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TWINS OR STRANGERS? DIFFERENCES AND SIMILARITIES BETWEEN INDUSTRIAL AND ACADEMIC SCIENCE

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ABSTRACT

Some scholars view academic and industrial science as qualitatively different knowledge production regimes. Others claim that the two sectors are increasingly similar. Large-scale empirical evidence regarding similarities and differences, however, has been missing. Drawing on prior work on the organization of science, we first develop a framework to compare and contrast the two sectors along four key dimensions: (1) the nature of research (e.g., basic versus applied); (2) organizational characteristics (e.g., degree of independence, pay); (3) researchers' preferences (e.g., taste for independence); and (4) the use of alternative disclosure mechanisms (e.g., patenting and publishing). We then compare the two sectors empirically using detailed survey data from a representative sample of over 5,000 life scientists and physical scientists employed in a wide range of academic institutions and private firms. Building on prior work that has emphasized different "research missions", we also examine how the nature of research is related to other characteristics of science within and across the two sectors.

Our results paint a complex picture of academic and industrial science. While we find significant industry-academia differences with respect to all four dimensions, we also observe remarkable similarities. For example, both academic institutions and private firms appear to allow their scientists to stay actively involved in the broader scientific community and provide them with considerable levels of independence in their jobs. Second, we find significant differences not just between industrial and academic science but also within each of the two sectors as well as across fields. Finally, while the nature of research is a significant predictor of other dimensions such as the use of patenting and publishing, it does not fully explain the observed industry-academia differences in those dimensions. Overall, our results suggest that stereotypical views of industrial and academic science may be misleading and that future work may benefit from a richer and more nuanced description of the organization of science.

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1 Introduction

Scholars of science as well as the general public often consider industrial and academic science as two distinct knowledge production regimes designed to perform different types of research. In particular, basic research, the domain of academia, is seen as best supported by a research organization that provides scientists with considerable freedom and emphasizes open disclosure in the form of publications (Dasgupta & David, 1994; Merton, 1973). Applied research, on the other hand, is seen as the domain of industrial science, where the research environment is more structured and results are kept secret or disclosed in the form of patents (Aghion, Dewatripont, & Stein, 2008; Cohen, Nelson, & Walsh, 2000). Moreover, assuming that all scientists share a "taste for science", it has been argued that industry must compensate applied scientists for a lack of freedom and the ability to publish by providing higher salaries than academia (cf. Aghion et al., 2008).

Recent studies suggest, however, that this abstract view of academic and industrial science may be misleading and that the mapping from the nature of research to organizational setting and disclosure mechanisms is far from straightforward. For example, academic scientists increasingly pursue research characterized by direct applications, while some firms are said to pursue "open science" approaches (Ding, 2010; Slaughter & Rhoades, 2004; Vallas & Kleinman, 2008). There is also considerable evidence that scientists in industry publish and scientists in academia patent, and that the "same" piece of knowledge can be disclosed in different ways (Cockburn & Henderson, 1998; Gans, Murray, & Stern, 2008; Hicks, 1995). The lines between academic science and industrial science may have become particularly blurred in the biomedical sciences (Murray, 2006; Vallas et al., 2008).

While there is a growing recognition of the need for a nuanced view of industrial and academic science, our knowledge of the differences between the two sectors, as well as our understanding of the relationships between the nature of research and the organization of research within the two sectors lacks a firm empirical foundation. For example, data on the basic versus applied nature of research is often inferred from characteristics of patent and publication output (e.g., Ding, 2006; Thursby & Thursby, 2009b), which may confound the nature of research and the mechanisms used to disclose research results. Similarly, measures of nonpecuniary job attributes such as researchers' freedom are typically not available. While wage differentials may be interpreted as reflecting differences in nonpecuniary job attributes this approach is unlikely to differentiate among different kinds of nonpecuniary job attributes and does not account for potential selection effects (Killingsworth, 1987; Roach & Sauermann, 2010; Rosen, 1986; Stern, 2004).

In this paper, we use a unique data set to compare and contrast industrial and academic science along four key dimensions: the basic versus applied nature of research, organizational characteristics (e.g., freedom provided to researchers), scientists' preferences, and the use of different disclosure mechanisms. Building on prior work that has emphasized different "research missions" of industry and academia, we also examine how the nature of research is related to other characteristics of science both across and within the two sectors.

Our empirical analysis exploits detailed data for a nationally representative sample of over 5,000 PhD-level life and physical scientists. The strength of our data is that the same survey instrument was administered to researchers working in industry and academia, allowing us to make direct comparisons between the two sectors and across fields. Among others, our data include a novel measure of the basic versus applied nature of research that is not conditioned by sector or by the disclosure strategy. The data also include measures of pecuniary and non-pecuniary job attributes as well as measures of scientists' preferences.

Our results paint a complex picture of academic and industrial science. On the one hand, we find significant differences between the two sectors with respect to the nature of research, the use of various disclosure mechanisms, organizational characteristics, and scientists' preferences. Despite significant differences, however, we also find remarkable similarities. To wit, while industrial scientists appear to enjoy less independence than academic scientists, over 50% of industrial scientists indicate that they are "very satisfied" with their level of independence. Similarly, scientists in *both* sectors publish extensively, with 60% of scientists in industry having published in a 5-year span. Over the same period, 16% of academics have applied for a patent. Many of the differences between sectors are smaller in the life sciences than in the physical sciences, suggesting that scholars should remain cautious about generalizing insights based on data from the life sciences to other fields. Moreover, our analyses also point to important differences *within* each of the two sectors, indicating that the broad industry versus academia distinction may obscure important nuances.

Consistent with the view that different "research missions" shape the organization of science in the two sectors, we find significant relationships between the basic versus applied nature of research on the one hand and the other three dimensions of science (organizational characteristics, scientists' preferences, and disclosure mechanisms) on the other. However, differences in the nature of research between sectors do not fully explain differences in the organization of research, scientists' preferences, or in the use of various disclosure mechanisms.

Our work makes several contributions. First, a growing body of theoretical work examines the division of labor between industry and academia, often focusing on differences in researcher freedom, pay, and the basic versus applied nature of research (Aghion et al., 2008; Lacetera, 2009; Murray & O'Mahony, 2007a). We complement this work by providing unique data on these key constructs and by empirically examining the relationships between them. Second, our observation that differences in patenting are not explained by differences in the nature of research provides indirect evidence of the important role that other factors—such as organizational norms—play in shaping scientific disclosure in the two sectors (Bercovitz & Feldman, 2008; Cohen et al., 2000; Gans et al., 2008). At the same time, our finding of quite weak relationships between the nature of research and disclosure mechanisms suggests that future work should be cautious in using patent- or publication-based measures as proxies for the nature of the underlying research. Third, we provide rare direct evidence of differences in non-pecuniary (independence) as well as pecuniary job attributes (pay) across sectors and organizations and find support for the notion that scientists make trade-offs between these factors (Aghion et al., 2008; Roach et al., 2010; Stern, 2004). Finally, our results may have important implications for managers and policy makers concerned with interactions between industrial and academic science and with the management of knowledge workers within each of the two sectors.

Our research plan is as follows. In Section 2 we review prior work and develop a conceptual framework to compare industrial and academic science. In Section 3 we discuss our data and measures. In section 4, we present descriptive data on similarities and differences between industrial and academic science ("industry-academia gaps") and also examine differences in industry-academia gaps between the life sciences and the physical sciences. In section 5, we use regression analysis to examine the relationships between the nature of research and other characteristics of science and we also explore differences in key variables *within* each of the two sectors. A summary and discussion follow in Section 6.

2 Background

2.1 Academic Science

According to the conventional view, the research mission of academia is the conduct of basic research, i.e., research resulting in fundamental insights. Knowledge resulting from basic research has characteristics of a public good and typically has little commercial value. As a consequence, financial incentives and a price-based market system fail to produce an efficient amount of such research (Arrow, 1962; Nelson, 1959; Stephan, 1996). To address these particular characteristics of basic research, academic science has developed a distinct incentive system that encourages the production and sharing of research findings based on non-financial incentives such as peer recognition from the scientific community (Dasgupta et al., 1994; Merton, 1973; Stephan, 1996). Recognition can only be achieved by making one's research publicly available, which makes active involvement in the scientific community and the rapid disclosure of research results via publications and presentations at conferences one of the defining characteristics of academic science. The timely and widespread disclosure of research results, in turn, fosters the accumulation of knowledge over time (Murray et al., 2007a; Sorenson & Fleming, 2004).

The basic character of research in academia is also linked to distinct ways in which research is organized in universities. In particular, academic scientists enjoy high levels of freedom in choosing which problems to attack, how to approach them, and how to disclose their results. In recent theoretical work, Aghion et al. (2008) argued that scientists derive utility from this freedom itself, thus accepting lower wages in return. While high levels of independence allow researchers to pursue promising research questions, the low wage levels ensure that they do so at relatively low costs, making academia the ideal place for exploratory research.[1]

While this abstract characterization may be useful to parsimoniously describe key characteristics of the academic sector, it appears overly simplistic. First, American universities have always been engaged not only in basic research but also in applied work; in fact, some academic institutions were founded with an explicit charge to assist their regional economies through applied work (cf. Furman & MacGarvie, 2007; Rosenberg & Nelson, 1994; Stokes,

[1] Stinchcombe (1994) provides fascinating evidence of a relationship between the nature of work and the freedom given to workers in a very different context. Applying an agency theory perspective, he found that slaves in the Carribean who were assigned tasks "that required the slave's consent and enthusiasm as a trusted agent" (e.g., pearl fishers or mistresses) were given significantly more freedom than slaves working on tasks that did not (e.g., plantation workers).

1997). Moreover, recent years have seen increasing patenting activities in academia (Henderson, Jaffe, & Trajtenberg, 1998; Jensen & Thursby, 2001; Mowery, Nelson, Sampat, & Ziedonis, 2001), which some scholars fear may jeopardize the basic research mission and the open disclosure of research results (Murray & Stern, 2007b; Slaughter et al., 2004). One key challenge of empirical research on these issues is that micro-level measures of the basic versus applied nature of research tend to rely on patent or publication metrics and are thus contingent on the disclosure mechanism chosen. The link between disclosure mechanism and the nature of research may be weak, however, especially if research creates both fundamental insights and solutions to applied problems, i.e., if it lies in "Pasteur's Quadrant" (Stephan & Levin, 1996; Stokes, 1997).

