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A Multidimensional View of Industrial and Academic Science

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ABSTRACT

We develop a conceptual framework to characterize science along four dimensions: (1) the nature of work; (2) characteristics of the workplace; (3) characteristics of workers; and (4) the disclosure of research results. Drawing on the broader organizational literature, we discuss relationships between these dimensions and derive predictions regarding differences and similarities in the four dimensions between industrial and academic science. We then employ detailed survey data from a representative sample of over 5,000 life scientists and physical scientists to examine key aspects of the framework. The descriptive results provide a nuanced and multidimensional view of industrial and academic science. Our analysis of relationships among dimensions suggests that the nature of work is a significant predictor of workplace characteristics and of the way in which research results are disclosed. However, important industry-academia differences in the latter dimensions remain even controlling for the nature of work, consistent with the view that sectoral differences in features of science also reflect distinct institutional logics.

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1 Introduction

A growing body of research examines features of academic and industrial science. Many scholars have emphasized differences between the two sectors with respect to the basic versus applied nature of research, levels of freedom for individual scientists, the use of patents and publications as a method of disclosure, and more general institutional logics that govern the conduct of science (Aghion et al., 2008; Dasgupta & David, 1994; Lacetera, 2009; Murray, 2010). Other streams of work suggest important similarities. For example, many universities seek to profit from the commercial potential of research, while some firms also invest significant effort in basic research that promises little direct return (Bercovitz & Feldman, 2008; Cockburn & Henderson, 1998; Cohen & Levinthal, 1990; Lim, 2004; Rosenberg, 1990; Slaughter & Rhoades, 2004; Thursby et al., 2001; Vallas & Kleinman, 2008). At the individual level, scientists in both sectors can face constraints in their choice of research projects and may at times limit the sharing of research inputs or the disclosure of research results (Blumenthal, 2003; Haas & Park, 2010; Hackett, 1990; Vallas & Kleinman, 2008; Walsh et al., 2005).

Despite a considerable body of work on particular aspects of industrial and academic science, we have a limited understanding of how different or similar the two sectors actually are. Conceptually, we lack a theoretically grounded framework that identifies a broader set of key dimensions of science and considers mechanisms that may lead to differences or similarities between sectors. Empirically, much of our understanding is based on insights gained from studies that independently examine selected aspects of science, often in only one of the sectors. Thus, there is little work that directly contrasts industrial and academic science using comparable measures and that considers interdependencies between features of science. We suggest that a deeper understanding of the features of science in each of the two sectors, and of differences and similarities between the sectors, may prove useful for organizational scholars, scholars of science, as well as managers and policy makers.

To advance the understanding of industrial and academic science, we develop a conceptual framework that connects four key dimensions: the nature of work, characteristics of the workplace, characteristics of workers, and the disclosure of research results. Drawing on organizational and disciplinary literatures, we discuss relationships between these four dimensions and mechanisms that may lead to differences in these dimensions between industrial and academic science. Building on prior work, we pay particular attention to differences in the nature of work across sectors as a driver of differences in the other dimensions of science. We then examine aspects of our framework empirically using detailed data for a nationally representative sample of over 5,000 PhD-level life and physical scientists. The strength of these 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.

Our empirical results paint a rich multidimensional picture of industrial and academic science. We find considerable differences with respect to certain dimensions but remarkable similarities with respect to others. We also observe considerable heterogeneity within sectors, e.g., across different types of universities and firms. Our analysis of relationships between dimensions shows 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, differences in the nature of work between sectors do not fully explain differences in these other dimensions, suggesting that scientific activity is also be shaped by different institutional logics.[1]

Our work makes several contributions. First, we provide a multidimensional framework that can serve as an analytical tool for future inquiry into features of the scientific system, both from a static and a dynamic perspective. Second, our empirical results should be of general interest to scholars of science and may provide a useful reference point for work that relies on certain assumptions regarding differences and similarities between industrial and academic science (e.g., Aghion et al., 2008; Lacetera, 2009). We also show along which dimensions industry-academia differences are most pronounced, pointing towards particularly fruitful areas for future work on underlying mechanisms. Third, we provide initial insights

[1] In line with prior work, we define institutional logics as patterns of missions, assumptions, values, incentives, and rules that characterize a particular institutional realm (Fini & Lacetera, 2010; Murray, 2010; Thornton & Ocasio, 2008).

regarding potential drivers of industry-academia differences, contrasting the nature of work and different institutional logics as two key factors suggested in prior work. Our results 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 on these relationships in an important yet understudied empirical setting. Finally, our results suggest 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.

2 A multidimensional framework of industrial and academic science

We propose a multidimensional framework of science, consisting of four key dimensions: (1) the nature of work; (2) characteristics of the workplace; (3) characteristics of workers; and (4) the disclosure of research results. Organizational and disciplinary literatures suggest important relationships between these dimensions such that industry-academia differences in one dimension may lead to differences in others. In addition to discussing the four dimensions, their relationships, and potential industry-academia differences, the following sections also address potential heterogeneity within each sector.[2] Given space and data limitations, our discussion will focus on selected facets within each dimension and on selected relationships between them. Figure 1 summarizes the framework.

--- Figure 1 about here ---

2.1 The nature of work

The starting point of much of the prior literature on industrial versus academic science is that the two sectors perform different types of research. In the conventional view, 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 & Liebeskind, 1998;

[2] Our framework abstracts from differences across scientific fields; we will consider field differences in the empirical analysis.

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).[3]

A growing body of work suggests that the division of labor between industry and academia is far from clear-cut, however. Some academic institutions were founded with an explicit charge to assist their regional economies through applied work (cf. Furman & MacGarvie, 2007; Rosenberg & Nelson, 1994) and universities may show an increasing interest in applied work as they turn towards industry to find new sources of funding (Hackett, 1990; Kleinman & Vallas, 2001; Thursby et al., 2001). Industrial firms, on the other hand, may have various reasons to engage in basic research activities. Among others, such research may increase firms' ability to absorb external knowledge (Cockburn & Henderson, 1998; Cohen & Levinthal, 1990), may provide a map for downstream R&D (Fleming & Sorenson, 2004), or may 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 question is how much scientific work differs across sectors with respect to its basic versus applied nature, and to what extent differences in the nature of work explain differences in other dimensions of science.

2.2 Characteristics of the workplace

To the extent that industry and academia differ in the basic versus applied nature of work, such differences may result in differences in the characteristics of the workplace. While many different characteristics could be examined, we follow the prior literature's focus on the levels of freedom and pay (Aghion et al., 2008; Dasgupta & David, 1994; Lacetera, 2009; Merton, 1973).

Organizational theory provides a useful lens to consider the relationships between the nature of work and the level of employee autonomy. More specifically, contingency theory as well as agency

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[3] Stokes (1997) suggests that some research can seek both fundamental knowledge and solutions to practical problems. While multi-dimensional classifications of research are a promising area for future work, we rely on the traditional distinction to be consistent with prior conceptual work and because our empirical measures also make this distinction.

theory suggest that higher levels of worker autonomy are beneficial in settings where there is uncertainty about the best approach to solving a given problem, effort is hard to observe, and managers lack expert knowledge (Donaldson, 1996; Eisenhardt, 1985; Foss & Laursen, 2005; Ouchi, 1979; Prendergast, 2002). These criteria are more strongly associated with basic research than with applied work or development, suggesting that the level of researcher freedom should be higher in basic research. Thus, academia's focus on basic research may lead to higher levels of autonomy granted to academic scientists.

