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Wesley M. Cohen
Duke University, wcohen@duke.edu

Henry Sauermann
European School of Management and Technology, henry.sauermann@esmt.org

Paula Stephan
Georgia State University, pstephan@gsu.edu

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Wesley M. Cohen
Duke University

Henry Sauermann
European School of Management and Technology

Paula Stephan
Georgia State University

Andrew Young School of Policy Studies

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ABSTRACT

Scholarly work seeking to understand academics' commercial activities often draws on abstract notions of the institution of science 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 patenting activities. We find that all four motives predict patenting, but their role differs systematically between the life sciences, physical sciences, and engineering. These field differences are consistent with differences in the payoffs from commercial activities, as well as with differences in the opportunity costs of time spent away from "traditional" research, reflecting the degree of overlap between traditional and commercializable research. We discuss implications for future research on the scientific enterprise as well as for policy makers, administrators, and managers.

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

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

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

1 Introduction

A large literature has examined academics' engagement in commercially oriented research and related commercial 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. Even though most of the evidence does not support these concerns (Agrawal & Henderson, 2002; Breschi et al., 2008; Buenstorf, 2009; Fabrizio & Minin, 2008; Goldfarb et al., 2009; Perkmann et al., 2013; Stephan et al., 2007; Thursby & 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 activity on the part of academics or to discourage such activity to prevent deflection from other research priorities, it is useful to understand why academics engage in commercially applicable research and related activities. Accordingly, much of the recent research has studied academics' underlying motives and incentives (Bercovitz & Feldman, 2008; Fini & Lacetera, 2010; Lam, 2011; Owen-Smith & Powell, 2001; Thursby et al., 2001). These efforts have resulted in important insights, yet two important gaps remain.

First, efforts to understand academics' commercial activities often rely on generalized notions of the institution of science and of an archetypical, representative scientist (Dasgupta & David, 1994; Merton, 1973). Relatedly, prior empirical work has examined large cross-field samples or studied activity in single fields (Ding et al., 2006; Lam, 2011; Murray & Stern, 2007; Owen-Smith & Powell, 2003). Yet, the benefits and costs of commercial activities, and thus academics' motives to engage in such activities, are likely to differ across fields. Studying such differences is important given that there are significant field differences in the *levels* of academics' commercial engagement (Breschi et al., 2008; Cohen et al., 2002; D'Este & Perkmann, 2011; Lim, 2004), and given field differences in the nature of research as well as in norms and reward systems (Fleming & Sorenson, 2004; Layton, 1976; Nelson, 2016; Sauermann & Stephan, 2013). If the drivers of academics' commercial activities differ across fields, policies and managerial practices that recognize and address such differences may be more effective than policies that use the same tools across very different contexts.

Second, much of the work on academics' motivations is grounded in the Mertonian paradigm that views peer recognition and career advancement as the scientists' primary goal (Merton, 1973). Although it has been recognized that scientists may also be driven by intrinsic motives and economic incentives (Dasgupta & David, 1994; Lam, 2011; Stephan & Levin, 1992), virtually absent from the typical image of the academic is the motive of social impact. This is surprising, not only because this motive is salient in historical and qualitative accounts (Shapin, 2008; Stokes, 1997), but also because expected social benefits are a key justification for the public funding of academic research as well as for efforts to increase academic entrepreneurship and technology transfer (Bush, 1945; Lane & Bertuzzi, 2011; Salter & Martin, 2001). Moreover, employees' social motives have been shown to have important impacts in other organizational settings (Bode & Singh, 2016; Fehr & Fischbacher, 2002; Grant, 2007). To the extent that the motive to benefit society is an important driver of individual scientists' commercial activities, we may need to reconsider our interpretation of their efforts and examine the degree to which institutional and national policies facilitate or hinder scientists' efforts to advance social welfare.

We address both gaps. We first develop a simple model of the role of motives and incentives in researchers' decisions to expend effort on traditional academic versus commercially applicable research and related activities (henceforth referred to as simply commercial activity). Key features of our model are that: (1.) efforts directed towards academic and commercial activity do not have to be mutually exclusive but can overlap depending on the distance between the two types of activity in a given field; and (2.) the incentives tied to commercial activity can vary across fields. As a result, the opportunity costs, as reflected in diminished academic career prospects, as well as the payoffs from engaging in commercial activity can vary across fields, leading to field differences in the levels of commercial effort as well as in the individual motives that are most strongly associated with such effort. We then provide empirical insights using micro-data on a sample of over 2,000 life scientists, physical scientists, and engineers working in over 100 U.S. academic institutions. Towards this end, we complement two waves of survey data from the National Science Foundation's Survey of Doctorate Recipients (SDR) with information on universities' policies regarding the sharing of licensing income as well as other data sources.

Although the data do not allow us to estimate the causal impact of academics' motives on commercial activities, they do allow us to explore these relationships empirically, with the model informing our expectations and providing a useful basis for interpreting the results.

In brief, we find that the four featured motives – career advancement, intellectual challenge, money and social impact – have significant relationships with our measure of commercial activity, patent applications, but these relationships differ across fields. These differences are consistent with our model, which incorporates differences in the incentives and the opportunity costs tied to commercial activity across fields. In the physical sciences, we find that patenting activity is lower than in other broadly defined fields, and those physical scientists who patent are characterized by particularly strong financial motives and are less concerned with advancing their academic careers. This observation is consistent with the notion that physical scientists face a sharper trade-off between traditional academic and commercial activity due to a smaller overlap between these activities. On the other hand, patenting is more common among academic engineers, and especially those with strong motives related to challenge and career advancement. The latter result likely reflects a greater overlap between academic and commercially relevant research in engineering, and that commercial activities and patenting are more generally accepted and rewarded in a field where the focus is on "doing" rather than "knowing" (Allen, 1977; Dym et al., 2005; Layton, 1976). Finally, patenting in the life sciences is strongly associated with the motive to have an impact on society, suggesting that those life scientists who apply for patents see commercial activities and patenting as an important vehicle for having an impact with their work.

Our results have broader implications for studies of science, innovation, and academic entrepreneurship. First, while much of the prior work relies on stylized notions of the institution of science, we argue that there are important field differences with respect to factors such as the nature of research and the researchers' costs and benefits from commercial activities. Our analysis suggests that it may be fruitful for scholars to consider more deeply the nature and consequences of such differences, and how our models of academic science – and its interactions with industry – can be enriched by incorporating differences across fields. Second, efforts to understand scientists' activities and choices may benefit from the consideration of a wider range of motives than those typically considered, especially the motive to impact social welfare. Finally, the data and results show considerable heterogeneity in scientists' motives even within given fields and add to a growing body of work suggesting that individual-level differences in motives may have important implications for scientists' activities and performance (Agarwal & Ohyama, 2013; Sauermann & Cohen, 2010; Stern, 2004).

For policy makers and administrators, our results suggest that policies and practices intended to encourage commercially relevant academic research need to be cognizant of a range of motives among academics. Moreover, even though financial returns from commercial activities are salient to outside observers (see also Heath, 1999), nonfinancial motives may play a more important role, at least in the life sciences and engineering. At the same time, a deeper understanding of the motives and incentives related to commercial activities may be required to illuminate the social welfare tradeoffs that are involved. For example, the impact of patenting on subsequent knowledge flows may be quite different depending on whether a scientist patents to appropriate financial returns, advance her academic career, or ensure that her invention has a broad social impact.

2 Conceptual Framework

The purpose of our theoretical model is to examine the relationship between academic researchers' motives (i.e., preferences for different goals 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.

2.1 Model

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, we characterize important possibilities in section 2.2 below.

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,

$$A = \alpha_r e_r + \alpha_c e_c \text{ and} \quad (1)$$

$$O = \gamma_r e_r + \gamma_c e_c. \quad (2)$$

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 licensing 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.[1] To make this overlap more explicit, we define a fixed *nominal* effort budget, B, and assume that

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

where φ indicates how different the effort expended on commercial activity is from effort dedicated to academic research (with $0 < \varphi \leq 1$ and $0 \leq e_r, e_c \leq B$). 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

[1] 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.

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 effort devoted to one versus the other (Toole & 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.[2] 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

[2] 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.

& Ohyama, 2013; Roach & 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), normalizing B to equal unity, and substituting for e_r, the utility function can be rewritten as:

$$U = \beta_1[\alpha_r(1 - \varphi e_c) + \alpha_c e_c] + \beta_2[\gamma_r(1 - \varphi e_c) + \gamma_c e_c] - e_c^2 - 1 + \varphi e_c. \qquad (5)$$

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:

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

Utility is maximized for

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

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,

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

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

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

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,

$$\partial e_c^* / \partial\gamma_c = \beta_2/2, \tag{10}$$

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 ($\partial^2 e_c^* / \partial\gamma_c\partial\beta_2 = ½ > 0$).

