NBER WORKING PAPER SERIES

WHAT MAKES THEM TICK? EMPLOYEE MOTIVES AND FIRM INNOVATION

Henry Sauermann
Wesley M. Cohen

Working Paper 14443
http://www.nber.org/papers/w14443

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2008

We thank the participants in the Duke University's Fuqua School of Business Strategy Seminar, in the "Workshop on Using Human Resource Data from Science Resources Statistics," and in the Sixth Roundtable for Engineering Entrepreneurship Research, as well as participants in seminars at the NBER, HBS, LBS, MIT, RPI, UCLA, INSEAD, the University of Michigan and the University of Bocconi for their comments. We thank especially Jim Adams, Ashish Arora, Scott Cook, Jeff Edwards, Jon Fjeld, Nimmi Kannankutty, Rachel Kranton, Rick Larrick, Mike Lenox, Megan MacGarvie, Will Mitchell, Luigi Orsenigo, Mike Roach, Scott Rockart, Paula Stephan, Scott Stern, and Marie Thursby. Financial support from the Ewing Marion Kauffman Foundation is gratefully acknowledged. We also thank the Science Resources Statistics Division of the National Science Foundation for providing the restricted-use SESTAT database employed in our empirical analysis. However, "the use of NSF data does not imply NSF endorsement of the research methods or conclusions contained in this report." The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

What Makes Them Tick? Employee Motives and Firm Innovation
Henry Sauermann and Wesley M. Cohen
NBER Working Paper No. 14443
October 2008
JEL No. O3,O30,O31,O32

ABSTRACT

We examine the impact of individual-level motives upon innovative effort and performance in firms. Drawing from economics and social psychology, we develop a model of the impact of individuals' motives and incentives upon their innovative effort and performance. Using data on over 11,000 industrial scientists and engineers (SESTAT 2003), we find that individuals' motives have significant effects upon innovative effort and performance. These effects vary significantly, however, by the particular kind of motive (e.g., desire for intellectual challenge vs. pay). We also find that intrinsic and extrinsic motives affect innovative performance even when controlling for effort, suggesting that motives affect not only the level of individual effort, but also its quality. Overall, intrinsic motives, particularly the desire for intellectual challenge, appear to benefit innovation more than extrinsic motives such as pay.

Henry Sauermann
Georgia Institute of Technology
College of Management
800 W. Peachtree St.
Atlanta, GA 30308
henry.sauermann@mgt.gatech.edu

Wesley M. Cohen
Fuqua School of Business
Duke University
1 Towerview Drive
Durham, NC 27708
and NBER
wcohen@duke.edu

1 Introduction

Dating from the 1950's and early 1960's, economists such as Schmookler (1962), Griliches (1957), Nelson (1959) and Arrow (1962) have argued that the rate and direction of technological change could be understood as the outcome of firms' rational, profit-driven investment in innovation. In making the case for the primacy of profit as a driving force behind technical change, economists sensibly focused scholars' attention on firms and their profit incentive since firms are indeed responsible for both a good deal of innovation, and particularly its commercialization. In doing so, they subordinated consideration of the impact of individuals and their motives on technical advance.

Individuals' motives may, however, have important effects on firm innovation. Among economists, Schumpeter (Schumpeter, 1934; 1942) suggests a critical role of individuals' pecuniary as well as nonpecuniary incentives for entrepreneurship and innovative activity. The R&D management literature and case studies also suggest that individuals' various motives have important impacts on innovative activity in firms, and that managers consider the motivation of their personnel a key priority (Cohen & Sauermann, 2007; Katz, 2004; Kidder, 1981; Manners, Steger, & Zimmerer, 1997; Pelz & Andrews, 1976). Recent explanations of the "paradox" of open source software development, namely that programmers develop software code despite the apparent absence of financial gain, have also highlighted the role of individual, and especially nonpecuniary, incentives associated with software innovation (Lakhani & von Hippel, 2003; Lerner & Tirole, 2005; Roberts, Hann, & Slaughter, 2006). Finally, the sociology and economics of science literatures have long featured the importance of individual-level motives such as intellectual challenge, curiosity and peer recognition in affecting the advance of science

(Dasgupta & David, 1994; Merton, 1973; Stephan, 1996; Stephan & Levin, 1992; Zuckerman, 1988).[1]

Although these literatures suggest an important role of individual-level motives and incentives, there is a dearth of large sample empirical research on the importance of individual motives and incentives—especially those which are nonpecuniary—for industrial innovation. We address this gap in this paper. Drawing from economics and psychology, we first develop a simple model of the impact of both pecuniary and nonpecuniary motives on innovation. In our empirical analysis, we describe the motives of over 11,000 scientists and engineers employed in firm R&D in a wide range of industries. Guided by our model, we then examine the relationships between employee motives and, respectively, innovative effort and performance. To prefigure the key results, we find that individual-level motives impact individual effort, but also innovative performance, controlling for effort. The effects of different types of motives (e.g., income vs. intellectual challenge) differ dramatically, however, and also depend on the particular task environment. Overall, the nonpecuniary desire for intellectual challenge appears to have the strongest positive association with both effort and innovative performance.