Even for a given type of research, however, academia may offer higher levels of autonomy than industry because of different institutional logics. 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 (Kuhn, 1962), as long as the contribution is judged to be significant by the community of peers or resulting commercially valuable knowledge can be transferred to the private sector for further development (Siow, 1998; Thursby et al., 2001). Firms, on the other hand, care less about new knowledge per se but primarily about knowledge that complements existing firm assets and increases profit, likely leading them to constrain scientists' choice of projects (Aghion et al., 2008).

While this discussion suggests higher levels of autonomy in academia compared to industry, differences may not be that large. Academic scientists do not have total freedom but may face constraints related to the broader agendas of internal or external funding sources (Hackett, 1990; Vallas & Kleinman, 2008). At the same time, case evidence suggest that industrial scientists also enjoy considerable freedom, as long as their choices are within broad guidelines and goals set by the organization (Copeland, 2007; Vallas & Kleinman, 2008). Indeed, firms recognize that some level of autonomy may be beneficial for knowledge work generally (Alvesson, 2000; Drucker, 1999; Lepak & Snell, 2002). Thus, the empirical question is how large the differences in researcher freedom actually are between sectors, and to what extent they are explained by differences in the nature of research versus other factors.

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 with other resources of the firm such as physical capital or marketing capabilities (Ceccagnoli et al., 2010; Cohen & Klepper, 1996). Further developing the notion of complementarities, Agarwal and Ohyama (2010) suggest that industry is also characterized by larger complementarities between basic and applied research than academia, resulting in higher and more similar wages for basic and applied researchers compared to academia. Even for a given value of the research, however, higher pay in industry may reflect different logics regarding how value is appropriated. The "open science" logic implies that much of the knowledge is given away for free and that the major reward to research comes from peer recognition and status in the scientific community (Merton, 1973; Murray, 2010). The commercial logic, in contrast, implies that firms and their employees seek to appropriate most of the value of the knowledge in the form of higher salaries and profits.

Several other mechanisms may lead to pay differences across sectors and we can only briefly raise some of them. Most interestingly in the context of our earlier discussion, Aghion et al. (2008) argue that industry has to pay higher wages in order to compensate for the relative lack of freedom compared to academia. This idea fits into a broader literature that considers compensating wage differentials across jobs that differ with respect to nonfinancial job attributes (Rosen, 1986; Stern, 2004). Second, much scientific work involves team production (Ding et al., 2010; Wuchty et al., 2007) and teams in academia may more often cross organizational boundaries than do teams in industry. Thus, firms may find it easier to measure and financially reward team performance than individual academic institutions, potentially leading to higher compensation in industry.[4]

While we focus on differences in workplace characteristics across sectors, there may be considerable heterogeneity *within* sectors as well. In industry, such heterogeneity 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, suggesting that larger and older firms may offer their employees less autonomy in their jobs (cf. Baron et al., 2001; Cardinal et al., 2004; Idson, 1990). It is not clear, however,

[4] We thank an anonymous reviewer for suggesting this idea.

how strong these relationships are in the particular context of science. For example, large, diversified firms may be better able than small firms to find commercialization opportunities for inventions that result from employees' self-directed exploration (cf. Nelson, 1959), potentially allowing them to provide scientists with more autonomy. Similarly, if science-based firms incorporate professional and academic norms early in their development (cf. Baron et al., 1999; Ding, 2011), they may be able to preserve employment models that emphasize autonomy even as they age. Firm age and size may also predict differences in levels of pay. In particular, prior work has shown that larger and older firms offer higher wages than small or young firms and has suggested asset complementarities, lower levels of nonpecuniary benefits, and higher degrees of specialization as possible explanations (Brown & Medoff, 1989; Idson & Feaster, 1990; Oi & Idson, 1999). Within academia, tier-one 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 may provide their scientists with higher levels of pay and autonomy in their work.

Predictions: Research positions in academia provide higher levels of freedom but lower pay than positions in industry. These differences are explained partly by differences in the nature of research. There is heterogeneity in freedom and pay within sectors, e.g., between firms of different size and age and between higher- and lower-tier universities.

2.3 Characteristics of workers

The third dimension of our framework captures characteristics of the individuals actually doing the scientific work. Continuing our discussion in the prior section, we focus on scientists' preferences for certain job characteristics such as research freedom or money.[5]

There are two views on scientists' preferences and potential differences across sectors. One view emphasizes that scientists in both sectors share common characteristics by virtue of their professional

[5] 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.

training in academic institutions; in particular, they share a "taste for science" and the desire for freedom in their choice of research (Aghion et al., 2008; Lacetera, 2009; Stern, 2004). As a consequence, scientists working in settings that offer less freedom must be paid compensating differentials (Aghion et al., 2008), may reduce their effort (Lacetera, 2009), or experience role strain (Kristof-Brown et al., 2005).

Another view suggests that there is heterogeneity across scientists and that preferences are related to characteristics of the workplace. If scientists have heterogeneous preferences when they enter the labor market, they are likely to self-select into the sector in which they expect to best satisfy their preferences (Agarwal & Ohyama, 2010; Roach & Sauermann, 2010; Rosen, 1986).[6] Building on our discussion of differences in levels of pay and freedom across sectors, we expect that scientists with a stronger desire for freedom self-select into academia while those with a stronger desire for financial income self-select into industry. In addition, industry-academia differences in preferences may be reinforced by socialization processes. For example, scientists who are faced with lower levels of freedom in industry may find that freedom becomes less important to them, while higher levels of pay may raise the salience and importance of financial rewards to the scientist (Allen & Katz, 1992; Kornhauser, 1962; Saks & Ashforth, 1997). Both mechanisms – selection and socialization – would lead to the following predictions.

Predictions: Academic scientists have stronger preferences for freedom and weaker preferences for pay than industrial scientists. These differences are explained partly by differences in actual levels of freedom and pay offered by employers.

2.4 Disclosure of research results

The final dimension of our framework relates to the mechanisms by which research results are disclosed. Disclosure may depend on the nature of the research itself. Since basic research promises little

[6] Roach and Sauermann (2010) surveyed PhD students at three universities and found that students with a stronger preference for money expressed greater interest in industry careers while those with a stronger preference for independence expressed a stronger preference for careers in academia. However, not all students will be able to realize their career goals, especially given the small number of faculty positions available (National Science Board, 2010). Moreover, preferences measured before scientists enter particular career paths will not reflect socialization processes that occur during employment.

financial return, its production is rewarded primarily with peer recognition and status in the scientific community. To obtain these rewards, however, scientists need to disclose their results widely and openly, typically in the form of publications (Dasgupta & David, 1994; Merton, 1973; Stephan, forthcoming). Downstream research, on the other hand, promises larger financial returns. These returns are reduced by an open disclosure in publications and are better captured through patents, which grant the inventor the right to exclude others from benefiting directly from that knowledge (Cohen et al., 2000; Reitzig & Puranam, 2009). While both publications and patents constitute 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 of results 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 applied results 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 various outcomes tied to different forms of disclosure. 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 (IPO, 2004; Lach & Schankerman, 2008). Scientists with a strong desire for peer recognition may instead choose to disclose their results more widely in the form of publications. The role of scientists' preferences may be limited however, to the extent that disclosure choices are made by managers and administrators rather than by the scientists themselves (Murray, 2010).

