APPENDIX

Not in the job description:
The commercial activities of academic scientists and engineers

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Model

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

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

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

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

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

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 royalty income). To structure the analysis, we assume that $\alpha_r > \alpha_c$, implying that the academic career payoff from academic research is greater than the academic payoff from commercial work. Similarly, we assume $\gamma_c > \gamma_r$, implying that the nonacademic payoff from commercial work is greater than the nonacademic payoff from academic research.

An important feature of our model is that effort dedicated to academic and commercial activity can overlap; as such, effort allocated to commercialization does not necessarily imply a reduction of effort towards academic research by the same amount. The intuition is that – depending on the field – the very same effort that advances commercial objectives may also advance a scientist's academic career. For example, research identifying a cellular target implicated in colon cancer may have considerable commercial value but may also contribute to fundamental understanding and be recognized as an important scholarly contribution.[1] To make this overlap more explicit, we define a fixed *nominal* effort budget, B, and assume that

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

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

[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.

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 and Czarnitzki, 2010). In engineering and the applied sciences, in contrast, a good deal of traditional academic research focuses on the solution of concrete problems and the creation of useful artifacts (Allen, 1977; Dym et al., 2005; Layton, 1976; Vincenti, 1990) such that effort dedicated to academic research is more likely to also yield commercializable outcomes (Crespi et al., 2011; Goldfarb et al., 2009). Consistent with this notion, Cohen et al.'s (2002) survey results show that firms report academic research in engineering and applied science fields to be useful across a much broader range of industries than is the case for research in the physical and biological sciences.[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 and Ohyama, 2013; Roach and Sauermann, 2010; Stern, 2004). Reflecting both types of payoffs as well as the costs of effort, the researcher's utility function can be written as:

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

where β_1 is the researcher's individual preference for academic advancement, A, and β_2 the researcher's preference for the other, nonacademic payoff, O. Following prior work (e.g., Stern,

[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.

2004), we conceptualize preferences as parameters in the utility function such that a stronger preference for a particular payoff increases the utility derived from a unit of that payoff.

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

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

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

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

Measures

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

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

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

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

Supplementary analyses

To examine whether the relationships between motives and patenting may reflect underlying differences in researchers' productivity (e.g., due to ability or different levels of total effort), we include individuals' (ln) number of publications in the regressions (Tables A3-A5, models 1 and 2). The number of publications has a strong positive relationship with PATS in all three fields, consistent with prior work (Azoulay et al., 2009; Stephan et al., 2007).[3] There is also a statistically significant relationship with ANYPAT in the life sciences, though not in the physical sciences and engineering. Most importantly, including these measures does not substantively change the coefficients of motives, although the negative coefficient of advancement motives in the physical sciences becomes even stronger, while the coefficient of advancement and income motives are slightly reduced in engineering.

Economists typically assume that individuals' motives and preferences are stable, and many social psychologists also consider preferences for work attributes to be "trait-like", i.e., relatively stable over time and across contexts (cf. Amabile et al., 1994; Cable and Edwards,

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

2004). It is conceivable, however, that individuals' reported preferences change over time, possibly in response to past decisions or outcomes. Our main strategy to address this issue is to use motives as reported in 2001 as predictors of patenting reported in 2003. In addition, we explicitly examined changes in motives by comparing individuals' responses to the 2001 and the 2003 survey. We regressed the observed changes in motives on PATS as well as ANYPAT as measured in 2001 (detailed results available upon request). Out of 24 coefficients, only two are statistically significant – ANYPAT is associated with a small but significant decrease (not increase) in the importance of contribution to society and challenge in the life sciences ($p<0.05$). We also re-estimated regressions using only those cases who reported no change in any of the motives, focusing on ANYPAT due to the smaller sample size (Tables A3-A5, models 3); the results are in line with our main models (Table 2, models 4-6).

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

To probe why variation in institutionally provided licensing incentives does not seem to influence academics' patenting,[4] 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

[4] 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 patents, or the licensing income per patent. More generally, research on the relationship between licensing incentives and commercial activities provides mixed results (Perkmann et al., 2013). Markman et al. (2004) observed that royalty shares set by universities were negatively related to the number of equity licenses. Markman et al. (2008) compared across universities the share of academic patents that "bypassed" TTOs and found no effect of the share of licensing income going to inventors. These ambiguous findings may reflect that studies examined different outcomes that may relate in distinct ways to licensing incentives. In addition, prior work tends to examine aggregate outcomes at the level of academic institutions while our analysis focuses on the level of individual researchers.

