Exhibit 25

The Sociological Quarterly ISSN 0038-0253

FOR MONEY OR GLORY? COMMERCIALIZATION, COMPETITION, AND SECRECY IN THE ENTREPRENEURIAL UNIVERSITY

Wei Hong
Tsinghua University

John P. Walsh*
Georgia Institute of Technology

Scholars have grown concerned that the commercialization of academic science is increasing secrecy at the expense of cooperation and information sharing. Using data from comparable surveys of academic scientists in three fields (experimental biology, mathematics, and physics), we test whether scientists have become more competitive and more secretive over the last 30 years. We also use the recent survey to test a multivariate model of the effects of scientific competition and commercialization (patenting, industry funding, and industry collaboration) on scientific secrecy. We find that secrecy has increased, and has increased particularly for experimental biologists. Only 13 percent of experimental biologists in 1998 felt safe discussing their ongoing research with all others doing similar work. Our multivariate analysis shows that this secrecy is most related to concerns about being anticipated (scientific competition). We find that patenting is associated with increased secrecy among mathematicians and physicists, but not for experimental biologists. We find that industry funding is associated with more secrecy, while industry collaboration is associated with less secrecy, across fields. Our results suggest that the recent concern over increasing scientific secrecy has merit. However, this increased secrecy seems to result from a combination of increasing commercial linkages and increased pressures from scientific competition. Our research highlights the central role that scientists' competition for priority plays in the system of science and that, while such competition spurs effort, it also produces negative effects that recent trends toward commercialization of academic science seem to be exacerbating.

INTRODUCTION

Contemporary capitalist societies depend strongly on the growth of new knowledge to fuel rising living standards (Nelson 1996). Prior work has described this knowledge as being produced in two fairly distinct institutional contexts: academic science and industrial research and development (R&D). These two institutional environments provide contrasting (and complementary) models for describing the production and dissemination of new knowledge.

*Direct all correspondence to John P. Walsh, School of Public Policy, Georgia Institute of Technology, 685 Cherry St, Atlanta, GA 30332-0345; e-mail: john.walsh@pubpolicy.gatech.edu

Academic science is built on the sometimes contradictory foundations of openness and secrecy. In the "ideal type," scientists are motivated by a priority-recognition reward system that encourages scientists to share their findings and thereby contribute them to the common stock of scientific knowledge, in exchange for recognition by the scientific community for this contribution, through citations, prizes, and other markers of esteem (Merton 1957). This priority-recognition system helps support the norm of communism by creating private incentives for scientists to contribute to the scientific commons (Merton 1942). In this academic model of science, the scientist's property right in his discovery is limited to the right to appropriate recognition for the contribution (a right, like many forms of social exchange, that is difficult to enforce). However, because recognition depends on priority, priority races, and the associated secrecy, have been endemic in science, from the beginnings of the institutionalization of the modern science system up to the present era (Merton 1957). Mitroff (1974) uses the terms "norms" and "counter-norms" to describe these contrasting pressures on scientific behavior (toward secrecy and openness) in their search for recognition through priority. Hackett (1990) describes researchers as operating in a multidimensional value space, with openness/secrecy being one dimension. Differing institutional contexts (for example, being in a university versus a firm) are likely to shift researchers' values along these several dimensions, leading to, for example, more or less openness.

In contrast with academic science, the market model of science emphasizes the incentives from privatizing the returns from scientific discoveries through first-mover advantages, secrecy, and patents (Levin et al. 1987; Stephan 1996; Cohen, Nelson, and Walsh 2000), with enforceable property rights covering the inventions. The independence of these institutions and their underlying logics is a relative one, with each institution having important influences on the other (Kline and Rosenberg 1986). Merton noted in 1942 that the scientific ethos of communism faced conflicts with the wider capitalist society within which it was embedded. Even in the pre-World War II period, prominent academic scientists were patenting their inventions, in part to ensure freedom to operate for themselves and others.

Today, as academic science becomes more intertwined with commercial activity, research is more likely to be driven by applicability rather than curiosity (Gibbons et al. 1994), and universities are expected to contribute to innovation by collaborating with government and industry (Leydesdorff and Etzkowitz 1996). Slaughter and Rhoades (1996) argue that the rise of the competitiveness political coalition in the United States shifted science and technology policy from fighting the Cold War and wars on diseases to emphasizing using science and technology to help the United States compete in the increasingly globalized economy, and pushed universities to contribute more directly to commercialized innovation. Many have argued that the culture of universities changes to accommodate competing values (Hackett 1990; Slaughter and Leslie 1997; Etzkowitz 1998), and that there are growing tensions within universities between these competing models of knowledge creation (Slaughter and Leslie 1997; Owen-Smith 2000; Nelson 2004; Nelson 2006; Glenna et al. 2007a). For example, Glenna et al. (2007b) argue that academic administrators at land grant universities are reframing the universities'

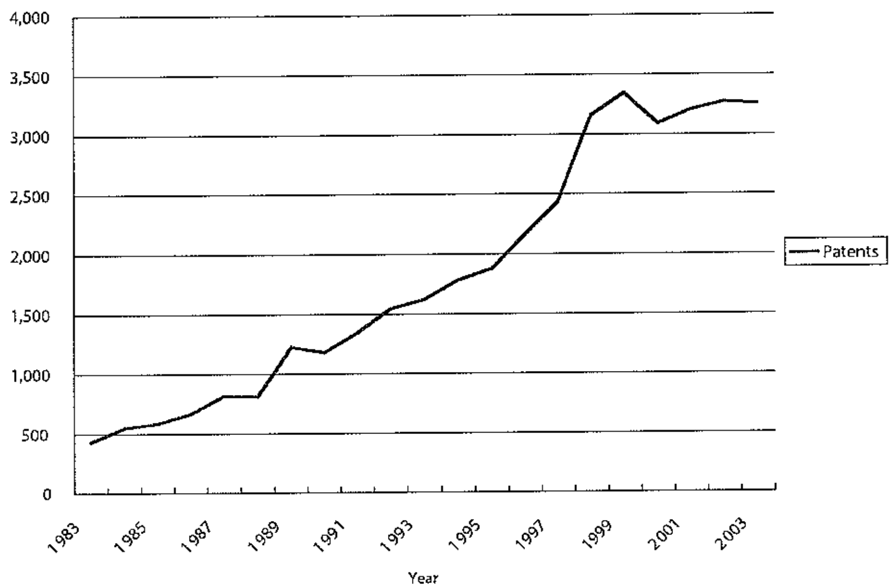

FIGURE 1. University Patents, 1983–2003.
Source: NSF (National Science Foundation). Science and Engineering Indicators, 2006.

missions to emphasize technology transfer as the goal of research and as fulfillment of the public good mission.