In addition to the nature of research and scientists' preferences, a third potential factor shaping patterns of disclosure may be broader institutional logics prevailing in industry and academia. Interestingly, these logics may be more similar with respect to publishing than with respect to patenting. Publishing has always been a key aspect of the academic logic, 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; Stephan, 2006). Moreover, firms have been shown to use publications as a strategic tool for various purposes, e.g., to pre-empt patenting by competitors (Parchomovsky, 1999), to signal scientific capabilities and a scientific work environment (Hicks, 1995; Penin, 2007), or to strengthen industry-academia collaborations (Cockburn & Henderson, 1998). The logics regarding patenting are likely to be more different between the sectors. Even though patenting has become more common in academia (Bercovitz & Feldman, 2008; Mowery et al., 2001), traditional norms of openness remain strong and some academics may see patenting as inappropriate even for downstream research (Argyres & Liebeskind, 1998; Gans & Stern, 2010; Murray, 2010; Owen-Smith & Powell, 2001). Moreover, academia is unlikely to value patents for the various "strategic" purposes documented 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).

Predictions: Academic scientists are more likely to publish but less likely to patent than industrial scientists. These differences are explained partly by differences in the nature of research and in researcher preferences. Controlling for these factors, the industry-academia gap in patenting is larger than that in publishing.

3 Data and measures

3.1 Data

We empirically examine key aspects of our framework drawing 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 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.

Response rates for the SESTAT surveys were well over 70%.[7] For this study, we use data on PhD scientists who work in either industry or academia. The “industry” subsample includes respondents whose employer is classified as a private-for-profit, non-educational entity. Included in the “academia” sample are respondents whose employer is classified as a 4-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 second most important work activity (see below for details). 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, while 43% work in the physical sciences.[8] Of the industrial scientists, 29% work in firms with under 500 employees, while 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, 28% in medical schools, and 29% in other academic institutions (e.g., doctorate granting or comprehensive). Fifty-one percent are tenured, 23% are on the tenure track but not tenured, and 26% are not on the tenure track.[9]

3.2 Measures and measurement issues

Table 1 summarizes our measures and table 2 provides descriptive statistics.

--- Tables 1 and 2 about here ---

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 most of their time in a typical work week, including basic research, applied research, and development. Each of these activities was defined in the

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

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

[9] The respondents who are not on the tenure track are primarily employed in tier 1 academic institutions and are likely working as staff scientists and research faculty.

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 & Thursby, 2010), our measure is independent of patents and publications and 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. At the same time, we cannot rule out 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 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 paid 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 a job attribute and individuals' satisfaction with that attribute has been widely documented, including in the R&D context (Cable & Edwards, 2004; Idson, 1990; Wood & LeBold, 1970). However, since an individual's satisfaction with independence may not only reflect actual levels of independence but also his preference for independence (Cable & Edwards, 2004; Freeman, 1978), we also estimate satisfaction models with the preference for independence as a control.[10]

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 & 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 may 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, effectively inflating an industry-academia gap in preferences. Any descriptive data on preferences we present should be interpreted in light of this possibility.

[10] 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, while those who are not very satisfied earn an average of $78,515. These relationships also hold in a regression context with additional controls.

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. A focus of this analysis will be the extent to which differences in one dimension explain differences in other dimensions. Given cross-sectional 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 also address potential differences across scientific fields (cf. Burton, 2001; Cohen et al., 2000; Lim, 2004) by including detailed field dummies and by analyzing key models separately for the life sciences and the physical sciences.

4.1 Basic versus applied nature of research

Table 2 shows that roughly two thirds of academics are engaged in basic research, while over 90% of industrial scientists work on applied research or development. Comparing the nature of research across fields, we find that academics in the life sciences are more likely to be engaged in applied work than academics in the physical sciences (32% vs. 21%), consistent with the notion that research in the academic life sciences more readily leads to practical applications and that basic and applied research may also be more complementary in the life sciences (cf. Agarwal & Ohyama, 2010; Mowery et al., 2001). In industry, life scientists are more likely to be engaged in basic research than their colleagues in the physical sciences (8% vs. 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

We find that academics report significantly higher satisfaction with the level of independence in their jobs: 78% of academics are "very satisfied", compared to 51% of industrial scientists. On the other hand, industry wages are higher by an average of approximately 25,000 USD (table 2). We employ regression analysis to examine the relationships between the nature of research and characteristics of the workplace, and the degree to which industry-academia gaps in freedom and pay are explained by differences in the nature of research. Models 1 through 3 in table 3 use the pooled sample to estimate probit regressions of the satisfaction with independence. Consistent with our prediction, they show that scientists involved in basic research are more likely to be very satisfied with independence than those involved in applied research. Moreover, controlling for the nature of research leads to a significant reduction in the industry-academia gap in independence (change of the INDUSTRY coefficient: $Chi^2(1)=4.09$; $p=0.043$).[11]

Focusing on the industry subsample (model 4), we find no significant differences in satisfaction with independence between individuals working on different types of R&D. 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. However, consistent with prior organizational literature, we find that larger firms provide less independence. In the academic subsample (model 5), we find no significant differences in independence between basic and applied researchers. However, we observe lower levels independence for academics in development, possibly reflecting that downstream work in academia is often tied to funding from industry or other agencies that may constrain project choice.[12] As expected, we also observe significantly higher

[11] Given that we do not observe exogenous variation in employment sectors, a variety of unobserved variables may underlie the industry-academia gaps that remain once we control for the nature of research (model 2) and selected individual-level variables (model 3). Thus, the coefficients on the INDUSTRY variable should not be interpreted as reflecting "causal" effects but rather as estimates of industry-academia differences conditional upon controlling for certain observed variables.

[12] The number of academics in development is small (n=56) and results for that subsample should be interpreted with caution.

levels of independence in tier I+II institutions than in lower-tier institutions. Models 6-8 additionally control for scientists' preference for independence to account for the possibility that satisfaction reflects not only actual levels of independence but also individuals' preferences. Our featured results are robust.

We conduct a similar set of analyses for salary, employing OLS regression. Consistent with our expectation, model 9 shows that applied researchers are paid more than basic researchers. However, including the nature of research (model 10) only slightly reduces the industry-academia gap in pay ($Chi^2(1)=3.33$, $p=0.068$).[13] Model 11 includes additional controls[14] and shows that the salary gap is not explained by differences in scientists' ability or experience – indeed, the gap increases once we account for the fact that academic scientists tend to have been trained at higher quality institutions, have more work experience, and supervise more people.[15]

Model 12 uses the industry sample and shows no significant pay differences between basic and applied researchers, although employees in development earn somewhat less. The lack of a pay differences between basic and applied research is consistent with the notion that basic and applied research are complements in industry, resulting in a sharing of rents between researchers (Agarwal & Ohyama, 2010). Consistent with our expectations, we also find that salary increases with firm size, with

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[13] 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 (table 3, model 14). While 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.

[14] We control for several variables that have been shown to relate to pay (e.g., gender, ability, and work experience), yet there are other unobserved factors that may explain the remaining wage gaps. Given space and data limitations, we leave a more detailed analysis of industry-academia wage differences to future research. However, evidence of a large wage gap even controlling for many commonly considered variables and for differences in the nature of research may prove useful in such efforts.

