMP_IND			0.104*	0.107	0.071	0.197	0.141			0.087	0.056	0.061	0.117	0.23
			[0.050]	[0.099]	[0.091]	[0.101]	[0.148]			[0.054]	[0.107]	[0.092]	[0.126]	[0.131]
DETAILED FIELD			incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.	incl.
YEARS_SINCE_GRAD			0.006*	0.006	0.000	0.013*	0.006			−0.033**	−0.042**	−0.042**	−0.017*	−0.040**
			[0.003]	[0.006]	[0.006]	[0.006]	[0.010]			[0.003]	[0.007]	[0.006]	[0.008]	[0.010]
(*YEARS_SINCE_GRAD*)^2			−0.001**	−0.002**	−0.001**	−0.001*	−0.001			0.001**	0.001*	0.002**	0.000	0.001
			[0.000]	[0.001]	[0.001]	[0.000]	[0.001]			[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
Ph.D. QUALITY			0.133**	0.277**	0.135*	0.042	−0.02			0.183**	0.127	0.186**	0.065	0.160*
			[0.033]	[0.075]	[0.060]	[0.058]	[0.087]			[0.033]	[0.079]	[0.062]	[0.068]	[0.070]
PEOPLE SUPERVISED			0.248**	0.316**	0.075	0.300**	0.198**			0.195**	0.158*	0.118*	0.132*	0.260**
			[0.026]	[0.066]	[0.057]	[0.044]	[0.062]			[0.030]	[0.068]	[0.055]	[0.060]	[0.081]
FIRM SIZE				−0.015	0.036						0.03	0.022		
				[0.018]	[0.019]						[0.020]	[0.019]		
FIRM AGE				−0.212	−0.434*						−0.234	−0.303		
				[0.151]	[0.201]						[0.180]	[0.191]		
NOT TENURE TRACK						0.082	−0.234						−0.025	−0.493*
						[0.108]	[0.207]						[0.153]	[0.206]
TENURED						−0.018	−0.276						0.123	−0.05
						[0.116]	[0.208]						[0.157]	[0.209]
LOWER TIER						−0.508**	−0.520**						−0.706**	−0.694**
						[0.121]	[0.142]						[0.124]	[0.131]
MEDICAL						0.074	0.081						0.006	0.695
						[0.085]	[0.264]						[0.128]	[0.485]
MALE			0.177**	0.278*	0.307*	0.118	0.055			0.088	0.295*	−0.108	0.084	0.138
			[0.055]	[0.115]	[0.130]	[0.082]	[0.168]			[0.063]	[0.123]	[0.137]	[0.107]	[0.150]
USCITIZEN			−0.04	0.125	−0.243	0.142	−0.234			−0.157	−0.164	−0.3	0.098	0.178
			[0.084]	[0.172]	[0.166]	[0.153]	[0.211]			[0.101]	[0.190]	[0.174]	[0.209]	[0.197]
RACE			incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.	incl.
Constant	−0.993**	−0.959**	−1.995**	−1.476**	−0.159	−2.051**	−0.142	1.413**	1.367**	0.964**	−0.049	0.411	1.326**	0.69
	[0.028]	[0.049]	[0.173]	[0.393]	[0.427]	[0.294]	[0.588]	[0.034]	[0.055]	[0.177]	[0.426]	[0.430]	[0.331]	[0.673]
Observations	5,018	5,018	5,018	848	983	1,993	1,194	5,018	5,018	5,018	848	983	1,993	1,194
χ^2	556.334	565.229	807.005	73.71	123.471	137.575	112.499	573.386	654.384	732.855	109.168	150.863	85.434	88.837
df	1	3	22	18	18	20	20	1	3	22	18	18	20	20

Notes. In Models 1–7, the dependent variable is *PATENT01*; in Models 8–14, the dependent variable is *PUBS01*. Robust standard errors are in brackets. Omitted categories are *APPLIED*, *TENURE TRACK BUT NOT TENURED*, and *CARNEGIE*.

*Significant at 5%; **significant at 1%.