Beginning around 1980, a series of policy changes reflecting this new competitiveness coalition have encouraged universities to engage in commercial activity (for a summary, see Slaughter and Rhoades 1996). One of the key changes was the Bayh-Dole Act (1980), which facilitated universities taking title to federally funded inventions and granting exclusive licenses. This policy initiative was based on an economic market model of science and was designed to "incentivize" the transfer of academic science and its development into industrial products or services (Mowery et al. 2001). Several key court decisions (e.g., *Diamond v. Chakrabarty*, Harvard's OncoMouse) also laid the foundation for the growth in commercial activity by universities, especially biotech-related activity. Finally, the success of some early patented technologies (e.g., the Cohen-Boyer patent) also served as a model for other universities. As a result of these changes in the institutional environment, patenting, licensing, and university–industry collaboration have all been increasing over the last two decades (Association of University Technology Managers [AUTM] 2000; National Science Board 2004). For example, Figure 1 shows the increase in patents issued to universities from 1983 to 2003. We see that patenting has grown by almost an order of magnitude, with 434 university patents issued in 1983 and 3,259 issued in 2003. Figure 2 shows data from AUTM's annual survey on university licensing income. Here, we see total annual income increasing from about $200 million in 1991 to about $1.3 billion in 2003. Figure 3 presents data on industry funding of research over the last 30 years. We see that funding increased from

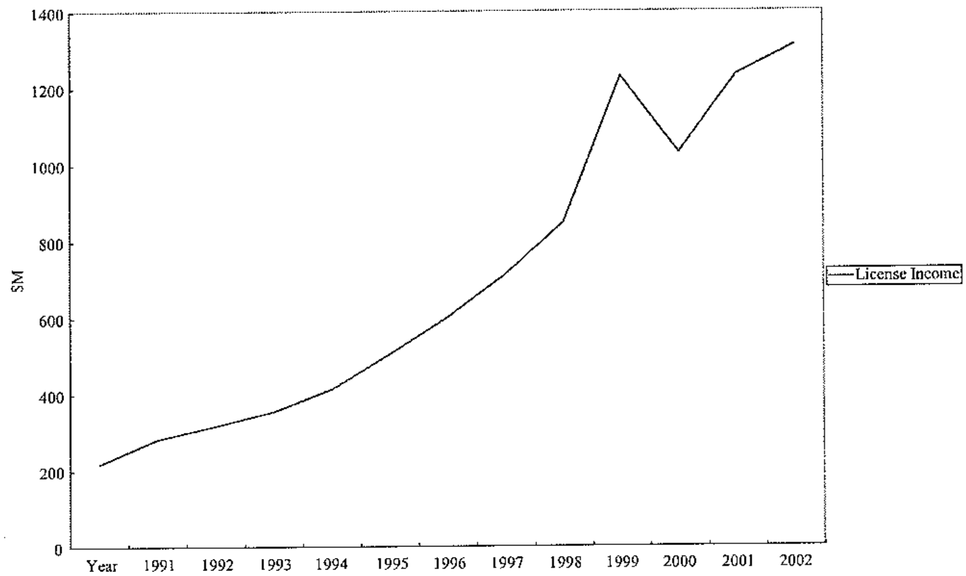

FIGURE 2. University License Income, U.S. Universities, 1991–2003.
Source: AUTM (Association of University Technology Managers).

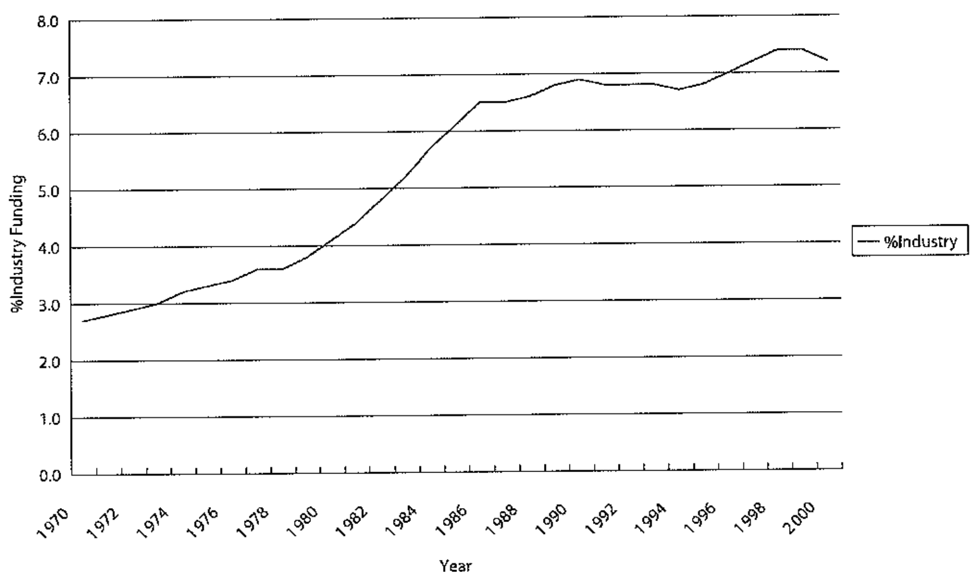

FIGURE 3. Industry Funding of University Research, 1980–2001.
Source: NSF. Science and Engineering Indicators, 2006.

less than 3 percent of total university research funds to over 7 percent.[1] Coauthorships can be seen as another type of university–industry linkage (Slaughter and Rhoades 1996). In 1988, 21 percent of academic papers had an industry coauthor. This increased to 26 percent by 2001 (National Science Board 2006).

This new environment for academic research leads us to ask the question of whether university professors' increasing integration into the market system of innovation is undermining the science system (Slaughter and Leslie 1997; Nelson 2004). In particular, there is a concern that market forces are causing scientists to become more secretive or, in other words, to abandon the norm of communism.

Prior work has raised several concerns about the resulting adverse effects of commercialization on the norms of science: an unwillingness to share research materials (Blumenthal et al. 1997; Campbell et al. 2002; Walsh, Cho, and Cohen 2005), publication delays (Blumenthal et al. 1997; Cohen, Florida, and Goe 1994), conflicts of interest resulting in biases in the research results reported (Bekelman, Li, and Gross 2003), and redirection of effort away from science and toward more applied, or more lucrative, research (Slaughter and Rhoades 1996; Henderson, Jaffe, and Trajtenberg 1998).

At the same time, there is reason to believe that scientific competition has increased (Slaughter and Leslie 1997). The growth of organized science (i.e., researchers regularly engaged in the production of scientific output) produces more competitors for scientific recognition, while rewards for such recognition (including both prestigious university positions and prestigious prizes) have not grown as quickly. In fact, Slaughter and Leslie (1997) argue that the key characteristic of what they term "academic capitalism" is the increasing competition in contemporary universities: competition for funding, for prestige, and for positions. Empirical work has found some evidence for the effects of both commercial activity and scientific competition on secrecy of various forms (Campbell et al. 2002; Walsh et al. 2005).

Thus, our research will focus on the incidence of such secretive behaviors and the factors that seem to be driving these behaviors. Using a unique set of matched surveys conducted about 30 years apart, we propose to test the strength of these competing institutional frameworks and normative orders in influencing scientists' behaviors by examining the effects of commercial activity and scientific competition on the communication behavior of academic researchers. The main sociological question is whether exposure to market ties or commercial activities undermines the scientific norm of communism, or whether these two institutional spheres are complementary at the level of the individual scientist. We will also examine the potential adverse effects of scientific competition, and evaluate the extent to which secrecy is driven primarily by market competition or by scientific competition. We can also test the conjecture that patenting (by providing more enforceable property rights in knowledge) might encourage more openness in science.

Two Contrasting Models of Science

Academic scientists are increasingly straddling two worlds, one organized through the academic priority-recognition system (with the ideal type described by Merton) and one organized by the rules of market competition. These two institutional domains differ significantly in how they treat the results of research and in the reward system for those who generate new results. Because of the public goods nature of knowledge, market-based systems (and the economists who study them) have long struggled with the problem of how to encourage the production (and dissemination) of knowledge (Nelson 1959; Dasgupta and David 1994; Scherer 2002). The lack of proper incentives, because of the difficulty in appropriating the rents from new knowledge, generally leads to the underproduction of public knowledge (Jaffe 1996). One solution is secrecy, which allows appropriability, but prevents widespread use of the knowledge and the social benefits that would come from such use (Cohen et al. 2000). Another widely used solution is patenting, which allows privatizing the results temporarily, creating an incentive, in exchange for disclosure and teaching of the invention (which then passes into the public domain after the expiration of the patent) (Scherer 1959; Cohen et al. 2000). Furthermore, to the extent that intellectual property rights are effective, such commercial orientation may lead to greater dissemination of scientific knowledge, even though the knowledge may have a nonzero price (Arora, Fosfuri, and Gambardella 2001).