[15] 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, forthcoming). Moreover, since 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 (cf.Allen & Katz, 1992).

time since graduation, and with managerial responsibilities. Using the academic sample (model 13), we find that academic 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.

--- Table 3 about here ---

4.3 Characteristics of workers: Scientists' preferences

Our conceptual discussion suggests that selection and socialization mechanisms may lead to systematic relationships between workplace characteristics and the characteristics of workers. Table 2 shows that industrial scientists indeed 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", while 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 preference for independence ($Chi^2(1)=19.20$, $p=<0.01$). Models 4 and 5 show separate regressions for industrial and academic scientists, respectively. We find a positive relationship between 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.

Models 6 to 10 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 ($Chi^2(1)=12.67$, $p=<0.01$), suggesting that the latter variables explain a significant part of the observed industry-academia gap in preference for money.

While our cross-sectional data do not allow us to conclusively distinguish selection and socialization mechanisms, we conduct some exploratory analyses. First, given that socialization would occur over time, we examine the relationships between preferences and time since graduation. We observe in table 4 that the preference for independence increases with time since graduation among academics but not among industrial scientists, consistent with a socialization process. However, the preference for money decreases with time since graduation in industry, inconsistent with a socialization process. The interpretation of these results is further complicated by the fact that we cannot disentangle age and cohort effects (Levin & Stephan, 1991). Second, we compute the industry-academia gap in preferences for scientists who graduated within the prior three years, 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 (0.60 in industry vs. 0.74 in academia) and for salary (0.54 in industry vs. 0.38 in academia), suggesting that selection may play an important role in driving the observed industry-academia differences in scientists' preferences.

--- Table 4 about here ---

4.4 Disclosure of research results

Fifty percent of all industrial scientists in our sample have at least one patent application in a five-year span, compared to 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 to 62% 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.[16] The industry-academia

[16] 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).

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%).

--- Figure 2 about here ---

In table 5, we use probit regression analysis to examine the extent to which industry-academia gaps in the use of disclosure mechanisms are explained by differences in the nature of research. Focusing first on patenting in the pooled sample, we find that scientists engaged in development are less likely to have a patent application than those in applied research. This finding may reflect that such projects are less likely to be sufficiently novel to be patentable or that knowledge from such projects is encoded primarily in physical artifacts rather than words (Allen, 1984). Despite this result, including the nature of research does not change the industry-academia gap in patenting. Model 3 additionally includes scientists' preferences for money and independence. We find no relationship between these preferences and patenting, perhaps reflecting that patenting decisions are made primarily by others, or that scientists patent for reasons other than money (Murray, 2010). Model 3 also includes additional controls but continues to predict very different probabilities of patenting across sectors. Evaluated at the mean of other independent variables, the predicted probability of patenting is 46% in industry versus 14% in academia.

Next, we estimate separate regressions for academia and industry and further differentiate between the life sciences and the physical sciences. We find that the negative coefficient on development is significant only among industrial life scientists. We find no significant differences in the likelihood of patenting between scientists doing basic and applied research in industry or among academic life scientists. In the physical sciences, however, academics engaged in basic research are much less likely to patent than those engaged in applied work.

We also observe significant heterogeneity in patenting within sectors. For example, physical scientists in young firms are more likely to have a patent than those in older firms, perhaps reflecting that young firms use patents as a signal of scientific capability and commercial potential (Hsu & Ziedonis, 2008). Moreover, the likelihood that an industrial scientist has a patent increases with the ranking of her PhD 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 research 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 (cf. Belenzon & Schankerman, 2009).

Models 8-14 examine the probability of publishing. In the pooled sample, 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 ($Chi^2(1)=38.84$, $p<0.01$), suggesting that publishing is less common among industrial scientists in part because they are more likely to be engaged in development work which is less likely to result in a publication. However, even controlling for the nature of research and other variables, academics are more likely to publish than industrial scientists (92% vs. 71%).

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 5-year span than older scientists. This result is consistent with prior work showing a decrease in research productivity over the life cycle (Levin & Stephan, 1991). In industry, that result may also reflect that firms have recently shifted towards open science by hiring more “academic” types of scientists (cf. Lacetera et al., 2004) or that freshly-minted PhDs publish their dissertation research after entering industry. To examine the latter possibility, we dropped those industrial scientists who graduated within the last five years but find that the effect of time since graduation remains highly significant.

Overall, the nature of research explains a significant share of the industry-academia gap in publishing but does little to explain differences in patenting. Moreover, controlling for the nature of research and scientists’ characteristics, the industry-academia gap in patenting is considerably larger than that in publishing. These results are consistent with the notion that the disclosure of research results in part reflects different institutional logics of industrial and academic science, and that these logics are more similar with respect to publishing than with respect to patenting. A more detailed analysis of patenting and publishing is reported in the appendix and reinforces the conclusions of our main analysis.

--- Table 5 about here ---

5 Discussion

Knowledge production in industrial and academic science has attracted increasing interest by organizational scholars, economists and sociologists. Yet, important conceptual and empirical gaps remain, especially with respect to comparisons between the two sectors. 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. We then examine key aspects of this framework using survey data for a nationally representative sample of over 5,000 PhD-level life and physical scientists. The data provide unique insights into industrial and academic science that should be of interest to scholars of science generally, and particularly useful for theoretical work that relies on certain assumptions regarding differences and similarities between sectors (Aghion et al., 2008; Lacetera, 2009). Our empirical results demonstrate the benefits of conceptualizing science as multidimensional: while we find large 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, in contrast to prior work that has discussed industry-academia differences primarily based on evidence from the biomedical sciences, our data allow us to provide comparative insights for the physical sciences, showing industry-academia gaps that are similar in sign but often different in magnitude.

The results regarding the relationships between various dimensions of science provide useful insights. 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 (Donaldson, 1996; Lepak & Snell, 2002). Similarly, we find strong relationships between features of the workplace and scientists' preferences, consistent with theories of selection and socialization (Agarwal & Ohyama, 2010; Besley & Ghatak, 2005; Rosen, 1986; Saks & Ashforth, 1997). 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 between industrial and academic science also reflect different institutional logics rather than simply differences in the nature of research (Dasgupta & David, 1994; Fini & Lacetera, 2010; Murray, 2010).

Our framework provides a useful basis for future conceptual and empirical work. 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; future work could examine other potentially relevant characteristics such as team size, 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. The framework may serve as a useful starting point for linking these variables to other dimensions of science and for thinking about how these variables might differ between the industrial and the academic sector. Second, future work could extend the framework by considering additional relationships among dimensions. In particular, while we followed prior literature in considering the nature of research as a driver of other dimensions of science, scholars may 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 "converge" over time (Hackett, 1990; Vallas & Kleinman, 2008), yet the empirical evidence is limited. 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.

We hope that our insights will be of use for 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 still conflicts with the academic logic. A different interpretation, however, is that certain similarities between sectors, e.g., regarding scientists' preferences and publishing activities, may actually facilitate collaboration. The conceptual framework and the empirical results presented in this paper may help managers to consider along which dimensions of science tensions with academic partners are 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, yet some of this preference may be due to biased perceptions of industrial science (cf. Roach & Sauermann, 2010). While 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. Finally, considering the relationships among dimensions of science may help in evaluating the implications of particular managerial or policy interventions. To illustrate, recent attempts to increase the levels of administrative oversight over academic researchers (as illustrated in Simon & Banchero, 2010) would seem a misfit with the task of basic research (the work – workplace link). Such reductions in freedom may also increase the attractiveness of outside job options for scientists who value freedom (the workplace – worker link), potentially requiring higher academic wages or leading to a greater flow of scientists with a strong "taste for science" into industry. The latter may then also lead to more openness in the private sector. While this example is simplistic, it suggests that considering interdependencies between dimensions of science is important in evaluating the broader implications of particular interventions.