2 Employee Incentives and Innovation

Our premise is that an individual's motive to perform an activity depends upon the expected pleasurable consequences—or benefits—from engaging in that activity, as well as upon the intensity of her preferences for these benefits. We refer to benefits that are contingent upon individuals' employment, effort, or performance as *incentives*. We refer to individuals' preferences for such contingent work benefits (incentives) as *motives*.

[1] Although typically not concerned with innovation per se, economic theorists have recently expanded their consideration of individual incentives to entertain the implications of agents' nonpecuniary motives for institutional design and performance (Akerlof & Kranton, 2005; Besley & Ghatak, 2005; Lacetera & Zirulia, 2008; Murdock, 2002).

Individuals may respond to a wide range of contingent benefits such as pay, intellectual challenge, or peer recognition. Clearly, one might distinguish between nonpecuniary and pecuniary benefits. The psychology literature proposes a different (though related) distinction, classifying benefits and motives as either extrinsic or intrinsic (Amabile, 1996; Gagne & Deci, 2005; Ryan & Deci, 2000). *Extrinsic benefits* are provided by some environmental entity such as a market or actor such as an employer, a superior, or a judging body, and they are typically conditioned upon an evaluation of an individual's effort or task outcome. Extrinsic benefits do not result directly from engaging in the task, but are indirect task outcomes. Extrinsic benefits are those often considered by economists, and within this class of benefits, economists typically focus on pecuniary benefits, which would include tangible rewards such as pay raises, research funding, or a paid vacation. In contrast, *intrinsic benefits* originate within the individual or the activity itself—not the environment—and often reflect an interaction between particular characteristics of the activity (e.g., challenge of the task) and of the individual (e.g., interest in the task).[2] Some intrinsic benefits such as task enjoyment and intellectual challenge are effort-contingent, realized directly from the process of engaging in certain activities (Amabile, 1996; Stephan, 1996). Others such as a feeling of achievement or mastery result from task performance or outcomes.

The nature of individuals' motives and incentives may have implications for both levels of effort as well as the quality or productivity of that effort. Assuming that R&D employees have some discretion over how much they actually work, stronger extrinsic and intrinsic motives and

[2] This implies that many intrinsic benefits are subjective and do not exist independently from a reference individual. A given work attribute may provide an intrinsic benefit in the eyes of one employee but not of another; for example, working on a particular research question may appear interesting to one researcher, thus conferring intrinsic benefits, while boring another.

incentives should influence the level of innovative effort. The interesting question is the relative magnitude of the effect of different motives and incentives on effort.[3]

The effects of different types of motives and incentives on the *quality* or *productivity* of effort are less obvious. Camerer and Hogarth (1999) report that pecuniary incentives in laboratory settings improve some features of individuals' cognition, including memory, recall and simple problem-solving functions, with the extent of such effects depending upon the nature of the task at hand and the capabilities of the individual. Considering the impact of the nature of motivation on creativity, Amabile and colleagues argue that intrinsic motivation may stimulate creativity by supporting riskier, more exploratory thinking while extrinsic rewards may undercut creativity by focusing individuals' attention on more expedient, more incremental approaches to solving problems. At the same time, however, some types of extrinsic rewards may complement intrinsic motivation by providing positive feedback (e.g., idea validation) (Amabile, 1996; Amabile, 1993; George, 2007; Hennessey & Amabile, 1998). In addition to possible effects on cognition, individuals' motives may also affect research productivity by driving or inhibiting intermediate behaviors, such as information sharing or project selection. For example, a scientist's preference for intellectual challenge may drive her to select more challenging, and thus potentially more technologically significant projects. Alternatively, someone whose work is motivated by the desire to minimize the risk of failure may select more incremental tasks with

[3] Deci and Ryan and others argue that extrinsic rewards may "crowd-out" intrinsic motivation (Deci, Koestner, & Ryan, 1999; Deci & Ryan, 1985; Frey & Jegen, 2001), possibly reducing overall levels of effort. While our results may reflect such a crowding out effect, crowding out is not the focus of this paper.

more certain outcomes, and may thus be less likely to achieve technologically significant results (cf. Dunbar, 1995).[4]

We conjecture that the productivity effects of motives may depend on the type of task. For example, individuals' choices over intermediate behaviors may matter primarily in upstream basic and applied research where they have more latitude in determining how they approach their work (cf. Fox, 1983; Holt, 1974). Similarly, the effects of motives on cognition should matter more in upstream research activity requiring more creativity or problem-solving capabilities.