Academic science, on the other hand, has developed a rival set of institutions for rewarding the production and dissemination of knowledge, where scientists receive recognition from their peers for being the first (or most convincing) to demonstrate a new discovery by communicating their results (and method) to the scientific community (Merton 1942, 1957; David 2003). This recognition is the scientist's intellectual property, but is, in the ideal type, the only property right the scientist maintains in his discoveries, since once they are announced they are common property:

> Once he has made his contribution, the scientist no longer has exclusive rights of access to it. It becomes part of the public domain of science. Nor has he the right of regulating its use by others by withholding it unless it is acknowledged as his. In short, property rights in science become whittled down to just this one: the recognition by others of the scientist's distinctive part in having brought the result into being. (Merton 1973:294–5)

Of course, this esteem from colleagues is both its own reward and is also translated into pecuniary rewards: primarily, well-paid research positions and well-funded labs, as well as the cash prizes associated with many scientific awards (the Nobel Prize, for example, is over $1 million). In addition, there is substantial debate in the sociology of science as to whether the norm of communism is in fact internalized by scientists (cf. Mitroff 1974; Zuckerman 1988; Hackett 1990). For example, Mitroff (1974) argues that scientists are always guided by norms and counter-norms (such as the norm of communism and the counter-norm of secrecy), which are in tension (although it is not clear when the norm or the counter-norm will dominate). Similarly, Hackett (1990) argues that we can think of scientific norms as arrayed in contrasting pairs, with one or the other being emphasized in different contexts (for example, in universities versus industry labs, or in one field versus another, or in universities before the rise of the competitiveness agenda versus after). The conflicting norms of openness and secrecy are one example. Thus, even within the world of academia, scientists have to reconcile these conflicting principles of conduct. However, even if we do not assume a strong norm of communism, the incentives associated with the priority-recognition system encourage dissemination of research findings. Thus, either through compliance with a communism norm, or in response to a recognition-based reward system, the academic world (in contrast with the market world) is one based on sharing of research results. This priority-based reward system leads to frenzied efforts by scientists to put more and more information into the public domain (as demonstrated both by the ever-increasing number and rate of publications in science and by the long hours that scientists work, particularly among those who are competing at the frontiers of high-profile fields). However, as Merton points out, as competition for priority increases (and as the rewards increase), the pressure for antisocial behavior also increases. As Merton puts it:

> The culture of science is, in this measure, pathogenic. It can lead scientists to develop an extreme concern with recognition. . . . Contentiousness, self-assertive claims, secretiveness lest one be forestalled . . . even the occasional theft of ideas and, in rare cases, the fabrication of data—all these have appeared in the history of science and can be thought of as deviant behavior in response to a discrepancy between the enormous emphasis in the culture of science upon original discovery and the actual difficulty many scientists experience in making an original discovery. (Merton 1973:323)

Therefore, even within the ideal-type scientific reward system, there are the contradictory forces of the drive for disclosure and the need for secrecy to protect one's lead time advantage in the priority race (Merton 1957; Mitroff 1974; Hackett 1990). This secrecy can take several forms. One of these is simply refusing to discuss ongoing research until it is published and priority has been established.[2] This can be taken further by limiting the disclosure of knowledge or the distribution of its material embodiments (such as new materials, equipment, cell lines, etc.) in order to protect the discoverers' advantage in exploring the follow-up research that the initial discovery opened up (Walsh et al. 2005). Merton (1957) gives several examples of scientists submitting sealed manuscripts to learned societies or announcing results in code, in order to establish priority without tipping off their competitors.[3] More recently, the researchers analyzing the Cave 4 Dead Sea Scrolls kept other researchers from accessing the original scrolls, and tried to prevent publication of their contents, in order to both protect their ability to continue publishing findings from these key materials and to prevent competitors who critiqued their theories from readily analyzing their data. Therefore, as scientific competition becomes more intense, we may observe a greater emphasis on secrecy, even within the domain of public science. Finally, tacit knowledge is also important in the production of scientific results (Polanyi 1967), and scientists may be reluctant to widely disseminate this tacit knowledge, in order to maintain a temporary monopoly over these techniques. These adverse effects result both from deliberate attempts to monopolize a research area, and from the passive result of lacking incentive to engage in the costly process of disseminating materials or training others in the newly discovered techniques (Campbell et al. 2002; Cohen and Walsh 2008). While the gift exchange system does provide important incentives for engaging in these sharing behaviors, these incentives may be outweighed by the benefits of spending that time producing one's own new discoveries.

No matter how different the two academic and market models of science are, universities have been increasingly involved in economic development in recent years. The Triple Helix perspective (Leydesdorff and Etzkowitz 1996), advocating close collaboration among universities, government, and industry, has been well received (Shinn 2002). Similarly, Stokes (1997) argues that by doing research in "Pasteur's Quadrant," scientists can both generate new knowledge and address applied needs. Gibbons et al. (1994), using the term "Mode 2", argue for knowledge production that is cross sectoral (spanning university and industry), interdisciplinary, and application-oriented. Slaughter and her colleagues (Slaughter and Rhoades 1996; Slaughter and Leslie 1997) argue that the new competitiveness coalition has shifted science policy to encourage universities to emphasize applied, commercializable research. These new perspectives on science policy emphasize university–industry cooperation, technology transfer, and a more applied focus for academic research. Hackett's (1990) competing values model of science suggests that the social and economic context in which the scientific institution is embedded has a big impact on its culture. Thus, when universities are increasingly dependent on industry funding, they will operate more like commercial entities and those industry-compatible values will accordingly gain dominance. Thus, Hackett's perspective implies that the two contrasting models of science ("academic/open science" and "industry/private science") are two competing sides of the institution of science, with the relative dominance of each side depending on the contingent social and economic context. Similarly, Slaughter and Leslie (1997) use the term "academic capitalism" to describe the shifting context and the associated changes in norms and practices, with university researchers increasingly taking on the characteristics of capitalist R&D labs, both in the competitive pressures they face and their responses to those pressures. Slaughter and Rhoades (2004) argue that as academic capitalism becomes institutionalized, the distinctions between the academic/open science model and the industry/private science model of knowledge production blur and merge into a new form that emphasizes knowledge production as a means of securing resources in a competitive environment, even among academic scientists.

Thus, this new "hybrid" paradigm suggests that university scientists should be especially sensitive to outside funding, and that the increasingly common acceptance of industry funding should be associated with greater secrecy (i.e., a weakening of the norm of communism). Similarly, this perspective suggests that the increasingly common collaborations with industry researchers should be associated with a shift toward the secrecy end of the openness/secrecy spectrum (Hackett 1990). For example, Walsh, Jiang, and Cohen (2007b) find that commercial activity is associated with greater adoption of market norms and weaker adherence to "expert science" (open science) norms. Similarly, commercial activity, such as patenting, should be a marker of a shift toward the market model and be associated with greater secrecy. In contrast, the priority-recognition-based model of academic science suggests that scientists should be especially sensitive to scientific competition and might be more secretive in the face of greater scientific competition. However, this model implies that industry funding, patenting, and industry collaboration are all likely to have weak effects, or possibly even be associated with less secrecy, as they can serve to provide resources to allow winning priority races.

Increasing Commercialization of Science and Increasing Secretive Behavior

Despite attempts to reframe this new model of science using such positive terms as Mode 2, Triple Helix, or Pasteur's Quadrant, there is substantial concern that the growing links between the academy and the market is undermining the centrality of the scientific reward system and leading academic scientists to engage in behaviors that undermine the social benefits of academic research. In particular, there are claims that academic science is becoming more secretive as professors shift from focusing on publishing in order to gain peer recognition, and toward patenting and licensing in order to garner market-based rewards for selling privatized knowledge.