In interpreting the results of this study, important limitations have to be kept in mind. First, while 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. While 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. However, 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.

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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. In the life sciences, these fields include agricultural and food sciences (5.9% of total), biomedical sciences including biochemistry and biophysics (36.6%), biomedical engineering (1.2%), health sciences (7.3%), and other life sciences (0.7%). In the physical sciences, these fields include physics (7.0%), chemistry (16.7%), earth sciences (6.26%), mathematics (8.15%), and other physical sciences (0.6%). We also include a separate dummy for individuals who self-classified as "R&D management".
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"; and • "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 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 (see below for a discussion). 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".
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 . . .". 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 5 years prior to the survey. We created a dummy variable coded as 1 if the respondent had at least one patent application in the 5-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 (cf. 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 5 years. 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 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 PhD degree (YRS_SINCE_GRAD).
PhD quality	We matched each respondent's PhD-granting institution and the PhD field to the National Research Council's evaluation of PhD 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"). 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	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 size	The survey asked respondents to estimate the number of employees in all locations of their employer combined, using 8 size categories (<10; 11-24; 25-99; 100-499; 500-999; 1,000-4,999; 5000-24,999; 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 5 years. We created a dummy variable that equals 1 if the employer is older than 5 years and 0 otherwise. Industry sample only.
Type of academic institution	We distinguish academic institutions using the Carnegie classification provided by NSF: Carnegie research 1 and 2 institutions, lower-tier institutions (e.g, doctorate granting, comprehensive) and medical schools. Academic sample only.
Academic position	Dummy variables indicating whether an academic scientist is tenured, on the tenure track but not tenured, or not on the tenure track. Academic sample only.
Race/Ethnicity	Dummies for white, Asian, and other
Gender	MALE =1 if respondent is male
U.S. citizen	USCITIZEN =1 if respondent is a U.S. citizen

Table 2: Descriptive statistics and industry-academia gaps

			Full Sample			Life Sciences			Physical Sciences			
			Industry	**Academia**	**Ind-Acad**	**Industry**	**Academia**	**Ind-Acad**	**Industry**	**Academia**	**Ind-Acad**	**Diff. in Gaps**
			N=1831	N=3187	**Gap**	N=848	N=1993	**Gap**	N=983	N=1194	**Gap**	**Life-Phys**
Dimension	**Variable**	**Type**	**Mean**	**Mean**		**Mean**	**Mean**		**Mean**	**Mean**		
Nature of work	Basic research	Dummy	0.06	0.70	-0.64 **	0.08	0.66	-0.59 **	0.04	0.77	-0.72 **	0.14 **
	Applied Research	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 work place	Actual salary	Continuous	106,081	81,326	24,755 **	107,052	84,063	22,989 **	105,256	76,739	28,517 **	-5,527 n.s.
	Satisfaction salary	Dummy	0.41	0.26	0.15 **	0.42	0.27	0.15 **	0.39	0.24	0.15 **	0.00 n.s.
	Satisfaction independence	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	Importance of salary	Dummy	0.47	0.37	0.10 **	0.49	0.39	0.10 **	0.46	0.34	0.12 **	-0.02 n.s.
	Importance of independence	Dummy	0.61	0.81	-0.20 **	0.63	0.82	-0.18 **	0.59	0.79	-0.20 **	0.02 n.s.
Disclosure mechanisms	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 **
	U.S. patent applications yes/no	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 *
	Publications yes/no	Dummy	0.62	0.92	-0.30 **	0.71	0.94	-0.23 **	0.54	0.90	-0.36 **	0.13 *
Controls	Years since graduation	Count	15.03	17.18	-2.15 **	14.33	16.79	-2.46 **	15.63	17.83	-2.21 **	
	NRC PhD program ranking score	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 I, II	Dummy		0.43			0.37			0.53		
	Lower tier	Dummy		0.28			0.19			0.43		
	Medical School	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.	
	U.S. Citizen	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%.

Table 3: Characteristics of the workplace: Independence and salary

		Full Sample		Industry	Academia	Full Sample	Industry	Academia		Full Sample		Industry	Academia	Full Sample
	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	OLS	OLS	OLS	OLS	OLS	OLS
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Sat_Ind	**Sat_Ind**	**Sat_Ind**	**Sat_Ind**	**Sat_Ind**	**Sat_Ind**	**Sat_Ind**	**Sat_Ind**	**Ln_Salary**	**Ln_Salary**	**Ln_Salary**	**Ln_Salary**	**Ln_Salary**	**Ln_Salary**
Industry	-0.738**	-0.663**	-0.575**			-0.496**			0.266**	0.233**	0.290**			0.300**
	[0.040]	[0.055]	[0.061]			[0.062]			[0.020]	[0.026]	[0.026]			[0.026]
Basic research		0.121*	0.159**	-0.041	0.092	0.150**	0.012	0.089		-0.048*	-0.058**	0.006	-0.070**	-0.060**
		[0.052]	[0.056]	[0.139]	[0.066]	[0.057]	[0.142]	[0.067]		[0.024]	[0.022]	[0.058]	[0.025]	[0.022]
Development		0.004	-0.015	0.001	-0.426*	0.005	0.026	-0.401*		0.003	-0.067*	-0.070*	0.053	-0.067*
		[0.062]	[0.064]	[0.067]	[0.189]	[0.064]	[0.068]	[0.182]		[0.033]	[0.031]	[0.034]	[0.051]	[0.031]
Imp. Independence						0.680**	0.601**	0.707**						
						[0.046]	[0.065]	[0.065]						
Sat. Independence														0.048*
														[0.021]
Detailed field			incl.	incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.
Yrs since grad			0.003	0.000	0.006	0.002	-0.001	0.005			0.021**	0.021**	0.017**	0.021**
			[0.003]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]			[0.001]	[0.002]	[0.001]	[0.001]
Yrs since grad_sq			0.001**	0.001**	0.000	0.001**	0.001**	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]
PhD quality			0.031	0.000	0.029	0.021	0.002	0.010			0.051**	0.039	0.031*	0.051**
			[0.029]	[0.045]	[0.039]	[0.029]	[0.045]	[0.040]			[0.012]	[0.024]	[0.014]	[0.012]
People supervised			0.122**	0.087*	0.107**	0.096**	0.060	0.086*			0.121**	0.072**	0.111**	0.119**
			[0.026]	[0.043]	[0.035]	[0.026]	[0.044]	[0.035]			[0.010]	[0.020]	[0.012]	[0.010]
Firm size				-0.051**			-0.051**					0.013*		
				[0.012]			[0.013]					[0.006]		
Firm age				0.162			0.173					-0.013		
				[0.114]			[0.116]					[0.061]		
Not tenure track					-0.469**			-0.392**					-0.177**	
					[0.083]			[0.085]					[0.029]	
Tenured					-0.126			-0.131					0.024	
					[0.090]			[0.092]					[0.028]	
Lower tier					-0.205**			-0.198**					-0.164**	
					[0.072]			[0.073]					[0.028]	
Medical school					-0.014			0.006					0.160**	
					[0.075]			[0.077]					[0.027]	
Male			-0.086	-0.171*	-0.073	-0.067	-0.146	-0.050			0.061**	0.002	0.089**	0.062**
			[0.050]	[0.082]	[0.064]	[0.050]	[0.083]	[0.065]			[0.022]	[0.040]	[0.027]	[0.022]
U.S. citizen			0.126	-0.017	0.278**	0.136	-0.014	0.300**			0.014	0.013	0.024	0.012
			[0.074]	[0.113]	[0.095]	[0.075]	[0.115]	[0.095]			[0.036]	[0.061]	[0.044]	[0.036]
Race			incl.	incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.
Constant	0.766**	0.683**	0.419**	0.615*	0.419*	-0.013	0.181	-0.004	11.165**	11.199**	10.414**	10.735**	10.541**	10.381**
	[0.026]	[0.045]	[0.151]	[0.275]	[0.200]	[0.156]	[0.286]	[0.208]	[0.012]	[0.021]	[0.069]	[0.123]	[0.088]	[0.068]
Observations	5018	5018	5018	1831	3187	5018	1831	3187	5018	5018	5018	1831	3187	5018
Chi-square	333.408	338.295	449.243	63.349	166.825	649.292	145.967	282.176						
R-squared									0.038	0.039	0.198	0.146	0.228	0.199