Figure 3 Predicted Probabilities of Patenting and Publishing for a Standardized Individual

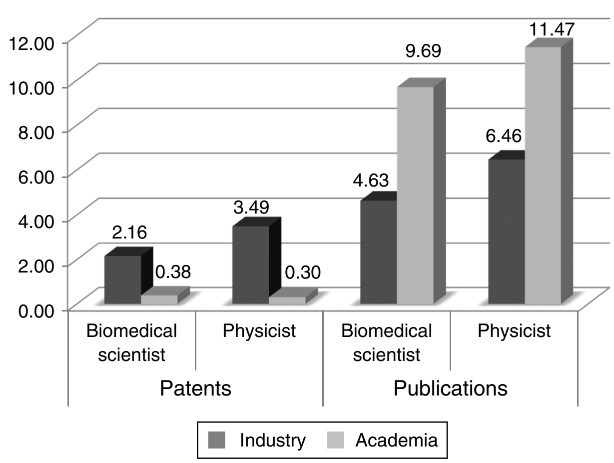


Note. The standardized individual is engaged in applied research; received his Ph.D. 10 years ago from an average Ph.D. program; supervises three other people; and is white, male, and a U.S. citizen.

define the standardized individual. One such standardized individual is a biomedical scientist who is engaged in applied research; graduated 10 years ago from an average Ph.D. program; supervises three other people; and is white, male, and a U.S. citizen. The second standardized individual is a physicist who otherwise has the same characteristics as the biomedical scientist.

Figure 3 shows large and statistically significant industry–academia gaps in the predicted probability of patenting for both scientists. The industry–academia gaps in the predicted probability of publishing are much smaller and not statistically significant. For comparison, Figure 4 shows the predicted *counts* of patents and publications for the same standardized individuals,

Figure 4 Predicted Counts of Patents and Publications for a Standardized Individual



Note. The standardized individual is engaged in applied research; received his Ph.D. 10 years ago from an average Ph.D. program; supervises three other people; and is white, male, and a U.S. citizen.

based on negative binomial regressions. Although the industry–academia gaps in the predicted likelihood of publishing are quite small, we continue to find sizeable gaps in predicted counts of publications. Thus, although firms appear to be open to publishing in principle, industrial scientists publish less frequently than comparable academics.[10]

5. Discussion

Scholars of science increasingly draw on the concept of institutional logics. The discussions often invoke ideal-type descriptions of the "academic logic" and a conflicting "commercial logic," yet a long stream of work suggests that these ideal types do not clearly map to the institutional realities of academic and industrial science. In this paper, we develop a deeper conceptual and empirical understanding of the institutional realities of science in the two sectors, making three broad contributions.

First, our conceptual discussion identifies important aspects of the institutional logics of science discussed in prior work and highlights sources of disagreement in the current debate. Drawing on this discussion as well as the broader organizational literature, we develop a multidimensional framework that considers four interdependent dimensions of science: the nature of work, characteristics of the workplace, characteristics of workers, and the way in which research results are disclosed. This framework provides the foundation for a systematic comparison of industrial and academic science and also begins to illuminate relationships among institutional features.

Second, we complement the conceptual discussion by providing empirical insights into the institutional logics of industrial and academic science. Drawing on survey data for a nationally representative sample of more than 5,000 Ph.D.-level life and physical scientists, our empirical results demonstrate the benefits of conceptualizing science as multidimensional. Although we find large sectoral differences in some aspects such as the nature of research, levels of pay, and the use of patenting, differences in other aspects, such as levels of freedom or the likelihood of publishing, are smaller. Moreover, we find important heterogeneity within sectors, such as across types of universities, types of research positions, or scientific fields. These results suggest that the ideal types of "academic logic" and "commercial logic" overstate differences between industrial and academic science while ignoring important heterogeneity within each sector. As such, although ideal types can be very useful in serving as reference points (see Thornton and Ocasio 2008, Weber 1949), they are less useful for descriptive purposes. Note that our results do not speak to the merits of the institutional logics approach per se; rather, they speak to the correspondence between two specific, commonly used ideal-type institutional logics and observable features of industrial and academic science. In some sense, therefore, our descriptive results can be interpreted as reflecting realistic (not ideal-type) "academic" and "industrial" logics. An alternative approach to arrive at a more nuanced picture is to conceptualize the practice of science in a given sector as shaped simultaneously by multiple different logics (Friedland and Alford 1991, Nelson 2005, Owen-Smith 2003); in that case, our empirical results regarding sector-level differences can be interpreted as the net effect of these various influences, providing insights into their relative strength.[11]