The stereotypical view of academic science may also inaccurately reflect the organizational context in which academic scientists work. In particular, researchers in most fields rely extensively on funding from government agencies or from industry and these funding sources often pursue particular research agendas. Scientists seeking to obtain funding may have to adjust to these external constraints, which effectively limits their research freedom (Hackett, 1990; Vallas et al., 2008). Similarly, funding agencies often consider researchers' track record in a particular research area when making funding decisions, limiting scientists' ability to change research trajectories. Thus, while academia offers high levels of independence in theory, a variety of constraints may limit that freedom in practice.

Much of the discussion around academic science considers academia as a rather homogeneous sector, but we expect considerable heterogeneity within the academe. First, increasing patenting rates as well as other aspects of the "commercialization of science" have been studied primarily in the life sciences. It is likely that the physical sciences show a somewhat different picture. Moreover, the academic sector is populated by different types of institutions, including not only top tier research institutions, but also lower tier institutions and medical schools with a potentially very different organization of research. Finally, there may be significant heterogeneity among individual scientists within a given institution because not all academics run their own lab. Staff scientists also make important contributions to academic science but are often supported on "soft money" and work for others, resulting in little freedom. This group of "unfaculty" scientists, to use a term of Hackett's (1990), has grown considerably in recent years and they "…populate an academic 'never-never land' made possible by the availability of research support but made miserable by the difficulty of obtaining such support and by their ambiguous status in the university" (pp. 252-253). Overall, it is likely that academic science comes in different shades and insights into this heterogeneity may significantly increase our understanding of the scientific enterprise.

2.2 Industrial Science

Industrial R&D has been studied extensively in prior decades (e.g., Miller, 1976; Pelz & Andrews, 1976; Ritti, 1968) and has received renewed interest in recent years. "Ideal type" industrial science, as portrayed by the earlier literatures and in some theoretical models, focuses on generating knowledge with direct commercial potential, i.e., applied research and development. In order to appropriate the financial returns to that knowledge, firms rely on secrecy and patenting and discourage researchers from publishing. Firms use a hierarchical research organization with little freedom for individual researchers. The scientists employed in industry, however, are thought to be heavily influenced by their academic training, resulting in a strong need for autonomy as well as the desire to publish and to develop a reputation in the larger field (Gouldner, 1957; Kornhauser, 1962; Miller, 1976; Stern, 2004). As a result, there is a mismatch between the organization of research in industry and the preferences of industrial scientists, which should result in compensating differentials in the form of higher wages. These higher wages, in turn, give academia an advantage in (labor intensive) basic research and reinforce industry's focus on more profitable applied research (Aghion et al., 2008).

While firms clearly focus on applied work that promises financial returns, some firms also devote resources to basic research because such research may increase their ability to absorb external knowledge or may result in longer-term financial payoffs (Cohen & Levinthal, 1990; Rosenberg, 1990). Moreover, some firms have shifted towards a more "academic" approach by allowing scientists to publish and by encouraging scientists' participation in the broader science community. This is especially the case in the life sciences (Cockburn et al., 1998; Henderson, 1994; Hicks, 1995; Rhoten & Powell, 2007; Stern, 2004; Vallas et al., 2008). Case evidence also suggests that PhD-trained life scientists working in industry have considerable freedom in choosing concrete lines of research (Copeland, 2007; Vallas et al., 2008) and some companies offer their R&D employees official or unofficial bootleg time to work on projects of their own choosing (Augsdorfer, 2008).

Again, there may be significant heterogeneity within the industrial sector. In particular, many startup firms have academic roots (i.e., they were founded by academics or graduate students) and may therefore provide scientists with more freedom and publishing opportunities than established firms (Ding, 2010; Gittelman & Kogut, 2003; Owen-Smith & Powell, 2004; Zucker, Darby, & Armstrong, 2002). Startups may also benefit more than other firms from disclosing research in the form of patents and papers because such disclosures serve as valuable signals to outside stake holders (cf. Hsu & Ziedonis, 2007).

While prior work suggests that industrial science may be more "academic" than reflected in the stereotypical view, individual researchers in industry may be *less* "academic" than commonly thought. Roach and Sauermann (2010) surveyed graduate students regarding their preferences and career choices and found that students who planned to pursue a research career in industry reported significantly lower preferences for independence and publishing than did those preferring to stay in academia. Similarly, earlier work raises the notion of "accommodation" whereby industrial scientists are socialized to become less academic and more commercially oriented over time (Allen & Katz, 1992; Kornhauser, 1962). Such differences in scientists' preferences across sectors are particularly interesting because they imply that the wage premium necessary to compensate industrial scientists for restrictions on basic research, publishing, or freedom may be lower than if all scientists shared the same preferences (Aghion et al., 2008; Rosen, 1986; Sauermann & Roach, 2010a).

2.3 Framework for Comparing Academic and Industrial Science

The abstract stereotypes of academic and industrial science paint a stark contrast between the two sectors. A more nuanced view suggests several similarities and perhaps even a further "convergence" over time. Before we examine similarities and differences between industrial and academic science empirically, it is useful to consider in more detail possible dimensions for such a comparison as well as the relationships between these dimensions.

Drawing on our review of prior work, we can distill four dimensions that capture the key features of science while also highlighting important conceptual differences. The first dimension is the nature of the research being done, in particular, whether research is basic or applied (Aghion et al., 2008; Rosenberg, 1990). We expect that academic scientists are more heavily engaged in basic research than their colleagues in industry, who tend to work on applied questions. A second dimension are organizational characteristics, including factors such as the degree of freedom afforded to researchers and financial compensation provided (Aghion et al., 2008; Dasgupta et al., 1994; Merton, 1973). As discussed earlier, a common argument is that academia and industry have developed different organizational and institutional characteristics to best fulfill their basic versus applied research missions (Dasgupta et al., 1994; Merton, 1973; Stephan, 1996). Accordingly, we expect that industry offers higher wages and less freedom than academia. Moreover, such differences in organizational characteristics should be explained by differences in the nature of research.[2]

A third dimension relates to characteristics of the individual scientists, in particular how scientists vary in terms of preferences for certain job characteristics such as research independence or money, or more generally in terms of a "taste for science" (Aghion et al., 2008; Allen et al., 1992; Sauermann, Roach, & Zhang, 2010b; Stern, 2004). We expect systematic differences in scientists' preferences between sectors because scientists with heterogeneous preferences likely self-select into the sector which they expect to best satisfy these preferences (Roach et al., 2010; Rosen, 1986). Moreover, differences in scientists' preferences may be reinforced by socialization processes, i.e., when individuals who enter a particular employment sector change their preferences in response to the actual characteristics of their employing organizations (Allen et al., 1992; Gundry, 1993; Harrison & Carroll, 1991). Because of both selection and socialization, we expect industrial scientists to have weaker preferences for independence and stronger preferences for money than academics.

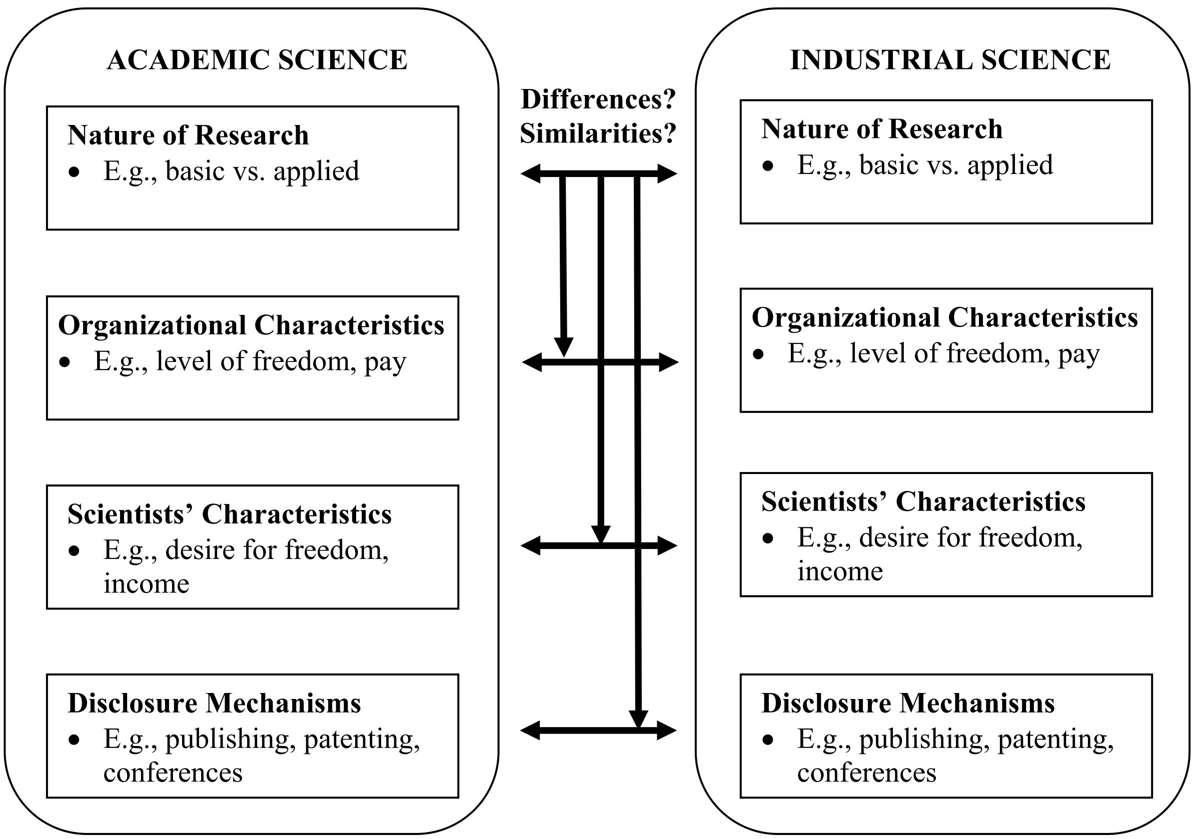
The final dimension of our framework relates to the mechanisms by which research results are disclosed and protected, including formal mechanisms such as patenting and publishing as well as more informal avenues such as personal interactions at conferences and in professional associations (Gans et al., 2008; Merton, 1973; Murray et al., 2007a; Sorenson et al., 2004). It is likely that differences in the nature of research across sectors are responsible for differences in the use of disclosure mechanisms, e.g., because knowledge resulting from basic research does not meet the criteria for patentability or because applied research loses much of its commercial value if openly disclosed in the form of publications (Merton, 1973; Stephan et al., 1996). At the same time, even the "same" type of knowledge can be patented as well as published, and some research results are disclosed using both mechanisms (Ducor, 2000; Gans et

[2] While we follow prior work in focusing on freedom and pay as key organizational characteristics, this dimension could be expanded to include other organizational factors such as the size of research teams, funding mechanisms, etc.

al., 2008). Disclosure decisions may also be shaped by various objectives of individuals and institutions and by different functions of patents and publications such that the nature of research alone may not fully explain industry-academia differences in patenting and publishing (Cohen et al., 2000; Murray, 2006; Sauermann, Cohen, & Stephan, 2009).