Robust standard errors in brackets. *=sig at 5%, **=sig at 1%. Omitted categories are Applied research, Tenure track but not tenured, Carnegie I+II.

Table 4: Characteristics of workers: Preferences

	Full Sample			Industry	Academia	Full Sample			Industry	Academia
	1	2	3	4	5	6	7	8	9	10
	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
	Imp_Ind	**Imp_Ind**	**Imp_Ind**	**Imp_Ind**	**Imp_Ind**	**Imp_Sal**	**Imp_Sal**	**Imp_Sal**	**Imp_Sal**	**Imp_Sal**
Industry	-0.592**	-0.403**	-0.338**			0.259**	0.124*	0.143*		
	[0.041]	[0.060]	[0.066]			[0.039]	[0.054]	[0.060]		
Basic research		0.056	0.047	-0.212	0.017		-0.116*	-0.091	-0.179	-0.093
		[0.057]	[0.061]	[0.142]	[0.071]		[0.049]	[0.052]	[0.137]	[0.060]
Development		-0.054	-0.066	-0.095	-0.082		0.015	-0.005	0.067	-0.583**
		[0.063]	[0.065]	[0.069]	[0.198]		[0.061]	[0.062]	[0.067]	[0.210]
Sat. independence		0.691**	0.673**	0.597**	0.700**		-0.061	-0.043	0.051	-0.130*
		[0.044]	[0.045]	[0.064]	[0.063]		[0.042]	[0.043]	[0.063]	[0.060]
Ln_Salary		0.103**	0.039	0.063	-0.001		0.151**	0.135**	0.141**	0.116*
		[0.030]	[0.033]	[0.048]	[0.048]		[0.032]	[0.035]	[0.050]	[0.049]
Detailed field			incl.	incl.	incl.			incl.	incl.	incl.
Yrs since grad			0.007**	0.003	0.008*			0.002	-0.010**	0.004
			[0.002]	[0.004]	[0.004]			[0.002]	[0.004]	[0.003]
PhD quality			0.05	-0.015	0.090*			-0.083**	-0.045	-0.114**
			[0.030]	[0.045]	[0.043]			[0.027]	[0.045]	[0.036]
People supervised			0.106**	0.108*	0.092*			0.043	0.046	0.026
			[0.027]	[0.045]	[0.036]			[0.024]	[0.043]	[0.030]
Firm size				-0.001					0.025*	
				[0.013]					[0.013]	
Firm age				-0.067					-0.092	
				[0.120]					[0.117]	
Not tenure track					-0.371**					0.029
					[0.084]					[0.076]
Tenured					0.021					0.150*
					[0.088]					[0.075]
Lower tier					-0.06					-0.03
					[0.075]					[0.066]
Medical school					-0.102					0.119
					[0.080]					[0.068]
Male			-0.095	-0.114	-0.116			0.102*	0.158	0.067
			[0.052]	[0.085]	[0.068]			[0.047]	[0.081]	[0.058]
U.S. citizen			-0.073	-0.027	-0.125			-0.181**	-0.147	-0.179
			[0.077]	[0.113]	[0.107]			[0.070]	[0.111]	[0.092]
Race			incl.	incl.	incl.			incl.	incl.	incl.
Constant	0.872**	-0.812*	-0.423	-0.388	-0.116	-0.325**	-1.886**	-1.548**	-1.778**	-1.219*
	[0.027]	[0.339]	[0.375]	[0.586]	[0.539]	[0.024]	[0.362]	[0.394]	[0.593]	[0.544]
Observations	5018	5018	5018	1831	3187	5018	5018	5018	1831	3187
Chi-square	204.109	459.172	493.378	125.649	247.908	44.086	73.967	149.731	49.828	108.88
df	1	5	22	23	25	1	5	22	23	25

Robust standard errors in brackets. *=sig at 5%, **=sig at 1%. Omitted categories are Applied research, Tenure track but not tenured, Carnegie I+II institution.