Going beyond a description of the four dimensions of science, the empirical results also advance our understanding of the relationships between them. For example, we find that the nature of research is significantly related to levels of freedom and pay, supporting more general organizational theories relating tasks to organizational characteristics. Similarly, we find strong relationships between features of the workplace and scientists' preferences, consistent with theories of selection and socialization. The latter finding is particularly relevant in light of a longstanding debate on the degree to which all scientists share similar characteristics versus exhibit heterogeneous preferences that lead them to self-select into "fitting" organizational settings (Kaplan 1964, Orth 1959, Roach and Sauermann 2010, Shapin 2004). Finally, we find that the nature of research has only limited power in explaining certain industry–academia gaps such as differences in freedom, pay, or patenting. The latter finding supports the notion that differences in institutional logics are not simply functional responses to different types of tasks but reflect deeper differences in missions and value systems (Dasgupta and David 1994). Future work on the sources of these differences may usefully draw on the history of science, political science, or social-constructivist views of scientific communities (see Callon 1995, David 2008, Knorr-Cetina 1999, Latour and Woolgar 1979).

We hope that our insights will be of use to managers and administrators concerned with the interactions between industrial and academic science and with managing knowledge workers within each sector. One possible interpretation of our findings is that the significant differences across sectors could inhibit industry–academia interactions, e.g., if firms emphasize patents while patenting is still less accepted in the academic logic. A different interpretation, however, is that similarities along other dimensions may actually facilitate collaboration. The conceptual framework and the empirical results presented in this paper may help managers in industry to consider along which dimensions of science are tensions with academic partners most likely to arise and which interventions or compromises may be needed to mitigate those tensions. Our descriptive results can also be of value to managers who seek to attract research personnel. Many junior scientists prefer employment in academia over employment in industry (Sauermann and Roach 2012), yet some of this preference may be due to biased perceptions of industrial science (see Roach and Sauermann 2010). Although R&D managers have tried to address these "misconceptions" in a qualitative way (e.g., Copeland 2007), data such as ours may help to convey a more objective picture of industrial science. Academic advisors seeking to advise students in their career decisions may similarly benefit from our descriptive insights.

Important limitations of our study have to be kept in mind. First, although our measure of the nature of R&D has unique benefits, objective and more fine-grained measures could provide additional insights. Second, we rely on scientists' satisfaction with independence as a proxy for actual independence. Even though the qualitative results regarding this measure are robust to the inclusion of various controls, it would be desirable to assess industry–academia gaps in freedom using more direct measures. Most importantly, our ability to make causal inferences is limited, and more work is needed to identify the exact mechanisms underlying observed industry–academia differences. Our conceptual discussion of possible mechanisms in conjunction with the empirical evidence regarding the existence and magnitude of sectoral differences should prove useful for such future work.

Our framework suggests additional avenues for future research. First, future work can consider additional facets within each of the four dimensions. For example, our discussion of characteristics of the workplace is limited to freedom and pay, and future work could examine other important characteristics such as the organization of research groups, levels of hierarchy, team composition, or physical resources. Similarly, we focus on scientists' preferences for freedom and pay. Future work could study other worker characteristics such as ability, gender, or the desire for peer recognition. Second, future work could extend the framework by considering additional relationships among dimensions. In particular, although we followed prior literature in considering the nature of research as a driver of other dimensions of science, it may be instructive to examine how research choices themselves are shaped by other variables. Finally, our framework may be useful in studying changes in the scientific system. For example, it has been suggested that industrial and academic science are "converging" over time (Hackett 1990, Vallas and Kleinman 2008). Our framework suggests a set of dimensions that could be tracked over time in a more systematic assessment of convergence and also predicts how convergence with respect to one dimension may lead to convergence in others. In the context of such dynamic considerations, our empirical results may also serve as a useful reference point against which future data can be compared.