The effects of motives and incentives on innovation have been little explored in real work settings using large sample empirical analysis. One exception is Stern's (2004) finding that new biology PhDs taking jobs in industry were willing to accept, on average, 25% lower salaries if prospective employers allowed them to pursue more academic-like science, to publish and participate in the scientific community, suggesting that these researchers were willing to pay to have the opportunity to pursue nonpecuniary goals. Consistent with the idea of "productivity effects" of motives (as well as higher effort levels due to stronger motives), Gambardella et al. (2006) observed that European inventors whose patenting was motivated by money, career, and prestige concerns tended to produce more valuable patents.

In this paper, we will examine the relationship between individuals' motives and their innovative effort and performance, using a sample of over 11,000 R&D employees spanning the manufacturing and service sectors.

[4] Manso et al. provide a complementary perspective on the selection of research approaches. Focusing on incentives rather than motives, they suggest that long-term financial incentives may lead individuals to adopt more exploratory approaches to addressing technological challenges, while short-term financial incentives may encourage individuals to adopt more incremental approaches (Ederer & Manso, 2008; Manso, 2006).

2.1 Model

We assume that the utility a researcher realizes from her effort is a function of the cost of that effort and of the *m* different types benefits, B^k, *k=1…m*, that result from that effort. Each type of benefit from work can have a component that is contingent upon the quantity of effort, *E*, and a component that depends upon innovative output, *Q*, which one can think of as some quality adjusted number of inventions.[5] Accordingly,

$$B^k = B^k(E, Q), \tag{1}$$

where $\partial B^k/\partial \mathrm{E} \equiv B^k_E \equiv \alpha^k \geq 0$, and $B^k_Q \equiv \gamma^k \geq 0$. The variables α^k and γ^k reflect the *incentives* (i.e., contingent benefits) facing the researcher, and we assume that $\alpha^k_E \leq 0$ and $\gamma^k_E \leq 0$. The subutility U^k derived from a particular type of benefit B^k is

$$U^k = U^k(B^k;\ I^k), \tag{2}$$

where $U^k_{B^k} = I^k \geq 0$. I^k reflects an individual's motives—her intensity of preference for a given benefit, and a stronger motive of a particular type, *k*, increases the individual's marginal utility derived from the associated *k*'th benefit. For simplicity, we assume motives and incentives to be exogenous.

The researcher also incurs a cost of effort,

$$C = C(E), \tag{3}$$

where $C_E > 0$ and $C_{EE} > 0$.

---

[5] Benefits may also have a component that is contingent only upon employment in a particular job (e.g., fixed salary). However, since employment-contingent benefits do not affect optimal effort or performance in our model, we focus on effort and performance contingent benefits. Also, while our model allows all types of benefits to be contingent upon both effort and performance, any given type of benefit may be predominantly contingent upon one of these. For example, the utility derived from intellectual challenge is primarily effort contingent whereas peer recognition will be primarily performance contingent.

The researcher's output, Q, is a function of her effort as well as her productivity (i.e., Q_E). We assume innovative productivity to be a function of a vector $\mathbf{T}$ of industry characteristics (e.g., technological opportunity), firm characteristics (e.g., size, resources, organizational structure, etc.), and individual characteristics (e.g., ability). In addition to motives ($\boldsymbol{I}$) and incentives ($\boldsymbol{\alpha}, \boldsymbol{\gamma}$) affecting the level of effort, we also allow them to affect productivity such that:

$$Q = Q(E; \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{\alpha}, \boldsymbol{\gamma}), \tag{4}$$

where $\partial Q/\partial \mathrm{E} \equiv Q_E > 0$ and $Q_{EE} \leq 0$. In Section 2 above, we suggest that the "productivity effects" of particular motives and incentives (e.g., $\frac{\partial Q_E}{\partial I^k}$) may be positive or negative. For example, while desire for intellectual challenge may stimulate innovative productivity, the desire to minimize the risk of failure may have the opposite effect. We also hypothesized that the magnitude of the effect of motives on productivity is likely to depend upon the nature of the task—whether it affords more discretion, or demands greater creativity.