As academic science has becoming increasingly linked to commercial activity, there has been heightened concern that, particularly in biomedical fields, scientific competition and concern about commercial gain have led to a dysfunctional increase in secretive behavior among academic scientists (Ceci 1988; McCain 1991; Blumenthal et al. 1997; Marshall 1997; Cook-Deegan and McCormack 2001; Campbell et al. 2002; Bekelman et al. 2003; Needham et al. 2003). Patenting can encourage a climate of secrecy that limits the free flows of ideas and information that are vital for successful science. For example, in a study done in the 1980s, McCain (1991) noted that in her population of geneticists, sharing of research tools and information generally proceeded smoothly, but warned that the increasing emphasis on formal property rights in information and materials was beginning to adversely affect the former gift exchange system. Over the next decade, secretive behavior in biomedical research seems to have increased. Blumenthal et al. (1997) find that 9 percent of life science faculty had refused to share research results with other university scientists. Concern over scientific priority was the most common reason cited, with expense or scarcity of the material close behind. Commercial considerations were also mentioned, although not as prominently. Refusing to share results was related to greater productivity and to greater commercialization. In addition, almost 20 percent of respondents delayed publication for more than six months, with concerns over patent issues being the most common justification and concern over scientific priority close behind. Publication delay was associated with having a research relationship with industry and with commercializing university research. Campbell et al. (2002) report that almost half of academic life scientists had been denied in at least one request for information, data or materials (with about 10 percent of all requests denied). About 12 percent reported denying such requests. The likelihood of denying a request was related to commercialization and to receiving many requests. Furthermore, a significant minority (35 percent) felt that such secretive behavior has been increasing over the last 10 years. Walsh et al. (2005) found that just a few years later, the percent of requests refused had increased to 18 percent, and that failing to provide requested research materials was related to commercial activity as well as to scientific competition. Thursby and Thursby (1999) report that 32 percent of sponsored research agreements include the right to delay publication (with an average of 2.6 months delay) and 58 percent include the right to delete information from research papers prior to submission for publication. Cohen et al. (1994) also find that industry sponsorship often includes an agreement to delay publication to allow time to patent the research results. Thus, we have evidence that secrecy in science (or, at least, in biomedical science) is not rare, and that the rate of secrecy may be increasing (for example, comparing Campbell et al. and Walsh et al.).

Such secretive behavior can have a variety of negative effects on scientists and on science. Campbell et al. (2002) report that, for their sample, 28 percent of respondents said secretive behavior prevented verification of published research, 24 percent said it slowed down follow-on work, and 21 percent said it caused them to abandon promising lines of research. Cook-Deegan and McCormack (2001) argue that the emphasis on secrecy and patents in genomics delays publication of much sequence information, greatly reducing its information value. Not only do these consequences affect individual scientists, but this secrecy could also result in duplication of work and the inability to check prior results and compare results to find inaccuracies and to learn from others' work, thereby delaying the progress of science as a collective effort (Hagstrom 1974; Marshall 1997; Cook-Deegan and McCormack 2001). However, a recent case of a scientist being "scooped" by his own data published on the web points to the complexity of the relationship between secrecy and competition, and between recognizing individual contributions and advancing science (Marshall 2002). Thus, scientific competition can drive secretive behavior, even at the potential cost of slowing the advance of science.[4]

Research Questions and Hypotheses

Thus, prior work suggests that secrecy is a critical concern in the operation of the science system and that scientific competition and commercial concerns may both be driving increased secrecy in academic science. Our research questions are: (1) Has secrecy increased in the past three decades (i.e., during the period of transition to the entrepreneurial university (Hackett 1990; Slaughter and Leslie 1997)? (2) Does the increase in secrecy differ across fields (i.e., is this particular to biomedical research)? (3) What are the factors associated with the increased secrecy? In particular, how do commercial ties and scientific competition each affect secrecy among academics? The competition for priority simultaneously drives scientists to disclose findings and to hoard them (and especially to hoard pieces of the results that help generate follow-up findings). Because of this, we might see increasing secrecy even without a shift in scientists' orientation away from the academic perspective and toward a commercial orientation to their research. On the other hand, if industry funding, patenting, and industry collaboration are measures of a shift toward a market or hybrid model of science, they should be associated with more secrecy (Cohen et al. 2000). If, however, there has not been a shift in the underlying model of academic science prevalent among university faculty, we would not expect these ancillary activities to substantially affect the core academic activity of sharing research results. We might even find positive effects, such that patenting, industry collaboration, and industry funding are associated with less secrecy, as they provide resources that allow for winning priority races. Thus, both scientific competition and market forces have potentially offsetting effects on sharing among scientists. On balance, we do not know which will dominate, or whether any observed increase in secrecy is because of the one or the other mechanism, although we will test the relations between scientific competition and secrecy over time, by field, to see if any rise in secrecy can, in part, be explained by increased scientific competition. Furthermore, we will use multivariate regression techniques to try to determine the relative effects of scientific competition and commercial activity, controlling for the other, which will help us contrast the underlying models of science that are likely to be driving these results.

Data and Method

To empirically test the hypotheses that secrecy has increased and that this secrecy is driven by commercialization and/or scientific competition, and to broaden our understanding of secrecy and information sharing among scientists, we decided to take advantage of a unique set of comparable surveys that were conducted about 30 years apart. The data come from two surveys of university scientists. The first was conducted in 1966 by Hagstrom, who surveyed a national random sample of 1,947 academic scientists in six fields (mathematics, experimental physics, theoretical physics, experimental biology, other biology, and chemistry) (Hagstrom 1974). The second survey, administered in 1998 by Walsh et al. (2000), includes a national random sample of 399 scientists from four fields (experimental biology, mathematics, physics, and sociology). For this study, we use the three fields of mathematics, physics, and experimental biology for comparison. The two surveys measure secrecy by asking how safe scientists feel in discussing their current research with others doing similar work. The surveys also include a measure of scientific competition, asking respondents how concerned they are about being anticipated in their current research. The later survey also includes measures of patenting, industry funding, industry collaboration, gender, institution type, seniority, and publication productivity.[5]

Using these surveys provides several important advantages. The primary advantage of these data compared with other recently published studies is that they allow over-time comparison. Also, while much of the recent focus has been on experimental biology (Blumenthal et al. 1997; Campbell et al. 2002), our data from different fields allow us to test if secrecy in experimental biology has become more prevalent relative to, for example, physics and mathematics. Given that our dependent variables are ordered categorical variables and that our data are grouped by a small number of discrete independent variables, we use cumulative logit models to test for changes in secrecy and/or competition over time and across field, as well as time–field interactions (Aldrich and Nelson 1984; Winship and Mare 1984).[6] In addition, we can use the 1998 data to test a multivariate model of secrecy that extends the earlier models (Blumenthal et al. 1997;

Campbell et al. 2002) by testing the relative impact of scientific competition versus market factors as explanations of secrecy.

RESULTS

Increasing Competition, Increasing Secrecy

Table 1 gives the comparisons over time and across fields for scientific competition and secrecy, presenting the responses as percent "Yes" to the questions, meaning the percentage who are at least slightly concerned about being anticipated or who are at least somewhat secretive (i.e., who responded something other than "I feel safe with all others" to the question about discussing current research). Using Hagstrom's data, we can see that the percentage of experimental biologists in the 1960s who were at least slightly concerned about being anticipated (63 percent) is not very different from the overall average (64 percent), and ranks between physics and mathematics. Comparing over time, we see in Table 1 that over the last 30 years, concern over scientific competition has increased in experimental biology (going from 63 to 81 percent "at least slightly concerned"). The overall average (across all fields) also increased from 64 to 74 percent.