Table 5: Disclosure: Patenting and publishing

	Full Sample			Industry		Academia		Full Sample			Industry		Academia	
				Life	Physical	Life	Physical				Life	Physical	Life	Physical
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Patent01	**Patent01**	**Patent01**	**Patent01**	**Patent01**	**Patent01**	**Patent01**	**Pubs01**	**Pubs01**	**Pubs01**	**Pubs01**	**Pubs01**	**Pubs01**	**Pubs01**
Industry	0.986**	1.017**	0.964**					-1.113**	-0.845**	-0.847**				
	[0.042]	[0.058]	[0.067]					[0.047]	[0.062]	[0.074]				
Basic research		-0.044	-0.100	0.053	0.014	0.099	-0.515**		0.087	0.049	0.352	0.360	0.118	-0.014
		[0.056]	[0.064]	[0.187]	[0.231]	[0.091]	[0.141]		[0.064]	[0.072]	[0.248]	[0.236]	[0.122]	[0.142]
Development		-0.173**	-0.211**	-0.324**	-0.127	-0.239	-0.111		-0.599**	-0.522**	-0.420**	-0.572**	-0.514	-0.235
		[0.062]	[0.066]	[0.106]	[0.094]	[0.341]	[0.367]		[0.063]	[0.065]	[0.106]	[0.095]	[0.299]	[0.378]
Imp. salary			0.044	-0.104	-0.016	0.083	0.231			-0.077	-0.188	-0.124	-0.076	-0.011
			[0.045]	[0.096]	[0.090]	[0.073]	[0.122]			[0.049]	[0.103]	[0.091]	[0.098]	[0.120]
Imp. independence			0.106*	0.101	0.072	0.195	0.14			0.093	0.064	0.051	0.106	0.215
			[0.050]	[0.099]	[0.091]	[0.101]	[0.150]			[0.054]	[0.106]	[0.092]	[0.123]	[0.133]
Detailed field			incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.	incl.
Yrs since grad			0.007**	0.005	0.003	0.014*	0.009			-0.033**	-0.041**	-0.043**	-0.017*	-0.038**
			[0.003]	[0.006]	[0.006]	[0.006]	[0.010]			[0.003]	[0.007]	[0.006]	[0.008]	[0.010]
Yrs since grad_sq			-0.001**	-0.002**	-0.002**	-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]
PhD quality			0.129**	0.277**	0.123*	0.039	-0.022			0.182**	0.140	0.187**	0.065	0.161*
			[0.033]	[0.074]	[0.060]	[0.058]	[0.087]			[0.033]	[0.078]	[0.062]	[0.068]	[0.070]
People supervised			0.272**	0.301**	0.140*	0.313**	0.211**			0.206**	0.151*	0.099	0.148*	0.278**
			[0.027]	[0.071]	[0.061]	[0.045]	[0.064]			[0.032]	[0.073]	[0.058]	[0.061]	[0.085]
Firm size				-0.015	0.032						0.027	0.024		
				[0.018]	[0.019]						[0.020]	[0.019]		
Firm age				-0.225	-0.445*						-0.243	-0.305		
				[0.151]	[0.201]						[0.180]	[0.192]		
Not tenure track						0.085	-0.244						-0.018	-0.515*
						[0.109]	[0.210]						[0.152]	[0.206]
Tenured						-0.011	-0.299						0.128	-0.056
						[0.116]	[0.210]						[0.158]	[0.210]
Lower tier						-0.506**	-0.548**						-0.706**	-0.699**
						[0.121]	[0.144]						[0.124]	[0.133]
Medical school						0.081	0.065						0.015	0.681
						[0.085]	[0.262]						[0.126]	[0.486]
Male			0.175**	0.278*	0.290*	0.117	0.029			0.070	0.271*	-0.106	0.084	0.133
			[0.055]	[0.115]	[0.130]	[0.082]	[0.169]			[0.063]	[0.122]	[0.137]	[0.107]	[0.150]
U.S. citizen			-0.026	0.122	-0.201	0.141	-0.237			-0.162	-0.174	-0.287	0.103	0.179
			[0.085]	[0.172]	[0.166]	[0.153]	[0.212]			[0.101]	[0.191]	[0.174]	[0.210]	[0.199]
Race			incl.	incl.	incl.	incl.	incl.			incl.	incl.	incl.	incl.	incl.
Constant	-0.993**	-0.959**	-2.052**	-1.424**	0.022	-2.069**	0.213	1.413**	1.367**	1.037**	-0.011	0.511	1.332**	0.836
Observations	5018	5018	5018	848	983	1993	1194	5018	5018	5018	848	983	1993	1186
Chi-square	556.334	565.229	806.499	72.426	128.082	138.419	115.359	573.386	654.384	729.189	100.653	153.924	89.576	85.177
df	1	3	23	19	19	21	21	1	3	23	19	19	21	20

Probit. Robust standard errors in brackets. *=sig at 5%, **=sig at 1%. Omitted: Applied research, Tenure track but not tenured, Carnegie I+II institution.

Figure 1: Conceptual framework

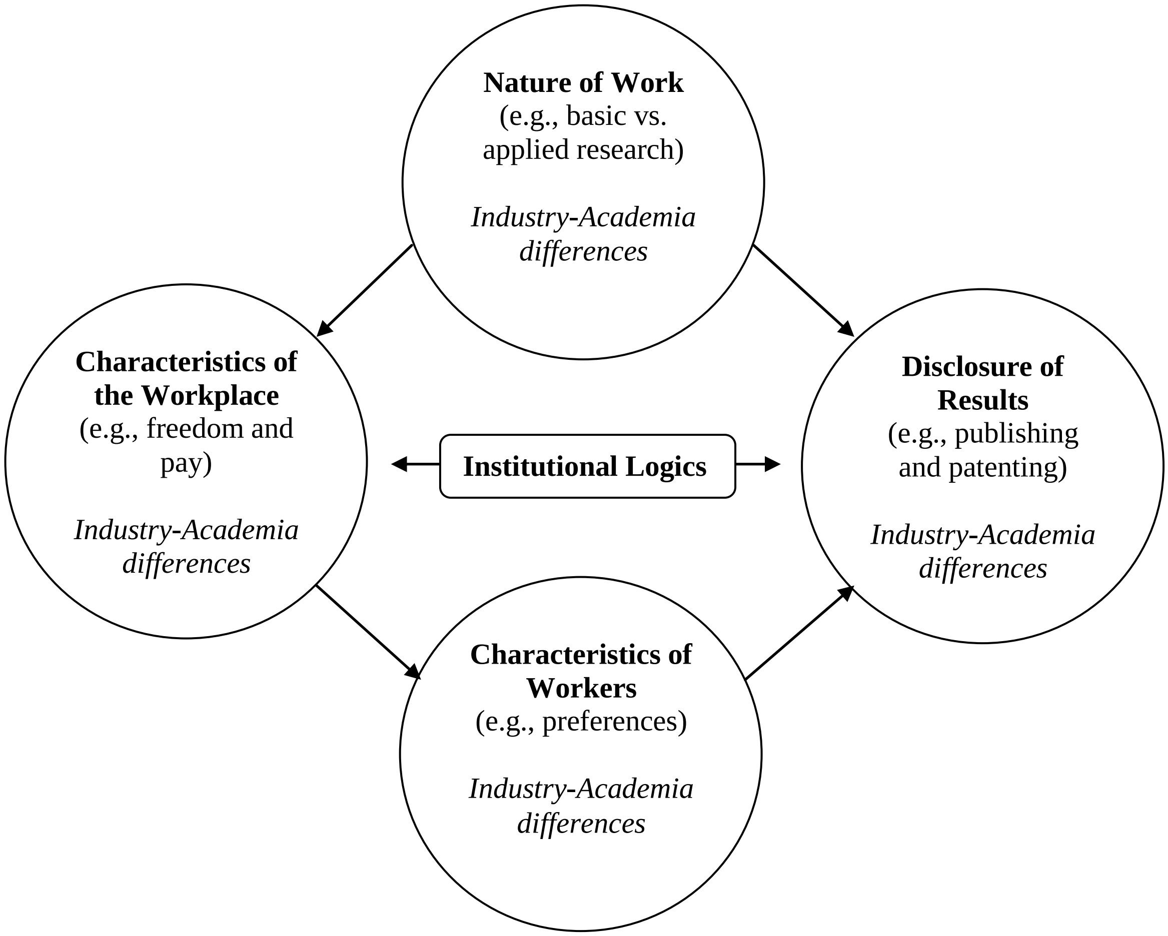
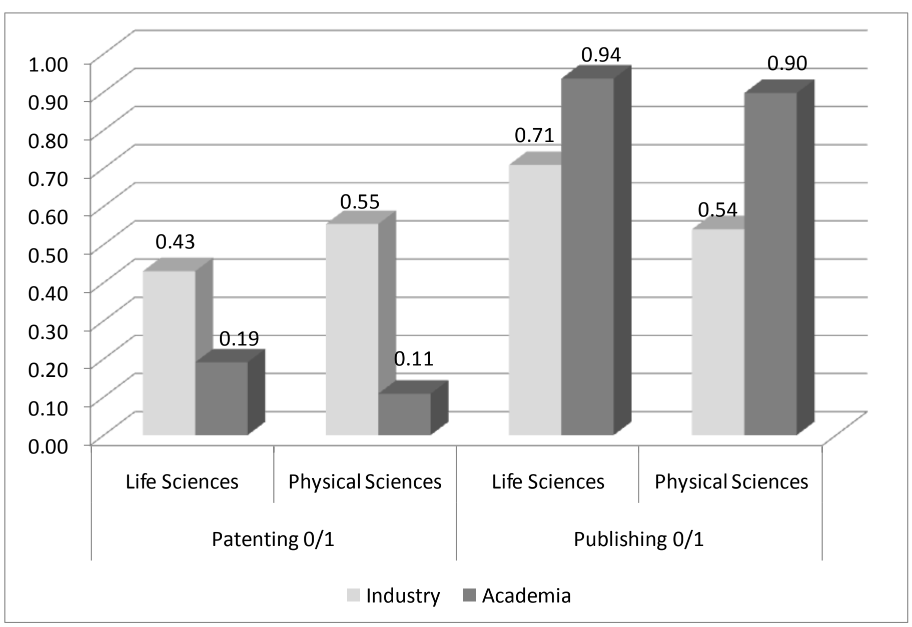