We will now assume that the researcher has unbiased expectations of her productivity as well as of the effort and performance contingent benefits and chooses a utility-maximizing level of effort, E^*. Assuming that the subutilities enter additively, the total utility function is:

$$U = \sum_{k=1}^{m} U^k \left(B^k\big(E, Q(E;\, \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{\alpha}, \boldsymbol{\gamma})\big)\right) - C(E). \tag{5}$$

Assuming (5) to be concave in effort over the relevant range, the optimal amount of effort E^* is implicitly defined by the first order condition:

$$\frac{\partial U}{\partial E} = \sum_{k=1}^{m} I^k(\alpha^k + \gamma^k * Q_E) - C_E = 0. \tag{6}$$

Applying the implicit function theorem to (6) shows, first, that optimal effort, E^*, decreases in the marginal cost of effort, C_E. Second, optimal effort is a positive function of Q_E

and thus of the factors that drive innovative productivity. Third, and of particular importance for our empirical analysis below, (6) also implies that:

$$\frac{\partial E^*}{\partial I^k} = -\frac{\alpha^k + \gamma^k Q_E + I^k \gamma^k \frac{\partial Q_E}{\partial I^k}}{I^k(\alpha_E^k + \gamma_E^k Q_E + \gamma^k Q_{EE}) - C_{EE}}. \qquad (7)$$

The denominator in (7), which is the second order condition, is negative by assumption. The numerator shows that the qualitative effect of I^k on E* depends on the productivity effects of motives, $\frac{\partial Q_E}{\partial I^k}$, since, of all the terms in the numerator of the right hand side of equation (7), only $\frac{\partial Q_E}{\partial I^k}$ can be negative. Thus, the effect of a particular motive I^k on optimal effort is negative if and only if I^k has a sufficiently large relative negative effect on productivity. Finally, equation (7) also shows that the effect of I^k on optimal effort is conditioned by the associated incentives, α^k and γ^k.[6]

In addition to addressing the effects of motives on innovative effort, our model also speaks to the determinants of innovative output, Q. It is trivial to see that effort will positively affect output. As suggested by our discussion of equation (4), we also expect motives to affect innovative output even controlling for effort. However, this qualitative effect of motives on productivity may differ, depending upon the specific motive. For example, as noted above, a desire for challenge may be associated with greater productivity, while the desire to minimize the risk of failure may reduce it.

[6] Although we do not empirically consider the impact of incentives on effort due to data limitations, it is easy to show, with application of the implicit function theorem to (7), that the qualitative effects of incentives, α^k and γ^k, on effort depend on their productivity effects. Specifically, if a given incentive has no negative productivity effects, then increasing it will yield higher effort. Similar to the result regarding the effect of a given motive, if the productivity effect of an incentive is negative and sufficiently large, then increasing that incentive will diminish effort.

In the following, we examine the impact of individuals' motives on innovative effort and performance empirically. Since we are unable to estimate the model directly given our data, we will test its qualitative implications. Just as importantly, the model also guides our interpretation of the results.

3 Data

For our empirical analysis, we use restricted-use data from the 2003 Scientists and Engineers Statistical Data System (SESTAT). The SESTAT database is maintained by the NSF (National Science Foundation, 2003) and the sample population includes individuals who have a science, engineering or related degree or who worked in a science, engineering or related occupation at the time the data were collected. Most data were collected via a mailed questionnaire; a smaller number of surveys were administered by computer-aided telephone interviews, in-person interviews, and via the internet. Response rates for the three component surveys ranged from 60-80%.[7]

We focus on a sample of 11,014 SESTAT respondents who possess Bachelors, Masters, or PhD degrees, and are employees of private for-profit firms active in a wide range of industries (see Table A1 in appendix). A majority of our respondents—6,049, or 54.9%—work in manufacturing, though a sizable minority—4,373 or 39.7%—work in services, with 1,496 respondents in R&D services. We include only respondents whose primary work classification is basic research, applied research, development, design, or computer applications; the distribution of respondents across these work types is shown in Table 1. Note that 3,649 respondents, or 33.1%, work in computer applications. Also, only 381, or 3.5% of the sample, work in basic

[7] For more information on the SESTAT data, including the survey instruments, see http://sestat.nsf.gov.

research, a proportion which is comparable to the share of R&D firms spend on basic research in the U.S. more generally (cf. National Science Board, 2008).

