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NOT IN THE JOB DESCRIPTION:
THE COMMERCIAL ACTIVITIES OF ACADEMIC SCIENTISTS AND ENGINEERS

Wesley M. Cohen
Henry Sauermann
Paula Stephan

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ABSTRACT

Scholarly work seeking to understand academics' commercial activities often draws on abstract notions of the academic reward system and of the representative scientist. Few scholars have examined whether and how scientists' motives to engage in commercial activities differ across fields. Similarly, efforts to understand academics' choices have focused on three self-interested motives – recognition, challenge, and money – ignoring the potential role of the desire to have an impact on others. Using panel data for a national sample of over 2,000 academics employed at U.S. institutions, we examine how the four motives are related to commercial activity, measured by patenting. We find that all four motives are correlated with patenting, but these relationships differ systematically between the life sciences, physical sciences, and engineering. These field differences are consistent with differences across fields in the rewards from commercial activities, as well as in the degree of overlap between traditional and commercializable research, which affects the opportunity costs of time spent away from "traditional" work. We discuss potential implications for policy makers, administrators, and managers as well as for future research on the scientific enterprise.

Wesley M. Cohen
The Fuqua School of Business
Duke University
Box 90120
Durham, NC 27708-0120
and NBER
wcohen@duke.edu

Paula Stephan
Department of Economics
Andrew Young School of Policy Studies
Georgia State University
Box 3992
Atlanta, GA 30302-3992
and NBER
pstephan@gsu.edu

Henry Sauermann
European School of Management and Technology
Berlin
Schlossplatz 1
10178 Berlin
Germany
henry.sauermann@esmt.org

1 Introduction

A large literature has examined academics' engagement in commercially oriented research and related activities. An important driver of this work are concerns that deepening ties with commerce may lead scientists to neglect academia's core mission of "pure" research or compromise access to research findings (e.g., Dasgupta and David, 1994). Even though most of the evidence does not support these concerns (Agrawal and Henderson, 2002; Azoulay et al., 2009; Breschi et al., 2008; Buenstorf, 2009; Fabrizio and Minin, 2008; Goldfarb et al., 2009; Perkmann et al., 2013; Thursby and Thursby, 2011), they remain salient in both the scholarly literature and the public discourse. On the other side of the ledger, there has been a hope, particularly among policy makers, that deepening commercial ties may increase the regional and national economic impact of academic knowledge. These hopes are reflected in a range of policies designed to encourage such interactions, most notably the Bayh-Dole Amendment (Mowery et al., 2001).

Whether the goal is to stimulate commercial engagement or to discourage it, it is useful to understand why academics engage in commercially applicable research. Guided by a conceptual framework, this paper examines the empirical relationships between academics' motives (i.e., desires for payoffs such as career advancement and money) and their commercial activities.[1] By highlighting individual differences in academics' motives as well as field differences in reward structures, our work also extends the seminal argument of Merton (1973). Postulating a universal set of values and norms, Merton's perspective has framed much of the prior literature on the scientific enterprise generally, and academics' commercial engagement in particular.

Although there is a growing body of research on the motives and incentives of academics who engage in commercial activities (Bercovitz and Feldman, 2008; Fini and Lacetera, 2010; Lam, 2011; Owen-Smith and Powell, 2001; Thursby et al., 2001), two important gaps remain. First, efforts to understand academics' commercial activities often rely on notions of a representative academic or have examined particular fields in isolation. Yet, the benefits and costs of commercial activities, and thus academics' motives tied to such activities, are likely to differ systematically across fields. Studying such differences is important given that there are

[1] In line with prior work (Sauermann and Cohen, 2010; Stern, 2004), we distinguish individual-level *motives* (e.g., the desire for money) from *rewards and incentives* that may be provided by the employer or other actors (e.g., money paid to the owner of a patent). The Appendix provides additional detail on the interplay between motives and incentives.

significant field differences in the *levels* of academics' commercial engagement (Cohen et al., 2002; D'Este and Perkmann, 2011; Lim, 2004) and given field differences in the nature of research (Fleming and Sorenson, 2004; Layton, 1976; Nelson, 2016; Sauermann and Stephan, 2013).

Second, much of the work on academics' motives around commercial engagement assumes that departures from goals of peer recognition and career advancement (Merton, 1973) are tied to other self-interested motives – not only money, but also intrinsic rewards (Dasgupta and David, 1994; Lam, 2011; Stephan and Levin, 1992). Notably absent is the motive of social impact. This is surprising given not only the salience of this motive in historical and qualitative accounts (Shapin, 2008; Stokes, 1997), but also because social benefits have been invoked to justify the public funding of academic research as well as policy efforts that promote academic entrepreneurship (Bush, 1945; Lane and Bertuzzi, 2011; Salter and Martin, 2001). Moreover, employees' social motives have been shown to have important impacts in other organizational settings (Bode and Singh, 2018; Fehr and Fischbacher, 2002; Grant, 2007).

To address these gaps, we first briefly outline our conceptual framework, which is formalized in the Appendix. We then use that framework to examine and interpret cross-field differences in the motives tied to commercial activity observed in a sample of over 2,000 life scientists, physical scientists and engineers working in over 100 U.S. academic institutions.

2 Conceptual Framework

We assume that those who have selected into research-oriented academic careers wish to advance those careers, and that the standard path for career advancement is achieving some degree of eminence via traditional academic research (Merton, 1973; Roach and Sauermann, 2010; Stern, 2004). We also assume that academics who allocate effort to commercial activity incur opportunity costs due to the loss of time dedicated to traditional academic research and the associated career benefits. This loss can, however, be offset by the rewards from commercially applicable research and related activity. Expanding upon much of the prior literature, a first important feature of our framework is that these rewards may include not only the prospect of greater income, but also the prospect for social impact.

A second important feature of this framework is that the loss of time dedicated to traditional academic research, as well as the rewards tied to commercial activity, may differ across fields. In particular, to the extent that traditional research in a field is closer to market applications, commercially applicable work will detract less from work that supports an academic career. For example, in the basic physical sciences, where traditional research advances understanding of natural phenomena, research results are typically far removed from commercial interest. Thus, effort spent on commercial research will tend to detract from academic research and its rewards (Toole and Czarnitzki, 2010). By way of contrast, in engineering and the applied sciences (henceforth referred to as engineering), a good deal of traditional academic research focuses on solving concrete problems and creating useful artifacts (Allen, 1977; Dym et al., 2005; Layton, 1976; Vincenti, 1990). Thus, generating commercializable outcomes requires less departure from traditional work in these fields (Crespi et al., 2011; Goldfarb et al., 2009). Moreover, we argue that in fields with a high degree of overlap between traditional work and commercial activity, commercial activity may yield not only rewards such as money or social impact, but may also contribute to academic advancement, further lowering the opportunity costs of doing commercial work. Supporting this idea, there is evidence that patenting can increase academics' reputation among peers (Audretsch et al., 2010; Haeussler and Colyvas, 2011) and, in some instances, prospects for academic promotion (Azoulay et al., 2007; Butkus, 2007; Lipka, 2006).[2]

Assuming that academics differ in their preferences for the different types of rewards, this logic offers implications regarding the motives we expect to characterize those academics who do commercially relevant work in a given field, and how such motives may differ across fields. In fields where opportunity costs of pursuing commercially relevant work are greater, the academics who choose to do such work are likely those who place a lower value than others on academic advancement and a higher value on rewards such as money or social impact. In fields where traditional research is closer to market applications, however, the motives of academics who pursue more commercially relevant research may not differ much from the motives of their colleagues who focus on traditional academic work.

In the following section, we explore the empirical relationships between academics' motives and their commercial activities. In light of data limitations, our analysis does not identify the

[2] Commercial activity may also benefit traditional research, e.g., because it provides additional financial resources or suggests novel ideas for research (Azoulay et al., 2009; Perkmann et al., 2013). In our model, such effects could be captured as commercial activity supporting career advancement (indirectly, through research productivity). Notwithstanding this possibility, we assume that individual academics face a fundamental trade-off between allocating a limited time budget to research versus commercialization, and that a unit of the former tends to yield greater career advancement than a unit of the latter.

causal impact of motives. Rather, our contribution is to document correlations between academics' commercial activities and a range of individual motives – including the desire for social impact – that may speak to the interplay of individual motives with field differences in the rewards and opportunity costs of commercial engagement.