2.2 Specific payoffs across fields

We will now discuss field differences in the payoffs tied to commercial work more concretely, examining potential differences in payoffs across the broadly defined fields of the life sciences, physical sciences, and engineering. Our model implied – and we argue below – that differences in the strength of these payoffs across fields will lead to differences in the individual motives that are most strongly associated with commercial activity. Our model considered, however, only two payoffs to academics' decisions to pursue traditional academic versus commercial activity – academic career advancement (A) and an unspecified "other" payoff (O). We propose that two potentially important payoffs - income and social impact - correspond to this other payoff, "O," in our model, and will consider how these payoffs may differ across fields. We will then consider a fourth payoff, intellectual challenge. This intrinsic payoff does not fit neatly with our distinction between A and O since it may be tied strongly to either academic or commercial activity. Given the salient role of challenge in prior work on the drivers of scientists' activities, it may be, however, an important complement to the other three motives considered (Lam, 2011; Sauermann & Cohen, 2010; Stephan, 2012). Taken together, the four payoffs and associated motives considered in this paper are those that have been discussed most prominently in the economics and sociology of science, although – as noted in the introduction – social impact has been considered primarily at the level of the overall system rather than individual scientists.

Career advancement. For academic scientists and engineers, research is the primary way to gain peer recognition and advance one's career (Kuhn, 1962; Merton, 1973; Stephan, 2012). However, reputational rewards may also result from commercial activities. In particular, research suggests that commercial achievements, including patents, can increase scientists' reputation among peers (Audretsch et al., 2010; Haeussler & Colyvas, 2011) and commercial activities are sometimes considered positively in tenure and promotion decisions (Azoulay et al., 2007; Butkus, 2007; Lipka, 2006).[3] At the same time, we expect significant field differences in

[3] We searched the promotion and tenure guidelines of universities with NRC-ranked science and engineering departments for evidence of the role of patents and commercial activities in tenure and promotion decisions. We found approximately 15 institutions that include such criteria, including institutions such as North Carolina State University, Cornell, and Purdue. However, it is likely that many other institutions also consider such activities on an informal basis, as reflected in a quote from Alan Paau, vice provost for technology transfer and economic development at Cornell University, who suggested that the concept of considering participation in tech commercialization in tenure and promotion decisions is not new – it just hasn't been officially codified before to avoid potential "patent counting" (as quoted in Butkus (2007)).

the degree to which commercial activities are recognized as a legitimate form of academic work, reflecting differences in fields' goals and norms. Science is concerned primarily with "knowing", i.e., understanding the natural world. Engineering (and some of the applied sciences), on the other hand, emphasize "doing" and manipulating the natural world to achieve certain objectives (Layton, 1976). Commercial outputs – which require usefulness but not necessarily an understanding of the underlying mechanisms – are arguably a better measure of achievement in a community that values "doing" than in a community that values "knowing," and are thus more likely to be recognized in engineering than in the sciences. Consistent with this conjecture, academic engineers believe that patenting has a greater influence on their reputation among peers than do basic scientists (Haeussler & Colyvas, 2011). To the extent that commercial activity indeed promises greater payoffs in terms of career advancement in engineering than in the sciences, equation 8 above would suggest that motives to advance one's academic career have a stronger positive (or weaker negative) relationship with commercial activity in engineering than in the sciences; this effect may be reinforced by the lower opportunity costs of doing commercial work tied to the greater proximity of engineering research to commercial applications.

Income. A desire for financial gain is often assumed to be the main driver of academics' commercialization activities (Jensen & Pham, 2011; Lach & Schankerman, 2008; Thursby et al., 2007). Such payoffs may take a variety of forms, including income from consulting and licensing income from patents (Stephan, 2012). Regarding licensing, university policies in the U.S. typically require that inventions are disclosed to the university's Technology Transfer Office (TTO) and that resulting patents are assigned to the university, which then receives any royalty income from licensing (Goldfarb & Henrekson, 2003). The Bayh Dole Amendment of 1980 stipulates that the net income must be shared with the inventor. While some academic patents have generated very large payoffs,[4] large payoffs are rare and the expected income is low (Lach & Schankerman, 2008). The share of royalty income going to the inventors is typically the same for all researchers at a given institution, but the expected amount of income may be higher in some fields than in others. Although we lack clear priors regarding such field differences in financial payoffs, equations 9 and 10 of our model suggest that scientists with stronger income

[4] For example, three Emory researchers shared more than $200 million from the sale of the HIV drug Emtriva. The academic inventor of the drug Taxol received an estimated $140 million in royalty income (Stephan, 2012). In 2016, Carnegie Mellon University (CMU) settled a patent dispute with Marvell Technology, and the two inventors are entitled to a "substantial share" of the $750 million received by CMU.

motives and those realizing more income from commercial activity – including larger shares of royalty income – should be more active in commercial activities.

Impact on society. Societal benefits from scientific research are a key justification for the public funding of academic science (Bush, 1945; Stokes, 1997). This goal, however, is typically ascribed to the institution of science as a whole, not to individual scientists.[5] At the same time, the motive to have a positive social impact is salient in historical accounts such as descriptions of Pasteur's efforts to understand basic disease mechanisms and even of physicists' decisions to join the Manhattan Project during World War II (Shapin, 2008; Stokes, 1997). Social impact also emerges in qualitative accounts of academics' decisions to engage in commercial activities such as patenting (Lam, 2011; Mowery & Sampat, 2001; Murray, 2010).

While both fundamental research and commercial activities can benefit society, the social impact of the latter may be more direct and more salient to researchers since commercialization brings technologies closer to the market and potential users. Although benefits to society from commercialization can take different forms in different fields, they are especially prominent in the life sciences, where commercialized inventions such as drugs or medical devices can lead to tangible improvements in people's lives. Similarly, patents play a more important role in facilitating downstream development in the life sciences than in other fields (Cohen et al., 2000). As such, and consistent with equation 9, we expect that the motive to have an impact on society has a stronger positive relationship with commercial activities in the life sciences than in other fields.

Intellectual challenge. In addition to extrinsic benefits, researchers also care about intrinsic rewards resulting from work on interesting and intellectually challenging problems (Kuhn, 1962; Sauermann & Cohen, 2010; Stephan & Levin, 1992). It is often assumed that academics consider traditional research activities to be more intrinsically motivating than commercially applicable research (Levin & Stephan, 1991; Thursby et al., 2007). However, even though researchers in the basic sciences may indeed find downstream work and patenting less intellectually engaging, applied scientists and engineers may derive considerable intrinsic rewards from building things and bringing them to market (Shapin, 2008). In other words, the

[5] The individual-level motive to have an impact on society is different from Merton's norm of "communism". The latter states that knowledge belongs to the community: "The scientists' claim to "his" intellectual "property" is limited to that of recognition and esteem which […] is roughly commensurate with the significance of the increments brought to the common fund of knowledge" (Merton 1973, p. 273). Communism does not, however, imply that scientists' *want* to give up ownership to their knowledge or that they – as individuals – care about the impact their findings have on society.

intrinsic benefits from commercially applicable work are likely higher for engineers than for scientists, both in an absolute sense but also relative to the intrinsic benefits from traditional research (i.e., γ_c vs. γ_r). As such, challenge motives are likely to have a stronger positive (or weaker negative) relationship with commercial work in engineering than in the sciences. Moreover, as implied by equation 9, this effect is likely reinforced by the lower opportunity costs of doing commercial work in engineering.

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.

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%.[6] 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. To address potential endogeneity concerns – addressed in more detail below – our dependent variables are taken from the 2003 survey, while

[6] More details about the SDR are available at http://www.nsf.gov/statistics/srvydoctoratework/.

most of our independent variables are taken from the 2001 survey. Our final sample includes 2,094 scientists and engineers at 160 institutions.

We augment the SDR data with data from additional sources. First, we obtained data on universities' policies regarding the share of licensing income going to the inventor from Saul Lach and Mark Schankerman (2008) as well as from university websites and inquiries with administrators. Second, we obtained data on the year in which academic institutions started a formal licensing / technology transfer office from Association of University Technology Managers (AUTM) surveys as well as from websites and through inquiries to administrators.[7] Finally, we use evaluations of PhD program quality from the National Research Council (Goldberger et al., 1995) as proxies for the quality of the PhD programs from which respondents graduated and of the departments in which they were employed.

3.2 Variables

This section discusses our key dependent and independent variables; additional variables are described in Table 1. Descriptive statistics by field are shown in Table 2.

<u>Commercial activity:</u> We proxy for academics' commercial activities using patent application counts. Each respondent reports 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 (PATS).[8] This patent measure captures all patent applications on which the respondent is listed as an inventor, not only those going through university TTO's, thus allowing us to examine academics' patenting activity more broadly. For supplementary analyses, we also created a dummy variable indicating if a respondent had any patent applications in the 5-year period (ANYPATS). Table 2 shows significant differences in patenting across fields. Engineers have by far the highest average count of patent applications (1.08) as well as the largest share of individuals with at least one patent application (28%), followed by life scientists and physical scientists. These field differences in levels of commercial activity are consistent with differences in the opportunity costs of engaging in commercial activity noted above, though they may also reflect differences in the associated incentives.

[7] For more information on the AUTM surveys, please see www.autm.net.

[8] Unfortunately, the SDR data are anonymized and cannot be matched to other data sources such as patent records.

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. The four factors and their associated motives are: Salary, intellectual challenge, contribution to society, and opportunities for advancement. Note that these measures are intended to capture respondents' general preferences for different kinds of work related payoffs (see also Agarwal & Ohyama, 2013; Sauermann & Cohen, 2010). As such, we will examine the relationships between motives and patenting through regression analyses rather than by asking respondents directly why they engage in commercial activities. This indirect approach is consistent with our theoretical model and mitigates concerns about social desirability and common methods bias (see below).