Using cumulative logit models on the ordinal (four-point) measure of competition, we test whether there has been a change over time, whether biology is different from the other two fields, and whether there is an interaction between year and field. Table 2 shows the results for competition. In model 1, we see that there has been a significant change overall in competition over time. However, we find no difference between biology and the other fields. When we add the year by biology interaction effect (model 2), however, we find that the increase over time is largely because of the increase in biology, with the main effects for biology and year now insignificant, and the interaction term significant. This model fits significantly better than the model without the interaction effect (change in chi-square = 14.5; 1 degree of freedom [d.f.], $p < .001$). In

TABLE 1. Competition and Secrecy in Three Fields across Time

	1966		1998	
	Competition	Secrecy	Competition	Secrecy
Field	Yes percentage (N)	Yes percentage (N)	Yes percentage (N)	Yes percentage (N)
Experimental biology	63 (316)	55 (316)	81 (80)	87 (89)
Mathematics	60 (275)	45 (282)	68 (38)	55 (42)
Physics	68 (438)	48 (444)	67 (58)	64 (61)
Total	64 (1,029)	49 (1,042)	74 (176)	72 (192)

Note: For Competition, "Yes" means at least "slightly concerned" about being anticipated. For Secrecy, "Yes" means that they do not feel safe talking with all others about their research. N is the number of respondents in each cell.

TABLE 2. Cumulative Logit Models of Competition on Year and Field

	Model 1			Model 2		
Independent variable	Coefficient	Standard error	Chi-square	Coefficient	Standard error	Chi-square
Year	.7317***	.1444	25.7	.2591	.1920	1.8
Biology	.1130	.1110	1.0	−.0799	.1229	.4
Year* biology				1.1284***	.2915	15.0
Intercept1	−2.6886***	.1181	518.3	−2.6566***	.1196	493.6
Intercept2	−0.8477***	.0742	130.4	−.7925***	.0754	110.3
Intercept3	.5516***	.0717	59.1	.6153***	.0740	69.2
Likelihood ratio test	27.2***			41.7***		
d.f.	2			3		
Number of respondents	1,235			1,235		

***$p < .001$ (two-tailed tests).

addition, for this model, using the Score test, we cannot reject the null hypothesis that the slopes are equal across categories of competition (chi-square = 8.9, 6 d.f., $p = .18$), suggesting that the effect is consistent across the range of the dependent variable.

As for secrecy, Table 1 shows that in 1966, the percentage saying they are not willing to discuss their research with all others is higher in experimental biology (55 percent) compared with physics (48 percent) or mathematics (45 percent). We also see that, in the marginals, across all fields, secrecy has increased substantially in the last 30 years (rising from 49 percent being unwilling to talk with all others in 1966 to 72 percent in 1998). While secrecy increased in each of the three fields, we see a substantial increase in secrecy in experimental biology. Eighty-seven percent of the 1998 sample report being at least somewhat unwilling to talk about their ongoing research. Table 3 shows the cumulative logit models testing for changes over time, fields and time by field interaction. In model 1, we see that there has been a significant change overall in secrecy over time. As expected, we also find that biology is significantly more secretive than the other fields. When we add the year by biology interaction effect (model 2), we find that, in addition to the year and field effect, there is a significant year by field interaction. In other words, not only is biology more secretive than other fields and not only has secrecy increased over time, but secrecy has particularly increased in biology. We replicated these analyses using Sullivan's (1975) data on biomedical researchers and find very similar results. These findings are consistent with the findings of Campbell et al. (2002) that show that biomedical researchers felt that secrecy had increased over time. However, our results further show not just an absolute increase, but an increase relative to mathematics and physics (where secrecy has also increased). This model fits significantly better than the model without the interaction effect (change in chi-square = 6.4, 1 d.f., $p < .05$). In addition, for this model, using the Score test, we cannot reject the null hypothesis that the slopes are equal across categories of secrecy (chi-square = 6.1, 3 d.f., $p = .11$).

TABLE 3. Cumulative Logit Models of Secrecy on Year and Field

	Model 1			Model 2		
Independent variable	Coefficient	Standard error	Chi-square	Coefficient	Standard error	Chi-square
Year	.7996***	.1554	26.5	.4640*	.2040	5.2
Biology	.4539***	.1190	14.5	.3131*	.1310	5.7
Year* biology				.7762*	.3129	6.2
Intercept1	−2.8330***	.1228	532.4	−2.8103***	.1246	508.8
Intercept2	−.1490***	.0716	4.3	−.1025***	.0735	1.9
Likelihood ratio test	47.7***			54.1***		
d.f.	2			3		
Number of respondents	1,234			1,234		

*$p < .05$, ***$p < .001$ (two-tailed tests).

Thus, we see evidence that secrecy has increased among academic scientists across fields, but especially in experimental biology. Furthermore, we find that this change in secrecy is associated with the growth in scientific competition during this period. These results are consistent with a Mertonian priority-reward model of academic/open science, since even an open science model includes the possibility of secrecy as a means of ensuring priority of discovery. At the same time, since academic capitalism includes the concept of increasing competition for the resources to do research, these results are consistent with Slaughter and colleagues' thesis that contemporary universities are becoming less open as a result of the rise of the competitiveness agenda and the shift to academic capitalism.

Competition, Commercialization, and Secrecy

Based on the work of Hackett (1990) and Slaughter and her colleagues (Slaughter and Rhoades 1996, 2004; Slaughter and Leslie 1997), we hypothesize that the growing links between universities and industry (the hybrid model) are associated with a shift in norms away from openness and toward secrecy, and that this secrecy is associated with commercial activity and industry ties. At the same time, Merton's priority-driven reward perspective (academic model) also predicts substantial secrecy in the face of scientific competition for priority and recognition, but with little impact from commercial activity or industry linkages expected. In this section, we simultaneously test the effects of scientific competition and commercial activity (i.e., patenting, industry funding, and university–industry collaboration) on secrecy (being unwilling to talk about ongoing research). We used the 1998 survey data and ran ordered logistic regressions. Using a specification similar to Campbell et al. (2002), we control for years since Ph.D., number of publications, gender, field, collaboration, and institution type (Carnegie Research I or not). We then test whether patenting, industry funding, university–industry collaboration, or scientific competition have significant effects on secrecy. Table A1 gives the descriptive statistics for these data, by field. Not surprisingly, experimental biologists are significantly more likely to apply for patents ($p < .001$), with 30 percent of respondents having applied for at least one patent in the last five years. However, in terms of industry funding or industry collaboration, experimental biology is not significantly different from the overall averages (which is also not surprising, as academic capitalism is not limited to biotech, but also includes many science and engineering fields [Slaughter and Rhoades 1996]).

Table 4 shows the multivariate models. Model 1 is the full model using available data. The only control variable with a significant effect is gender. We find that men are less secretive than women. This gender difference may be because of the relatively more vulnerable position of women scientists, which leads them to be more careful about disclosing their findings, less they lose credit for their discoveries. Other than gender, none of the control variables are significantly associated with secrecy. In particular, scientific productivity, as measured by number of papers published, is not associated with either greater or lesser secrecy (Hagstrom 1974; Blumenthal et al. 1997; Campbell et al. 2002).