3 Data and Measures

3.1 Data sources

Our empirical analysis is based on two waves of the Survey of Doctorate Recipients (SDR), obtained from the National Science Foundation under a restricted-use license. The SDR is a longitudinal survey and its sampling population includes individuals who have obtained a doctoral degree in a science, engineering or health field from a U.S. institution and lived in the U.S. at the time of the surveys. In 2001 and 2003, the SDR achieved response rates of approximately 80%.[3] In this paper, we focus on those PhDs who are full-time employees in academia (defined as educational institutions by NSF) and for whom research is either the most important or second most important work activity. We exclude postdoctoral researchers since they may pursue both academic and nonacademic career paths and tend to have limited control over the allocation of research effort. Our final sample includes 2,094 scientists and engineers at 160 institutions. As discussed below, we distinguish between academics in the life sciences, the physical sciences, and engineering.

We augment the SDR data with data on: 1.) universities' policies regarding the share of licensing income going to the inventor from Lach and Schankerman (2008) as well as from university websites and inquiries with administrators; 2.) the year in which academic institutions started a formal technology transfer office from Association of University Technology Managers (AUTM) surveys as well as from websites and through inquiries to administrators; and 3.) PhD program quality from the National Research Council (Goldberger et al., 1995) as proxies for the quality of the departments in which respondents were educated and employed.

[3] Details about the SDR are available at http://www.nsf.gov/statistics/srvydoctoratework/.

3.2 Measures

This section describes key dependent and independent variables; Table 1 shows summary statistics for all variables by field.

Commercial activity: We proxy for academics' commercial activities using patent application counts (PATS). Each respondent reported in 2003 the number of U.S. patent applications in which he or she was named as an inventor over the 5 years prior to the survey.[4] We also code a dummy variable, ANYPAT, which takes on the value of 1 for academics with at least one patent application. These measures capture all patent applications on which respondents are listed as inventors, not only those going through university Technology Transfer Offices (TTO's).

We observe significant differences in patenting across fields: Engineers have the highest average count of patent applications, followed by life scientists and physical scientists (see also Figure A1 for histograms). These field differences in levels of commercial activity are consistent with differences in the costs of engaging in commercial activity noted above, though they may also reflect differences in the associated rewards.

Motives: In 2001, respondents were asked "When thinking about a job, how important is each of the following factors to you . . ." Respondents rated the importance of each factor on a 4-point scale anchored by 1 (very important) and 4 (not important at all); for ease of interpretation, we reverse coded these items such that higher scores indicate higher importance. We feature four factors and associated motives: Opportunities for advancement, salary, intellectual challenge, and contribution to society. These measures capture respondents' general preferences for different kinds of work related payoffs (see also Agarwal and Ohyama, 2013; Sauermann and Cohen, 2010). In this analysis, we use the desire for salary to represent the desire for financial income more generally.[5] Although the average importance ratings for all four job attributes are generally high, the correlations between them, ranging from -0.06 (salary and challenge in engineering) to 0.36 (advancement and salary in the physical sciences), are not, suggesting that the measures capture distinct constructs (Table A1).

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[4] The SDR data are anonymized and cannot be matched to other data sources such as patent records.

[5] In our conceptual model, financial payoffs may result from traditional research (e.g., rewards for publications, or salary raises indirectly resulting from career advancement) as well as from commercial activities (e.g., royalty income from patents). Unfortunately, desire for "salary" may not exactly reflect the importance individuals assign to other sources of financial income. We assume that these preferences are, however, positively correlated, i.e., that individuals who state a high importance of salary also care strongly about money more generally.

The means of motives are similar across fields. Indeed, we find no significant differences in the importance of salary, intellectual challenge, or advancement reported by life scientists, physical scientists, and engineers. Motives related to social impact, however, are slightly higher among life scientists and engineers than among physical scientists. Although levels of motives must be interpreted with caution given potential response biases (see Appendix), the observed differences in social impact motives across fields are consistent with sorting of individuals into fields as well as with ex post socialization effects (see Azoulay et al., 2017; Sauermann, 2018).

Academic field: As noted, we distinguish between respondents who received their PhD in the life sciences (N=1037), physical sciences (N=585), and engineering and the applied sciences (N=472). In the regression analyses, we also control for fields at a more detailed level (biochemistry, cell and molecular biology, microbiology, food sciences, environmental and health sciences, other biological sciences; physics, chemistry, earth sciences, mathematics; computer science, chemical engineering, electrical engineering, mechanical engineering, civil and industrial engineering and other engineering, including materials engineering).

Table A2 in the Appendix describes control variables such as type of academic institution, age of the university's TTO, the share of patent royalty income going to the inventor, quality of PhD training and current department, publication productivity, as well as a range of demographic characteristics.

4 Empirical Specification

Our featured dependent variable is the number of patent applications in the prior five years. To address the count nature of this variable, we estimate QML Poisson regression models (Silva and Tenreyro, 2006). The following is our benchmark specification:

$$\text{PATS}_i = f(\varepsilon_i; \beta_0 + \boldsymbol{\beta_1}\textbf{MOTIVES}_\mathbf{i} + \boldsymbol{\beta_2}\textbf{CONTROLS}),$$

where PATS_i is respondent i's patent application count over the 1998-2003 time period (as reported in 2003) and $\textbf{MOTIVES}_\mathbf{i}$ is a vector of motives measured in 2001, reflecting preferences for career advancement, income, intellectual challenge, and social impact. **CONTROLS** is a vector of control variables taken from the 2001 survey and from other data sources, and ε_i is a random error term. While regressions of PATS provide insights into the intensive margin of patenting (i.e., the number of patent applications), we also estimate similar regressions using ANYPAT (indicating whether a respondent had any patent applications at all) to gain insights into the extensive margin. These regressions are estimated using linear probability models. Standard errors for all regressions are clustered at the level of the university.

Since our framework suggests different effects of motives on academics' commercial effort across fields, we estimate our regressions separately for researchers in the life sciences, physical sciences, and engineering, and compare the resulting coefficients. This approach also implies that the coefficients we estimate reflect heterogeneity across individuals *within fields* (e.g., some scientists in a particular field care more about a particular motive and those individuals also patent more) rather than differences in motives across fields (e.g., all scientists in a particular field care more about a particular motive and also patent more).

5 Results

Table 2 shows significant relationships between academics' motives and their patenting activities. More importantly, these relationships differ across fields. We begin by briefly reporting the basic results and then interpret the results, focusing on cross-field differences.

In the life sciences (model 1), we find a significant positive relationship between patent application counts and the desire for social impact. Researchers with a one standard deviation higher motive to contribute to society have a 59.8% higher expected patent count. Income, challenge, and career advancement motives have no significant relationship with patenting. In the physical sciences (model 2), the advancement motive has a significant *negative* relationship with patenting; a one-SD higher score is associated with a 33.0% lower patent count. Income, challenge, and social impact motives have no significant relationship with patenting. Among engineers (model 3), we find a strong positive coefficient on the challenge motive as well as the career advancement motive. One-SD higher scores on the two motives are associated with 68.3% and 35.6% higher expected patent counts, respectively. Motives related to income or social impact have no significant coefficients. Formal tests confirm that the differences in the coefficients of motives across fields are statistically significant.[6]

Models 4-6 in Table 2 show the results for the ANYPAT regressions, estimated using linear probability models. In the life sciences and engineering, the qualitative patterns for the

[6] We can reject the equality of coefficients of motives in the life sciences and physical sciences ($Chi^2(4)=21.88$, $p<0.01$), the life sciences and engineering ($Chi^2(4)=13.77$, $p<0.01$), and the physical sciences and engineering ($Chi^2(4)=26.70$, $p<0.01$).

motive variables are largely the same as for the PATS regressions. In the physical sciences, the negative coefficient on advancement motive loses its significance, while the positive coefficient on social impact motives becomes significant.

Our framework suggests that these different relationships between motives and commercial activity across fields may reflect differences in the opportunity costs of commercial engagement as well as in the associated rewards. We now discuss these possibilities in more detail for each of the four motives.