Figure 2: Probability of patenting and publishing, by field and sector



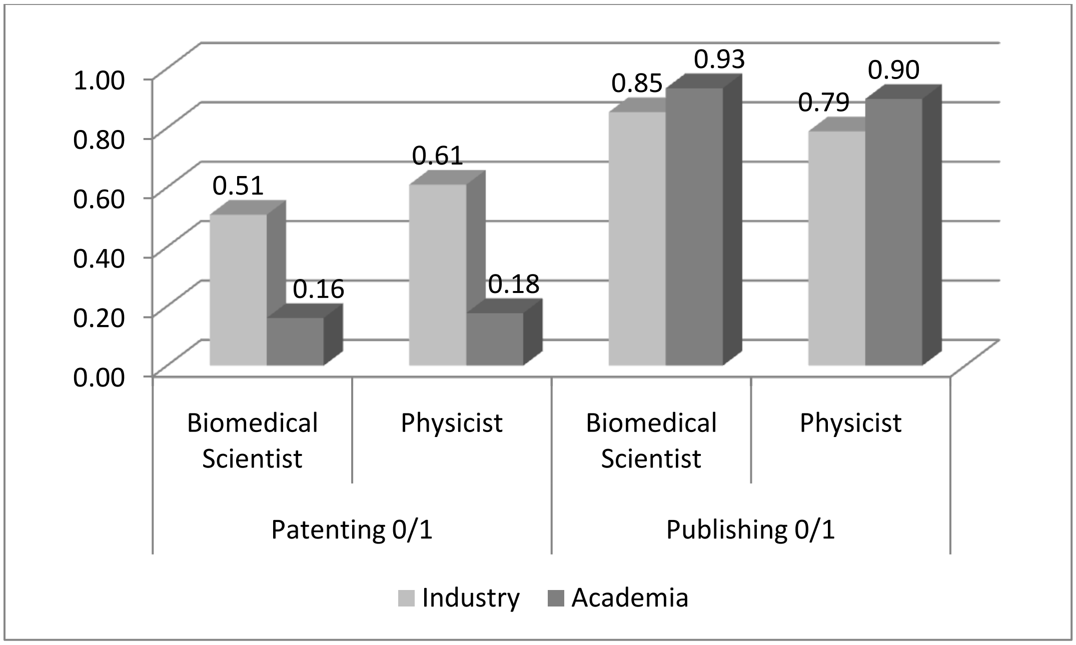
Online Appendix: Disclosure by a "Standardized Individual"

The regressions using the pooled sample showed that significant industry-academia gaps in publishing and especially patenting remain even controlling for the nature of R&D and various other factors (Table 5). However, these regressions constrained the coefficients of independent variables to be the same across sectors and subfields. To address this limitation, 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 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 PhD 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 A1 shows large and statistically significant predicted industry-academia gaps in the probability of patenting for both scientists. However, the predicted industry-academia gaps in the probability of publishing are much smaller and not statistically significant. For comparison, figure A2 provides the predicted *counts* of patents and publications for the same "Standardized Individuals", based on negative binomial regressions. While the industry-academia gaps in the predicted likelihood of publishing were quite small, we continue to find sizeable gaps in predicted counts of publications. Thus, while firms appear to be open to publishing in principle, industrial scientists publish much less frequently than comparable academics.

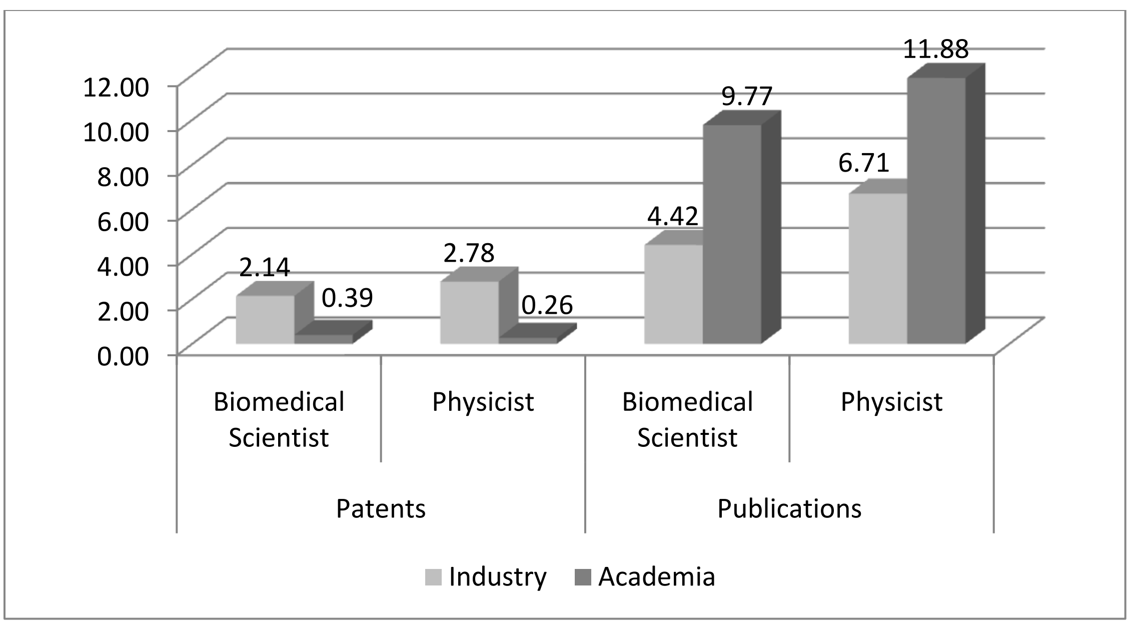
Our data do not allow us to disentangle various potential drivers of the remaining differences in the use of disclosure mechanisms, some of which we discussed in the conceptual part of this paper. However, by separating out differences associated with the nature of research and important scientist characteristics, we provide estimates of the potential magnitude of these effects.

Figure A1: Predicted probabilities of patenting and publishing for a "Standardized Individual", by field and sector



Based on probit regressions by sector and subfield. The "Standardized Individual" is engaged in applied research, received his Ph.D. 10 years ago from average Ph.D. program, supervises three other people, is white, male, and U.S. citizen.

Figure A2: Predicted counts of patents and publications for a "Standardized Individual", by field and sector



Based on negative binomial regressions by sector and subfield. The "Standardized Individual" is engaged in applied research, received Ph.D. 10 years ago from average Ph.D. program, supervises three other people, is white, male, and U.S. citizen.