Figure 1 summarizes our framework for analysis, highlighting the central role of differences in the nature of research as a direct or indirect driver of differences in organizational characteristics, characteristics of scientists, and disclosure mechanisms.

Figure 1: Framework to Compare Academic and Industrial Science



3 Data and Measures

3.1 Data

Our empirical analysis is based on restricted-use data from the 2003 Scientists and Engineers Statistical Data System (SESTAT) provided by the National Science Foundation (NSF, 2003). The sampling population of the SESTAT surveys includes all individuals living in the United States in the reference week (week of October 1, 2003) who either have a degree in a science or engineering (S&E) field or who 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. Data were collected primarily via self-administered mail survey, supplemented by online surveys and computer-assisted interviews. Response rates for the SESTAT surveys were well over 70%.[3]

For this study, we use only data on respondents who hold a PhD degree in a science field and who work in industry or academia; i.e., we exclude scientists working in government and non-profits. Included in the "industry" subsample are respondents whose employer is classified as a private-for-profit, non-educational entity. Included in the "academia" group are respondents whose employer is classified as a 4-year college or university or as a medical school. Given our interest in science, 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 second most important work activity (see below for details). We exclude postdoctoral fellows because postdoctoral positions are by design temporary and may be followed by employment in either industry or academia (Davis, 2005; Regets, 1998).

Our sample includes 5,018 scientists; 1,831 (36%) are employed in industry and 3,187 (64%) are employed in academia. Industrial employment spans a range of industries including scientific R&D services (42% of industrial scientists), pharma (15%), and chemicals (12%). The majority of industrial scientists work in large established firms (more than 5000 employees, older than 5 years; 52%), smaller numbers work in startups (fewer than 100 employees, younger than 6 years; 8 %) and other firms (40%).

Of the academics, 43% are employed in Carnegie I and II institutions, 28% in medical schools, and 29% in other academic institutions (e.g., doctorate granting, comprehensive, and liberal arts). 51% are tenured, 23% are on the tenure track but not tenured, and 26% are not on the tenure track.[4]

[3] Detailed information on the SESTAT data file is available at http://www.nsf.gov/statistics/sestat/.

[4] Academics could be not on the tenure track either because the employing institution does not have a tenure system or because an existing tenure system does not apply to the individual's particular position. A closer look at these cases shows that they are primarily employed in tier 1 academic institutions and the preponderance of non-tenure track individuals in our sample are likely working as staff scientists and research faculty.

3.2 Measures

Table 1 provides a summary of our key measures.

Table 1: Measures

VARIABLE NAME	MEASURE DESCRIPTION
Classification variables	
Employment sector INDUSTRY	Dummy variable indicating whether respondent works in industry (=1) or academia (=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 field dummies to control for 11 different fields in our regression analyses.[5]
Dimensions of Science	
Type of R&D BASIC, APPLIED, DEVELOPMENT	The survey asked respondents to indicate which of a list of work activities were most important / 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 whether a particular activity was the most important R&D activity.
Salary (SALARY)	Respondents reported the amount of their basic annual salary received at their current employer.
Satisfaction with independence and income SAT_IND, SAT_SAL	The survey asked respondents to rate on a 4-point scale how satisfied they were at their current employer with salary and independence. We use these measures as proxies for organizational characteristics, where higher levels of satisfaction with a particular job attribute should reflect higher availability of that particular job attribute (see below for a discussion). Given the prevalence of high ratings, we dichotomized these measures such that 1 indicates "very satisfied" and 0 indicates a rating lower than "very satisfied".
Scientists' 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 . . .". Since responses are clustered at the higher end of the

[5] In the life sciences, these fields include agricultural and food sciences (5.9% of total), biomedical sciences (36.6%), biomedical engineering (1.2%), health sciences (7.3%), and other life sciences (0.7%). In the physical sciences, these fields include chemistry (16.7%), earth sciences (6.26%), mathematics (8.15%), physics (7.0%) and other physical sciences (0.6%). We also include a separate dummy for individuals who self-classified as "R&D management".

IMP_IND, IMP_SAL	scale (anchors "somewhat important" and "very important"), we dummy coded these measures such that 1 indicates "very important" and 0 indicates a rating lower than "very important".
U.S. Patent applications USPAPP, USPAPP01	Each respondent reported the number of U.S. patent applications in which he or she was named as an inventor over the last 5 years prior to the survey (USPAPP). We created a dummy variable coded as 1 if the respondent had at least one patent application in the 5-year period (USPAPP01). Our empirical analysis focuses on this indicator variable rather than patent counts because our main interest is in the question whether scientists are generally willing to disclose research findings in the form of patents and whether their employing organizations allow them to patent. Thus, we are less interested in the quantity or value of patent output than in its existence. Our 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 officials (cf. Thursby, Fuller, & Thursby, 2009a). Note that NSF confidentiality restrictions prevent us from matching the SESTAT data to other data sources such as patent citations.
Publications PUBS, PUBS01	Each respondent reported the number of (co)authored articles that have been accepted for publication in a refereed professional journal over the last 5 years (PUBS). We focus our analysis on a dummy variable coded as 1 if the respondent had at least one publication in the 5-year period (PUBS01), indicating that an individual is willing to publish and that the employer allows the individual to publish.
Attendance at professional meetings PROFMEET	Respondents indicated whether they had attended any professional society or association meetings or professional conferences in the past year (PROFMEET=1 if yes). While attendance at meetings does not necessarily mean that a scientist communicates with others about his/her research, we interpret this measure as relating to "disclosure mechanisms".
Memberships in professional societies PROFSOCIETIES	Respondents indicated the number of professional societies or associations they currently belong to. We interpret this measure as relating to "disclosure mechanisms".
Control Variables	
Experience (YRS_GRAD)	Time since obtaining highest degree, in years.
Ability (PHD_NRC_SCORE)	We matched each respondent's PhD-granting institution and the PhD field to the National Research Council's evaluation of PhD program quality (Goldberger, Flattau, & Maher, 1995), using the rating of "program effectiveness in educating research scholars and scientists". The scale ranges from 0 ("not effective") to 5 ("extremely effective"). This measure 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 PhD programs.
Number of individuals supervised (LN_SUPDIR)	Respondents indicated how many people they supervised directly in their jobs. We interpret this (logged) measure as a proxy for managerial status and, for those scientists running their own labs, as a proxy for the size of the laboratory.
Firm type (STARTUP, OTHERFIRM, ESTABLISHED)	The survey contains data on the age and size of the employer. We created three dummy variables indicating startups (smaller than 100 employees, younger than 6 years), large established firms (larger than 5000 employees, older than 5 years), and all other firms. Applies only to industry sample.
Type of academic institution (CARN12, LOWTIER, MEDSCHOOL)	We distinguish academic institutions using the Carnegie classification provided by NSF: Carnegie 1 and 2 institutions, lower-tier institutions (e.g, doctorate granting, liberal arts) and medical schools. Applies only to academic sample.
Academic position (TENURED, TENTRACK, NONTENTRACK)	Dummy variables indicating whether an academic scientist was tenured, on tenure track but not tenured, or not on the tenure track. Applies only to academic sample.
Race/Ethnicity (RACE)	Dummies for white, Asian, and other.
Gender (MALE)	MALE =1 if respondent is male
U.S. citizen (USCITIZEN)	USCITIZEN =1 if respondent is U.S. citizen

3.3 Measurement Issues

The measure of the nature of R&D is critical to our analysis and deserves further discussion. As described earlier, respondents indicated the type of work that occupied the most of their time in a typical work week, including basic research, applied research, and development. Each of the R&D related options was defined in the NSF instrument and the definitions were the same regardless of employment sector. Among the few studies that have measured the nature of the work of individual researchers, a common approach is to classify research based on the publication outlet, on citation patterns, or on terms appearing in publications (e.g., Ding, 2006; Narin, Pinski, & Gee, 1976; Thursby et al., 2009b). While this approach has many benefits, the choice of disclosure mechanisms may be endogenous to the nature of R&D and bibliometric measures of the nature of R&D may provide only limited insights into the relationships between the nature of R&D and disclosure mechanisms. A key advantage of our measure is that it is not contingent on the disclosure mechanism or on disclosure per se. Moreover, our measure captures the nature of the work a researcher typically does, rather than the nature of only a particular piece of knowledge produced (e.g., a particular publication) and our measure captures both successful and unsuccessful research effort. At the same time, we cannot rule out that researchers in academia and industry apply the NSF definitions in slightly different ways, although it is difficult to sign any potential bias.[6] Despite its limitations, our measure provides a unique perspective and complements prior work based on other measures of the nature of research.