Table 2 shows that the average importance ratings for all four job attributes are quite high, reflecting that they are generally evaluated positively. The correlations between measures of motives range from -0.06 (salary and challenge in engineering) to 0.36 (advancement and salary in the physical sciences) (Table A1). These relatively low correlations suggest that the measures capture distinct constructs, mitigating concerns about common methods bias. It is notable that the means of motives are very similar across fields. Only the desire to contribute to society is somewhat higher in engineering and the life sciences than in the physical sciences.

Financial incentives: Although we have no measure of financial incentives for all commercially relevant research and related activities, we do have information on the share of patent royalty income going to the inventor from two sources.[9] First, Saul Lach and Mark Schankerman graciously provided us with royalty shares for 111 institutions from their 2008 study. These data reflect royalty shares as of 2001. We collected information on the remaining institutions from their websites and by contacting administrators in 2009. Policies for the distribution of royalty income differ significantly across institutions. Of our 160 institutions, 109 use a linear schedule, i.e., the share going to the inventor remains the same for all levels of net income. Another 49 institutions have a regressive schedule, and two institutions have more complex schedules. Because most disclosed inventions generate little income and the average

[9] It is likely that licensing income is related to other sources of income from the commercial sphere, e.g., because firms that license university patents often use consulting relationships with the inventors to access uncodified knowledge (Goldfarb & Henrekson, 2003; Jensen & Thursby, 2001). Consistent with this notion, the Carnegie Mellon Survey data show that licensing is significantly correlated with consulting as sources of information from universities that are used by firms conducting R&D (r = 0.33) (for details on this survey, see Cohen et al. (2002)).

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 (Share50).

Academic field: We distinguish broadly between respondents who received their PhD in the life sciences (N=1037), physical sciences (N=585), and engineering and the applied sciences (N=472). For economy of exposition, we will refer below to engineering and the applied sciences as simply engineering. In the regression analyses, we 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).

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

3.3 Potential for social desirability bias and common methods bias

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 & 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 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 (e.g., D'Este & Perkmann, 2011; 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, in particular, life scientists, may be socialized into thinking they should care about others and thus report stronger motives to contribute to society. As reported earlier, the average rating of contribution to society is somewhat higher for life scientists than for physical scientists, but very similar to the average rating for engineers. More importantly, we run our regressions within field and 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.

4 Empirical specification

Our goal is to understand the relationships between academic scientists' motives and their commercial activity. Our featured dependent variable is the number of respondents' patent applications in the prior five years. To address the count nature of this variable and the significant degree of overdispersion, we estimate negative binomial regression models. The following is our benchmark specification:

$$PATS_i = f(\varepsilon_i;\ \beta_0 + \boldsymbol{\beta_1 MOTIVES_i} + \beta_2 SHARE50_j + \beta_3 IMPINC_i{*}SHARE50_j + \boldsymbol{\beta_4 CONTROLS}), \quad (11)$$

where $PATS_i$ is respondent i's patent application count over the 1998-2003 time period (as reported in 2003) and $\mathbf{MOTIVES_i}$ is a vector of motives measured in 2001, reflecting preferences for career advancement, income, social impact and intellectual challenge. We also include a measure of financial incentives, $SHARE50_j$, which is the royalty share set by the 2001 employer j, as well as the interaction between the income motive, $IMPINC_i$, and the royalty share (both variables are centered before computing the interaction). **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.[10] All patenting regressions are adjusted for exposure time because patents are

[10] The interpretation of interaction terms in nonlinear models is not straightforward. We also estimated interaction terms using the methods suggested by Chungrong and Norton (2003) and obtained qualitatively similar results. We also estimated linear

observed over 5 years but some respondents have only 3 or 4 years of work experience (Long & Freese, 2005). Since our theoretical model 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. Standard errors are clustered at the level of the university.

Although our data include rich measures of individuals' motives, measures of incentives (α_r, α_c, γ_r, and γ_c in the model) are limited. We measure financial incentives for patenting at the university level using the royalty share. Other institution-level incentives may be partly captured through controls such as the NRC rating or the age of the TTO. To further address institution-level factors, we perform robustness checks using fixed effects regressions, exploiting only variation observed within universities.

5 Results

5.1 Main analysis

Consistent with our expectations, Table 3 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 – particularly the cross-field differences – through the lens provided by our model.

5.1.1 Basic results

In the life sciences (models 1-3), 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 46% higher expected patent count (model 3). Income, challenge, and advancement motives have no relationship with patenting.

In the physical sciences (models 5-7), we also find a significant positive relationship between the motive to contribute to society and patenting; a one-SD higher motive is associated with a 32% higher expected patent count. In addition, the income motive has a significant, positive coefficient – a one SD higher income motive is associated with a 35% higher predicted patent count. The advancement motive has, however, a significant *negative* relationship with

probability models predicting whether a respondent has a patent at all and the estimated interaction terms are consistent with our results from the logit regressions reported in section 5.2.

patenting in the physical sciences; a one-SD higher score is associated with a 39% lower patent count.

Among engineers (models 9-11), we find a strong positive coefficient on the challenge motive as well as a marginally significant positive coefficient on the advancement motive ($p<0.10$). One-SD higher scores on the two motives are associated with 91% and 25% higher expected patent counts, respectively. Motives related to income or social impact have no significant coefficients.

5.1.2 Interpreting the results

Consistent with our argument that the motives underlying academics' decisions to allocate effort to commercial activity differ across the three broadly defined fields of life sciences, physical sciences, and engineering, formal tests confirm that the observed differences in the coefficients of motives across fields are statistically significant.[11] Our model suggests that these different relationships may reflect differences across fields in in the incentives to do commercial work and in the opportunity costs tied to commercially applicable research. We now discuss these possibilities in more detail.

A notable result in Table 3 is the significant, negative relationship between advancement motives and patenting in the physical sciences, suggesting that those physical scientists who care strongly about their academic careers allocate less effort to commercial activity. This contrasts most sharply with engineering, where the coefficient of advancement motives is marginally positive. Equation 8 of our model suggests two complementary explanations for this difference. First, it may reflect that career advancement incentives are more closely tied to commercial activity in engineering than in the physical sciences. As noted in section 2.2., for example, it has been argued that patents can serve as a legitimate measure of performance in engineering fields but less so in the physical sciences where commercial activities do not "count" as much toward academic advancement.[12] Second, and closely related to the first explanation, the coefficient of advancement motives may be less negative in engineering than in the physical sciences because

[11] Tests using Stata's suest routine reject the equality of coefficients of motives in the life sciences and physical sciences ($Chi^2(4)=9.50$, $p<0.05$), the life sciences and engineering ($Chi^2(4)=20.06$, $p<0.001$), and the physical sciences and engineering ($Chi^2(4)=27.50$, $p<0.001$).

[12] In one of our interviews (see section 5.1.3. below), 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".

the distance between commercial activity and traditional academic research is smaller in engineering. As a consequence, engineers who allocate time to commercial activity have to make less of a sacrifice in terms of lost time for research and the associated career benefits. For both of these reasons, the opportunity cost of commercial activity is less in the engineering fields. Conversely, physical scientists who are particularly concerned with career advancement may allocate less time to commercialization both because advancement payoffs from such activities are smaller than from research ($\alpha_c < \alpha_r$) and because the distance between research and commercialization (φ) is large, implying a higher opportunity cost of commercial activity. It is interesting to note that there is no significant relationship between career advancement motives and patenting in the life sciences. This result may reflect that the life sciences occupy an intermediate position between the physical sciences and engineering with respect to incentives for commercial activity as well as the distance between traditional academic and commercial work. Although biomedical sciences account for the bulk of academic patenting (Mowery et al., 2001), our results suggest that they do so for reasons other than the contribution of patenting to the advancement of biomedical scientists' academic careers.

The observation that career advancement motives do not predict commercial activity in the life sciences, and even have a negative coefficient in the physical sciences, raises the question what other motives may lead scientists towards more active involvement in commercial activity. While we had no priors about which of the other benefits would be more important, common discussions of academic entrepreneurship highlight income as a potential candidate. Table 3 indeed shows a strong positive relationship between financial motives and patenting in the physical sciences. However, we observe no such relationship in the life sciences or engineering, suggesting that it is primarily in the physical sciences where pecuniary motives apply. This result, along with the negative, significant coefficient for career advancement, does not necessarily imply that physical scientists will give up on their academic goals if sufficiently compensated by income. Rather, these results suggest that those academics in the physical sciences who have stronger preferences for income, and weaker preferences for career advancement, devote more effort to commercially related work, at least as reflected by their patenting behavior.[13]

[13] Note that, per equation 9, the result that financial motives appear to motivate patenting does not necessarily imply that financial payoffs to patenting are higher in the physical sciences than in other fields, but only that the financial payoff is high relative to that from traditional research in the physical sciences.

Perhaps the most interesting finding in Table 3 is the significant relationship between commercial activity and the motive to have a social impact in the life sciences (and to a lesser degree in the physical sciences). As implied by equation 9, this relationship suggests that life scientists who engage in commercial activity expect significant social benefit from doing so (i.e., γ_c is high). Our model indicates this relationship may be reinforced if the distance between academic research and commercial work (i.e., φ) is small, reducing the opportunity costs of pursuing social goals through commercial engagement. The former interpretation is consistent with the notion that, in the life sciences, the social benefits from commercial activity are especially salient.[14] The latter is consistent with the notion that life scientists often work in Pasteur's quadrant, where research can yield fundamental insights while also yielding considerable social dividends (Stokes, 1997). And obviously both mechanisms may be operative.