We were able to obtain two important additional control variables—firm identities and the school awarding the respondent's PhD (employed below as a proxy measure for ability) — for a subset of our respondents comprised entirely of PhDs (n=2,805). We use this subsample ("PhD-sample") in a series of robustness checks. Apart from the fact that the PhD-sample is comprised entirely of PhDs, the key difference between the two samples is that the PhD-sample has relatively fewer respondents in design and computer applications (see Table A2 in appendix).

4 Measures

Unless otherwise indicated, all measures are taken from respondents' survey questionnaires and are included in the SESTAT database. As we show below, the SESTAT data provide some unique measures reflecting a wide range of motives, as well as measures of our two key dependent variables, innovative effort and performance. Descriptive statistics for all measures are shown in Table 1; correlations are shown in Table A5 in the appendix.

Dependent Variables: Innovative Effort and Performance

<u>Quantity of effort:</u> Respondents reported the number of hours they work on their main job in a typical work week (continuous measure). We use this measure as a proxy for the quantity of effort dedicated to innovation (HRSWORKED). Mean effort in our sample is 45 hours, with a range of 35 - 96.

<u>Innovative Performance:</u> Each respondent reports the number of U.S. patent applications in which he or she was named as an inventor over the last 5 years prior to the survey (USPAPP). The average number of U.S. patent applications per respondent over the prior five years is 1.2. Patent application rates are considerably higher in basic research (1.44), applied research (2.53)

and development (1.67) than in design (0.77) and computer applications (0.23). The distribution is highly skewed with only 24% of cases reporting any applications, and only 10% reporting more than 2 applications.

Patent application output is an imperfect measure of innovative performance. First, not all inventions are patented (Cohen, Nelson, & Walsh, 2000). Thus, as discussed below, we include several industry and firm level variables to control for the likelihood of whether a given invention is patented. Another recognized limitation is the enormous variability in the technical importance and economic value of patented innovations. To assess the robustness of our results to this latter limitation, we also employ the self-reported number of granted patents (mean 0.60). Even more revealing, another alternative measure is the number of granted patents licensed or resulting in a commercialized product (mean 0.26) because such patents would tend to reflect more valuable inventions (see appendix).

Featured Independent Variables: Motives (Preferences for Work Benefits)

Our measure for motives (I^k in our model) are respondents' ratings of the importance of eight work benefits in response to the following question: "When thinking about a job, how important is each of the following factors to you . . ."   The importance of each benefit was scored on a 4-point scale anchored by 1 (very important) and 4 (not important at all); for ease of interpretability, we reverse coded these items such that higher scores indicate higher importance. The eight work benefits and their associated motives are: salary (IMP_SAL), fringe benefits (IMP_BEN), job security (IMP_SEC), intellectual challenge (IMP_CHAL), independence

(IMP_IND), opportunities for advancement (IMP_ADV), responsibility (IMP_RESP), and contribution to society (IMP_SOC).[8]

The means and standard deviations for the motive measures are reported in Table 1. The correlations between the eight motives vary considerably, ranging from -0.01 to 0.50, with only about a third exceeding 0.30. Relatively low mean correlations suggest that the eight measures reflect distinct constructs and are not obviously subject to a common methods bias.[9] We report more detailed analyses of the preferences measures in the appendix, including a factor analysis and comparisons of motives across different types of individuals.

Additional Measures

The table below briefly describes the other variables and associated measures employed in our analyses.

Variable Name	**Measure Description**
Determinants of R&D productivity	
Industry classification (IND_NAICS)	Dummies for 28 industries (2- to 4-digit NAICS classification). Industry dummies are intended to control for differences in technological opportunity and other industry-level conditions affecting R&D productivity, as well as for cross-industry differences in patent propensities (Cohen et al., 2000).
Employer firm size (EMSIZE)	Respondents were asked to estimate the number of employees in their firm in all locations. We represent their categorical responses by a set of dummy variables: EMSIZE1: 10 or fewer employees; EMSIZE2: 11-24; EMSIZE3: 25-99; EMSIZE4: 100-499; EMSIZE5: 500-999; EMSIZE6: 1000-4999; EMSIZE7: 5000-24999; EMSIZE8: 25000+ employees.
Firm age (NEWBUS)	Dummy = 1 if firm was founded within the last five years

[8] As discussed below, while providing rich data on researchers' motives, the available measures are limited. For example, our interviews have suggested two other motives that may importantly affect R&D employees behavior—the desire to solve practical problems and the desire to contribute to a project team.
[9] Self-reported motives may be affected by social desirability bias (Moorman & Podsakoff, 1992). Such a bias is problematic for our econometric analysis if it affects the correlations between motives and outcome measures. While we cannot explicitly assess the presence of social desirability bias in our data, we see no compelling reason to expect a significant bias.