While we have an objective measure of the salary offered by the employing organization, we rely on a satisfaction measure as a proxy for the level of independence offered. Our rationale is that a positive relationship between the actual level of an attribute and individuals' satisfaction with that attribute has been widely documented in the literature, including in the R&D context (Cable & Edwards, 2004; Idson, 1990; Wood & LeBold, 1970). Because an individual's satisfaction with independence may depend not only on the actual level of independence but also on the individual's preference for independence we estimate satisfaction models with scientists' preferences as a control.[7]

A general concern with survey data is the possibility of social desirability bias (SDB). More specifically, the concern is that individuals might inflate ratings of preferences that they think are socially desirable and give artificially low scores to preferences that may seem less socially desirable (Moorman & Podsakoff, 1992). SDB that applies to both industrial and academic scientists should not affect our results regarding comparisons between the two groups. However, it is conceivable that SDB affects the two groups differently. In particular, academic scientists may think that they are expected to care more strongly about independence than industrial scientists, and the latter may think it is less problematic to state a strong preference for income, effectively inflating an industry-academia gap in preferences. Any descriptive data on preferences we present should be interpreted in light of the possibility of such a bias. More importantly, however, SDB should be less of a concern regarding measures of satisfaction, measures of the nature of R&D, and measures of disclosure mechanisms.

[6] It is possible that academics draw on established stereotypes and have a bias towards classifying their work as basic while industrial scientists may be more likely to see the applied aspects of their work. In that case, our measure should overstate true differences in the nature of research. On the other hand, if academic research is generally basic while industrial research tends to be applied, a particular project may appear *relatively* basic to an industrial scientist while an academic would consider it *relatively* applied, which may result in a downward bias in the measured industry-academia gap in the nature of research.

[7] Our salary measures provide additional support for the suggested relationships between actual job attributes, preferences for attributes, and satisfaction. Those scientists who are "very satisfied" with their salary earn an average of $111,050, while those who are not very satisfied earn an average of $78,515. In a regression context, salary has a large positive impact on the satisfaction with salary; moreover, the interaction between salary and the importance of salary is positive and significant.

A final important concern is that relationships between variables may reflect common methods bias, i.e., that relationships between variables may be inflated if similar scales are used for dependent and independent variables (Podsakoff, MacKenzie, & Lee, 2003). In our context, the fact that academic and industrial scientists received the same survey instrument could also lead them to give similar answers, biasing estimated industry-academia gaps downwards. However, a closer examination of our measures suggests that common methods bias should be limited because the survey used a variety of different question formats, most of which are objective and quantitative.

4 Descriptive Analysis of Industry-Academia Gaps

4.1 Basic Sector Comparisons

Table 2 compares the means of our key variables for industry and academia and computes the "industry-academia gap". The table also shows significance levels for the industry-academia gaps, based on regressions models most appropriate for a given dependent variable.[8]

First, we find that only 6% of industrial scientists report being engaged primarily in basic research, compared to 70% of academic scientists, resulting in an industry-academia gap of 64 percentage points. On the other hand, 58% of industrial scientists are engaged in applied research, compared to 28% in academia. Development is the primary activity for 36% of industrial scientists, compared to 2% of academics. We examine differences across fields (life sciences versus physical sciences) below.

With respect to organizational characteristics, we find a salary gap of approximately 25,000 USD, which is consistent with a significantly higher satisfaction with salary reported by industrial scientists. On the other hand, academics report significantly higher satisfaction with the level of independence in their jobs: 78% of academics are "very satisfied" with their degree of independence compared to 51% of industrial scientists who are "very satisfied" with their independence. While the gap in satisfaction is significant, it is also remarkable that slightly more than half of all industrial scientists are very satisfied with independence; this contrasts with the common stereotype that industry provides very low levels of independence.[9]

[8] For example, we test differences in the nature of R&D by regressing the R&D type dummies on the INDUSTRY dummy using probit regression.
[9] While our results suggest that higher pay is a key advantage of employment in industry, there may be other characteristics that make industrial science attractive. In particular, Roach and Sauermann (2010) found that PhD students associated industrial R&D with higher levels of access to cutting-edge equipment and resources for research.

Scientists' preferences also vary across sectors. Industrial scientists find money more important than academics; in contrast, 81% of academics rate independence as "very important", while only 61% of industrial scientists do so. Whether these differences appear small or large depends on one's priors; however they do suggest that not all scientists share the same preferences and that systematic differences in scientists' preferences may need to be considered in future work on industrial versus academic science.

Finally, we also observe significant industry-academia gaps in disclosure mechanisms. 50% of all industrial scientists have at least one patent application in a five-year span, with an average count of 2.9. In contrast, only 16% of academics report one patent application, with an average count of 0.5. The industry-academia gap in publishing has the opposite sign – 92% of academics have at least one publication in five years, with an average of 12 publications. This compares to 62% publishing scientists in industry, with an average of 3.5 publications. Again, while the gaps in publishing and patenting are significant and large, these numbers also show that both sectors employ both disclosure mechanisms.[10]

Disclosure and "openness" in a more general sense may also be reflected in conference attendance and interactions in professional associations. We find that 87% of academics have attended at least one professional meeting in the prior year, compared to 74% of industrial scientists. Similarly, we find an average of 3 memberships in professional societies among academics, compared to 1.9 among industrial scientists. These comparisons show industrial scientists to have a remarkable level of engagement in the broader scientific community, even if that engagement does not reach the levels observed among academics.[11]

4.2 Industry-Academia Gaps in the Life Sciences versus the Physical Sciences

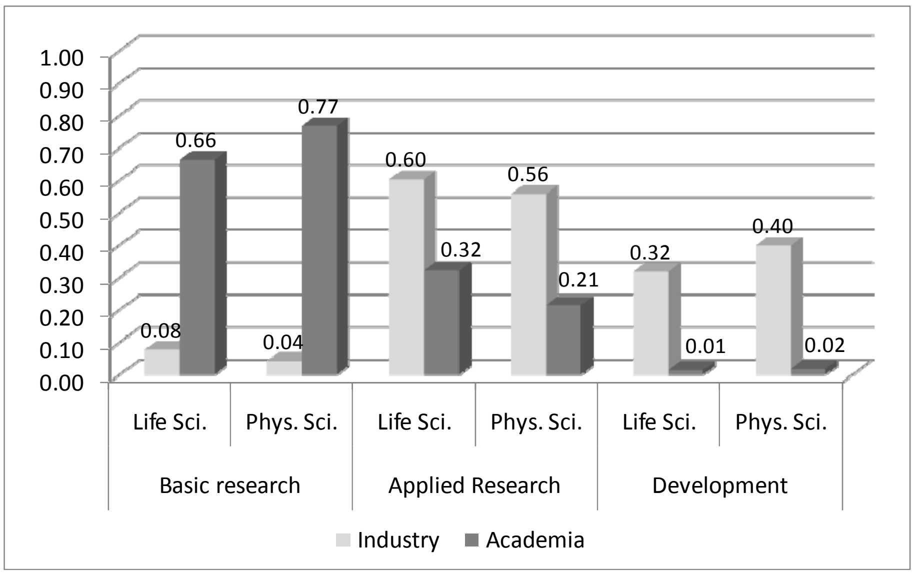
Our analysis thus far has focused on differences between industrial and academic science broadly. However, most of the prior work on "academic" features in industry and "commercial" aspects in academic science has been done in the life sciences. Thus, it is important to examine whether industry-academia gaps are smaller in the life sciences than in the physical sciences.

[10] In interpreting patent and publication counts, it has to be kept in mind that we focus on PhD trained scientists who are research active. Numbers of patents and publications are likely to be lower for non-PhDs (e.g., BS and MS degrees) or for individuals who are not research active (e.g., teaching faculty).

[11] We do not have data on the specific conferences and professional associations and we cannot tell to what extent scientists from the two sectors interact at conferences/in professional associations. However, many important professional associations such as the American Association for the Advancement of Science (AAAS) and the Institute of Electrical and Electronics Engineers (IEEE) have large numbers of members from industry as well as academia, suggesting that professional associations as well as conferences (which are often organized by those organizations) may provide important venues for industry-academia interactions.

Table 3 reports means and industry-academia gaps separately for the life sciences and the physical sciences. A first observation in table 3 is that industry-academia differences in the nature of research are significantly smaller in the life sciences. Figure 2 visualizes these gaps in the nature of research and also reveals that two sources contribute to the smaller gap in the life sciences: (1) academics in the life sciences are more likely to be engaged in applied work than their colleagues in the physical sciences and (2) life scientists in industry are more likely to be engaged in basic research than their colleagues in the physical sciences. These patterns are consistent with the notion that there is more of an overlap between basic and applied research in the life sciences than in the physical sciences ("Pasteur's Quadrant").

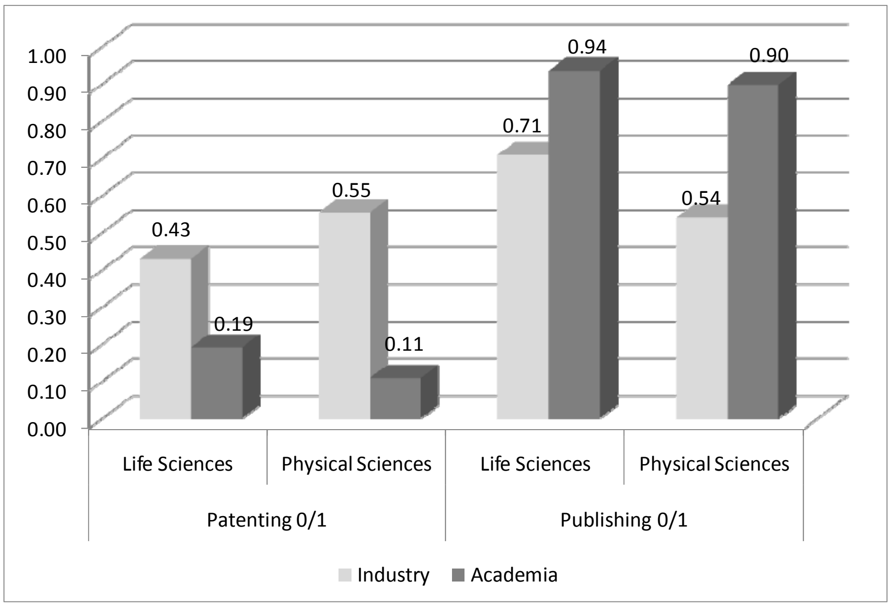
Figure 2: Nature of R&D, by Sector and Field



The industry-academia gaps with respect to organizational characteristics are, however, similar in the life sciences and the physical sciences. Specifically, we find no significant field difference in the salary premium reported by industrial scientists or in the relative advantage academia has in providing independence. Consistent with this result, we also do not observe differences in the industry-academia gap in scientists' preferences.