One notable result in Table 2 is the significant, negative relationship between advancement motives and patent counts in the physical sciences (model 2), suggesting that physical scientists who care strongly about their academic careers allocate less effort to commercial activity. This contrasts sharply with engineering, where advancement motives have a significant positive coefficient in the count and in the linear probability models. Interpreted in light of our framework, these contrasting results are consistent with the existence of higher opportunity costs of commercial work in the physical sciences than in engineering; physical scientists who engage in commercial activities may give up more "traditional" research as well as the associated career rewards than do engineers. In addition, the observed differences may also reflect that fields differ in the career incentives associated with commercial activities, i.e., that commercial outputs such as patents are looked upon more favorably by academic peers in engineering than in the physical sciences (Azoulay et al., 2007; Haeussler and Colyvas, 2011).[7] We can only speculate why, in the physical sciences, the negative coefficient of advancement motives is not significant in the ANYPAT regression. One conjecture is that physical scientists may still be able to reconcile a small amount of commercial work with maintaining traditional lines of research, limiting detrimental effects on career advancement. Generating higher volumes of commercial output, however, may require a more fundamental shift away from traditional areas of research, especially in a field where the distance between commercial work and traditional research is large.

Perhaps the most notable result is the significant relationship between commercial activity and the social impact motive in the life sciences. A possible explanation is that life scientists who engage in such activity expect significant social benefit, consistent with the notion

[7] In one of our interviews (see Appendix), an accomplished physicist likened patenting to "writing a textbook" in the sense that both may result in extra income but do little to further one's career. He noted, however, that "this is different in engineering… those guys like patents".

that the social benefits from commercial activity are particularly salient in the life sciences. Our particular measure, patenting, may also reinforce this interpretation: Life scientists are likely aware of the fact that, for society to realize the health benefits from new discoveries, securing patents is essential in order to provide companies the incentive to make the downstream investments typically required to bring new drugs or therapies to market (Cohen et al., 2000; Sampat et al., 2003).[8] Note that we find the strong positive relationship between the importance of social impact and patenting *within* the sample of life scientists; this relationship is thus unlikely to reflect that life scientists typically have a stronger desire to contribute to society and also happen to patent more. Indeed, our interpretation is consistent with the observation that the social impact motive has a significant coefficient in the ANYPAT regression also among physical scientists (even though physical scientists rate social impact overall less important than life scientists or engineers; Table 1). Although this coefficient is relatively small, it suggests that perceived social impact may be one of the factors that compensates physical scientists for the opportunity costs of allocating effort to commercial activity.

We had no priors as to whether intrinsic rewards such as intellectual challenge are more strongly tied to traditional academic work or to commercial activity. The results suggest that the answer depends on the field: We find no significant association with challenge motives in the sciences but a significant positive coefficient in engineering. It appears that engineers – in contrast to their colleagues in the sciences – perceive considerable intrinsic benefits from doing commercially relevant work (see Layton, 1976). This result may be of broader relevance for our understanding of scientists' motivations: Much of the seminal work on intrinsic motivation thinks of this construct in abstract terms and identifies factors that promote (or reduce) intrinsic motivation generally (Amabile, 1996; Frey and Jegen, 2001; Hackman and Oldham, 1976). However, intrinsic rewards are subjectively generated, and tasks that some people find interesting and challenging may not be perceived as such by others. Future research on how scientists perceive intrinsic rewards, and what role is played by the broader organizational context or field, seems particularly interesting (to us).[9]

[8] In the words of the late Susan Lindquist, who was a pioneer in the study of protein folding: "Patenting activity is necessary for my life's work to make a difference… In the early 1980's, scientists did not realize that. Now they do." Quoted by Marie Thursby, 2010 DRUID debate on academic entrepreneurship. http://www.druid.dk/index.php?id=20

[9] Such work could build on a large body of research in areas such as education, which has studied how people become "interested" in some subjects rather than others (Sauermann and Franzoni, 2013; Silvia, 2006), as well as research studying what level of difficulty and challenge people chose when setting goals (Locke and Latham, 2006).

Finally, Table 2 shows no systematic relationship between income motives and patenting in either of the three fields. Incidentally, our control for the share of royalty income going to academic inventors also has no significant relationship with patenting. As such, the data show less of an association between commercial activities and financial motives or incentives than might be expected given the prominence of financial payoffs from patenting in the public discussion. One explanation might be that, notwithstanding the very large financial payoffs resulting from a few outlier patents, the expected financial returns from patenting are very low (Lach and Schankerman, 2008; Stephan, 2012). It may also be that our measure of the importance of salary only partly captures income motives in a more general sense. Additional analyses to probe these results regarding financial motives and incentives leave the main conclusions unchanged (see Appendix).

The Appendix reports a number of supplementary analyses, including regressions that control for scientific productivity, examine potential changes in motives over time, interact motives with financial incentives (royalty shares), and use university fixed effects to control for other factors that may shape academics' decisions to engage in commercial activity. The observed relationships between motives and commercial activity are consistent with our main analysis.

6 Discussion

Using two waves of survey data on over 2,000 academics at U.S. institutions, we document correlations between individuals' motives and their commercial activity. We find that these relationships differ across broadly defined academic fields. In the life sciences, those academics who most actively engage in commercial activities are characterized by strong preferences for social impact. In the physical sciences, the most active patenters are those who have little concern for career advancement, although social impact motives predict which scientists patent at all. In engineering, patenting relates to motives of challenge and advancement. These results highlight the importance of considering heterogeneity in individuals' motives *within* fields, as well as differences in the rewards and opportunity costs tied to commercial work *across* fields.

Our results are subject to a number of limitations. First, while we consider a broader set of motives than typically discussed in the economics and sociology of science, there may be additional motives for commercial engagement that are not captured by our measures, including, for example, patenting as a way to ensure freedom to work on certain problems, or commercial activities as a means to acquire resources for research (Murray, 2010; Owen-Smith and Powell, 2001; Perkmann et al., 2013). Second, we focus on patenting as one of several possible facets of commercial activity. While patenting is likely complementary to – and correlated with – other commercial activities such as consulting or new venture creation (Haeussler and Colyvas, 2011; Jensen and Thursby, 2001), future work is needed to study how individual motives relate to other commercial activities, and how such relationships differ across fields. Third, the opportunity costs and rewards from commercial activities may change as "traditional research" in fields evolves, as commercial activities become more accepted among academics, and as universities and policy makers consider commercial activities as part of "broader impact" efforts (Bercovitz and Feldman, 2008; Butkus, 2007; Stokes, 1997). As such, it would be useful to study how academics' institutional environment is changing and how such changes affect the relationships explored in this paper. Fourth, variables employed in the analysis may be subject to measurement error. For example, our measures of motives are quite coarse and may be affected by response biases (see Appendix for a more detailed discussion). Similarly, patent applications may not fully capture academics' intent to patent since Technology Transfer Offices also play an important role in decisions over whether to file for a patent. Finally, we do not estimate the causal impact of motives on commercial activity, but document associations between measures of motives and patent applications that are likely conditioned by sorting across fields and may be subject to other sources of endogeneity. Nonetheless, the observed correlations are consistent with a view that differences in the rewards and opportunity costs of commercial activity across fields are linked to the motives of academics that pursue such activity within those fields.

The observed correlations between motives and commercial activities, as well as the differences across fields suggest potential implications for public and managerial policies. First, a major objective of the Bayh-Dole legislation was to generate social benefits by increasing the use and exploitation of knowledge developed in academia (Sampat et al., 2003). To the extent that academics care not only about private benefits but also about making a difference in society, their objectives may be more aligned with policy objectives than previously thought. Second, the opportunity costs and rewards from commercial activities differ across fields. Thus, policies and management practices that take into account field differences may be more effective than those that apply the same tools in very different contexts. For example, there may be less reason for concern about distractions from traditional work in fields where academic and commercial work are closely aligned (Azoulay et al., 2007; Fabrizio and Minin, 2008).

Our findings may also be useful in light of discussions about potential detrimental effects of commercial activities – patenting in particular – on the sharing and diffusion of academic knowledge (Murray and Stern, 2007; Perkmann et al., 2013). Intellectual property rights can be used in different ways, and their effects on knowledge flows are likely to depend on the motives of the inventors and patent holders. A scientist who patents in order to improve social welfare, for example, may be willing to share knowledge more freely than a scientist who patents in order to appropriate financial returns.