Firm fixed effects (EMPLIDCT)	Employer names are available for our PhD-sample. We created a set of 122 dummy variables to control for firm fixed effects for each firm that had at least 5 individuals in our PhD-sample (EMPLIDCT5).
Primary work type (WAPRI)	Respondents indicated on which of a list of work activities they spend the most hours during a typical work week.
Non-R&D activities (WA_NONRD)	Respondents indicated which of a list of 9 non-R&D work activities (accounting, employee relations, management, production, professional services, sales/marketing, quality management, teaching, other) occupied more than 10% of their time. We summed the number of these activities to control for time spent on non-R&D activities that are not expected to result in patent applications.
Highest degree (DEGREE)	Dummy coding for Bachelors, Masters, and PhD
Ability (ABILITY)	For our PhD-sample, we had the names of the PhD-granting institution. We matched these institution names and the PhD field to the National Research Council's evaluation of PhD program quality (Goldberger, Flattau, & Maher, 1995). The particular quality measure used is a survey rating of "program effectiveness in educating research scholars and scientists". The scale ranges from 0 ("not effective") to 5 ("extremely effective"). While this measure formally captures the quality of an individual's graduate education, it is also likely to reflect innate ability to the extent that high-ability individuals self-select or are selected into high-quality PhD programs.
Field of highest degree (HD_FIELD)	Dummy coding for 16 fields (biology, health/medical sciences, food sciences, chemistry, physics, earth sciences, computer science, materials science, metallurgical engineering, aerospace/astronautical engineering, computer engineering, electrical engineering, mechanical engineering, other engineering, mathematics, other).
Experience (HDTENURE, HDTENURE_SQ)	Time since obtaining highest degree, in years. Serves as measures of field-specific skills and knowledge. In addition, this measure could also capture cohort effects (Stephan, 1996). We also have measures of individuals' age and tenure in the current job. Since both variables are highly correlated with HD_TENURE, we only include the latter in our key regressions. Robustness checks using age and job tenure show very similar results.
Relevance of education (JOBDEGREE)	Extent to which the current work is related to the field of the highest degree, 3-point scale; serves as measure of relevance of the skills and knowledge acquired during academic training.
Control variables	
Salary (LN_SALARY)	Respondents reported their current basic annual salary, not including bonuses or overtime compensation. The salary distribution is highly skewed and we use the natural log of this variable in our econometric analyses (LN_SALARY). Since base salary is not predicted to affect effort or performance in our model, we use it only as a control variable.
Research sensitivity (GOVT_DOD, GOVT_NASA)	Two dummy variables indicating whether the individual's work was supported by a contract with / a grant from the U.S. department of defense or the NASA. We expect that findings resulting from such work are less likely to be disclosed in patent applications.

Managerial status (LN_SUPDIR)	Natural log of the number of people the respondent supervises directly.
Gender (MALE)	Dummy =1 if respondent is male
Race (RACE)	Dummies for white, Asian, black, other
US citizenship (USCITIZEN)	Dummy = 1 for U.S. citizens
Marital status (MARRIED)	Coded 1 for individuals who are married or living in a marriage-like relationship. Married individuals presumably have more family obligations than individuals who are not married. This variable serves as a proxy for time constraints in our effort regressions.
Children (CHILDREN011)	Count of children under the age of 12 living in the same household as the respondent. This variable serves as a proxy for time constraints in our effort regressions.

5 Specifications and Estimation

5.1 Specifications

We estimate two sets of regressions, distinguished by the two dependent variables: 1.) Innovative effort, measured by HRSWORKED; and 2.) innovative performance, measured by USPAPP. In the effort regressions, we regress HRSWORKED on measures of: 1.) motives 2.) variables affecting individuals' average productivity, and 3.) control variables. Contrasting this specification with our theoretical model suggests several important differences that affect the interpretation of our results. First, we do not have measures for the incentives facing our respondents (α^k and γ^k in our model). Since incentives condition the effect of motives on optimal effort (see equation 7 above), a lack of measures for incentives implies that estimated coefficients of the motives (I^k) reflect a compound effect of the motives and of the unobserved incentives. Our qualitative predictions for the effects of the motives should, however, still hold as long as the motives and associated incentives are either uncorrelated or positively correlated. The latter can be expected in light of research suggesting that individuals self-select into organizations offering benefits that "fit" their preferences (Cable & Edwards, 2004; Holland, 1997; Sauermann, 2005), suggesting a positive relationship between benefits and the respective motives, and, as a consequence, between incentives and motives. Second, our model also predicts an interaction between the determinants of R&D productivity and individuals' motives. We estimated multiplicative models, but the interactive terms were never significant. Thus, we focus on main effects alone.