However, we observe smaller publishing and patenting gaps in the life sciences than in the physical sciences. Figure 3 illustrates these patterns by showing the probability of patenting and publishing across fields and sectors. We see that the industry-academia gap in patenting is smaller in the life sciences for two reasons: (1) life scientists in academia are *more* likely to patent than physical scientists in academia and (2) life scientists in industry are *less* likely to patent than physical scientists in industry.[12] The gap in publishing is smaller in the life sciences primarily because life scientists in industry are more likely to publish than physical scientists in industry (71% vs. 54%). Overall, these results are consistent with the notion that industrial science is more "open" in the life sciences than in the physical sciences. But again, even physical scientists in industry show a remarkable level of publishing activity (as well as conference attendance, see table 3).

Figure 3: Probability of Patenting and Publishing, by Sector and Field



5 Relationships between Dimensions of Science and Differences within Sectors

We now use regression analysis to examine industry-academia differences in more depth. First, we examine the relationships between the nature of research on the one hand and organizational characteristics, scientists' preferences, and disclosure mechanisms on the other. In so doing, we address the earlier conjecture that different "research missions" of academia and industry may explain differences in other dimensions. Second, we consider the possibility that there may be systematic differences within each sector, e.g., between academics of different tenure status within academia or between startups and established firms in industry.

[12] Lower patenting rates in the life sciences might seem surprising given prior work showing that patents tend to be more effective in protecting intellectual assets in the life sciences than in the physical sciences. However, 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 (cf. Cohen et al., 2000). We discuss these issues in more detail below.

5.1 Model Specifications

We begin by regressing the focal dependent variable on the INDUSTRY dummy using the full sample. The coefficient on INDUSTRY reflects the mean difference in the dependent variable between the two sectors, i.e., the "industry-academia gap".[13] For example,

$$\text{Patents}_i = f\,(\alpha + \beta\text{INDUSTRY}_i + \varepsilon_i). \tag{1}$$

Next, we additionally include the measures of the type of R&D:

$$\text{Patents}_i = f\,(\alpha + \beta\text{INDUSTRY}_i + \boldsymbol{\gamma}\mathbf{RAND_i} + \varepsilon_i), \tag{2}$$

where **RAND** is a vector of dummies indicating the nature of research (BASIC, DEVELOPMENT; APPLIED is omitted). The coefficients on these dummies indicate differences in the dependent variable across types of R&D. Moreover, a reduction in the absolute magnitude of β suggests that differences in the nature of R&D (partially) explain the industry-academia gap in the dependent variable.

Next, we estimate regression models separately by sector and field and include a range of additional sector-specific controls. For example, the regressions for the industry sub-sample include dummies indicating the firm type (e.g., startup and established firm), and the academia regressions include dummies indicating the type of academic institution as well as tenure status of the scientist (e.g., medical school or Carnegie I+II institution; tenure track vs. not on the tenure track). These regressions also include additional individual-level controls and detailed sub-field dummies. For example,

$$\text{Patents}_i = f\,(\alpha + \boldsymbol{\gamma}\mathbf{RAND_i} + \boldsymbol{\delta}\mathbf{CONTROLS_i} + \varepsilon_i), \tag{3}$$

where **CONTROLS** is a vector of sector- and individual-specific controls. These split sample regressions provide additional insights into differences within sectors, providing a more nuanced view of industrial and academic science than the basic sector comparisons reported above.

Finally, we use the coefficients from split-sample regressions to predict the likelihood that a given individual patents or publishes in industry and academia, respectively, holding the nature of research as well as control variables constant. This approach more accurately reflects industry-academia differences in disclosure mechanisms than equation (2) because it effectively allows independent variables to have different coefficients in the two sectors. Any remaining difference in predicted values would arguably reflect effects of other determinants of disclosure

[13] Note that we are concerned with differences across sectors and not with any "causal" effects of sector on the dependent variables.

mechanisms, e.g., different organizational norms regarding patenting and publishing or different functions of patents in the two sectors.

5.2 Organizational Characteristics

Table 4 shows the results using our two measures of organizational characteristic, salary and independence, as dependent variables. Model 1, which regresses log salary on the INDUSTRY dummy using OLS, shows a large and significant industry-academia gap in salary. The coefficient is reduced once we include BASIC and DEVELOPMENT in model 2 (Chi2(1)=3.33, p=0.068), but it remains large and significant. We also find that individuals engaged in basic research earn somewhat less than those in applied research. Models 3 and 4 use only the industry sample. We find no significant pay differences between basic and applied researchers, although employees in development earn somewhat less. Consistent with prior work (e.g., Oi & Idson, 1999), we find that large established firms pay more than "other" firms that are not startups, that salary increases with experience, and that salary increases with management responsibilities. Using the academic sample only (models 5 and 6), we observe that academic scientists engaged in basic research earn significantly less than those primarily engaged in applied research once all controls are included. This finding suggests that compensating wage differentials may exist not only between industry and academia (Aghion et al., 2008) but also within academia.

Models 7-15 examine differences in the level of independence and are of particular interest in light of the growing body of theoretical work surrounding independence in industry versus academia (e.g., Aghion et al., 2008; Lacetera, 2009). Model 7 shows a large and significant industry-academia gap; in model 8 we observe that scientists involved in basic research have somewhat more independence than those involved in applied research, and the composition of research explains a small but significant (Chi2(1)=4.09; p=0.043) part of the observed industry-academia gap. We find no significant differences in independence between basic and applied research for those working in industry (model 9). One potential interpretation is that, given the heterogeneity in firms' activities (e.g., R&D, marketing, and production), different types of R&D are *relatively* similar from the firm's perspective and are thus organized in similar ways. In contrast, we find some evidence that independence differs across types of research activities in academia, with somewhat higher levels for scientists in basic research and somewhat lower level for academics in development (model 11).[14] While this result may reflect that downstream work in academia is often tied to funding from industry or other agencies that may limit researcher independence, the differences across types of R&D virtually disappear once we control for a broader set of controls (model 12). Regarding other differences within academia, we find significantly higher levels of independence in tier I+II institutions than in lower-tier institutions. We also find much lower levels of independence for scientists who are not on the tenure track, likely reflecting that these individuals tend to work for other scientists and tend to have a lower status within the institution. Similarly, independence increases with the number of individuals an academic supervises, i.e., with the size of the researchers' laboratory. Our results regarding independence hold when we additionally control for scientists preferences for independence to account for the possibility that a given level of (objective) independence results in higher levels of satisfaction (or utility) for those individuals who care strongly about having independence. [15]

5.3 Scientists' Preferences

Table 5 reports regressions for scientists' preferences, starting with the preference for salary. We find that industrial scientists care significantly more about salary than academics (model 1), which is to some extent explained by the fact that scientists engaged in basic research assign a lower importance to salary than those engaged in applied research or development (model 2). We find little heterogeneity in the salary preferences within the industry sample. However, among academics, those engaged in basic research and those trained at higher-rated PhD institutions tend to report somewhat weaker preferences for salary, while those at medical schools report somewhat stronger salary preferences. Somewhat surprisingly, academics engaged in development report significantly lower salary preferences. The number of cases in this cell is very small, but assuming that scientists engaged in development have lucrative options in

[14] Note that the number of academics primarily engaged primarily in development is quite small (n=56) and any results for that sub-sample should be interpreted with caution.

[15] The joint observation of higher salaries and lower independence in industry raises the question whether these gaps are causally connected, i.e., 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 also at the level of the individual. We examined these relationships but generally found either no or weak positive correlations between salary and independence. Moreover, in a regression context, differences in independence across sectors do not explain differences in salary. Our earlier findings regarding differences within sectors provide an explanation: certain scientists (e.g., tenure-track faculty and managers) tend to enjoy higher levels of both salary and independence, while others receive low levels of both factors. As pointed out by Stern (2004), compensating differentials should be studied for a given individual and (unobserved) heterogeneity limits the insights that can be gained from a cross-sectional analysis. Thus, while the aggregate industry-academia gaps are consistent with compensating differentials, different data are needed to clearly establish the existence and size of these differentials at the level of the individual (cf. Sauermann et al., 2010a; Stern, 2004).

industry, this finding could reflect that only those with low preferences for money decide to work in academia.

With respect to the desire for independence (models 7-12), we observe a large industry-academia gap, consistent with the gap in levels of actual independence. However, we observe no significant difference in preferences among scientists involved in different kinds of R&D and the industry-academia gap changes relatively little once we control for the type of R&D.

Overall, we find significant industry-academia differences with respect to individuals' preferences, and these differences are broadly consistent with the differences in organizational characteristics. As discussed earlier, both selection effects (scientists with particular preferences self-select into sectors offering the desired organizational attributes) as well as socialization effects (organizations change employees' preferences) may be responsible for these patterns. Unfortunately, our cross-sectional data do not allow us to disentangle selection and socialization mechanisms because we cannot separately identify cohort and aging effects (cf. Levin & Stephan, 1991).

5.4 Disclosure Mechanisms

It is often assumed that basic research is disclosed primarily in the form of publications, while applied research and development are disclosed in the form of patents (or kept secret). To the extent that this mapping between the nature of research and disclosure mechanisms holds, higher rates of publications in academia could be explained by the fact that academics are more likely to be engaged in basic research, while higher patenting rates in industry could be the result of a larger share of applied research and development being done in industry. Because our measure of the nature of research is independent of the disclosure mechanism, we are able to examine the validity of this assumption.

Our analysis is reported in table 6. Models 1-6 focus on USPAPP01, indicating whether a scientist had at least one patent application in the prior 5 years. Models 7-12 examine PUBS01, indicating whether a scientist had at least one peer-reviewed publication. As discussed in the measurement section, we use indicators rather than counts because we are interested in scientists' decision to become involved in patenting/publishing and in organizations' policies towards these activities rather than a scientists' productivity conditional upon engaging in a particular form of disclosure.

Model 1 uses the pooled sample and shows a large industry-academia gap in patenting. When we include BASIC and DEVELOPMENT (model 2), we find that scientists engaged in development are less likely to patent than those in applied research. A potential explanation for the negative DEVELOPMENT coefficient is that results of development projects are less likely to be sufficiently novel to be patentable. We do not observe a difference in patenting between basic and applied research. Interestingly, the coefficient on INDUSTRY *increases* slightly once we include DEVELOPMENT, suggesting that once we control for the fact that industry does more development and development is less likely to be patented, the industry-academia gap in patenting is even larger than reflected in a simple mean comparison.