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Endnotes

[1]Even though Merton's perspective has arguably had the greatest influence on the subsequent literature, several other important models of science have been developed (e.g., Bourdieu 1975, Hagstrom 1975, Knorr-Cetina 1999, Latour and Woolgar 1979, Polanyi 1962). Callon (1995) provides an insightful synthesis, distinguishing models of science as the production of rational knowledge, models of science as competition, models of science as a sociocultural practice, and models of science as extended translation.

[2]Our conceptual model draws primarily on the conceptual logics view and a smaller number of alternative perspectives. We will discuss additional issues and mechanisms in the interpretation of our empirical results. Similarly, although our framework abstracts from differences across scientific fields, we will consider field differences in the empirical analysis.

[3]Space constraints prevent us from discussing other important individual-level characteristics such as ability, gender, or work experience. We will consider these characteristics in the empirical analysis.

[4]Although the academic logic strongly encourages openness with respect to the disclosure of final research results, it does not necessarily prescribe that scientists also openly share intermediate results or data and materials. Indeed, both theoretical and empirical studies suggest that the competition for priority in discovery can lead scientists to be secretive about ongoing projects and to withhold data or materials from competitors (Blumenthal et al. 2006, Haeussler et al. 2009, Hagstrom 1974, Walsh et al. 2005).

[5]The SESTAT data also include industry codes for industrial employers. Because our focus is on comparisons between industry and academia, we use field classifications rather than industry codes that have no direct correspondence in academia.

[6]The salary measures provide additional support for the suggested positive relationship between actual job attributes and satisfaction. In particular, those scientists who are "very satisfied" with their salary earn an average of $111,050, whereas those who are not very satisfied earn an average of $78,515.

[7]The joint observation of higher salaries and lower independence in industry raises the question whether higher salaries are used to compensate industrial scientists for lower levels of independence (Aghion et al. 2008). In that case, we would expect a negative correlation between salary and independence. We estimated additional regressions of salary including the measure of satisfaction with independence but generally find a positive relationship. Moreover, including the satisfaction measure does not reduce the estimated salary gap across sectors (see Model 19 in Table 3(b)). Although these observations do not support the notion that higher salaries compensate for lower levels of freedom, they should not be interpreted as evidence against such compensating differentials. As discussed by Stern (2004), cross-sectional estimates of compensating differentials are likely to be biased by unobserved individual characteristics, and a more appropriate empirical approach is to control for individual fixed effects.

[8]Lower levels of experience and supervisory responsibilities in industry may reflect that an increasing share of younger cohorts has entered industry careers rather than careers in academia (Stephan 2012). Moreover, because we restrict our sample to research-active scientists, it excludes scientists who have stopped doing research to pursue a "management track," which is more common in industry (see Allen and Katz 1992).

[9]Inventions in the life sciences tend to be less complex, likely resulting in fewer patents for a given invention. Moreover, firms in complex industries such as semiconductors and electronics (which tend to draw on the physical sciences) patent extensively for several strategic reasons, further increasing the role of patents (see Cohen et al. 2000).

[10]Sectoral differences in the counts of publications and patents should be interpreted with caution because our proxies for ability may not control for all industry–academia differences in research ability. To the extent that higher-ability scientists are more likely to enter academia (Sauermann and Roach 2011), unobserved ability may, to some extent, explain the higher publishing rates in academia (though not higher patenting rates in industry). Given the large differences in patenting and publishing rates across sectors as well as the broad range of proxies for ability and experience included in our analysis, we do not believe that unobserved ability is a significant driver of the observed differences in patent or publishing output.

[11]Conceptualizing science as simultaneously shaped by two different logics versus a single, more nuanced logic may lead organizational researchers to examine different kinds of research questions. For example, the former approach may lead researchers to focus primarily on conflicts between the logics and how individual scientists experience and resolve these conflicts (see Murray 2010, Perkmann et al. 2011).

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