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. This interpretation is consistent with recent survey evidence showing that many faculty members are not familiar with their institution's TTO (Huyghe et al., 2016). It may well be, however, that these shares become more salient once a license is taken out or royalty income is generated, possibly leading researchers to invest more time by working with licensees to increase the value of a license (Jensen and Thursby, 2001; Lach and Schankerman, 2008).[5]

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

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

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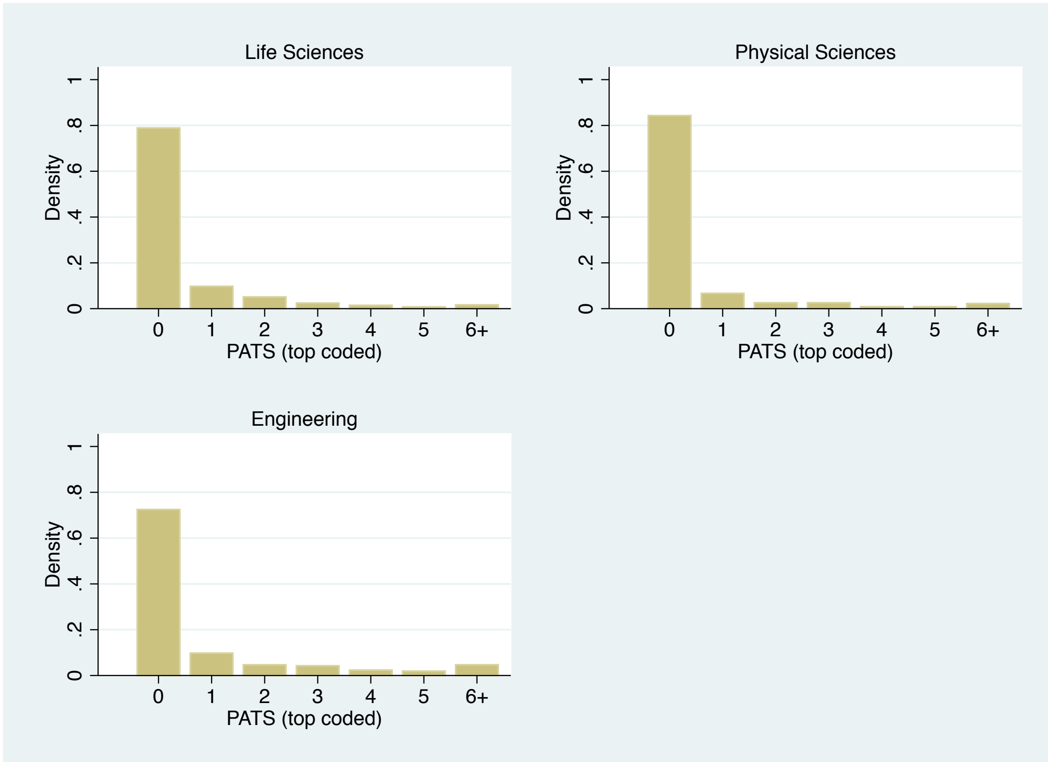
Figure A1: Distribution of U.S. Patent Application Counts (PATS) by Field