Next, we estimate split regressions for academia and industry, separately for the life sciences and the physical sciences. The negative coefficient on DEVELOPMENT is stronger in the life sciences than in the physical sciences, particularly among industrial scientists. We find no significant differences between basic and applied research in the life sciences, which is consistent with the view that the two types of research overlap to a significant degree ("Pasteur's Quadrant"). In the physical sciences, however, academics engaged in basic research are much less likely to patent than those engaged in applied work.

We also see other interesting differences in patenting within sectors. In the life sciences, scientists in startups are significantly more likely to have a patent than those in established firms, perhaps reflecting that life sciences startups use patents as a signal of scientific capability and commercial potential (Hsu et al., 2007). Patenting among industrial scientists also increases with the ranking of the PhD granting institution, possibly reflecting an effect of ability on the quality of research.[16] In the academic life sciences, patenting rates are significantly lower in lower-tier institutions and significantly higher in medical schools, compared to Carnegie I/II institutions.

Models 7-12 focus on the likelihood of publishing. We find no significant differences in publishing between basic and applied scientists, 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; industrial scientists are less likely to publish partly because they are more often engaged in development work which is less likely to result in a publication.

[16] Our interpretation of patent and publication counts as "disclosure mechanism" implicitly assumes that all individuals have generated research results that can be disclosed. While we know that all individuals in our sample are research active, we do not have an independent measure of their research productivity. Control variables for ability (PHD_NRC_SCORE) and experience (YRS_GRAD) should capture a significant share of the unobserved variation in underlying research productivity.

Our split sample regressions show that the lower likelihood of publishing for scientists in development is driven primarily by scientists in industry. We also find that industrial scientists trained at highly ranked institutions are more likely to publish. However, the likelihood of publishing decreases with time since graduation, i.e., younger industrial scientists are more likely to have a publication than older scientists. This result may reflect the fact that newly-minted scientists arrive with a stock of research findings ready for publication or a recent shift on the part of firms towards more open science by hiring more "academic" types of scientists. It could also reflect that scientists become less interested in publishing over time due to socialization.[17]

5.5 Publishing and Patenting by a "Standardized Individual"

The regressions using the pooled sample showed that large industry-academia gaps in publishing and especially patenting remain even if we control for the nature of R&D. However, these regressions constrained the coefficients of the nature of work to be the same across sectors and fields and did not control for a range of individual-level variables such as gender or ability. We, therefore, estimated regressions separately by sector and field (similar to models 3-6 and 9-12, but excluding sector-specific controls) and use the results of these to predict the probability that a "standardized individual" patents or publishes when working in industry versus academia. Using this method, we effectively predict the industry-academia gap for a given type of research and a given individual, allowing for different effects of the nature of R&D and of characteristics of the individual on the focal outcome across sectors and fields. This approach provides the best estimates of differences in the use of disclosure mechanisms that can be attributed to the sectors *per se*, rather than to differences in the nature of work or in scientists' characteristics. For the most part, we use the median or mean values in our sample to define the "standardized individual." In the life sciences, this "standardized individual" is a biomedical scientist who is engaged in applied research, graduated 10 years ago (HDTENURE=10) from an average PhD program (PHD_NRC_SCORE=3.45), supervises two other people, and is white, male and a U.S. citizen. In the physical sciences, the "standardized individual" is a physicist who otherwise has the same characteristics as the biomedical scientist.

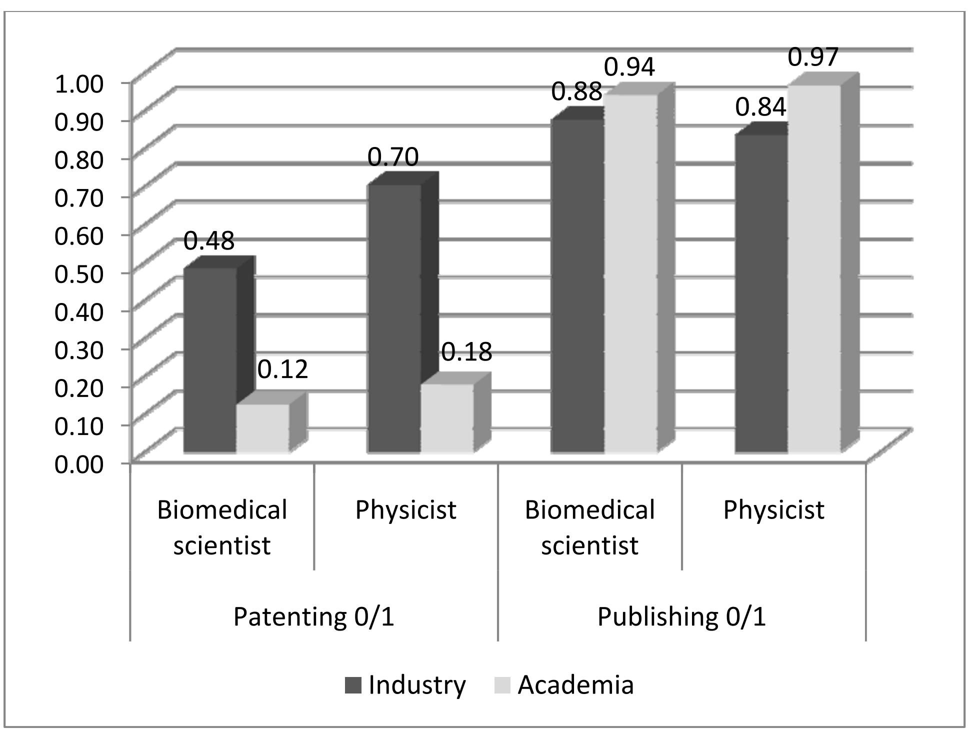
Figure 5 gives the predicted probabilities of patenting and publishing. We find large predicted industry-academia gaps in the probability of patenting for both the biomedical scientist

[17] When we drop individuals who graduated within 5 years, the negative effect of time since graduation is reduced but remains significant, especially in the life sciences.

and the physicist. However, the predicted industry-academia gaps in the probability of publishing are much smaller than those for patenting, and the publishing gap is insignificant for the biomedical scientist (0.88 vs. 0.94). The large remaining gaps in the probability of patenting even controlling for the nature of research likely reflect different norms regarding disclosure and different functions of patenting across sectors. For example, it is well known that firms use patents for purposes other than the protection of the focal invention, i.e., to build patent fences or to obtain bargaining power in cross-licensing negotiations (Cohen et al., 2000). Such uses are less relevant in academia. Moreover, such strategic uses are particularly important in industries such as semiconductors and electronics, which may explain why the remaining gap is larger in the physical sciences than in the life sciences.

Our data do not allow us to clearly identify strategic disclosure, norms, or other mechanisms underlying the remaining industry-academia gaps in the use of disclosure mechanisms. However, by separating out differences associated with the nature of research and scientists' characteristics, we provide estimates of the potential magnitude of these effects and our results suggest that such factors are more important with respect to patenting than with respect to publishing.

Figure 5: Predicted Probabilities of Patenting and Publishing for a "Standardized Individual" Engaged in Applied Research



6 Summary and Discussion

The stereotypical view of academic and industrial science depicts the two sectors as qualitatively different. Recent evidence, however, suggests many similarities and, perhaps, increasing convergence. Unfortunately, a sound empirical basis to assess similarities and differences between the two sectors has been missing. Moreover, we have a limited understanding of the relationship between the nature of research, which is often seen as the key driver of sectoral differences, and other characteristics of industrial and academic science.

Drawing on prior theoretical and empirical work on industrial and academic science, we develop a framework of comparison involving four key dimensions of science: the nature of work (e.g., basic versus applied), organizational characteristics (e.g., level of freedom), scientists' characteristics (e.g., preference for freedom), and disclosure mechanisms (e.g., publishing and patenting). We then use detailed survey data from a representative sample of over 5,000 life scientists and physical scientists working in industry and academia to compare the two sectors along the four dimensions. We also examine differences within each sector and the relationships between the four dimensions of science. With respect to the latter, we are particularly interested in the extent to which differences in the nature of research explain differences in other characteristics of science.

We find significant industry-academia differences with respect to all four dimensions. But we also find remarkable similarities. For example, while 78% of academics are very satisfied with their level of independence, more than 50% of industrial scientists are very satisfied as well. Similarly, over 60% of industrial scientists publish, compared to 92% in academia. Our data allow us to quantify differences and similarities such as these along all four dimensions, painting an unusually nuanced and representative picture of academic and industrial science. Moreover, our analyses also show important differences *within* each sector, e.g., between top tier versus lower tier academic institutions, between scientists with different tenure statuses, or between startups and large established firms.

Our econometric analyses show several significant relationships between the nature of research and the other dimensions of science. However, differences in the nature of research do not fully explain differences in those other dimensions. For example, a higher likelihood of patenting in industry is not explained by the fact that industrial research tends to be more downstream.

Our paper makes several contributions. First, although prior work has questioned simplistic views of industrial and academia science, empirical studies typically focus on a limited set of attributes (e.g., publishing) or on only one sector (e.g., either academia or industry). Here we compare industrial and academic science directly along four key dimensions using a large representative sample. Prior work suggests that our findings of significant differences *and* remarkable similarities have important implications. For example, Aghion et al. (2008) and Lacetera (2008) show theoretically that differences in the level of freedom granted to scientists in industry and academia directly affect important issues such as wages, the division of labor across sectors, or collaborative relationships between sectors. While our finding of higher levels of freedom in academia suggest that the mechanisms proposed by Aghion et al. and Lacetera may indeed be operating, our findings that the majority of industrial scientists are very satisfied with their level of freedom suggests that the difference in freedom may be less pronounced than their models assume. Overall, and returning to our title question, our results suggest that industrial and academic science may be better characterized as "siblings" rather than "twins" or "strangers". However, neither of these simple labels may sufficiently describe the relationship between the two sectors since we find different industry-academia gaps across the four dimensions of science as well as a significant amount of heterogeneity even within each sector.