Although we interpret the link between patenting and the desire for social impact as reflecting scientists' motives to engage in commercial activity in general, there is an additional reason why the motive of social impact may be tied to our particular measure of commercial activity, namely patenting. Life scientists are likely cognizant of the fact that downstream development costs in the life sciences are high and that securing patents is essential for providing companies the incentive to make the considerable downstream investments required to bring a drug or another therapy to market and, in turn, to provide the health benefits from new discoveries (Cohen et al., 2000; Sampat et al., 2003). In the words of the late Susan Lindquist, who was a member at the Whitehead Institute and 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."[15]

Although motives related to money and social impact appear to be important predictors of commercial activity in the physical and life sciences, respectively, neither of these motives is related to patenting in engineering. Engineers who patent are not distinguished by stronger financial or social impact motives. Engineers who allocate more time to commercial activity are, however, characterized by a stronger desire for career advancement ($p<0.1$), consistent with our

[14] We find the strong positive relationship between the importance of contributing to society and patenting *within* the sample of life scientists; this relationship is thus unlikely to reflect that life scientists generally have a stronger desire to contribute to society and also happen to patent more.
[15] Quoted by Marie Thursby, 2010 DRUID debate on academic entrepreneurship. http://www.druid.dk/index.php?id=20

discussion above suggesting that patenting may count toward promotion in engineering in some settings. Engineers who patent more also report a stronger desire for intellectual challenge. We had no priors as to whether intrinsic benefits such as challenge are more strongly tied to traditional academic work or to commercial activity (see section 2.2). It appears, however, that engineers – in contrast to their colleagues in the sciences – perceive considerable intrinsic benefits from doing commercially relevant work. Moreover, to the extent that the distance between commercial activity and traditional engineering research is small, engineers who pursue commercial work for its intellectual challenge face low opportunity costs in terms of time lost for traditional research or, as discussed at the beginning of this section, in terms of career advancement. Thus, it is not surprising that engineers have the highest rates of commercial activity and patenting (Table 2), consistent with our conceptual discussion.

5.1.3 Other variables

Contrary to our expectations, our only measure of incentives, the share of licensing income going to inventors (Share50), as well as its interaction with the income motive, has no significant relationship with the number of patent applications in any of the three fields.[16] Including this measure of financial incentives leads to no appreciable changes in the coefficients of the four motives.

To probe why variation in institutionally provided licensing incentives does not seem to influence academics' patenting, 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

[16] 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, however, 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. Finally, Markman et al. (2008) compared across universities the share of academic patents that "bypassed" Technology Transfer Offices 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.

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 academics.[17] 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 & Thursby, 2001; Lach & Schankerman, 2008).[18]

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) or differences in the nature of research, we include individuals' number of publications and a proxy for the basic versus applied nature of research in the regressions (Table 3, models 4, 8, 12). Applied research predicts higher patent counts in the physical sciences and in engineering. The number of publications has a strong positive relationship with patent counts in all three fields, consistent with prior work. Most importantly in our context, including these measures has little impact on the coefficients of motives, except that the motive to have an impact on society becomes insignificant in the physical sciences.

Finally, there are noticeable differences across fields in the coefficient of the National Research Council's (NRC) rating of respondents' academic department. In particular, for the physical sciences, the more highly rated the department, the fewer the patents applied for on the part of its faculty ($p < .05$). In the life sciences, we observe a positive relationship ($p < .01$). In light of our earlier observation that career advancement motives have a negative relationship with patenting in physics but an (insignificant) positive relationship in the life sciences, these results may suggest that patentable work may detract from academic standing in physics but not in the life sciences. In Stokes' (1997) terms, one might infer that the most highly ranked physics departments live squarely in Bohr's quadrant where research towards commercial applications detracts from contributions to fundamental understanding and garners less respect. In contrast,

[17] 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).

[18] 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.

work in Pasteur's quadrant – seeking both basic insight and potential application – is more common and respected in the life sciences, and may even distinguish the best departments. Interestingly, the NRC score has no relationship with patenting in engineering – perhaps because considerations of use are central to engineering generally (Layton, 1976), and do not distinguish more from less esteemed departments.

--- Table 3 about here ---

5.2 Any patents

Complementing our analysis of patent counts, we estimate regressions of ANYPATS, indicating whether a respondent patents at all (Table 4). These regressions are estimated using random-effects logit to account for potential non-independence within institutions.

The results are broadly consistent with those reported earlier and we focus here on differences compared to the regressions of patent counts. First, we see that in the sample of physical scientists, the positive relationship between financial motives and patenting remains, but the coefficients of advancement motives and of the desire to impact society become insignificant. The advancement motive now has a significant positive coefficient at conventional levels in the sample of engineers, consistent with our conjecture that patenting is beneficial for career advancement in fields that focus on "doing" and on creating useful artifacts (Layton, 1976). Finally, the interaction between Share50 and the importance of salary is positive and significant in the sample of engineers, suggesting that financial incentives may play a role in leading engineers with a strong interest in money to consider patenting their work. Again, however, the estimated coefficients remain effectively unchanged with the inclusion of the licensing share variable.

--- Table 4 about here ---

5.3 Robustness checks

We take additional steps to account for unobserved heterogeneity. First, we include a proxy for researchers' lab size (the log of the number of employees supervised). This measure should control for the possibility that some researchers may be named on patents that result largely from the work of other lab members, although this problem should be less pronounced than in the case of publications (Haeussler & Sauermann, 2013; Lissoni et al., 2013). Lab size may also capture otherwise unobserved research productivity. Lab size has a strong positive coefficient in the life sciences and physical sciences but the coefficients of motives and incentives are robust (Tables A2-A4, model 1).

Second, we drop individuals working at Research II and Doctoral granting institutions from the sample and focus exclusively on individuals working at Research I institutions and medical schools (model 2). Our rationale is that lower rated institutions may be less focused on research and may have a less developed technology transfer infrastructure than Research I institutions and medical schools. While we observe no qualitative changes in the coefficients of Share50, we find that the coefficient of the advancement motive becomes more negative in the sample of physical scientists (change from -0.492 to -0.702, $p<0.05$). As per equation 8 of our model, one possible interpretation is that career advancement is tied more strongly to research performance in top tier institutions.

Third, we include university fixed effects to account for unobserved university characteristics, such as tenure policies, norms regarding engagement in commercialization, or differences in the cost of living tied to location. Due to the relatively small sample size, we estimate these models using ANYPATS and linear probability models (model 3). The only noticeable difference compared to the baseline models (Table 4) is that the coefficient of the importance of contribution to society is now statistically significant at conventional level also in the sample of physical scientists.

Finally, it is conceivable that PhD programs systematically socialize their students with respect to motives as well as research and patenting activities, resulting in spurious correlations between these measures. In order to address this concern, we estimated key regressions with fixed effects for respondents' PhD granting institutions (Tables A2-A4, model 4). Our qualitative findings remain robust.

Economists typically assume that individuals' motives and preferences are exogenous and 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 & Edwards, 2004). It is conceivable, however, that individuals' reported preferences change 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. To further mitigate this concern, we explicitly examined changes in motives by comparing individuals' responses to the 2001 and the 2003 survey. We regressed the observed changes in motives on PATS as well as ANYPATS as measured in 2001 (detailed results available upon request). Out of 24 coefficients, only two are significant – ANYPATS is associated with a small but significant decrease in the importance of challenge and of contribution to society in the life sciences ($p<0.05$) – contrary to the direction of change we would expect due to endogeneity. These results therefore suggest that reverse causality is unlikely to be the driver of our featured results. We also re-estimated regressions using only those cases who reported no change in any of the motives (Tables A2-A4, model 5); the key results are robust.[19]

The potential for reverse causality has to be considered also with respect to the royalty share measure. While academic institutions arguably do not set royalty shares in response to any particular individual's preferences or performance, it is conceivable that institutions with historically low commercial activity among their faculty seek to encourage more activity by setting high royalty shares. In order to partly address this issue, we included controls for the quality of the institution and for the age of the technology transfer office in our featured regressions. It is also possible, however, that researchers engaged in commercial work or with stronger financial motives self-select into institutions with higher royalty shares. If these individual-level characteristics are unobserved, estimates of the effects of the royalty share on patenting activity may be inflated (Lach & Schankerman, 2008). These concerns are mitigated due to the fact that we explicitly include measures of motives, ability, and the nature of research into our regressions. Moreover, such a selection bias would imply a *positive* bias in the royalty share -patenting relationship, yet we observe no significant relationship. We nevertheless explored whether academics systematically move to universities offering higher royalty shares. Using data from those scientists and engineers who changed employers between 2001 and 2003 (N=210), we find no evidence of systematic self-selection into universities with higher royalty shares based on individuals' motives, the basic versus applied nature of research, or patenting activities.

Finally, for researchers at universities with nonlinear royalty sharing schedules, the expected royalty share depends on the expected licensing income. For universities with nonlinear

[19] One notable difference to our baseline models is that the importance of challenge now has a negative coefficient in the life sciences sample.

schedules, we thus replace our measure of the royalty share for the first $50,000 of licensing income (Share50) with the expected royalty share given the average income per license in a given university, using the expected shares computed by Lach & Schankerman (2008). Model 6 in Tables A2-A4 shows that the expected royalty share has no significant coefficient, consistent with our main results.