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

Table A1: Correlations Between Motives by Field

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

Note: *=significant at 5%

Table A2: Additional Measures

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

Table A3: Supplementary Analyses – Life Sciences

	With publications		No change	With interactions		Univ. fixed effects
	1	2	3	4	5	6
Variable	PATS	ANYPAT	ANYPAT	PATS	ANYPAT	ANYPAT
Imp. advancement	0.378	0.005	0.064	0.309	0.013	0.006
	[0.269]	[0.021]	[0.044]	[0.198]	[0.023]	[0.023]
Imp. income	-0.133	0.007	0.005	0.006	0.004	0.017
	[0.185]	[0.023]	[0.044]	[0.164]	[0.023]	[0.025]
Imp. challenge	-0.211	-0.013	-0.075	-0.015	0.009	0.017
	[0.381]	[0.032]	[0.085]	[0.318]	[0.032]	[0.038]
Imp. contrib. society	0.820**	0.089**	0.101*	0.806**	0.082**	0.078**
	[0.198]	[0.020]	[0.040]	[0.176]	[0.021]	[0.024]
Ln publications	0.748**	0.098**				
	[0.181]	[0.016]				
Motives*Royalty share				incl.	incl.	
Carnegie II	0.765*	0.094	0.179	0.683+	0.091	
	[0.379]	[0.064]	[0.110]	[0.364]	[0.065]	
Doctorate granting	-0.081	0.039	-0.004	-0.052	0.041	
	[0.399]	[0.058]	[0.077]	[0.380]	[0.058]	
Medical school	0.726*	0.065*	0.136**	0.806*	0.077**	
	[0.302]	[0.027]	[0.051]	[0.318]	[0.029]	
Private university	-0.494+	-0.030	-0.132**	-0.380	-0.020	
	[0.282]	[0.032]	[0.047]	[0.277]	[0.033]	
TTO age	0.004	0.001	0.001	0.002	0.001	
	[0.006]	[0.001]	[0.003]	[0.007]	[0.001]	
Royalty share	1.177	-0.269+	-0.310	0.151	-0.228	
	[1.521]	[0.143]	[0.280]	[1.129]	[0.148]	
Not tenure track	-0.231	-0.045	-0.102+	-0.568+	-0.082**	-0.084*
	[0.340]	[0.029]	[0.058]	[0.325]	[0.031]	[0.036]
Dept. NRC score	0.713**	0.036+	0.097**	0.784**	0.043*	0.077+
	[0.268]	[0.019]	[0.033]	[0.266]	[0.021]	[0.045]
PhD NRC score	0.044	-0.004	-0.018	0.111	0.002	0.003
	[0.194]	[0.021]	[0.035]	[0.175]	[0.022]	[0.024]
Male	0.374	0.006	-0.042	0.565+	0.021	0.006
	[0.285]	[0.025]	[0.044]	[0.316]	[0.027]	[0.031]
U.S. citizen	0.557	0.048	0.067	0.347	0.052	0.081
	[0.378]	[0.048]	[0.074]	[0.391]	[0.048]	[0.054]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-12.171**	-0.490+	0.034	-11.169**	-0.389	-0.565+
	[3.163]	[0.260]	[0.623]	[2.746]	[0.267]	[0.303]
Observations	1,037	1,037	332	1,037	1,037	1,037
Log Pseudo-Likelihood	-1270			-1347		
R-squared		0.128	0.201		0.091	0.083

Note: Omitted category is Carnegie I institution. Columns 1 and 4 show estimates from QML Poisson regressions of patent application counts, PATS. Columns 2, 3, 5, and 6 show estimates from linear probability models; the dependent variable ANYPAT takes on the value of 1 if the scientist applied for at least one patent. Robust standard errors in brackets, clustered at the level of the university. +p<0.1, *p<0.05, **p<0.01.

Table A4: Supplementary Analyses – Physical Sciences

	With publications		No change	With interactions		Univ. fixed effects
	1	2	3	4	5	6
Variable	PATS	ANYPAT	ANYPAT	PATS	ANYPAT	ANYPAT
Imp. advancement	-0.727**	-0.026	-0.118+	-0.604**	-0.018	-0.023
	[0.213]	[0.030]	[0.070]	[0.214]	[0.029]	[0.033]
Imp. income	0.390	0.063+	0.175*	0.405	0.066*	0.047
	[0.322]	[0.033]	[0.069]	[0.253]	[0.033]	[0.034]
Imp. challenge	-0.331	-0.000	0.046	-0.359	0.006	-0.053
	[0.299]	[0.048]	[0.178]	[0.303]	[0.049]	[0.061]
Imp. contrib. society	-0.043	0.042*	0.062	-0.101	0.042*	0.057*
	[0.207]	[0.021]	[0.058]	[0.206]	[0.021]	[0.024]
Ln publications	0.516**	0.028				
	[0.158]	[0.018]				
Motives*Royalty share				incl.	incl.	
Carnegie II	-0.134	0.026	-0.034	-0.275	0.014	
	[0.404]	[0.068]	[0.115]	[0.411]	[0.068]	
Doctorate granting	-0.081	0.031	0.019	-0.349	0.033	
	[0.525]	[0.059]	[0.102]	[0.552]	[0.061]	
Medical school	0.988*	0.036	0.062	1.088**	0.040	
	[0.396]	[0.075]	[0.137]	[0.381]	[0.075]	
Private university	-0.036	0.018	0.051	0.034	0.022	
	[0.266]	[0.041]	[0.080]	[0.278]	[0.043]	
TTO age	-0.004	-0.001	-0.001	-0.005	-0.000	
	[0.009]	[0.001]	[0.004]	[0.010]	[0.001]	
Royalty share	-2.675	-0.037	-0.196	-3.497*	-0.069	
	[1.746]	[0.184]	[0.289]	[1.675]	[0.196]	
Not tenure track	0.818*	0.032	-0.004	0.490	0.015	0.014
	[0.405]	[0.044]	[0.078]	[0.407]	[0.043]	[0.050]
Dept. NRC score	-0.166	-0.003	0.012	-0.082	-0.001	0.055
	[0.159]	[0.023]	[0.049]	[0.181]	[0.023]	[0.047]
PhD NRC score	0.154	-0.005	0.001	0.096	-0.007	0.024
	[0.202]	[0.021]	[0.045]	[0.191]	[0.021]	[0.022]
Male	0.316	-0.026	-0.058	0.398	-0.016	-0.029
	[0.338]	[0.038]	[0.077]	[0.362]	[0.037]	[0.038]
U.S. citizen	0.678	-0.029	-0.062	1.136+	-0.026	-0.020
	[0.559]	[0.054]	[0.091]	[0.626]	[0.052]	[0.054]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-1.292	-0.073	-1.704	-0.264	-0.084	-0.042
	[1.999]	[0.349]	[1.204]	[1.859]	[0.351]	[0.370]
Observations	585	585	175	585	585	585
Log Pseudo-Likelihood	-539.9			-546.8		
R-squared		0.164	0.232		0.166	0.161