Our study also has implications for the broader literature on science and innovation. First, although the Mertonian paradigm has allowed us to understand the distinctive features of science, future research may benefit from considering more explicitly how the norms and incentives of scientists differ across fields or organizational contexts (Crespi et al., 2011; Sauermann and Stephan, 2013). Second, although much of the prior literature has focused on the representative scientist characterized by self-interested motives, our results reveal important heterogeneity across scientists, as well as the relevance of social motives that have received little attention in prior work. Recognizing these aspects may provide a richer foundation for future work on scientists' decisions such as which career path to take, which employer to work for, or what research problems to tackle (see Besley and Ghatak, 2005; D'Este et al., 2018; Francois, 2007; Salter et al., 2017). More generally, a broader view of scientists' motives and the consideration of differences in the scientific enterprise across fields has the potential to enrich the study of science and allow us to provide more robust advice to managers, university administrators, and policy makers.

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Table 1: Summary Statistics

Variable	Variable type	Life Sciences		Physical Sciences		Engineering	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
PATS (U.S. patent applications)	count	0.62	3.43	0.55	2.69	1.08	3.19
ANYPAT	dummy	0.21	0.41	0.16	0.36	0.28	0.45
Imp. advancement	4-point	3.48	0.61	3.40	0.65	3.44	0.64
Imp. salary	4-point	3.36	0.55	3.29	0.59	3.38	0.53
Imp. challenge	4-point	3.87	0.35	3.91	0.29	3.89	0.32
Imp. contrib. society	4-point	3.57	0.57	3.44	0.62	3.59	0.57
Carnegie I	dummy	0.44	0.50	0.70	0.46	0.66	0.47
Carnegie II	dummy	0.09	0.28	0.09	0.28	0.14	0.34
Doctorate granting	dummy	0.04	0.19	0.13	0.33	0.12	0.32
Medical school	dummy	0.44	0.50	0.08	0.27	0.08	0.27
Private university	dummy	0.27	0.44	0.28	0.45	0.26	0.44
Department NRC score	continuous	3.25	0.81	3.24	0.90	3.05	0.85
PhD NRC score	continuous	3.50	0.66	3.72	0.74	3.53	0.76
TTO age	continuous	20.02	11.98	19.19	13.04	19.75	14.29
Royalty share	continuous	0.42	0.10	0.42	0.11	0.41	0.10
Not tenure track	dummy	0.35	0.48	0.28	0.45	0.12	0.33
Male	dummy	0.69	0.46	0.84	0.37	0.84	0.36
Age	continuous	47.99	9.09	48.56	10.47	46.06	9.45
White	dummy	0.75	0.43	0.78	0.41	0.63	0.48
Asian	dummy	0.16	0.36	0.13	0.34	0.21	0.41
Other race	dummy	0.09	0.29	0.09	0.28	0.15	0.36
U.S. citizen	dummy	0.93	0.26	0.90	0.30	0.89	0.31
Exposure	continuous	4.94	0.30	4.94	0.28	4.91	0.34
Ln publications	continuous	2.35	0.86	2.41	0.95	2.19	0.86

Table 2: Main Regression Results

Variable	Life Sci 1 PATS	Physical Sci 2 PATS	Engineering 3 PATS	Life Sci 4 ANYPAT	Physical Sci 5 ANYPAT	Engineering 6 ANYPAT
Imp. advancement	0.395	-0.616**	0.475*	0.013	-0.021	0.068*
	[0.272]	[0.220]	[0.211]	[0.022]	[0.030]	[0.030]
Imp. salary	-0.047	0.398	-0.375+	0.005	0.063+	0.012
	[0.171]	[0.341]	[0.203]	[0.023]	[0.033]	[0.037]
Imp. challenge	-0.149	-0.307	1.633*	0.007	0.002	0.196**
	[0.371]	[0.301]	[0.730]	[0.032]	[0.049]	[0.049]
Imp. contrib. society	0.826**	-0.084	-0.079	0.082**	0.043*	-0.013
	[0.203]	[0.207]	[0.230]	[0.021]	[0.021]	[0.041]
Carnegie II	0.721+	-0.184	-0.236	0.092	0.019	-0.062
	[0.373]	[0.412]	[0.499]	[0.065]	[0.068]	[0.056]
Doctorate granting	-0.010	-0.198	-0.998**	0.037	0.027	-0.032
	[0.385]	[0.529]	[0.364]	[0.058]	[0.059]	[0.058]
Medical school	0.813*	1.006**	0.082	0.077**	0.041	0.031
	[0.339]	[0.360]	[0.369]	[0.029]	[0.074]	[0.088]
Private university	-0.397	0.076	0.432	-0.020	0.018	0.014
	[0.295]	[0.273]	[0.313]	[0.033]	[0.042]	[0.045]
TTO age	0.002	-0.006	-0.011	0.001	-0.001	-0.001
	[0.006]	[0.009]	[0.008]	[0.001]	[0.001]	[0.001]
Royalty share	1.167	-3.101+	-0.184	-0.244+	-0.061	-0.069
	[1.546]	[1.594]	[0.979]	[0.147]	[0.181]	[0.206]
Not tenure track	-0.561	0.555	-0.437	-0.083**	0.017	-0.042
	[0.353]	[0.419]	[0.455]	[0.031]	[0.044]	[0.070]
Dept. NRC score	0.803**	-0.042	-0.006	0.042*	0.002	0.038
	[0.276]	[0.179]	[0.157]	[0.020]	[0.023]	[0.029]
PhD NRC score	0.144	0.124	0.377*	0.002	-0.006	0.026
	[0.181]	[0.199]	[0.162]	[0.022]	[0.021]	[0.029]
Male	0.570+	0.557	0.693+	0.020	-0.023	0.085
	[0.316]	[0.358]	[0.358]	[0.027]	[0.038]	[0.053]
U.S. citizen	0.355	0.976+	0.604	0.051	-0.028	0.168**
	[0.380]	[0.552]	[0.468]	[0.048]	[0.053]	[0.056]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-11.558**	-0.913	-10.519**	-0.369	-0.052	-1.189**
	[2.966]	[1.960]	[3.123]	[0.261]	[0.336]	[0.453]
Observations	1,037	585	472	1,037	585	472
R-squared				0.090	0.160	0.144

Note: Omitted category is Carnegie I institution. +=significant at 10%; *=significant at 5%; **=significant at 1%. Regressions of PATS estimated QML Poisson, of ANYPAT using LPM. Standard errors clustered by university in brackets.

APPENDIX

Model

The purpose of our model is to examine the relationship between academic researchers' motives (i.e., preferences for different payoffs or incentives) and their allocation of effort toward commercial activity. Accordingly, we model academics' decisions to dedicate effort to commercial activity as a function of their motives, while incorporating potential field differences in the payoffs (i.e., incentives) tied to commercial activity as well as in the overlap of academic and commercial activity that drives academics' opportunity costs of commercial work. In addition to offering empirical implications, the model serves to structure the subsequent empirical analysis and inform the interpretation of results.

For simplicity, we assume that an academic researcher's effort can yield two different payoffs: peer recognition and the associated career advancement in academia, *A*, and some "other," – nonacademic – payoff, *O*. While our theoretical model is agnostic as to the concrete nature of this "other" payoff, our empirical analysis considers financial income, intellectual challenge, and social impact as three important possibilities.

The researcher can obtain *A* and *O* by expending effort on traditional academic research, e_r, and on commercial activity, e_c. The latter may broadly encompass activities such as R&D with commercial applicability as well as working with a university's technology transfer office (TTO), licensing partners, or a startup. Our model allows for the possibility that each type of effort can yield both academic advancement and the "other" nonacademic payoff, though at different rates (α_r, α_c, γ_r, and γ_c). Accordingly,

$$A = \alpha_r e_r + \alpha_c e_c \text{ and} \tag{1}$$

$$O = \gamma_r e_r + \gamma_c e_c. \tag{2}$$

These rates, α_r, α_c, γ_r, and γ_c, may reflect incentives embedded in the broader professional community, the market environment, or incentive systems designed by particular employers (e.g., university tenure guidelines or university policies around inventors' share of royalty income). To structure the analysis, we assume that $\alpha_r > \alpha_c$, implying that the academic career payoff from academic research is greater than the academic payoff from commercial work.