6 Discussion

Research seeking to understand academics' commercial activities often draws on general notions of the institution of science. Few scholars have considered how academics' incentives to engage in commercial activities, as well as the associated opportunity costs, may differ across scientific fields. Similarly, efforts to understand academics' commercial activities have focused on an archetypical, representative scientist who seeks to satisfy self-interested motives, neglecting the potential role of academics' desire to have a positive impact on others. Using two waves of survey data on over 2,000 academic scientists and engineers at 160 U.S. institutions, we relate academics' patenting activities to their academic and nonacademic motives. We find that the motives most strongly related to commercial activities differ across the broadly defined fields of life sciences, physical sciences, and engineering. In the life sciences, it is the researchers with stronger motives to contribute to society who most actively engage in commercial activities. In the physical sciences, patenting is predicted by financial motives, and, less robustly, by the desire to contribute to society, while career advancement motives have a negative relationship with patenting. In engineering, patenting relates to the motives of challenge and advancement. These differences are largely consistent with our model that incorporates differences across individuals in their motives, as well as differences across fields in the incentives and opportunity costs tied to commercial activity.

Our results are subject to important limitations. First, while we consider a broader set of motives than typically considered 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 & Powell, 2001; Perkmann et al., 2013). Second, we focus on patenting as one of several possible facets of commercial activity; future work using different data sources could fruitfully explore other activities such as consulting or the founding of new ventures (Buenstorf, 2009; Perkmann et al., 2013; Toole & Czarnitzki, 2010). Third, we have measures of financial incentives in the form of royalty shares but lack direct measures for other types of incentives. To the extent that motives and incentives are correlated or interact (as per the cross partials discussed in section 2.1), the estimated coefficients of motives may partly reflect the influence of unobserved incentives. In this regard, it is comforting to note that our estimated coefficients on motives are entirely robust to the inclusion of both the royalty share variable and university fixed effects that may correspond to other unobserved incentives.[20] While a cleaner separation of the effects of motives versus incentives would be desirable, our results provide strong evidence of the role of different types of motivational factors (motives as well as incentives), and of differences in such factors across fields. Fourth, while response biases are unlikely to have a major influence on our regression results, they remain a potential weakness of survey-based measures. However, survey measures provide a unique opportunity to gain insights into motivational factors that are difficult to capture using other data sources. Finally, despite our efforts to mitigate endogeneity concerns by using two waves of survey data and including a wide range of control variables, we can still make no claims regarding causality. As such, future research is needed to more clearly identify the causal nature of the relationships observed in our data.

Despite these limitations, we see several implications for policy makers and managers. 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 academic scientists and engineers care not only about their careers, intellectual challenge, or money, but also about making a difference in society, their objectives may be more aligned with policy objectives than previously thought. Moreover, to the extent that this is true, Bayh-Dole may have influenced commercial activities less by strengthening financial incentives than by providing a support function for scientists to advance the commercialization of their research without having to make prohibitive sacrifices in their academic work (Goldfarb & Henrekson, 2003). Similarly, TTO's may be able to increase faculty participation by highlighting not only

[20] Although there is considerable variation in universities' policies regarding the sharing of licensing income, our results show no relationship between financial incentives in the specific form of royalty shares and individuals' patenting. This result does not imply, however, that money plays no role in scientists' decisions to engage in commercial activities. Money may play a significant role, for example, in academics' decisions to start their own companies or to take stakes in startups based on their inventions. Similarly, financial incentives – including royalty shares – may affect the amount of effort that faculty are willing to commit to working with a licensing firm on the further development of an invention (Jensen & Thursby, 2001).

the potential for royalty income, but also the opportunities technology transfer provides for having a broader social impact. An interesting tension may arise between TTO's and faculty, however, when the primary goal of a university's TTO is to generate licensing revenues while that of the faculty is to increase social welfare.

This last point highlights the utility of a deeper understanding of scientists' *private* motives to engage in commercial activities and their relationship with *societal* costs and benefits. In particular, observers have been concerned about possible detrimental effects of commercial activities – patenting in particular – on the sharing and diffusion of academic knowledge (Murray & Stern, 2007; Perkmann et al., 2013). We suggest that intellectual property rights can be used in different ways, and their effects on knowledge flows likely depend on the motives of the inventors and patent holders. A scientist who patents in order to gain peer recognition or to protect the public commons, for example, may share knowledge more freely than a scientist who patents in order to appropriate financial returns. As such, non-financial motives may explain why many scientists continue to publish actively even when they engage in commercial activities (Azoulay et al., 2007; Fabrizio & Minin, 2008), or why they disclose knowledge with potential commercial value in both patents and publications (Gans et al., 2017). Given our finding that the motives associated with commercial activities differ systematically across fields, however, future work should examine carefully whether and how the societal impacts of commercial activities also differ across fields. Similarly, there has been a concern that commercial activities may undermine effort directed towards traditional academic research. Our discussion suggests that the magnitude of such effects should differ across fields, depending on the "distance" between commercial and conventional academic work. As such, there may be little reason for concern in fields where academic and commercial work are closely aligned (Crespi et al., 2011; Fabrizio & Minin, 2008). Commercial outputs may require a greater re-allocation of effort, however, in fields where commercial work is more distant from traditional academic research.

Insights into academics' motives to engage with the commercial sector should also be of interest to firms who seek to build linkages with academia in order to improve innovative capabilities (Cockburn & Henderson, 1998; Fleming & Sorenson, 2004; Gittelman & Kogut, 2003; Zucker et al., 2002). While scientists will expect financial compensation for their efforts, they may also consider the degree to which collaborations with firms can help them achieve other goals such as making a difference in people's lives. Prior work has shown that scientists are willing to give up pay in order to publish research results and gain peer recognition (Sauermann & Roach, 2014; Stern, 2004) and future research could study whether scientists make similar trade-offs between pay and the opportunity to have a broader societal impact (see Bode & Singh, 2016).

Our study also has implications for the broader literature on science and innovation. First, as noted above, much of the existing conceptual and empirical work studies the institution of science using a rather abstract perspective, often building on the seminal work of Robert Merton (1973). Such work has allowed us to understand the distinctive features of science, yet future research may benefit from considering more explicitly how the institution of science varies across fields or organizational contexts (Crespi et al., 2011; Sauermann & Stephan, 2013). Attention to such differences may provide novel insights into many important questions such as the interactions between "science" and "technology" (Dasgupta & David, 1994), the societal impact of publicly funded research, or scientists' collaborations and mobility. Second, much of the literature views scientists' decisions as reflecting motives related to career advancement, intellectual challenge, or money (Dasgupta & David, 1994; Gans et al., 2017; Stephan, 2012). Our results suggest that future work should consider a broader range of motives, notably the desire to have an impact on society. We suspect that this motive may play an important role not just in scientists' decisions to engage in commercial activities but also in other decisions such as which career path to take, which employer to work for, or what research problems to tackle (see Besley & 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 functioning of the scientific enterprise across fields may enrich the study of science and may allow us to provide more robust advice to managers, policy makers, university administrators and other stakeholders.

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Table 1: Additional Measures

Variable Name	Measure Description
Applied research	Respondents indicated on a list of work activities the first and second most important activities for them in terms of time spent. Among those activities is “basic research”, defined on the survey instrument as “study directed toward gaining scientific knowledge primarily for its own sake” and “applied research”, defined as “study directed toward scientific knowledge to meet a recognized need”. We created a variable APPLIED that is coded as 1 if the respondent indicated that he was only engaged in basic research, 2 if the respondent was engaged in both basic and applied research, and 3 if the respondent was engaged only in applied research.[21] This measure is independent of the disclosure mechanism and thus complements existing work using patent- or publication based proxies of the nature of research.
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.
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.
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 (Employer 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).
Tenure status	Dummy variables indicating whether a respondent was not on the tenure track, on the tenure track but not tenured (omitted category), or tenured.
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.
Gender	Dummy = 1 if respondent is male
Race	Dummies for Asian, white, and other
Citizenship status	Dummy = 1 for U.S. citizens

[21] Other activities that are frequently mentioned in this question include teaching and managing or supervising.