Note: Omitted category is Carnegie I institution. Columns 1 and 4 show estimates from QML Poisson regressions of patent application counts, PATS. Columns 2, 3, 5, and 6 show estimates from linear probability models; the dependent variable ANYPAT takes on the value of 1 if the scientist applied for at least one patent. Robust standard errors in brackets, clustered at the level of the university. +p<0.1, *p<0.05, **p<0.01.

Table A5: Supplementary Analyses – Engineering

Variable	With publications 1 PATS	2 ANYPAT	No change 3 ANYPAT	With interactions 4 PATS	5 ANYPAT	Univ. fixed effects 6 ANYPAT
Imp. advancement	0.435+	0.067*	0.061	0.532*	0.067*	0.037
	[0.230]	[0.030]	[0.084]	[0.222]	[0.031]	[0.038]
Imp. income	-0.443*	0.007	-0.022	-0.410+	0.028	0.039
	[0.212]	[0.037]	[0.081]	[0.227]	[0.037]	[0.050]
Imp. challenge	1.452*	0.186**	0.247+	2.345**	0.200**	0.195**
	[0.740]	[0.049]	[0.125]	[0.868]	[0.050]	[0.068]
Imp. contrib. society	-0.082	-0.015	0.002	-0.100	-0.010	-0.010
	[0.229]	[0.041]	[0.081]	[0.225]	[0.039]	[0.048]
Ln publications	0.423**	0.038				
	[0.133]	[0.024]				
Motives*Royalty share				incl.	incl.	
Carnegie II	-0.124	-0.051	0.117	-0.230	-0.053	
	[0.516]	[0.058]	[0.097]	[0.496]	[0.056]	
Doctorate granting	-0.948*	-0.023	0.085	-1.000**	-0.040	
	[0.385]	[0.059]	[0.134]	[0.386]	[0.058]	
Medical school	0.093	0.025	0.114	0.093	0.052	
	[0.359]	[0.089]	[0.165]	[0.373]	[0.089]	
Private university	0.348	0.010	0.053	0.449	0.011	
	[0.327]	[0.046]	[0.084]	[0.317]	[0.045]	
TTO age	-0.009	-0.001	0.001	-0.011	-0.001	
	[0.008]	[0.001]	[0.003]	[0.008]	[0.001]	
Royalty share	0.040	-0.065	0.339	-2.792*	-0.155	
	[1.065]	[0.209]	[0.514]	[1.148]	[0.212]	
Not tenure track	-0.150	-0.016	-0.018	-0.540	-0.037	-0.095
	[0.460]	[0.074]	[0.145]	[0.534]	[0.071]	[0.083]
Dept. NRC score	-0.038	0.036	0.082+	-0.046	0.036	-0.055
	[0.167]	[0.030]	[0.048]	[0.156]	[0.029]	[0.065]
PhD NRC score	0.393*	0.024	0.090+	0.409**	0.033	-0.020
	[0.176]	[0.029]	[0.046]	[0.157]	[0.029]	[0.037]
Male	0.619+	0.075	0.019	0.694*	0.079	0.094
	[0.350]	[0.054]	[0.113]	[0.352]	[0.055]	[0.063]
U.S. citizen	0.654	0.176**	0.309**	0.637	0.174**	0.160*
	[0.473]	[0.057]	[0.096]	[0.488]	[0.057]	[0.066]
Age cat. fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Race fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Subfield fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
Exposure	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-10.351**	-1.166*	-1.741+	-12.263**	-1.235**	-0.646
	[3.209]	[0.451]	[0.876]	[3.515]	[0.442]	[0.556]
Observations	472	472	165	472	472	472
Log Pseudo-Likelihood	-787.9			-797.9		
R-squared		0.149	0.222		0.160	0.126

Note: Omitted category is Carnegie I institution. Columns 1 and 4 show estimates from QML Poisson regressions of patent application counts, PATS. Columns 2, 3, 5, and 6 show estimates from linear probability models; the dependent variable ANYPAT takes on the value of 1 if the scientist applied for at least one patent. Robust standard errors in brackets, clustered at the level of the university. +p<0.1, *p<0.05, **p<0.01.