Similarly, we assume $\gamma_c > \gamma_r$, implying that the nonacademic payoff from commercial work is greater than the nonacademic payoff from academic research.

An important feature of our model is that effort dedicated to academic and commercial activity can overlap; as such, effort allocated to commercialization does not necessarily imply a reduction of effort towards academic research by the same amount. The intuition is that – depending on the field – the very same effort that advances commercial objectives may also advance a scientist's academic career. For example, research identifying a cellular target implicated in colon cancer may have considerable commercial value but may also contribute to fundamental understanding and be recognized as an important scholarly contribution.[10] To make this overlap more explicit, we define a fixed *nominal* effort budget, B, and assume that

$$e_r = B - \varphi e_c, \qquad (3)$$

where φ indicates how different the effort expended on commercial activity is from effort dedicated to academic research (with $0 < \varphi \leq 1$; $0 \leq e_r, e_c \leq B$; e_r, e_c are integer-valued). Thus, φ can be thought of as the *distance* between the outputs of academic research and those required for commercialization, with a smaller distance (i.e., lower φ) implying a larger overlap between research and commercialization. If φ=1, the two activities are completely distinct, and effort on one activity does not advance the other. As φ approaches zero, academic and commercial activity increasingly overlap such that the effort spent towards commercial activity also counts as effort advancing academic research objectives. In other words, φ indicates the degree to which commercial activity detracts from traditional academic research, with a higher φ implying a higher opportunity cost of engaging in commercial activity. In our model, having greater overlap between academic and commercial research (i.e., φ approaching zero) allows the total *effective* effort spent on both activities to exceed the nominal budget ($B \leq e_r + e_c \leq 2B$).

We suggest that φ differs systematically across fields, leading to differences in the opportunity costs that academic researchers face when engaging in commercial activity. Consider, for example, the basic physical sciences, where "traditional" research advances understanding of natural phenomena, but the results are typically far removed from commercially applicable outcomes. As such, effort spent on commercial research will tend to detract from academic research and its associated rewards, implying a strong trade-off between

[10] In contrast to some prior work, we do not model the researcher's choice between "basic" and "applied" research, but that between "traditional" academic research in a particular field and commercial activity.

effort devoted to one versus the other (Toole and Czarnitzki, 2010). In engineering and the applied sciences, in contrast, a good deal of traditional academic research focuses on the solution of concrete problems and the creation of useful artifacts (Allen, 1977; Dym et al., 2005; Layton, 1976; Vincenti, 1990) such that effort dedicated to academic research is more likely to also yield commercializable outcomes (Crespi et al., 2011; Goldfarb et al., 2009). Consistent with this notion, Cohen et al.'s (2002) survey results show that firms report academic research in engineering and applied science fields to be useful across a much broader range of industries than is the case for research in the physical and biological sciences.[11] Similarly, the share of academically trained PhDs taking jobs in industry is considerably larger in engineering than in the physical sciences, possibly reflecting – among other factors – easier applicability of the knowledge acquired during academic training to the private sector (National Science Foundation, 2006).

We assume that, in addition to yielding different types of payoffs, effort also imposes a cost in the form of disutility, and that the disutility of commercial activity increases at a greater rate than that tied to traditional research. The rationale for this assumption is that academics have self-selected into academia rather than industry due to their strong "taste for science" (Agarwal and Ohyama, 2013; Roach and Sauermann, 2010; Stern, 2004). Reflecting both types of payoffs as well as the costs of effort, the researcher's utility function can be written as:

$$U=\beta_1 A + \beta_2 O - e_c^2 - e_r, \qquad (4)$$

where β_1 is the researcher's individual preference for academic advancement, A, and β_2 the researcher's preference for the other, nonacademic payoff, O. Following prior work (e.g., Stern, 2004), we conceptualize preferences as parameters in the utility function such that a stronger preference for a particular payoff increases the utility derived from a unit of that payoff.

Given equations (1), (2), and (4), and substituting for e_r, the utility function can be rewritten as:

$$U = \beta_1[\alpha_r(B - \varphi e_c) + \alpha_c e_c] + \beta_2[\gamma_r(B - \varphi e_c) + \gamma_c e_c] - e_c^2 - B + \varphi e_c. \qquad (5)$$

[11] In Cohen et al. (2002), the percentage of R&D managers reporting academic research to be at least "moderately useful" exceeds 60% in four industries for computer science, seven industries for materials science, and seven industries for electrical engineering. The corresponding figures are one industry (semiconductors) for physics, two industries for chemistry, and one industry (drugs) for biology.

For simplicity of exposition, we omit subscripts indicating levels of analysis. Effort levels (e_c, e_r), motives (β_1, β_2), as well as utility (U) and realized payoffs (A, O) are at the level of the individual researcher. Incentives (α_r, α_c, γ_r, γ_r) reflect policies and norms at the level of universities but also the broader professional community or market environment specific to fields. Regarding the distance between traditional research and commercial activity (φ), we focus on systematic differences across fields and abstract from potential heterogeneity within fields.

The marginal utility from effort dedicated to commercial activity is:

$$\partial U/\partial e_c = \beta_1(\alpha_c - \varphi\alpha_r) + \beta_2(\gamma_c - \varphi\gamma_r) - 2e_c + \varphi. \tag{6}$$

Utility is maximized for

$$e_c^* = [\beta_1 (\alpha_c - \varphi\alpha_r) + \beta_2(\gamma_c - \varphi\gamma_r) + \varphi]/2. \tag{7}$$

Equation (7) shows how optimal commercial effort depends on individuals' preferences for academic (β_1) and nonacademic payoffs (β_2), the structure of incentives (α_r, α_c, γ_r, and γ_c), and the distance between commercial and academic effort, φ. In the following, we highlight three relationships that are central to our empirical analysis, which focuses on the association between academics' commercial activities and their preferences for different types of payoffs (i.e., "motives"). First,

$$\partial e_c^* / \partial\beta_1 = (\alpha_c - \varphi\alpha_r)/2. \tag{8}$$

Thus, the impact of preferences for career advancement (β_1) on commercial effort depends on the relative size of academic advancement payoffs from academic and commercial activities (α_r vs. α_c), as well as the degree to which commercial effort detracts from traditional research (φ). Given that $\alpha_r > \alpha_c$ and $0 < \varphi \leq 1$, the sign of the derivative is ambiguous. If the academic payoff from commercial research (α_c) is sufficiently low and the distance between academic and commercial activity (φ) is sufficiently high, equation (8) implies that those researchers with stronger preferences for academic advancement will allocate less effort to commercial activity than those with weaker advancement motives. In contrast, researchers with stronger advancement motives will allocate more effort to commercial activity if career benefits from commercial activity (α_c) are sufficiently high (e.g., patents receive significant weight in promotion decisions) and if the distance between traditional research and commercialization is small, implying low opportunity costs of commercial effort. The important role of opportunity costs is reflected in the negative cross partial derivative, $\partial^2 e_c^* / \partial\beta_1\partial\varphi = -\alpha_r/2$, which suggests that the effect of advancement motives on commercial activity becomes less positive (or more negative) as the distance between the two activities, φ, increases.

The impact of preferences for the other, nonacademic payoff on commercial effort is

$$\partial e_c^* / \partial\beta_2 = (\gamma_c - \varphi\gamma_r)/2, \qquad (9)$$

which is unambiguously positive given that $\gamma_c > \gamma_r$ and $\varphi \leq 1$. Thus, unsurprisingly, preferences for the other payoff will have a positive relationship with commercial effort. However, the negative cross partial with respect to φ, $\partial^2 e_c^* / \partial\beta_2\partial\varphi = -\gamma_r/2$, indicates that this positive relationship is attenuated as the distance between academic and commercial work, φ, increases, increasing the opportunity costs to engaging in commercial activity. Conversely, the positive effect of preferences for the other payoff intensifies as the opportunity costs of commercial activity decrease.