Table 2: Descriptive Statistics

	Variable type	Life Sciences Mean	Life Sciences SD	Physical Sciences Mean	Physical Sciences SD	Engineering Mean	Engineering SD
Patent applications	count	0.62	3.43	0.55	2.69	1.08	3.19
Any patent applications	dummy	0.21		0.16		0.28	
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. Advancement	4-point	3.48	0.61	3.40	0.65	3.44	0.64
Imp. Contr. Society	4-point	3.57	0.57	3.44	0.62	3.59	0.57
Share 50	continuous	0.42	0.10	0.42	0.11	0.41	0.10
Applied research	3-point	1.62	0.83	1.46	0.77	2.20	0.92
Publications	count	13.71	13.96	15.62	16.73	11.50	11.73
Ln_publications	continuous	2.35	0.86	2.41	0.95	2.19	0.86
Carnegie I	dummy	0.44		0.70		0.66	
Carnegie II	dummy	0.09		0.09		0.14	
Doctorate granting	dummy	0.04		0.13		0.12	
Medical school	dummy	0.44		0.08		0.08	
Private university	dummy	0.27		0.28		0.26	
Male	dummy	0.69		0.84		0.84	
Age	continuous	47.99	9.09	48.56	10.47	46.06	9.45
Not tenure track	dummy	0.35		0.28		0.12	
Tenure track not tenured	dummy	0.19		0.14		0.31	
Tenured	dummy	0.45		0.58		0.57	
Employer 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
White	dummy	0.75		0.78		0.63	
Asian	dummy	0.16		0.13		0.21	
Other	dummy	0.09		0.09		0.15	
US citizen	dummy	0.93		0.90		0.89	
Changed employer	dummy	0.12		0.10		0.07	
Employees supervised	count	4.56	7.67	3.59	5.82	4.38	5.44

Table 3: Patent Counts

	Life Sciences				Physical Sciences				Engineering			
	1	2	3	4	5	6	7	8	9	10	11	12
	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg
	PATS	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**	**PATS**
Imp. Salary	0.021	0.024	0.022	0.028	0.439*	0.473*	0.505*	0.523*	-0.131	-0.125	-0.112	-0.125
	[0.160]	[0.161]	[0.162]	[0.177]	[0.220]	[0.224]	[0.222]	[0.226]	[0.186]	[0.190]	[0.193]	[0.197]
Imp. Challenge	0.04	0.033	0.027	-0.163	-0.103	-0.077	-0.058	-0.092	2.047**	2.060**	2.037**	1.839**
	[0.309]	[0.309]	[0.310]	[0.321]	[0.422]	[0.417]	[0.421]	[0.435]	[0.568]	[0.563]	[0.566]	[0.558]
Imp. Advancement	0.226	0.227	0.239	0.165	-0.467*	-0.488*	-0.492*	-0.605**	0.342	0.347	0.346	0.319
	[0.172]	[0.172]	[0.176]	[0.183]	[0.217]	[0.220]	[0.218]	[0.222]	[0.178]	[0.179]	[0.178]	[0.164]
Imp. Contr. Society	0.663**	0.665**	0.664**	0.720**	0.494*	0.449*	0.451*	0.305	-0.098	-0.1	-0.099	-0.215
	[0.172]	[0.171]	[0.171]	[0.156]	[0.224]	[0.222]	[0.222]	[0.228]	[0.202]	[0.203]	[0.207]	[0.195]
Share50		-0.313	-0.286	-0.642		-1.797	-1.735	-1.398		-0.282	-0.632	-0.467
		[1.007]	[1.009]	[1.002]		[1.385]	[1.391]	[1.386]		[1.082]	[1.321]	[1.264]
Imp. Salary X Share50			0.931	0.704			0.791	0.133			1.755	2.457
			[1.345]	[1.255]			[1.794]	[1.612]			[2.046]	[1.993]
Applied research				0.071				0.373*				0.263*
				[0.117]				[0.175]				[0.105]
Ln_Publications				0.664**				0.467**				0.461**
				[0.126]				[0.136]				[0.135]
Carnegie II	0.63	0.637	0.625	0.504	-0.66	-0.742	-0.701	-0.455	-0.29	-0.302	-0.315	-0.098
	[0.335]	[0.330]	[0.331]	[0.355]	[0.396]	[0.403]	[0.398]	[0.418]	[0.346]	[0.354]	[0.355]	[0.354]
Doct. Granting	0.181	0.204	0.193	0.144	-0.735	-0.687	-0.693	-0.617	-0.33	-0.325	-0.348	-0.305
	[0.444]	[0.444]	[0.437]	[0.493]	[0.501]	[0.509]	[0.502]	[0.446]	[0.426]	[0.427]	[0.438]	[0.439]
Medical school	0.763**	0.776**	0.781**	0.656**	1.229*	1.095*	1.122*	0.993	0.644	0.638	0.649	0.74
	[0.207]	[0.197]	[0.197]	[0.193]	[0.497]	[0.518]	[0.531]	[0.513]	[0.417]	[0.421]	[0.423]	[0.391]
Private university	-0.327	-0.33	-0.334	-0.505*	0.069	0.192	0.19	0.16	-0.027	-0.006	0.011	0.035
	[0.231]	[0.235]	[0.234]	[0.227]	[0.315]	[0.349]	[0.350]	[0.324]	[0.220]	[0.240]	[0.244]	[0.252]
TTO age	0.01	0.009	0.009	0.01	-0.003	-0.008	-0.008	-0.004	-0.007	-0.008	-0.01	-0.008
	[0.005]	[0.006]	[0.007]	[0.007]	[0.008]	[0.009]	[0.009]	[0.009]	[0.007]	[0.008]	[0.009]	[0.008]
Employer NRC score	0.573**	0.576**	0.577**	0.487**	-0.448*	-0.474*	-0.472*	-0.512*	0.201	0.203	0.199	0.119
	[0.159]	[0.160]	[0.161]	[0.161]	[0.213]	[0.216]	[0.216]	[0.217]	[0.194]	[0.194]	[0.195]	[0.192]
Not tenure track	-0.164	-0.164	-0.163	-0.306	0.374	0.443	0.485	0.596	0.185	0.185	0.199	0.573
	[0.229]	[0.229]	[0.231]	[0.264]	[0.526]	[0.523]	[0.484]	[0.488]	[0.408]	[0.409]	[0.410]	[0.449]
Tenured	0.689**	0.689**	0.695**	0.174	-0.208	-0.221	-0.183	-0.335	0.840*	0.831*	0.858*	0.823*
	[0.234]	[0.233]	[0.234]	[0.252]	[0.476]	[0.473]	[0.447]	[0.473]	[0.347]	[0.351]	[0.349]	[0.364]
PhD NRC score	-0.02	-0.02	-0.016	0.084	0.153	0.15	0.152	0.267	0.244	0.24	0.246	0.307
	[0.147]	[0.147]	[0.147]	[0.159]	[0.191]	[0.192]	[0.193]	[0.191]	[0.167]	[0.166]	[0.168]	[0.171]
Subfield	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Male	0.346	0.351	0.36	0.302	-0.077	-0.032	-0.031	-0.063	0.567	0.586	0.59	0.457
	[0.201]	[0.199]	[0.199]	[0.188]	[0.378]	[0.361]	[0.365]	[0.341]	[0.311]	[0.314]	[0.317]	[0.303]
Age	0.153	0.154	0.157	0.14	0.169	0.187	0.179	0.113	-0.144	-0.141	-0.149	-0.232*
	[0.108]	[0.107]	[0.108]	[0.098]	[0.131]	[0.131]	[0.135]	[0.134]	[0.097]	[0.097]	[0.097]	[0.103]
Age squared	-0.001	-0.001	-0.002	-0.001	-0.002	-0.002	-0.002	-0.001	0.001	0.001	0.001	0.002*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Race	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
US citizen	0.588	0.588	0.599	0.466	0.271	0.262	0.259	0.168	0.685*	0.690*	0.697*	0.626
	[0.342]	[0.343]	[0.341]	[0.411]	[0.475]	[0.462]	[0.460]	[0.457]	[0.334]	[0.337]	[0.338]	[0.372]
Constant	-12.808**	-12.700**	-12.824**	-12.818**	-6.384	-5.962	-6.032	-5.736	-9.494**	-9.526**	-9.188**	-7.253*
	[2.777]	[2.865]	[2.916]	[2.781]	[3.861]	[3.842]	[3.831]	[3.971]	[3.319]	[3.315]	[3.305]	[3.229]
Observations	1037	1037	1037	1037	585	585	585	585	472	472	472	472
alphaest	4.61	4.612	4.614	4.018	5.25	5.152	5.127	4.701	3.751	3.747	3.725	3.4
Chi-Square	133.182	139.877	139.903	173.883	153.124	157.883	156.674	212.57	111.036	110.6	106.305	134.002
df	24	25	26	28	22	23	24	26	24	25	26	28

Note: Negative binomial regression, clustered standard errors. Omitted categories are Carnegie I institution, Tenure track but not tenured. *=significant at 5%; **=significant at 1%.