Second, our results provide novel evidence regarding the relationships between the nature of R&D and the use of different disclosure mechanisms across the two sectors. In particular, we find that the significantly higher level of patenting activity in industry is not explained by the fact that industrial R&D is more downstream than academic research – indeed, the industry-academia gap in patenting slightly *increases* when we account for the nature of research because development work, which is more common in industry, is less likely to be associated with patenting than basic or applied research. One interpretation of the remaining patenting gaps is that industry and academia are characterized by very different norms and incentives regarding patenting, or by different functions and uses of patents. On the other hand, we find that an individual working on the "same" type of research is almost as likely to have a publication in industry as in academia (though counts of publications remain much lower), suggesting that the two sectors are more similar with respect to the drivers of publishing.

Third, our findings provide support for the notion that scientists make trade-offs between pecuniary and nonpecuniary job attributes (cf. Stern, 2004). We find that academics earn objectively less and are less satisfied with salary than their colleagues in industry but they are more satisfied with their level of independence. While prior work has documented pay differences across sectors, we also document offsetting differences in nonpecuniary job attributes. However, our finding of weaker preferences for nonpecuniary factors in industry suggests that the observed salary premium in industry may be smaller than what would be necessary to induce a randomly selected scientist to work in industry (cf. Aghion et al., 2008; Rosen, 1986). Our descriptive results also inform research on scientific labor markets. Roach & Sauermann (2010) asked current PhD students about their perceptions of scientific careers in industry and academia and found that students perceived the sectors to be dramatically different with respect to factors such as independence, salaries, and publishing opportunities. Our results suggest that actual differences between industrial and academic science may be smaller than those expected by students, potentially leading to suboptimal career decisions.

Fourth, our findings may have important implications for research on academia-industry interactions and technology transfer. One possible interpretation of our findings is that the significant *differences* across sectors could inhibit industry-academia interactions, e.g., if academic collaborators are more interested in working independently on challenging projects, while industrial collaborators are more interested in financial payoffs, or if academics get rewarded for publishing while industrial scientists get rewarded for patents. However, a different interpretation is that the remarkable *similarities* between sectors, e.g., regarding scientists' preferences and publishing activities, may actually facilitate collaboration. Similarly, our finding of high levels of conference attendance and memberships in professional associations among industrial as well as academic scientists complements prior evidence suggesting that such "informal" knowledge channels may be important mechanisms for knowledge exchange within as well as across sectors (cf. Cockburn et al., 1998; Cohen, Nelson, & Walsh, 2002).

Finally, our work goes beyond qualitative comparisons and provides quantitative estimates of differences and similarities, opening up the possibility of using such quantities as independent variables in future work. For example, future studies could examine whether the "distance" between industrial and academic science explains important outcomes such as academic entrepreneurship or labor mobility. Moreover, longitudinal studies employing quantitative measures of the "industry-academia gap" could provide a more rigorous basis for assessing the "convergence" between the industrial and the academic sector over time.

Our findings suggest several areas for future research. First, while we provide rich data on differences and similarities between sectors, we have made only limited progress in explaining the observed differences. Future work is needed to examine the underlying mechanisms, including institutional norms and incentives as drivers of differences in patenting and publishing. Second, longitudinal studies are needed on changes in the four dimensions. While changes in the four dimensions are interesting per se, longitudinal studies may also inform us about the relative importance of selection effects and socialization effects in driving observed industry-academia gaps in scientists' preferences. Given universities' increasing interest in commercialization and firms' increasing interest in tapping into the benefits of open science, the question of how and how much individuals' preferences can change to support those strategies is particularly relevant from a policy and management perspective.

Our study is not without limitations. First, while our measure of the nature of R&D has several unique benefits, a more fine-grained measure that can explicitly identify research in "Pasteur's Quadrant" would be desirable. Second, we had to rely on scientists' satisfaction with independence as a proxy of actual independence. While satisfaction gaps were robust to the inclusion of various controls, it would be desirable to assess industry-academia gaps in organizational characteristics using more direct measures. Third, while our data allow us to compare and contrast academic and industrial research along a wide range of dimensions, they do not capture all potentially relevant attributes. For example, it would be interesting to compare the two sectors with respect to organizational characteristics such as the role of teams and access to resources for research or with respect to the impact and value of the knowledge generated. Finally, most of our measures were obtained from survey questionnaires and are self-reported by respondents; NSF confidentiality restrictions prevented us from matching our data to external data sources. While self-reports using the same survey instrument facilitate comparisons across a wide range of individuals and institutions, future work should also employ secondary data sources such as patent statistics.

Despite these limitations, our study provides novel insights into the scientific enterprise and may also help decision makers in their efforts to improve research effectiveness in industry and academia and to foster productive relationships between the two sectors.

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Table 2: Descriptive Statistics and Mean Comparisons Across Sectors

Dimension	Variable	Variable Type	Industry N=1831 Mean	Industry SD	Academia N=3187 Mean	Academia SD	Ind-Acad Gap
Nature of R&D	Basic research	Dummy	0.06	0.23	0.70	0.46	-0.64 **
	Applied Research	Dummy	0.58	0.49	0.28	0.45	0.30 **
	Development	Dummy	0.36	0.48	0.02	0.13	0.35 **
Organizational characteristics	Actual salary	Continuous	106,081	53,248	81,326	42,179	24,755 **
	Satisfaction salary	Dummy	0.41	0.49	0.26	0.44	0.15 **
	Satisfaction independence	Dummy	0.51	0.50	0.78	0.42	-0.27 **
Preferences	Importance of salary	Dummy	0.47	0.50	0.37	0.48	0.10 **
	Importance of independence	Dummy	0.61	0.49	0.81	0.39	-0.20 **
Disclosure mechanisms	U.S. patent applications	Count	2.91	6.82	0.51	2.58	2.41 **
	U.S. patent applications yes/no	Dummy	0.50	0.50	0.16	0.36	0.34 **
	Publications	Count	3.49	6.09	12.00	13.89	-8.50 **
	Publications yes/no	Dummy	0.62	0.49	0.92	0.27	-0.30 **
	Professional meetings attendance	Dummy	0.74	0.44	0.87	0.33	-0.13 **
	Professional societies memberships	Count	1.90	1.68	3.09	2.23	-1.19 **
Controls	Male	Dummy	0.81	0.41	0.76	0.45	0.05 **
	Years since graduation	Count	15.03	9.12	17.18	10.35	-2.15 **
	NRC PhD program ranking score	Continuous	3.41	0.71	3.47	0.73	-0.06 **
	People supervised	Count	2.77	3.47	3.71	7.42	-0.93 **
	Startup	Dummy	0.08				
	Large established firm	Dummy	0.40				
	Other firm	Dummy	0.52				
	Not tenure track	Dummy			0.25		
	Tenure track not tenured	Dummy			0.21		
	Tenured	Dummy			0.54		
	Carnegie I, II	Dummy			0.43		
	Medical school	Dummy			0.28		
	Lower tier	Dummy			0.29		

*=significant at 5%; **=significant at 1%. Significance based on regressions with INDUSTRY dummy as RHS variable.

Table 3: Means and Industry-University Gaps by Field of Occupation

		Life Sciences			Physical Sciences			
		Industry	Academia	Ind-Acad	Industry	Academia	Ind-Acad	
		N=848	N=1993		N=983	N=1194		
Dimensions	**Variable**	**Mean**	**Mean**	**Gap**	**Mean**	**Mean**	**Gap**	**Diff. in Gaps**
Type of R&D	Basic research	0.08	0.66	-0.59 **	0.04	0.77	-0.72 **	0.14 **
	Applied Research	0.60	0.32	0.28 **	0.56	0.21	0.34 **	-0.06 *
	Development	0.32	0.01	0.30 **	0.40	0.02	0.38 **	-0.08 n.s.
Organizational characteristics	Actual salary	107,052	84,063	22,989 **	105,256	76,739	28,517 **	-5,527 n.s.
	Satisfaction salary	0.42	0.27	0.15 **	0.39	0.24	0.15 **	0.00 n.s.
	Satisfaction independence	0.52	0.79	-0.27 **	0.51	0.76	-0.26 **	-0.01 n.s.
Preferences	Importance of salary	0.49	0.39	0.10 **	0.46	0.34	0.12 **	-0.02 n.s.
	Importance of independence	0.63	0.82	-0.18 **	0.59	0.79	-0.20 **	0.02 n.s.
Disclosure mechanisms	U.S. patent applications	2.23	0.60	1.63 **	3.50	0.35	3.14 **	-1.51 **
	U.S. patent applications yes/no	0.43	0.19	0.24 **	0.55	0.11	0.45 **	-0.21 **
	Publications	3.94	12.02	-8.08 **	3.10	11.95	-8.85 **	0.77 *
	Publications yes/no	0.71	0.94	-0.23 **	0.54	0.90	-0.36 **	0.13 *
	Professional meetings attendance	0.81	0.87	-0.06 **	0.67	0.87	-0.19 **	0.14 **
	Professional societies memberships	2.07	3.32	-1.25 **	1.76	2.70	-0.94 **	-0.31 n.s.