The major predictor of secrecy (in terms of variance explained) is scientific competition (chi-square = 14.4, 1 d.f., $p < .0001$, odds ratio = 2.2). In contrast, the effects of commercial activity are quite mixed. Having applied for a patent has no effect, which is different from prior studies (Blumenthal et al. 1997; Campbell et al. 2002). However, like the earlier studies, ours finds a positive relation between industry funding and secrecy (chi-square = 4.5, 1 d.f., $p < .05$, odds ratio = 6.4). In contrast, having industry collaborators is associated with *less* secrecy, with an effect size close to the inverse of the funding effect (chi-square = 3.5, 1 d.f., $p < .10$, odds ratio = .2). The prior studies did not explicitly test for the effects of collaborating with industry scientists.[7]

We also ran a model (model 2) imputing missing values for the independent variables. The results are qualitatively similar. The big substantive change is for industry funding, which is still positive but not significant. This is one of the variables with the most missing data. Gender is no longer significant. Other control variables also fluctuate in magnitude and sign. However, none of these differences change the fundamental interpretation of the impacts of academic competition and commercial activity on secrecy.

Much of the prior work on secrecy and commercial activity in science has focused on experimental biology and biomedical researchers (Blumenthal et al. 1997; Cook-Deegan and McCormack 2001; Campbell et al. 2002; Bekelman et al. 2003). In order to test whether the effects vary by disciplines, we ran separate models for experimental biologists (model 3) and mathematicians/physicists (model 4). We can see that the effect of scientific competition is much stronger for biologists than for mathematicians/physicists (field difference in the coefficients is significant, $p < .05$).[8] The effect of "Concern over competition" for biologists is about three times of that for mathematicians/physicists. Publication also increases biologists' secrecy, which again suggests that competition may be driving secrecy, since the most publication-active scientists are also the most secretive (field differences in the coefficients are not quite significant at conventional levels,

TABLE 4. Ordered Logistic Regression of Secrecy on Scientific Competition, Patenting, and Industry Funding

	Model 1 (all)	Model 2 (impute missing)	Model 3 (exp. bio)	Model 4 (phys/math)
Independent variable	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
Concern over competition	.7905*** (.2086)	.7061*** (.1689)	1.5094*** (.4020)	.4929† (.2726)
Applied for patent	−.0404 (.4726)	−.1156 (.4130)	−.4495 (.7450)	1.3564† (.8211)
Industry funded	1.8631* (.8758)	.7997 (.7046)	1.3777 (1.1634)	3.8671* (1.9180)
Industry collaborator	−1.5790† (.8463)	−1.3384† (.7378)	−1.7402 (1.2428)	−3.1741† (1.7638)
Male	−1.3339* (.6042)	−.7149 (.5161)	−.8623 (.8251)	−1.9163† (1.0351)
Publications	.0368 (.0437)	.0042 (.0417)	.1288† (.0751)	−.0140 (.0589)
Years since Ph.D.	.0097 (.0161)	.0052 (.0156)	−.0063 (.0260)	.0290 (.0225)
Carnegie R1 University	.0665 (.3842)	−.0719 (.3193)	.7883 (.6065)	−.2348 (.5446)
Collaborate	−.1712 (.4316)	.3753 (.3670)	−.7810 (.7833)	.0545 (.5356)
Biology	1.0720* (.4483)	1.0091** (.3706)		
Intercept1	−4.3944*** (.9392)	−4.3935*** (.7532)	−5.7581** (1.8099)	−4.0419** (1.3820)
Intercept2	−.3449 (.8381)	−.6563 (.6681)	−1.1278 (1.5674)	.4758 (1.1927)
Likelihood ratio test	46.8033***	N/A[a]	27.6216***	14.3496
d.f.	10	10	9	9
Number of respondents	143	202	64	79

[a]The multiple imputation method that we use creates five imputed data sets and generates estimates of model 1, respectively. The final imputed results (coefficients shown in model 2) are averages from those individual imputations. Although a Likelihood Ratio Test is available for each individual imputation, it is not available for the multimodel average.

†$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed tests).

$p < .15$). However, the effects of other market factors are far stronger for mathematicians/physicists. Applying for a patent becomes marginally significant in predicting the secrecy behavior of mathematicians/physicists (field differences not quite significant, $p < .11$). Industry-funded mathematicians or physicists are more likely to be secretive (than are industry-funded biologists), while those mathematicians and physicists with industry collaborators are more open regarding their findings (than are biologists with industry collaborators). These effects are consistent with model 1, but stronger in their magnitude. However, because of the large standard errors, we cannot reject the hypotheses that these effects are the same across fields. Similarly, being male has a negative effect in both models, with the effect larger in mathematics/physics, although we cannot reject the hypothesis that the two effects are equal.

Biology has been highlighted as a field where research ethics are particularly vulnerable to commercial activity. Yet even for experimental biologists, we find that scientific competition is the predominant factor contributing to secretive behavior. We also see that industry funding (but not patenting) is associated with greater secrecy, although patenting is associated with increased secrecy for physics/mathematics. While these across-field differences are important, we can also see that scientific competition (concern over competition) and market factors (industry funded or industry collaborator) essentially have the same effects (in terms of direction) on scientists' secretive behavior across fields, although they differ somewhat in magnitude. Therefore, we can conclude that our results are robust to missing data and across fields.

CONCLUSIONS

Our results suggest that concerns over secrecy and the increase in secretive behavior in science, and biomedical research in particular, may have substantial merit. We see a substantial increase in secrecy over the last 30 years, with the effect most pronounced in experimental biology. This period coincides with the rise of the competitiveness agenda and the entrepreneurial university in the United States. Interestingly, recent research on industrial R&D also finds evidence that researchers are becoming more secretive (Cohen et al. 2000), consistent with Slaughter and Leslie's (1997) arguments about the growth in global competition. Furthermore, we find that scientific competition is a significant predictor of secrecy. These findings are consistent with Campbell's findings that the primary causes of failure to share were the effort involved and concerns about publication, with patenting and licensing concerns far down the list (Campbell et al. 2002). Similarly, Walsh et al. (2007a) find that scientific competition is an important predictor of the withholding of research materials and unpublished data. Unlike prior studies by Campbell, Blumenthal, and colleagues, for our full sample, we do not find a significant relationship between patenting and secrecy, although patenting has a marginal effect on secrecy for mathematicians/physicists (Blumenthal et al. 1997; Campbell et al. 2002). Differences in measures and in sample sizes may account for some of this difference.[9] Like earlier studies, we do find that industry funding is associated with increased secrecy. However, we also find that university–industry collaboration is associated with less secrecy (which prior studies did not test). Thus, unlike prior work that highlights the negative aspects of university–industry linkages, our results suggest a more complicated and interesting picture. These university–industry collaborations can be viewed as part of a professor's strategy to share findings and expertise with the wider scientific and technical community. For companies, timeliness and customization of information are often more important than exclusivity, so they may be willing to tolerate, even encourage, their academic collaborators' participation in the shared conversation of a scientific field, thereby giving the company access to the whole community's expertise (Zucker, Darby, and Armstrong 2002). In contrast to these collaborations, industry funding alone is often associated with a university laboratory acting as a subcontractor to a company's R&D project, and may produce the associated secretive behaviors. Thus, although we need to be wary of the strings attached to industry funding, perhaps university–industry collaborative research should be encouraged, or at least not discouraged, especially if it can be framed in an academic/open science context. The findings of a negative relation between industry collaboration and secrecy suggests that exposure to the norms of industry scientists does not necessarily undermine the open science norm of communism among academic scientists, and that these two institutional spheres can be compatible at the level of the individual scientist.