Table 4: Any Patents

	Life Sciences				Physical Sciences				Engineering			
	1	2	3	4	5	6	7	8	9	10	11	12
	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit	xtlogit
	ANYPATS	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**	**ANYPATS**
Imp. Salary	0.042	0.048	0.055	0.056	0.567*	0.566*	0.552*	0.537*	0.079	0.09	0.143	0.121
	[0.156]	[0.155]	[0.156]	[0.163]	[0.256]	[0.256]	[0.260]	[0.261]	[0.237]	[0.238]	[0.241]	[0.244]
Imp. Challenge	0.071	0.078	0.074	-0.038	-0.076	-0.081	-0.089	-0.08	1.828**	1.865**	1.944**	1.954**
	[0.286]	[0.286]	[0.286]	[0.295]	[0.544]	[0.542]	[0.543]	[0.539]	[0.647]	[0.649]	[0.655]	[0.663]
Imp. Advancement	0.074	0.071	0.076	0.018	-0.178	-0.178	-0.171	-0.252	0.451*	0.461*	0.460*	0.435*
	[0.151]	[0.151]	[0.151]	[0.157]	[0.255]	[0.255]	[0.256]	[0.261]	[0.214]	[0.215]	[0.216]	[0.220]
Imp. Contr. Society	0.601**	0.607**	0.607**	0.655**	0.494	0.494	0.492	0.423	-0.075	-0.091	-0.083	-0.129
	[0.172]	[0.172]	[0.172]	[0.176]	[0.267]	[0.267]	[0.268]	[0.269]	[0.216]	[0.216]	[0.218]	[0.220]
Share50		-1.663	-1.604	-1.665		-0.564	-0.552	-0.375		-1.143	-1.63	-1.53
		[1.018]	[1.030]	[1.060]		[1.575]	[1.580]	[1.577]		[1.260]	[1.325]	[1.356]
Imp. Salary X Share50			1.182	1.205			-0.73	-0.714			5.693*	6.454**
			[1.516]	[1.544]			[2.195]	[2.219]			[2.339]	[2.406]
Applied research				0.029				0.348				0.289*
				[0.118]				[0.188]				[0.135]
Ln_Publications				0.687**				0.301				0.278
				[0.115]				[0.168]				[0.151]
Carnegie II	0.608	0.627	0.625	0.622	0.205	0.186	0.172	0.264	-0.316	-0.364	-0.356	-0.344
	[0.332]	[0.330]	[0.330]	[0.339]	[0.546]	[0.548]	[0.552]	[0.552]	[0.400]	[0.404]	[0.406]	[0.410]
Doct. Granting	0.14	0.178	0.178	0.145	0.35	0.363	0.356	0.336	-0.157	-0.148	-0.227	-0.221
	[0.547]	[0.546]	[0.547]	[0.570]	[0.556]	[0.556]	[0.558]	[0.556]	[0.435]	[0.434]	[0.441]	[0.448]
Medical school	0.512**	0.539**	0.538**	0.471*	0.171	0.166	0.159	0.031	0.3	0.302	0.377	0.356
	[0.194]	[0.194]	[0.194]	[0.199]	[0.485]	[0.485]	[0.485]	[0.487]	[0.421]	[0.422]	[0.430]	[0.439]
Private university	-0.202	-0.174	-0.175	-0.274	0.13	0.152	0.151	0.081	0.127	0.176	0.197	0.17
	[0.220]	[0.217]	[0.217]	[0.224]	[0.375]	[0.378]	[0.380]	[0.376]	[0.270]	[0.275]	[0.278]	[0.280]
TTO age	0.01	0.005	0.006	0.007	-0.004	-0.006	-0.006	-0.005	-0.006	-0.01	-0.012	-0.013
	[0.008]	[0.008]	[0.008]	[0.009]	[0.013]	[0.014]	[0.014]	[0.014]	[0.009]	[0.010]	[0.010]	[0.010]
Employer NRC score	0.300*	0.285*	0.288*	0.253	0.06	0.052	0.052	0.023	0.259	0.261	0.273	0.285
	[0.144]	[0.142]	[0.142]	[0.146]	[0.244]	[0.244]	[0.245]	[0.245]	[0.191]	[0.192]	[0.193]	[0.195]
Not tenure track	-0.542*	-0.539*	-0.532*	-0.443	0.083	0.099	0.094	0.119	-0.083	-0.079	-0.017	0.063
	[0.251]	[0.251]	[0.251]	[0.259]	[0.489]	[0.490]	[0.491]	[0.496]	[0.424]	[0.424]	[0.428]	[0.442]
Tenured	0.149	0.159	0.155	-0.086	-0.221	-0.227	-0.232	-0.273	0.636	0.641	0.718*	0.715*
	[0.257]	[0.257]	[0.257]	[0.265]	[0.488]	[0.488]	[0.489]	[0.490]	[0.346]	[0.348]	[0.352]	[0.357]
PhD NRC score	-0.02	-0.023	-0.019	-0.05	0.036	0.04	0.037	0.091	0.05	0.04	0.045	0.078
	[0.132]	[0.132]	[0.132]	[0.137]	[0.219]	[0.219]	[0.220]	[0.222]	[0.180]	[0.180]	[0.181]	[0.184]
Subfield	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Male	0.146	0.148	0.152	0.049	-0.101	-0.101	-0.1	-0.105	0.495	0.536	0.514	0.426
	[0.186]	[0.186]	[0.186]	[0.192]	[0.397]	[0.397]	[0.398]	[0.395]	[0.341]	[0.344]	[0.348]	[0.352]
Age	0.06	0.064	0.067	0.05	0.23	0.234	0.237	0.203	-0.156	-0.159	-0.194	-0.213
	[0.091]	[0.090]	[0.091]	[0.091]	[0.145]	[0.145]	[0.146]	[0.146]	[0.124]	[0.124]	[0.125]	[0.127]
Age squared	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002	0.001	0.001	0.002	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Race	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
US citizen	0.339	0.331	0.336	0.352	-0.272	-0.28	-0.279	-0.275	1.026*	1.066*	1.103*	1.110*
	[0.379]	[0.379]	[0.379]	[0.392]	[0.509]	[0.509]	[0.510]	[0.506]	[0.467]	[0.470]	[0.475]	[0.479]
Constant	-8.337**	-7.625**	-7.815**	-8.241**	-10.577*	-10.384*	-10.384*	-10.539*	-9.370*	-8.972*	-8.525*	-9.010*
	[2.642]	[2.672]	[2.681]	[2.707]	[4.298]	[4.325]	[4.332]	[4.288]	[4.071]	[4.089]	[4.095]	[4.148]
Observations	1037	1037	1037	1037	585	585	585	585	472	472	472	472
Chi-Square	72.828	75.381	75.791	102.087	59.052	59.1	59.031	62.272	54.463	54.556	57.722	62.826
df	24	25	26	28	22	23	24	26	24	25	26	28

Note: Random effects logit. Omitted categories are Carnegie I institution, Tenure track but not tenured. *=significant at 5%; **=significant at 1%.

APPENDIX

Table A1: Correlations Between Motives by Field

			1	2	3
Full Sample	1	Imp. Salary	1		
	2	Imp. Challenge	-0.0254	1	
	3	Imp. Advancement	0.2984*	0.2179*	1
	4	Imp. Contr. Society	0.02	0.2703*	0.1970*
Life Sciences	1	Imp. Salary	1		
	2	Imp. Challenge	-0.02	1	
	3	Imp. Advancement	0.2541*	0.2416*	1
	4	Imp. Contr. Society	0.0028	0.2996*	0.2123*
Physical Sciences	1	Imp. Salary	1		
	2	Imp. Challenge	-0.0008	1	
	3	Imp. Advancement	0.3585*	0.2088*	1
	4	Imp. Contr. Society	0.0574	0.2086*	0.1422*
Engineering	1	Imp. Salary	1		
	2	Imp. Challenge	-0.0582	1	
	3	Imp. Advancement	0.3046*	0.1939*	1
	4	Imp. Contr. Society	-0.0297	0.3157*	0.2248*

Note: *=significant at 5%

Table A2: Supplementary Analyses – Life Sciences

	Full	Top&Med	Full	Full	No change	L&S2008
	1	2	3	4	5	6
	nbreg	nbreg	xtlogit	xtlogit	nbreg	nbreg
	PATS	**PATS**	**ANYPATS**	**ANYPATS**	**PATS**	**PATS**
Imp. Salary	-0.006	0.022	0.128	0.015	0.47	-0.065
	[0.166]	[0.178]	[0.167]	[0.167]	[0.381]	[0.180]
Imp. Challenge	-0.118	-0.043	0.167	0.075	-2.587**	0.124
	[0.302]	[0.347]	[0.308]	[0.323]	[0.692]	[0.319]
Imp. Advancement	0.181	0.299	0.011	0.06	0.257	0.185
	[0.179]	[0.183]	[0.160]	[0.158]	[0.359]	[0.188]
Imp. Contr. Society	0.630**	0.621**	0.482**	0.735**	1.876**	0.629**
	[0.158]	[0.189]	[0.181]	[0.186]	[0.416]	[0.176]
Share50	-0.802	-0.42		-1.276	-0.859	
	[1.015]	[1.126]		[1.095]	[2.199]	
Imp. Salary X Share50	1.033	-0.122	0.781	-0.079	-2.802	
	[1.280]	[1.515]	[1.748]	[1.503]	[2.758]	
ShareExp.						0.635
						[0.589]
Imp. Salary X ShareExp.						-0.133
						[0.955]
Ln_Employees superv.	0.878**					
	[0.133]					
Employer FE			incl.			
PhD FE				incl.		
Carnegie II	0.487			0.618	0.84	0.747
	[0.341]			[0.340]	[0.509]	[0.469]
Doct. Granting	0.006			-0.316	-15.507**	-0.359
	[0.367]			[0.627]	[0.794]	[0.492]
Medical school	0.678**	0.825**		0.597**	1.736**	0.864**
	[0.172]	[0.195]		[0.208]	[0.410]	[0.218]
Private university	-0.438	-0.280		0.044	-1.575**	-0.241
	[0.224]	[0.247]		[0.225]	[0.457]	[0.274]
TTO age	0.007	0.012		0.003	0.006	0.016*
	[0.007]	[0.007]		[0.009]	[0.013]	[0.007]
Employer NRC score	0.475**	0.519**	0.406	0.212	1.152**	0.423*
	[0.149]	[0.168]	[0.424]	[0.149]	[0.330]	[0.197]
Not tenure track	-0.02	-0.138	-0.525*	-0.477	-0.483	-0.39
	[0.264]	[0.239]	[0.263]	[0.270]	[0.449]	[0.248]
Tenured	0.383	0.743**	0.084	0.031	1.012**	0.495
	[0.245]	[0.244]	[0.271]	[0.276]	[0.326]	[0.261]
PhD NRC score	-0.114	0.011	0.013	-0.189	-0.019	-0.071
	[0.145]	[0.158]	[0.144]	[0.546]	[0.230]	[0.167]
Subfield	incl.	incl.	incl.	incl.	incl.	incl.
Male	0.279	0.304	0.054	0.244	0.275	0.204
	[0.199]	[0.211]	[0.196]	[0.203]	[0.343]	[0.226]
Age	0.023	0.208	0.048	0.096	0.093	0.249*
	[0.112]	[0.118]	[0.096]	[0.099]	[0.136]	[0.108]
Age squared	0.000	-0.002	-0.001	-0.001	-0.001	-0.002*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Race	incl.	incl.	incl.	incl.	incl.	incl.
US citizen	0.22	0.675	0.509	0.464	0.484	0.566
	[0.395]	[0.379]	[0.387]	[0.440]	[1.054]	[0.385]
Constant	-8.342**	-13.967**			-8.477	-14.499**
Observations	1037	908	889	837	332	832
df	27	24	20	26	26	26