Finally,

$$\partial e_c^* / \partial\gamma_c = \beta_2/2, \qquad (10)$$

which indicates that commercial effort increases with the degree to which it yields a greater nonacademic payoff. Moreover, this relationship should be stronger for researchers with strong preferences for the other, nonacademic payoff ($\partial^2 e_c^* / \partial\gamma_c\partial\beta_2 = ½ > 0$).

To summarize our discussion of the different payoffs and motives bearing on the commercial work of academics, academics who allocate effort to commercial activity are likely to incur opportunity costs due to the loss of time dedicated to traditional academic research and the loss of associated career benefits. This loss can be offset by other payoffs from commercial activity, including income, social impact and even the intellectual challenge tied to commercially applicable work. As such, we expect academics to allocate effort towards commercial activities based on their preferences for career advancement and these other types of payoffs. Moreover, the opportunity costs and operative payoffs from commercial activities are likely to differ across fields, partly reflecting the distance between commercial work and traditional academic research. Thus, we expect important field differences in the levels of academics' commercial activity and in the individual motives associated with commercial engagement.

Measures

Key dependent and independent variables are discussed in the main text. Additional variables are explained in Table A2. In the following, we briefly discuss potential measurement concerns.

A concern with survey data is the possibility of social desirability bias. In particular, individuals might inflate ratings of motives that they think are socially desirable (e.g., contribution to society) and give artificially low scores to motives that may seem less socially desirable (Moorman and Podsakoff, 1992). Any descriptive data on motives should be interpreted in light of the possibility of such a bias. More importantly, we do not expect that any such social desirability bias will affect the correlations between the measures of motives and of commercial activities. In contrast to other surveys that directly ask individuals why they engage in commercial activities (Giuri et al., 2007; Lam, 2011), the survey questions regarding motives were asked in a more general context and separately from the questions on patents; it is thus unlikely that respondents altered their responses to the question of motives to justify or rationalize responses to the question on patenting. A further concern is that certain groups of individuals may be socialized into thinking they should care about others and thus report stronger motives to contribute to society. As shown in Table 1, the average rating of contribution to society is somewhat higher for life scientists and engineers than for physical scientists, which may reflect such bias but also true differences due to sorting or socialization. More importantly, we run our regressions within field and any social desirability bias that is common to all individuals in a particular field will not affect our results.

A second important concern is that relationships between variables may be inflated because variables are measured using a common method. Common methods bias may result from the use of similar scales for dependent and independent variables, implicit theories respondents hold regarding the relationships between variables, or from priming effects of collocated questions (Podsakoff et al., 2003). While common methods bias may increase the correlations among our measures of motives, it should be less of an issue with respect to relationships between motives and other variables since variables were measured using a number of different types of scales. Moreover, our key dependent and independent variables were measured on different pages of the survey and in different years; such proximal and temporal separation should further reduce common methods bias (Podsakoff et al., 2003). The royalty share measures as well as some control variables originate from different data sources, further reducing concerns regarding common methods bias.

As discussed in the main text, a limitation of our measure of patent applications is that it only captures one kind of commercial activity; future work should explore other aspects such as consulting or new venture creation. Another limitation is that patent applications reflect not only individual academics' decisions but often also those of other actors, such as the TTO, which decides whether the university will apply for a patent on an invention disclosed by an academic. Taken together, our patent measure is likely conservative in that an observed patent application indicates commercial activity, but not all commercial activity will be reflected in a patent application.

Supplementary analyses

To examine whether the relationships between motives and patenting may reflect underlying differences in researchers' productivity (e.g., due to ability or different levels of total effort), we include individuals' (ln) number of publications in the regressions (Tables A3-A5, models 1 and 2). The number of publications has a strong positive relationship with PATS in all three fields, consistent with prior work (Azoulay et al., 2009; Stephan et al., 2007).[12] There is also a significant relationship with ANYPAT in the life sciences, though not in the physical sciences and engineering. Most importantly, including these measures does not substantively change the coefficients of motives, although the negative coefficient of advancement motives in the physical sciences becomes even stronger, while the coefficient of advancement and income motives are slightly reduced in engineering.

Economists typically assume that individuals' motives and preferences are stable, and many social psychologists also consider preferences for work attributes to be "trait-like", i.e., relatively stable over time and across contexts (cf. Amabile et al., 1994; Cable and Edwards, 2004). It is conceivable, however, that individuals' reported preferences change over time, possibly in response to past decisions or outcomes. Our main strategy to address this issue is to use motives as reported in 2001 as predictors of patenting reported in 2003. In addition, we explicitly examined changes in motives by comparing individuals' responses to the 2001 and the

[12] The positive relationship between patents and publications may reflect a number factors such as unobserved heterogeneity in researcher quality, complementarities between applied and basic research, as well as complementarities between patenting and publishing (Azoulay et al., 2009; Fabrizio and Minin, 2008; Gans et al., 2017).

2003 survey. We regressed the observed changes in motives on PATS as well as ANYPAT as measured in 2001 (detailed results available upon request). Out of 24 coefficients, only two are significant – ANYPAT is associated with a small but significant decrease (not increase) in the importance of contribution to society and challenge in the life sciences ($p<0.05$). We also re-estimated regressions using only those cases who reported no change in any of the motives, focusing on ANYPAT due to the smaller sample size (Tables A3-A5, models 3); the results are in line with our main models (Table 2, models 4-6).

The relationship between individual motives and commercial activities may be moderated by incentives. For example, academics' income motives may be more strongly related to patenting in an organization that offers high financial rewards for patenting. Although we have measures of four different kinds of motives, we only have one measure of incentives – the share of royalty income going to inventors. In models 4 and 5 of Tables A3-A5, we include the interaction between the royalty share and income motives (and, for robustness, also the interactions between the royalty share and other motives). The main coefficients of motives as well as the royalty share are unaffected, while the interaction effects are largely insignificant.

To probe why variation in institutionally provided licensing incentives does not seem to influence academics' patenting,[13] we conducted structured interviews by phone with a small random sample of 25 scientists and engineers at universities included in our main sample. When asked about royalty shares at their universities, all respondents were aware of the existence of income sharing policies, but only 5 out of 25 respondents knew the royalty share at their institution. Five respondents guessed but all of them underestimated the true royalty share. Fifteen respondents simply did not know what share of licensing income inventors received at their institution. The latter group included some individuals who indicated that their research had no commercial potential but also several who did see commercial potential. While small in number, these interviews suggest that variation in the royalty share across institutions may not show a relationship with scientists' patenting because the exact shares are not salient to most

[13] This result is not inconsistent with research by Lach and Schankerman (2008), who show that a positive relationship between royalty shares and university licensing income is driven primarily by the quality of licenses rather than the number of licenses. Unfortunately, the data do not allow us to examine the quality of licenses, or the licensing income per patent. More generally, research on the relationship between licensing incentives and commercial activities provides mixed results (Perkmann et al., 2013). Markman et al. (2004) observed that royalty shares set by universities were negatively related to the number of equity licenses. Markman et al. (2008) compared across universities the share of academic patents that "bypassed" TTOs and found no effect of the share of licensing income going to inventors. These ambiguous findings may reflect that studies examined different outcomes that may relate in distinct ways to licensing incentives. In addition, prior work tends to examine aggregate outcomes at the level of academic institutions while our analysis focuses on the level of individual researchers.

academics. This interpretation is consistent with recent survey evidence showing that many faculty members are not familiar with their institution's TTO (Huyghe et al., 2016). It may well be, however, that these shares become more salient once a license is taken out or royalty income is generated, possibly leading researchers to invest more time by working with licensees to increase the value of a license (Jensen and Thursby, 2001; Lach and Schankerman, 2008).[14]

In a final analysis, we include university fixed effects to account for other university characteristics that may influence the rewards (and opportunity costs) to commercial activities, such as tenure policies, norms regarding engagement in commercialization, or differences in the cost of living tied to location. Due to small sample size, we estimate these models using ANYPAT (Tables A3-A5, models 6). The only noticeable difference compared to the baseline models (Table 2, models 4-6) is that the positive coefficient of career advancement motives now becomes insignificant in the engineering sample. This may reflect that university fixed effects absorb some of the variation in career incentives tied to commercial activities, i.e., that some institutions indeed consider engineers' commercial activities favorably in tenure and promotion decisions (Azoulay et al., 2007; Haeussler and Colyvas, 2011).