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

Table 4: Organizational Characteristics

	Full sample		Industry		Academia		Full sample		Industry		Academia		Full Sample	Industry	Academia
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	OLS	OLS	OLS	OLS	OLS	OLS	probit	probit	probit	probit	probit	probit	probit	probit	probit
	ln_salary	**ln_salary**	**ln_salary**	**ln_salary**	**ln_salary**	**ln_salary**	**sat_ind**	**sat_ind**	**sat_ind**	**sat_ind**	**sat_ind**	**sat_ind**	**sat_ind**	**sat_ind**	**sat_ind**
Industry	0.266**	0.233**					-0.738**	-0.663**					-0.565**		
	[0.020]	[0.026]					[0.040]	[0.055]					[0.056]		
Basic research		-0.048*	-0.089	0.005	-0.040	-0.070**		0.121*	-0.050	-0.023	0.128*	0.092	0.109*	0.028	0.089
		[0.024]	[0.058]	[0.058]	[0.027]	[0.025]		[0.052]	[0.134]	[0.139]	[0.058]	[0.066]	[0.053]	[0.142]	[0.067]
Development		0.003	-0.004	-0.071*	0.041	0.053		0.004	0.038	0.003	-0.442*	-0.426*	0.020	0.027	-0.401*
		[0.033]	[0.036]	[0.034]	[0.062]	[0.051]		[0.062]	[0.065]	[0.067]	[0.190]	[0.189]	[0.063]	[0.068]	[0.182]
Imp. Independence													0.710**	0.604**	0.707**
													[0.045]	[0.065]	[0.065]
Startup				-0.043						0.181				0.147	
				[0.063]						[0.123]				[0.124]	
Other firm				-0.069*						0.121				0.136*	
				[0.033]						[0.066]				[0.067]	
Lower tier						-0.164**						-0.205**			-0.198**
						[0.028]						[0.072]			[0.073]
Medical school						0.160**						-0.014			0.006
						[0.027]						[0.075]			[0.077]
Not tenure track						-0.177**						-0.469**			-0.392**
						[0.029]						[0.083]			[0.085]
Tenured						0.024						-0.126			-0.131
						[0.028]						[0.090]			[0.092]
Field				incl.		incl.				incl.		incl.		incl.	incl.
PhD_NRC_Score				0.040		0.031*				-0.006		0.029		-0.004	0.010
				[0.024]		[0.014]				[0.045]		[0.039]		[0.045]	[0.040]
Yrs since grad				0.022**		0.017**				0.000		0.006		-0.001	0.005
				[0.002]		[0.001]				[0.004]		[0.004]		[0.004]	[0.004]
Yrs grad _sq				-0.001**		0.000				0.001**		0.000		0.001**	0.000
				[0.000]		[0.000]				[0.000]		[0.000]		[0.000]	[0.000]
ln_Supdir				0.074**		0.111**				0.084*		0.107**		0.057	0.086*
				[0.020]		[0.012]				[0.043]		[0.035]		[0.044]	[0.035]
Male				-0.001		0.089**				-0.164*		-0.073		-0.139	-0.050
				[0.040]		[0.027]				[0.081]		[0.064]		[0.083]	[0.065]
U.S. Citizen				0.011		0.024				-0.014		0.278**		-0.010	0.300**
				[0.062]		[0.044]				[0.113]		[0.095]		[0.115]	[0.095]
Race				incl.		incl.				incl.		incl.		incl.	incl.
Constant	11.165**	11.199**	11.438**	10.863**	11.193**	10.541**	0.766**	0.683**	0.018	0.294	0.686**	0.419*	0.145*	-0.133	-0.004
	[0.012]	[0.021]	[0.021]	[0.118]	[0.023]	[0.088]	[0.026]	[0.045]	[0.040]	[0.249]	[0.048]	[0.200]	[0.057]	[0.260]	[0.208]
Observations	5018	5018	1831	1831	3187	3187	5018	5018	1831	1831	3187	3187	5018	1831	3187
R-squared	0.038	0.039	0.001	0.145	0.001	0.228									

Robust standard errors in brackets; * significant at 5%; ** significant at 1%

Omitted categories are Applied Research, Large established firm, Carnegie I+II institution, Tenure track but not tenured

Table 5: Scientists' Preferences

	Full Sample		Industry		Academia		Full Sample		Industry		Academia	
	1	2	3	4	5	6	7	8	9	10	11	12
	probit	probit	probit	probit	probit	probit	probit	probit	probit	probit	probit	probit
	imp_sal	**imp_sal**	**imp_sal**	**imp_sal**	**imp_sal**	**imp_sal**	**imp_ind**	**imp_ind**	**imp_ind**	**imp_ind**	**imp_ind**	**imp_ind**
Industry	0.259**	0.174**					-0.592**	-0.525**				
	[0.039]	[0.053]					[0.041]	[0.058]				
Basic research		-0.126*	-0.160	-0.187	-0.145**	-0.105		0.076	-0.217	-0.206	0.123*	0.038
		[0.049]	[0.136]	[0.137]	[0.053]	[0.060]		[0.056]	[0.135]	[0.139]	[0.061]	[0.070]
Development		0.015	0.070	0.058	-0.565**	-0.557**		-0.052	-0.056	-0.095	-0.250	-0.196
		[0.061]	[0.065]	[0.067]	[0.203]	[0.210]		[0.063]	[0.066]	[0.068]	[0.199]	[0.206]
Startup				-0.116						0.180		
				[0.125]						[0.125]		
Other firm				-0.085						-0.039		
				[0.066]						[0.067]		
Lower tier						-0.042						-0.095
						[0.065]						[0.074]
Medical school						0.136*						-0.093
						[0.068]						[0.078]
Not tenure track						0.026						-0.447**
						[0.076]						[0.083]
Tenured						0.153						0.008
						[0.080]						[0.091]
Field				incl.		incl.				incl.		incl.
PhD_NRC_Score				-0.034		-0.111**				-0.013		0.092*
				[0.044]		[0.035]				[0.045]		[0.042]
Yrs since grad				-0.009*		0.006				0.004		0.007
				[0.004]		[0.004]				[0.004]		[0.005]
Yrs grad _sq				0.000		0.000				0.000		0.000
				[0.000]		[0.000]				[0.000]		[0.000]
ln_supdir				0.062		0.034				0.129**		0.117**
				[0.043]		[0.030]				[0.044]		[0.035]
Male				0.156		0.079				-0.146		-0.128
				[0.081]		[0.058]				[0.083]		[0.067]
U.S. Citizen				-0.130		-0.190*				-0.024		-0.031
				[0.113]		[0.093]				[0.114]		[0.106]
Race				incl.		incl.				incl.		incl.
Constant	-0.325**	-0.238**	-0.082*	-0.087	-0.215**	-0.085	0.872**	0.821**	0.314**	0.596*	0.793**	0.3
	[0.024]	[0.042]	[0.040]	[0.248]	[0.045]	[0.186]	[0.027]	[0.048]	[0.041]	[0.257]	[0.051]	[0.217]
Observations	5018	5018	1831	1831	3187	3187	5018	5018	1831	1831	3187	3187

Robust standard errors in brackets; * significant at 5%; ** significant at 1%

Omitted categories are Applied Research, Large established firm, Carnegie I+II institution, Tenure track but not tenured

Table 6: Patenting and Publishing

	Full		industry		academia		Full		industry		academia	
			life	phys	life	phys			life	phys	life	phys
	1	2	3	4	5	6	7	8	9	10	11	12
	probit	probit	probit	probit	probit	probit	probit	probit	probit	probit	probit	probit
	uspapp01	**uspapp01**	**uspapp01**	**uspapp01**	**uspapp01**	**uspapp01**	**pubs01**	**pubs01**	**pubs01**	**pubs01**	**pubs01**	**pubs01**
Industry	0.986**	1.017**					-1.113**	-0.845**				
	[0.042]	[0.058]					[0.047]	[0.062]				
Basic research		-0.044	0.053	0.014	0.096	-0.527**		0.087	0.357	0.360	0.121	-0.012
		[0.056]	[0.186]	[0.227]	[0.091]	[0.142]		[0.064]	[0.243]	[0.238]	[0.122]	[0.142]
Development		-0.173**	-0.317**	-0.131	-0.262	-0.144		-0.599**	-0.422**	-0.576**	-0.497	-0.244
		[0.062]	[0.106]	[0.094]	[0.346]	[0.367]		[0.063]	[0.107]	[0.094]	[0.296]	[0.368]
Startup			0.468**	0.286					0.082	0.235		
			[0.163]	[0.219]					[0.194]	[0.212]		
Other firm			0.001	-0.162					-0.188	-0.110		
			[0.101]	[0.094]					[0.106]	[0.095]		
Lower tier					-0.516**	-0.552**					-0.706**	-0.695**
					[0.121]	[0.145]					[0.124]	[0.132]
Medical school					0.083	0.037					0.010	0.645
					[0.084]	[0.259]					[0.127]	[0.493]
Not tenure track					0.052	-0.261					-0.038	-0.540**
					[0.108]	[0.207]					[0.151]	[0.206]
Tenured					-0.010	-0.301					0.118	-0.075
					[0.116]	[0.209]					[0.160]	[0.211]
Field			incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.
PhD_NRC_Score			0.278**	0.132*	0.039	-0.020			0.149	0.192**	0.072	0.167*
			[0.074]	[0.060]	[0.058]	[0.086]			[0.077]	[0.062]	[0.067]	[0.069]
Yrs since grad			0.006	0.003	0.014*	0.011			-0.040**	-0.043**	-0.016*	-0.037**
			[0.006]	[0.006]	[0.006]	[0.010]			[0.007]	[0.006]	[0.008]	[0.010]
Yrs grad _sq			-0.002**	-0.002**	-0.001*	-0.001			0.001*	0.002**	0.000	0.001
			[0.001]	[0.001]	[0.000]	[0.001]			[0.001]	[0.000]	[0.000]	[0.000]
Ln_supdir			0.308**	0.152*	0.320**	0.218**			0.160*	0.104	0.150*	0.281**
			[0.071]	[0.062]	[0.045]	[0.064]			[0.073]	[0.058]	[0.061]	[0.084]
Male			0.265*	0.272*	0.112	0.036			0.249*	-0.121	0.078	0.142
			[0.114]	[0.128]	[0.082]	[0.168]			[0.122]	[0.136]	[0.107]	[0.148]
U.S. Citizen			0.123	-0.210	0.126	-0.256			-0.172	-0.292	0.108	0.178
			[0.172]	[0.166]	[0.154]	[0.207]			[0.194]	[0.173]	[0.209]	[0.198]
Race			incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.
Constant	-0.993**	-0.959**	-1.759**	-0.093	-1.872**	0.312	1.413**	1.367**	0.01	0.401	1.356**	0.918
	[0.028]	[0.049]	[0.352]	[0.409]	[0.282]	[0.620]	[0.034]	[0.055]	[0.362]	[0.424]	[0.314]	[0.499]
Observations	5018	5018	848	983	1993	1194	5018	5018	848	983	1993	1186
Chi-square	556.334	565.229	71.575	126.686	135.284	112.146	573.386	654.384	100.563	146.614	87.999	81.923
df	1	3	17	17	19	19	1	3	17	17	19	18

Robust standard errors in brackets; * significant at 5%; ** significant at 1%

Omitted categories are Applied Research, Large established firm, Carnegie I+II institution, Tenure track but not tenured