Note: Omitted categories are Carnegie I institution, Tenure track but not tenured. *=significant at 5%; **=significant at 1%.

Table A3: Supplementary Analyses – Physical Sciences

	Full	Top&Med	Full	Full	No change	L&S2008
	1	2	3	4	5	6
	nbreg	nbreg	xtlogit	xtlogit	nbreg	nbreg
	PATS	**PATS**	**ANYPATS**	**ANYPATS**	**PATS**	**PATS**
Imp. Salary	0.584*	0.486	0.59	0.552*	1.320**	0.843**
	[0.240]	[0.259]	[0.331]	[0.277]	[0.412]	[0.245]
Imp. Challenge	0.045	0.477	-0.627	-0.258	0.585	0.024
	[0.420]	[0.437]	[0.703]	[0.639]	[0.825]	[0.424]
Imp. Advancement	-0.540*	-0.702**	-0.28	-0.427	-1.121**	-0.449*
	[0.230]	[0.246]	[0.279]	[0.278]	[0.403]	[0.223]
Imp. Contr. Society	0.331	0.536*	0.714*	0.552	0.326	0.275
	[0.218]	[0.257]	[0.356]	[0.305]	[0.442]	[0.257]
Share50	-1.376	-2.015		-0.094	-0.12	
	[1.307]	[1.499]		[1.673]	[2.442]	
Imp. Salary X Share50	0.916	0.322	-0.816	1.052	-2.416	
	[1.743]	[1.790]	[2.743]	[2.422]	[3.961]	
ShareExp.						-0.837
						[1.118]
Imp. Salary X ShareExp.						1.503
						[1.755]
Ln_Employees superv.	0.388**					
	[0.141]					
Employer FE			incl.			
PhD FE				incl.		
Carnegie II	-0.506			-0.296	-0.583	-0.195
	[0.382]			[0.695]	[0.618]	[0.536]
Doct. Granting	-0.534			-0.171	0.025	-0.569
	[0.499]			[0.611]	[0.790]	[0.516]
Medical school	1.126*	0.965		0.279	0.142	1.238*
	[0.533]	[0.556]		[0.583]	[0.602]	[0.585]
Private university	0.257	0.406		0.24	-0.166	0.473
	[0.331]	[0.395]		[0.377]	[0.463]	[0.363]
TTO age	-0.005	-0.019*		-0.017	0.000	-0.008
	[0.009]	[0.009]		[0.016]	[0.020]	[0.008]
Employer NRC score	-0.485*	-0.533*	0.357	0.03	-0.221	-0.642**
	[0.216]	[0.235]	[0.543]	[0.267]	[0.401]	[0.234]
Not tenure track	0.635	0.352	0.59	0.366	1.071	1.113*
	[0.470]	[0.549]	[0.586]	[0.628]	[0.741]	[0.567]
Tenured	-0.263	-0.528	-0.005	0.276	1.381*	0.425
	[0.444]	[0.555]	[0.595]	[0.628]	[0.680]	[0.507]
PhD NRC score	0.181	0.228	0.439	1.151	0.308	0.188
	[0.192]	[0.236]	[0.309]	[0.904]	[0.302]	[0.211]
Subfield	incl.	incl.	incl.	incl.	incl.	incl.
Male	-0.057	0.280	-0.137	0.389	-0.137	0.091
	[0.360]	[0.426]	[0.532]	[0.521]	[0.540]	[0.420]
Age	0.143	0.292	0.211	0.327	0.646**	0.196
	[0.129]	[0.155]	[0.163]	[0.180]	[0.237]	[0.136]
Age squared	-0.001	-0.003	-0.002	-0.003	-0.006**	-0.002
	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.001]
Race	incl.	incl.	incl.	incl.	incl.	incl.
US citizen	0.205	-0.028	-0.243	-0.835	-0.299	-0.121
	[0.444]	[0.500]	[0.613]	[0.582]	[0.660]	[0.500]
Constant	-5.93	-9.975*			-22.544**	-7.740*
Observations	585	459	298	428	175	474
df	25	22	18	24	24	24

Note: Omitted categories are Carnegie I institution, Tenure track but not tenured. *=significant at 5%; **=significant at 1%.

Table A4: Supplementary Analyses – Engineering

	Full	Top&Med	Full	Full	No change	L&S2008
	1	2	3	4	5	6
	nbreg	nbreg	xtlogit	xtlogit	nbreg	nbreg
	PATS	**PATS**	**ANYPATS**	**ANYPATS**	**PATS**	**PATS**
Imp. Salary	-0.087	0.251	0.263	0.141	-0.376	-0.088
	[0.197]	[0.204]	[0.284]	[0.275]	[0.371]	[0.192]
Imp. Challenge	2.027**	1.862**	1.944**	1.490*	14.832**	1.389*
	[0.570]	[0.588]	[0.713]	[0.667]	[0.820]	[0.628]
Imp. Advancement	0.344	0.118	0.342	0.521*	0.663	0.378*
	[0.177]	[0.230]	[0.257]	[0.258]	[0.386]	[0.187]
Imp. Contr. Society	-0.11	-0.217	-0.182	0.048	0.452	-0.059
	[0.212]	[0.270]	[0.287]	[0.257]	[0.453]	[0.290]
Share50	-0.622	-1.693		-1.936	1.949	
	[1.327]	[1.436]		[1.697]	[2.791]	
Imp. Salary X Share50	1.748	2.973	6.672*	5.56	-1.13	
	[2.044]	[2.156]	[3.013]	[2.866]	[4.146]	
ShareExp.						0.647
						[0.897]
Imp. Salary X ShareExp.						1.408
						[1.360]
Ln_Employees superv.	0.05					
	[0.119]					
Employer FE			incl.			
PhD FE				incl.		
Carnegie II	-0.334			-0.573	1.199*	0.112
	[0.344]			[0.576]	[0.517]	[0.467]
Doct. Granting	-0.343			-0.394	0.112	-0.577
	[0.442]			[0.537]	[0.852]	[0.678]
Medical school	0.668	0.539		0.077	1.113*	0.317
	[0.421]	[0.442]		[0.539]	[0.510]	[0.407]
Private university	0.017	0.327		0.437	-0.713	0.192
	[0.245]	[0.290]		[0.339]	[0.372]	[0.297]
TTO age	-0.01	-0.016		-0.015	0.015	-0.003
	[0.009]	[0.009]		[0.012]	[0.015]	[0.009]
Employer NRC score	0.194	0.252	-0.278	0.279	0.479	0.399
	[0.194]	[0.214]	[0.444]	[0.221]	[0.311]	[0.217]
Not tenure track	0.211	0.084	-0.012	0.217	1.287	-0.151
	[0.409]	[0.447]	[0.487]	[0.488]	[0.667]	[0.483]
Tenured	0.870*	0.909*	0.700	0.641	0.838	1.027*
	[0.352]	[0.372]	[0.434]	[0.402]	[0.458]	[0.422]
PhD NRC score	0.242	0.194	-0.252	0.311	0.369	-0.045
	[0.169]	[0.199]	[0.239]	[0.498]	[0.271]	[0.186]
Subfield	incl.	incl.	incl.	incl.	incl.	incl.
Male	0.585	0.642*	0.574	0.516	0.78	0.769*
	[0.321]	[0.324]	[0.423]	[0.391]	[0.456]	[0.341]
Age	-0.151	-0.252*	-0.184	-0.234	-0.281	-0.051
	[0.099]	[0.105]	[0.150]	[0.151]	[0.158]	[0.105]
Age squared	0.001	0.002*	0.001	0.002	0.003	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
Race	incl.	incl.	incl.	incl.	incl.	incl.
US citizen	0.693*	0.472	0.843	1.110*	2.471**	0.306
	[0.334]	[0.376]	[0.523]	[0.557]	[0.668]	[0.471]
Constant	-9.115**	-5.112			-64.541**	-9.768**
Observations	472	351	348	388	165	352
df	27	24	20	26	26	26

Note: Omitted categories are Carnegie I institution, Tenure track but not tenured. *=significant at 5%; **=significant at 1%.