Our results have several limitations that suggest caution in interpreting the findings. First, the multivariate results are cross sectional, so we do not know the directions of the relationships we observe. In addition, the sample size is modest and so we may not be able to detect some effects. Also, we did not measure other types of secrecy, such as delay in publication or being unwilling to share materials. Similarly, broader measures of commercial activity (including levels of funding or participating in licensing or start-ups) might better capture the concept of "participating in market-based science."[9] Similarly, we would want to know whether other measures of scientific competition (number of competitors, the extent to which being second reduces recognition, difficulty in getting public funding for one's research) might similarly affect secrecy. In addition, we have modeled these relationships at the individual level. However, we suspect that organizational-level factors are also important. In particular, not only do individual scientists compete, but universities also compete for prestige and resources (Slaughter and Leslie 1997), and future work should test both the organizational-level responses to scientific competition and commercial opportunities, and test the multilevel interactions between individual and organizational-level competition (see Walsh, Jiang, and Cohen 2007b). Thus, further work is needed to see how robust our findings are to other measures and samples. In particular, we want to know how robust our scientific competition findings are to other tests of its role in explaining secrecy in science relative to market activity. Also, while much of the research in this area has the implicit concern that secrecy may harm scientific progress, we need to demonstrate the relationships between particular forms of secrecy and various scientific outcomes. Secrecy, competition, and openness form a complicated relationship in scientific communities, as scientists attempt to provide timely and certified (substantially) correct results in order to establish scientific reputations (which encourages openness), in the face of competition from rival scientists who are trying to accomplish the same thing (which encourages secrecy until the work can be completed) (Merton 1973; Cohen and Walsh 2008). The overall impact is not clear. For example, overall, we see no relation (positive nor negative) between individual productivity and secrecy, although there is a positive relationship if we restrict our sample to experimental biologists. More importantly, we would like to see the impact of secrecy on the net productivity of scientific communities, perhaps by comparing across fields, over time, and between institutional environments (e.g., universities, government labs, and industry), or comparing different countries. Of course, finding a measure of the "progress of science" that can be applied across broad samples has proven to be difficult.

Thus, while there is some evidence that academics are now operating under a new paradigm, we also see evidence that the changing institutional context of university research is reinforcing the long-standing academic model of science, and perhaps exacerbating some of the fault lines in that system. This increase in scientific competition (and the associated increase in secrecy) can be seen as an intensification of the open science, priority-recognition model (Merton 1957), or as the result of the changing institutional context as a result of the rise of the competitiveness coalition's view of science policy and the resulting pressures on universities and their faculty to be productive in order to generate their own resources (Slaughter and Leslie 1997). There is evidence of the hybrid or academic capitalism model in the relation between industry funding and secrecy (Gibbons et al. 1994; Slaughter and Leslie 1997; Slaughter and Rhoades 2004), which suggests that the search for resources may be leading scientists to back away from their communism norms in order to gain research resources from the industry. Or, this relation between secrecy and industry funding may be endogenous to an overall shift in norms toward a more industry/private science agenda (perhaps at the urging of university administrators or in response to signals from federal and state science policies), producing both more secrecy and greater interest in gaining industry funding.

Overall, these findings (and related studies) suggest that secrecy has increased among academic scientists, but that the focus on commercialization as the cause may underestimate the effects of scientific competition. We need to unpack the various dimensions of commercialization, sharing, and secrecy to see what aspects are affected by what. Although it is right to raise concerns about the negative effects of publication restrictions associated with industry funding, we should also focus on the adverse effects of scientific competition. Our research highlights the central role that scientists' competition for priority plays in the system of science, and that while such competition spurs effort, it also produces negative effects that recent trends toward commercialization of academic science seem to be exacerbating. We should keep these results in mind when discussing policy initiatives designed to foster more openness in science, such as mandatory data sharing requirements. While recent increases in U.S. government funding for science may help to lower the intensity of competition, as well as the dependence on industry funding, it is also possible that they will increase the payoffs from engaging in academic capitalism, as researchers and universities compete to advance in the prestige and funding hierarchies.

So long as university research is judged by the competitiveness coalition's agenda, it may be difficult to reduce secrecy. While it might be hard to conceive in the contemporary policy context, a shift to a more secure funding stream, uncoupled from immediate (and immediately commercializable) results, would likely reduce the negative effects of scientific competition and help bolster the norm of communism. As noted earlier, it is an open question, and worth debating, whether this shift away from academic capitalism would result in a decrease or increase in the progress of science, with the private incentives of the industry/private science model balanced against the efficiency gains from an open science model with various researchers building off a common knowledge base, and in turn contributing to that base, to build up both Bohr's and Pasteur's Quadrants. However, both from the perspective of the sociology (and economics) of science and from a science policy perspective, it is worth considering how alternative institutional arrangements might achieve the widely accepted goal of promoting scientific advance and industrial innovation.

ACKNOWLEDGMENTS

We would like to thank Lowell Hargens for providing field-level data from the Hagstrom survey. This research was supported by an Abe Fellowship from the Center for Global Partnership, and by a grant from the UIC Center for Human Resource Management. This paper has benefited from comments from William Bridges, Mildred Cho, Robert Kneller, Steven Wolinsky, Wes Cohen, Mujuan Jiang, Peter Kivisto, Jason Owen-Smith, Moshe Semyonov, and the anonymous reviewers. We would also like to thank the participants at the ASA annual meeting in San Francisco, 2004, for their questions and suggestions, and our research assistants, Yu Meng and Nancy Maloney.

NOTES

[1]Recently, the percent of industry funding has begun to decline, dropping from a peak of just over 7 percent down to about 5 percent in 2004 (NSB 2004).

[2]Merton (1973 [1957]) gives the example of Descartes' competition with Hobbes, citing a letter by Descartes saying, "I also beg you to tell him [Hobbes] as little as possible about what you know of my unpublished opinions, for if I'm not greatly mistaken, he is a man who is seeking to acquire a reputation at my expense and through shady practices."

[3]Sir J. J. Thompson is quoted in Merton (1957:315) as saying, "In the seventeenth century, for example, and even as late as the nineteenth, discoveries were sometimes reported in the form of anagrams—as with Galileo's 'triple star' of Saturn and Hooke's law of tension—for the double purpose of establishing priority of conception and of yet not putting rivals on to one's original ideas, until they had been further worked out. . . . As late as the nineteenth century, the physicists Balfour Stewart and P.G. Tait reintroduced this practice and 'to secure priority . . . [took] the unusual step of publishing [their idea] as an anagram in *Nature* some months before the publication of the book' " (quotation was originally found on p. 22 of Thompson's *Recollections and Reflections* [London: G. Bell, 1936]). A contemporary example comes from research on superconductivity, where Paul Chu was accused of deliberately introducing a "typo" into his two

papers submitted to *Physical Review Letters* (substituting Yb (ytterbium) for Y (yttrium) in a key formula) in order to throw off reviewers, who were also potential competitors. He also applied for a patent after submitting the papers. Although reviewers are supposed to keep manuscripts confidential, news of the discovery leaked (including the mistaken formula). Chu then corrected the error before submitting the final proofs to the journal, causing some who followed the (incorrect) leaked formula to accuse Chu of deliberately trying to throw them off the trail. Others in the field say that, even if it was the honest mistake Chu said it was, they would understand someone doing this deliberately in such a high-stakes race as superconductivity was in the late 1980s, with Nobel prizes and possibly substantial commercial applications at stake (Kolata 1987; see also Fox 1994).

[4]In a study of a different kind of investigative work (the Detective Division of the Chicago Police Department), Walsh (1991) found a similar result, reporting that police detectives felt that a new crime-mapping system was a failure because it allowed a patrol officer to quickly solve a set of taxi robberies before the detectives could make the arrest, costing the detectives credit.