[14] When we inquired more generally about reasons not to patent potentially valuable results, opportunity costs emerged as a common theme. Some respondents simply felt too busy with their primary job of running a lab. Others saw the process as very cumbersome and costly in terms of time, partly due to insufficient support from the TTO.

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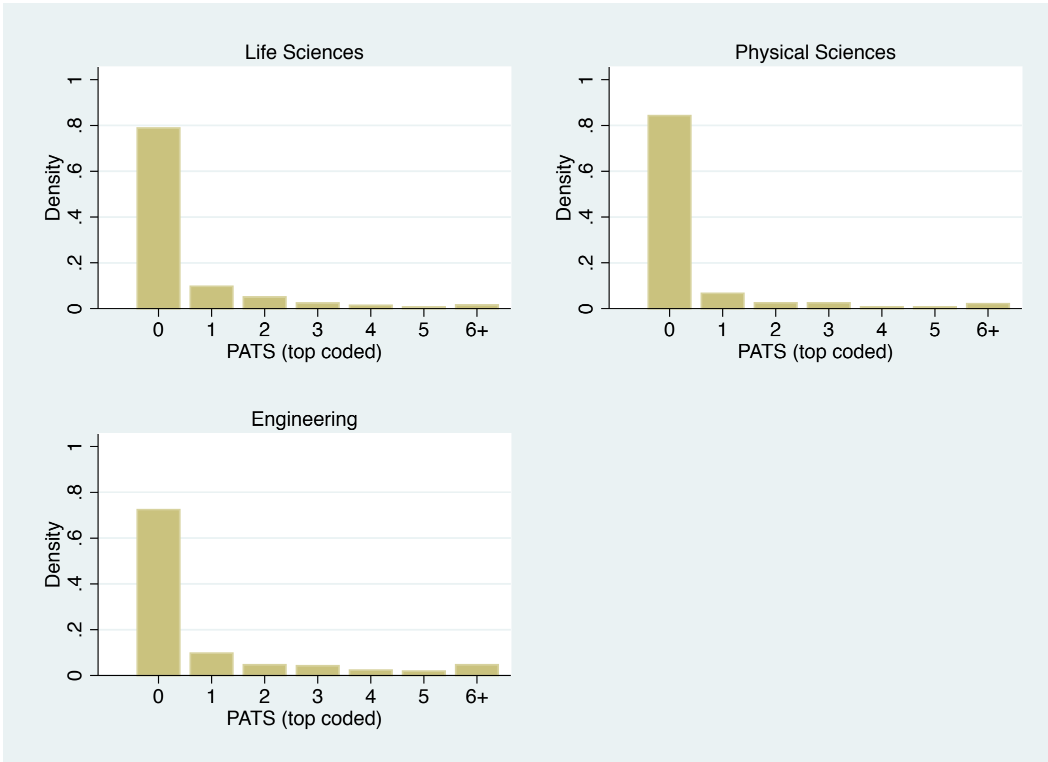
Figure A1: Distribution of U.S. Patent Application Counts (PATS) by Field



Note: Top coded at "6 or more" in order to meet NSF confidentiality requirements. Counts in each reported bin are above the NSF confidentiality threshold.

Table A1: Correlations Between Motives by Field

			1	2	3
Life sciences	1	Imp. advancement	1		
	2	Imp. salary	0.2541*	1	
	3	Imp. challenge	0.2416*	-0.02	1
	4	Imp. contrib. society	0.2123*	0.0028	0.2996*
Physical sciences	1	Imp. advancement	1		
	2	Imp. salary	0.3573*	1	
	3	Imp. challenge	0.2091*	-0.0011	1
	4	Imp. contrib. society	0.1409*	0.058	0.2081*
Engineering	1	Imp. advancement	1		
	2	Imp. salary	0.3046*	1	
	3	Imp. challenge	0.1939*	-0.0582	1
	4	Imp. contrib. society	0.2248*	-0.0297	0.3157*

Note: *=significant at 5%

Table A2: Additional Measures

Variable Name	Measure Description
Type of academic institution	Dummy variables indicating whether academic employer is a Carnegie I (omitted), Carnegie II, Doctorate granting institution, or medical school.
Private/public status of academic institution	Dummy = 1 if academic institution is private.
Age of TTO	Years since the employing institution started a formal technology transfer office. Used as a proxy for institutional support for commercial activities as well as for past commercial activities at the level of the institution.
Financial incentives for patenting (Royalty share)	The share of patent royalty income going to the academic inventor, as set by the 2001 academic employer. Because most disclosed inventions generate little income and the average licensing revenue lies in the $25,000-$50,000 range (Jensen et al., 2007), we focus on the share of the first $50,000 of net income generated by a license.
Quality of PhD program (PhD NRC score)	We matched the names of the PhD-granting institution and the field of the PhD to the National Research Council's 1993 evaluation of PhD program quality (Goldberger et al., 1995). The particular quality measure we use is a survey rating of "program effectiveness in educating research scholars and scientists", ranging from 0 ("not effective") to 5 ("extremely effective"). This measure formally captures the quality of an individuals' graduate education, but should also reflect innate ability to the extent that high-ability individuals self-select or are selected into high-quality PhD programs.
Quality of employer department (Department NRC score)	As a proxy for the quality of the employer, we use the 1993 NRC ratings of faculty quality in the respondents' field at the respondents' current employer (e.g., the ratings for the quality of the physics faculty for an individual with a PhD in physics).
Not tenure track	Dummy variable indicating whether a respondent was on the tenure track/tenured (0) or not on the tenure track (1).
Age	Age of the respondent at the time of the second survey. To allow for flexible estimation, we use dummies for 5-year intervals in regressions.
Race	Dummies for Asian (not Hispanic), white, and other
Citizenship status	Dummy = 1 for U.S. citizens
Exposure	Time since obtaining the PhD, top coded at 5 years. Serves to control for the fact that output is measured over 5 years but some respondents have worked for less than 5 years (Long and Freese, 2005).
Publications	Each respondent reported the number of (co)authored articles that have been accepted for publication in a refereed professional journal over the last 5 years. We interpret this measure as a proxy for research productivity and the amount of knowledge that is potentially patentable (cf. Azoulay et al., 2007). Given the skewed nature of this measure, we use the natural logarithm in our regression analyses.

Table A3: Supplementary Analyses – Life Sciences

Variable	With publications 1 PATS	2 ANYPAT	No change 3 ANYPAT	With interactions 4 PATS	5 ANYPAT	Univ. fixed effects 6 ANYPAT
Imp. advancement	0.378	0.005	0.064	0.309	0.013	0.006
	[0.269]	[0.021]	[0.044]	[0.198]	[0.023]	[0.023]
Imp. salary	-0.133	0.007	0.005	0.006	0.004	0.017
	[0.185]	[0.023]	[0.044]	[0.164]	[0.023]	[0.025]
Imp. challenge	-0.211	-0.013	-0.075	-0.015	0.009	0.017
	[0.381]	[0.032]	[0.085]	[0.318]	[0.032]	[0.038]
Imp. contrib. society	0.820**	0.089**	0.101*	0.806**	0.082**	0.078**
	[0.198]	[0.020]	[0.040]	[0.176]	[0.021]	[0.024]
Ln publications	0.748**	0.098**				
	[0.181]	[0.016]				
Motives*Royalty share				incl.	incl.	
Carnegie II	0.765*	0.094	0.179	0.683+	0.091	
	[0.379]	[0.064]	[0.110]	[0.364]	[0.065]	
Doctorate granting	-0.081	0.039	-0.004	-0.052	0.041	
	[0.399]	[0.058]	[0.077]	[0.380]	[0.058]	
Medical school	0.726*	0.065*	0.136**	0.806*	0.077**	
	[0.302]	[0.027]	[0.051]	[0.318]	[0.029]	
Private university	-0.494+	-0.030	-0.132**	-0.380	-0.020	
	[0.282]	[0.032]	[0.047]	[0.277]	[0.033]	
TTO age	0.004	0.001	0.001	0.002	0.001	
	[0.006]	[0.001]	[0.003]	[0.007]	[0.001]	
Royalty share	1.177	-0.269+	-0.310	0.151	-0.228	
	[1.521]	[0.143]	[0.280]	[1.129]	[0.148]	
Not tenure track	-0.231	-0.045	-0.102+	-0.568+	-0.082**	-0.084*
	[0.340]	[0.029]	[0.058]	[0.325]	[0.031]	[0.036]
Dept. NRC score	0.713**	0.036+	0.097**	0.784**	0.043*	0.077+
	[0.268]	[0.019]	[0.033]	[0.266]	[0.021]	[0.045]
PhD NRC score	0.044	-0.004	-0.018	0.111	0.002	0.003
	[0.194]	[0.021]	[0.035]	[0.175]	[0.022]	[0.024]
Male	0.374	0.006	-0.042	0.565+	0.021	0.006
	[0.285]	[0.025]	[0.044]	[0.316]	[0.027]	[0.031]
U.S. citizen	0.557	0.048	0.067	0.347	0.052	0.081
	[0.378]	[0.048]	[0.074]	[0.391]	[0.048]	[0.054]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-12.171**	-0.490+	0.034	-11.169**	-0.389	-0.565+
	[3.163]	[0.260]	[0.623]	[2.746]	[0.267]	[0.303]
Observations	1,037	1,037	332	1,037	1,037	1,037
R-squared		0.128	0.201		0.091	0.083