In our performance regressions, we regress patent applications (USPAPP) on measures of 1.) motives 2.) effort 3.) variables affecting individuals' productivity and 4.) control variables. For the full sample, we focus our discussion on additive specifications of the performance regressions since interaction terms including effort and various productivity determinants turned out to be insignificant. Consistent with our model, however, the interaction between effort and ability is significant in the PhD-sample where a better measure of ability (quality of graduate education) is available.

5.2 Estimation Issues

5.2.1 Distribution of Dependent Variables

Our sample includes only individuals who are full-time employees, defined as working an average of at least 35 hours per week. Since OLS can produce inconsistent results for truncated dependent variables, we feature truncated regression in our analysis of effort.

The number of U.S. patent applications filed over the prior five years (USPAPP) is a discrete measure of innovative performance and, as noted above, has a skewed distribution with only 24% of our respondents having one or more patent applications. A family of count models that accounts for skewed count outcomes and also allows for different processes generating zero counts are zero-inflated negative binomial (ZINB) models (Cameron & Trivedi, 1998). Estimating a ZINB model amounts to simultaneously estimating two regression models. One model is a logit predicting membership in an "always-0" group, where individuals are not at risk of patenting (e.g., because of the nature of their work or because of firm policies regarding secrecy). The other is a negative binomial model for those cases that are not in the "always-0" group. In our ZINB models, we excluded several individual-level variables, such as our preference measures, HDTENURE, and LN_SUPDIR from the logit component, emphasizing the role of firm characteristics (firm size, startup status, industry) and individuals' type of work, field of highest degree, and type of degree in affecting the likelihood of an individual being at risk of patenting. In addition, the logit component includes two dummy variables indicating whether the individual's research was funded by a contract with or grant from the Department of Defense or the NASA. All count models are adjusted for exposure time because some respondents have fewer than five years work experience.

5.2.2 Endogeneity

The cross-sectional nature of our data warrants careful consideration of endogeneity, especially with respect to individuals' motives. Economists routinely assume individuals' motives and preferences to be exogenous and stable, and many social psychologists consider preferences for work attributes to be "trait-like"—i.e., relatively stable over time (cf. Amabile, Hill, Hennessey, & Tighe, 1994; Cable et al., 2004). It is, however, conceivable that individuals' reported preferences change in response to realized performance and benefits. For example, individuals may rationalize the receipt of little financial reward from their innovative efforts by reporting that such rewards matter little to them (cf. Festinger, 1957). To investigate this possibility with respect to the one type of preference where we have some data on the actual level of the benefit (though not so clearly a contingent benefit), we examined the correlation between the importance of salary (IMP_SAL), the satisfaction with salary,[10] and actual (logarithmized) salary levels (LN_SALARY). IMP_SAL and LN_SALARY are not significantly correlated ($r=-0.01$, n.s.), while the correlation between satisfaction with salary (SAT_SAL) and LN_SALARY is positive and highly significant ($r=0.19$, $p<0.001$). These correlations suggest that, while satisfaction with a particular benefit may depend on its level, the rated importance of the benefit—i.e., the motive—is largely exogenous. We will consider the potential for endogeneity of motives in more detail below.

With innovative effort (HRSWORKED) on the right hand side of our performance regressions, we consider the possibility that innovative effort may be endogenous with respect to realized performance. According to our model, effort is exogenous with respect to *realized* performance, but is endogenous with respect to *expected* performance to the extent respondents believe future performance is associated with performance-contingent benefits. Thus, HRSWORKED may be endogenous in these regressions if individuals' expectations with respect to benefits and performance are influenced by their past performance. Using CHILDREN011 and MARRIED as instruments for effort, we did not find evidence for endogeneity of HRSWORKED in any of our performance regressions.[11]

---

[10] Our respondents reported their satisfaction with the eight work benefits in their current job. While satisfaction will generally be a positive function of realized benefits, it is a complex psychological construct, which is still not well understood (Cable et al., 2004; Judge, Thoresen, Bono, & Patton, 2001). Thus, we do not use satisfaction scores as measures of either the level of benefits or of incentives in our empirical analysis.