[5]For the Hagstrom data, we combine experimental and theoretical physics. As a robustness check, we also used the Sullivan data on clinical biomedicine as an alternative measure of biomedical research for the 1960s period (Sullivan 1975). Using the Sullivan data produces results that are substantially the same as those reported here. For the Walsh data, we excluded industry respondents. A technical appendix (Appendix A) gives the details of question wording, measures, and samples for the three surveys. Table A1 provides descriptive statistics for the variables used in the analyses.

[6]We also used log-linear models to analyze the tables, which produced similar results (Fienberg 1980).

[7]As a robustness check, we tested models that used a dummy variable coding for levels of competition, and also models with "already anticipated" recoded as missing, or as "5" (i.e., above "high competition"). The results are qualitatively similar. Prior work tends to code commercial activity as binary, since it is seen as a shift from an academic/open science model to an industry/private science model (see, for example, Bercovitz et al. 2001 and Campbell et al. 2002). However, to check whether a continuous measure of patenting would provide different results, we tested models that replaced patent application (yes/no) with number of granted patents. The results are very similar. Finally, for industry funding, we do not have data on the amount of industry funding. Again, prior studies tend to use a binary variable (Blumenthal et al. 1997; Campbell et al. 2002). Furthermore, Walsh et al. (2007b) find that, while industry funding (yes/no) is associated with more publication delay, there is no effect from the amount of funding. Still, if data were available, we would like to have explored the effects of different levels of funding on secrecy. Finally, we test a specification where we control for collaboration by dummy variables of industry collaborator and nonindustry collaborator, with no collaborator as the excluded category. Again, the results are substantively similar. (Results of alternative specifications are available from the corresponding author.)

[8]We use a model interacting field (biology) with all the predictor variables to test for the significance of the differences in coefficients across fields (results available from corresponding author).

[9]For example, the Blumenthal study and the Campbell study use a much broader measure of "patenting-related activity": coding a respondent as commercially active if their research has resulted in a patent application (the current study's measure), issued patent, patent license, trade secret, product under regulatory review, product or service currently being marketed, *or* a start-up company.

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APPENDIX A. SAMPLES, MEASURES, AND DESCRIPTIVE STATISTICS

I. Samples:

A. The Hagstrom data were collected in 1966, using a mail questionnaire with phone follow-up of nonrespondents. He surveyed a random sample of mathematicians and statisticians, physicists, chemists, and biologists in U.S. universities offering graduate degrees in these fields. The final sample size was 1,947 respondents, with an 89% response rate.

B. The Sullivan data were collected in 1968, using face-to-face interviews with mail questionnaire follow-up of nonrespondents. He surveyed biomedical researchers (90 percent were M.D.s) from two hospitals. The final sample size 387 respondents, with a 72 percent response rate.

C. The Walsh et al. data were collected in 1998, using a mail questionnaire with multiple mail follow-ups. They surveyed a national random sample of experimental biologists, mathematicians, physicists, and sociologists. The sampling frame was the relevant professional society membership directory. The directories used were those of the Federation of American Societies of Experimental Biology (Biochemical and Molecular Biology and Cell Biology divisions), American Mathematical Society, American Physical Society, and American Sociological Association. The data consist of responses from 399 scientists, representing 51.3 percent of the eligible sample. A comparison between respondents and nonrespondents finds no difference in terms of gender, but shows the sample to somewhat underrepresent those from Carnegie Research I universities. For this study, we limit the sample to Ph.D./M.D. respondents from experimental biology, mathematics, and physics, and who are not working in industry. This gives us an N of 202.

II. Measures:

The surveys each provide very similar measures of secrecy and of scientific competition, although there are slight differences in question and response wordings, reported below.

A. Secrecy

1. Hagstrom

"Would you feel quite safe in discussing your current research with other persons doing similar work in other institutions?"

a. Feel safe with all others
b. Feel safe with most others
c. Feel safe only with a few I can trust

2. Sullivan

"Would you feel quite safe in discussing your current research with other persons doing similar work in other institutions or do you think it necessary to conceal the details of your work from some of them until you are ready to publish?"

a. I feel safe in discussing my work with *all* others
b. I feel safe in discussing my work with *most* others
c. I feel safe in discussing my work with only a few I can trust

3. Walsh et al.

"How safe do you feel in discussing your current work with other persons doing similar work (other than your collaborators)?"

a. I feel safe with all others
b. I feel safe with most others
c. I do not feel safe

B. Competition

1. Hagstrom

"How concerned are you that you might be anticipated in your current research?"

a. I have already been anticipated
b. Very concerned
c. Moderately concerned
d. Slightly concerned
e. Not at all concerned

3. Walsh et al.

"How concerned are you that you might be anticipated in your current research?"

a. I have already been anticipated
b. I am very concerned
c. I am moderately concerned
d. I am slightly concerned
e. I am not at all concerned

In our analysis, we reverse the coding, so that 1 = not at all concerned and 5 = I have already been anticipated, thus making this a measure of increased concern about scientific competition. Following Hagstrom (1974) we also combined "I have already been anticipated" and "very concerned," creating a four-point scale. When we ran the multivariate model without the recoding, or with "I have already been anticipated" coded as missing, the results are qualitatively the same (available from author). Sullivan did not report results for the competition question by response category.

C. Other Variables

To measure the impact of market orientation, the Walsh et al. survey asks if the respondent has, in the last five years, applied for a patent based on his research. We code this as a binary variable, with 1 = "yes" and 0 = "no." In addition, this survey contains a question asking if the respondent has research funding and if so, the source of the funding. Based on this item, we coded a binary variable as 1 if they have industry funding and 0 otherwise. The survey also asks respondents if they are currently involved in any collaborative research. We code this as a binary variable, with 1 = "yes," 0 = "no." For those who are collaborating, we ask for the institutional affiliation of up to seven collaborators. From this data we coded a binary variable, with 1 = (at least one collaborator from a commercial firm), and zero otherwise. If a respondent has no collaborators, this variable equals zero (no industry collaborator).

The Walsh et al. survey also has several control variables similar to those used in the prior studies. These include gender (1 = male, 0 = female); institution type (1 = Carnegie Research I, 0 = other); years since Ph.D. (which is likely to be closely correlated with academic rank); and publication productivity (number of papers published in refereed journals in the prior two years). Descriptive statistics and tests of field differences are reported in Table A1 below.

TABLE A1. Descriptive Statistics on Secrecy, Competition, Commercialization, and Control Variables, Means (Standard Errors)

Variable	All	Exp. Bio.	Math.	Phys.	Sig
Secrecy	1.84 (.04)	2.03 (.06)	1.62 (.10)	1.70 (.08)	***
Concern over competition	2.41 (.07)	2.69 (.11)	2.20 (.16)	2.13 (.12)	***
Patent	.19 (.03)	.30 (.05)	.02 (.08)	.15 (.04)	***
Industry fund.	.05 (.02)	.07 (.03)	.00 (.00)	.06 (.03)	n.s.
Industry collaborator	.06 (.02)	.05 (.03)	.03 (.03)	.08 (.03)	n.s.
Collaborate	.70 (.03)	.73 (.05)	.63 (.07)	.71 (.06)	n.s.
Publications (2 years)	4.26 (.31)	5.19 (.47)	2.50 (.35)	4.11 (.61)	***
Years since Ph.D.	22 (.96)	25 (1.40)	17 (2.11)	22 (1.60)	***
Male	.85 (.03)	.80 (.04)	.82 (.06)	.94 (.03)	*
Research I university	.43 (.04)	.56 (.05)	.45 (.08)	.22 (.05)	***
N =	202	91	44	67	

*$p < .05$, ***$p < .001$ (two-tailed tests).

Notes: Mean for Secrecy is on a three-point scale, and for Competition, is on a four-point scale (with "already anticipated" recoded as "very concerned"); see Appendix. Significance tests are for field differences, using one-way analysis of variance (ANOVA).