Note: Omitted category is Carnegie I institution. +=significant at 10%; *=significant at 5%; **=significant at 1%. Regressions of PATS estimated QML Poisson, of ANYPAT using LPM. Standard errors clustered by university in brackets.

Table A4: Supplementary Analyses – Physical Sciences

	With publications		No change	With interactions		Univ. fixed effects
	1	2	3	4	5	6
Variable	PATS	ANYPAT	ANYPAT	PATS	ANYPAT	ANYPAT
Imp. advancement	-0.727**	-0.026	-0.118+	-0.604**	-0.018	-0.023
	[0.213]	[0.030]	[0.070]	[0.214]	[0.029]	[0.033]
Imp. salary	0.390	0.063+	0.175*	0.405	0.066*	0.047
	[0.322]	[0.033]	[0.069]	[0.253]	[0.033]	[0.034]
Imp. challenge	-0.331	-0.000	0.046	-0.359	0.006	-0.053
	[0.299]	[0.048]	[0.178]	[0.303]	[0.049]	[0.061]
Imp. contrib. society	-0.043	0.042*	0.062	-0.101	0.042*	0.057*
	[0.207]	[0.021]	[0.058]	[0.206]	[0.021]	[0.024]
Ln publications	0.516**	0.028				
	[0.158]	[0.018]				
Motives*Royalty share				incl.	incl.	
Carnegie II	-0.134	0.026	-0.034	-0.275	0.014	
	[0.404]	[0.068]	[0.115]	[0.411]	[0.068]	
Doctorate granting	-0.081	0.031	0.019	-0.349	0.033	
	[0.525]	[0.059]	[0.102]	[0.552]	[0.061]	
Medical school	0.988*	0.036	0.062	1.088**	0.040	
	[0.396]	[0.075]	[0.137]	[0.381]	[0.075]	
Private university	-0.036	0.018	0.051	0.034	0.022	
	[0.266]	[0.041]	[0.080]	[0.278]	[0.043]	
TTO age	-0.004	-0.001	-0.001	-0.005	-0.000	
	[0.009]	[0.001]	[0.004]	[0.010]	[0.001]	
Royalty share	-2.675	-0.037	-0.196	-3.497*	-0.069	
	[1.746]	[0.184]	[0.289]	[1.675]	[0.196]	
Not tenure track	0.818*	0.032	-0.004	0.490	0.015	0.014
	[0.405]	[0.044]	[0.078]	[0.407]	[0.043]	[0.050]
Dept. NRC score	-0.166	-0.003	0.012	-0.082	-0.001	0.055
	[0.159]	[0.023]	[0.049]	[0.181]	[0.023]	[0.047]
PhD NRC score	0.154	-0.005	0.001	0.096	-0.007	0.024
	[0.202]	[0.021]	[0.045]	[0.191]	[0.021]	[0.022]
Male	0.316	-0.026	-0.058	0.398	-0.016	-0.029
	[0.338]	[0.038]	[0.077]	[0.362]	[0.037]	[0.038]
U.S. citizen	0.678	-0.029	-0.062	1.136+	-0.026	-0.020
	[0.559]	[0.054]	[0.091]	[0.626]	[0.052]	[0.054]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-1.292	-0.073	-1.704	-0.264	-0.084	-0.042
	[1.999]	[0.349]	[1.204]	[1.859]	[0.351]	[0.370]
Observations	585	585	175	585	585	585
R-squared		0.164	0.232		0.166	0.161

Note: Omitted category is Carnegie I institution. +=significant at 10%; *=significant at 5%; **=significant at 1%. Regressions of PATS estimated QML Poisson, of ANYPAT using LPM. Standard errors clustered by university in brackets.

Table A5: Supplementary Analyses – Engineering

Variable	With publications		No change	With interactions		Univ. fixed effects
	1	2	3	4	5	6
	PATS	ANYPAT	ANYPAT	PATS	ANYPAT	ANYPAT
Imp. advancement	0.435+	0.067*	0.061	0.532*	0.067*	0.037
	[0.230]	[0.030]	[0.084]	[0.222]	[0.031]	[0.038]
Imp. salary	-0.443*	0.007	-0.022	-0.410+	0.028	0.039
	[0.212]	[0.037]	[0.081]	[0.227]	[0.037]	[0.050]
Imp. challenge	1.452*	0.186**	0.247+	2.345**	0.200**	0.195**
	[0.740]	[0.049]	[0.125]	[0.868]	[0.050]	[0.068]
Imp. contrib. society	-0.082	-0.015	0.002	-0.100	-0.010	-0.010
	[0.229]	[0.041]	[0.081]	[0.225]	[0.039]	[0.048]
Ln publications	0.423**	0.038				
	[0.133]	[0.024]				
Motives*Royalty share				incl.	incl.	
Carnegie II	-0.124	-0.051	0.117	-0.230	-0.053	
	[0.516]	[0.058]	[0.097]	[0.496]	[0.056]	
Doctorate granting	-0.948*	-0.023	0.085	-1.000**	-0.040	
	[0.385]	[0.059]	[0.134]	[0.386]	[0.058]	
Medical school	0.093	0.025	0.114	0.093	0.052	
	[0.359]	[0.089]	[0.165]	[0.373]	[0.089]	
Private university	0.348	0.010	0.053	0.449	0.011	
	[0.327]	[0.046]	[0.084]	[0.317]	[0.045]	
TTO age	-0.009	-0.001	0.001	-0.011	-0.001	
	[0.008]	[0.001]	[0.003]	[0.008]	[0.001]	
Royalty share	0.040	-0.065	0.339	-2.792*	-0.155	
	[1.065]	[0.209]	[0.514]	[1.148]	[0.212]	
Not tenure track	-0.150	-0.016	-0.018	-0.540	-0.037	-0.095
	[0.460]	[0.074]	[0.145]	[0.534]	[0.071]	[0.083]
Dept. NRC score	-0.038	0.036	0.082+	-0.046	0.036	-0.055
	[0.167]	[0.030]	[0.048]	[0.156]	[0.029]	[0.065]
PhD NRC score	0.393*	0.024	0.090+	0.409**	0.033	-0.020
	[0.176]	[0.029]	[0.046]	[0.157]	[0.029]	[0.037]
Male	0.619+	0.075	0.019	0.694*	0.079	0.094
	[0.350]	[0.054]	[0.113]	[0.352]	[0.055]	[0.063]
U.S. citizen	0.654	0.176**	0.309**	0.637	0.174**	0.160*
	[0.473]	[0.057]	[0.096]	[0.488]	[0.057]	[0.066]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-10.351**	-1.166*	-1.741+	-12.263**	-1.235**	-0.646
	[3.209]	[0.451]	[0.876]	[3.515]	[0.442]	[0.556]
Observations	472	472	165	472	472	472
R-squared		0.149	0.222		0.160	0.126

Note: Omitted category is Carnegie I institution. +=significant at 10%; *=significant at 5%; **=significant at 1%. Regressions of PATS estimated QML Poisson, of ANYPAT using LPM. Standard errors clustered by university in brackets.