[11] We tested for endogeneity by including the residual from an OLS first-stage effort regression into different specifications of second-stage performance regressions (Wooldridge, 2001). The instruments for effort, CHILDREN011 and MALExCHILDREN011, are jointly significant ($F(2,10936)=11.31$). We estimated performance regressions using Poisson, negative binomial, and zero-inflated negative binomial models with robust as well as bootstrapped standard errors. The first-stage residual was never significant ($Chi2(1)=1.69$, $p=0.19$ for the NBREG case). Given this result and given the lack of an appropriate instrument for performance, we did not estimate the effort and performance regressions simultaneously as a system.

6 Results

6.1 Effort

Table 2 reports the results of our effort regressions. Column 1 shows the results of a regression of HRSWORKED on the variables conditioning productivity and other controls. In model 2, we add our measures of respondents' motives. Four of the measures have significant effects on effort. The measure of the desire for intellectual challenge (IMP_CHAL) has the strongest positive effect, followed by the importance of responsibility and independence. What is notable about these results is the dominance of an intrinsic motive—desire for intellectual challenge.

In addition to these positive effects, we observe a significant negative coefficient for the importance of salary. According to our model, such a negative coefficient would be expected only if the salary motive also has a strong negative effect on productivity. However, as our performance regressions below show, the productivity effect of the salary motive is actually positive. Thus, a more likely explanation for the negative effect of the salary motive on effort is that the importance of salary reported by individuals reflects their opportunity cost of time, which should have a negative effect on effort. We should, however, not make too much of this negative coefficient because it is observed only for non- PhDs (cf. Table A6).[12]

While our model does not predict an effect of basic (non-contingent) salary on individuals' effort, we also estimated an effort regression including LN_SALARY as an

[12] In order to address high correlations between some of the preference measures, we also estimated the truncated regression models with one preference measure at a time. All eight measures are individually significant, with negative effects of the importance of salary, benefits, and job security, and positive effects of the other five measures. On the basis of the model reported in Table 2, col. 2, we also tested various subsets of coefficients for joint significance. The measures of the importance of salary, job security, and fringe benefits correspond to the class of extrinsic motives; these three measures are jointly highly significant (Chi2(3)=38.94, p<0.001). Of the remaining five preference measures, the importance of challenge, independence, and advancement map most clearly to intrinsic factors; these 3 measures are also jointly significant (Chi2(3)=40.30, p<0.001).

additional control (model 3). Its inclusion yields slight changes in the coefficients of the measures of some motives, but the qualitative results remain unchanged. The negative effect of IMP_SAL becomes even stronger. Salary itself has a large positive coefficient. However, we are cautious in interpreting this result since we do not have adequate instruments to address potential simultaneity between effort and salary.

We conducted robustness checks involving different estimation methods as well as different subsamples (see appendix). The positive effects of the importance of challenge as well as responsibility are very robust, while the effects of the importance of independence and salary are fragile. Also, using the limited sample of PhD respondents, we were able to include a much better control for ability. These results show ABILITY has the expected positive effect on effort. Most importantly, the inclusion of this measure has no noticeable effect on the estimated coefficients for our motive variables.

Finally, the coefficients of some of our control variables also deserve attention (Table 2, model 2). For example, we find that the amount of time spent on the job increases with the number of different (non-R&D) tasks the individual regularly performs (WA_NONRD). Also, women with children between the ages of 0 and 11 work significantly fewer hours than individuals without children. PhDs spend more time on the job than respondents with either Masters or Bachelor's degrees. Finally, our results suggest that effort varies significantly by firm size and firm age. These differences in motives and effort across firm types are examined in more detail in a companion paper (Sauermann & Cohen, 2007).

6.2 Innovative Performance

6.2.1 Main Analyses

Our model predicts that individuals' motives may affect innovative output even controlling for the quantity of effort ("productivity effects"). We examine these relationships in a series of zero-inflated negative binomial regressions reported in Table 3. Model 1 includes only our control variables. We observe that PhDs have a significantly larger number of patent applications than non- PhDs and that individuals engaged in applied R&D have more patent applications than individuals in development (omitted category). Individuals engaged in computer applications and systems design have the lowest number of patent applications. The number of patent applications also increases with the number of subordinates (LN_SUPDIR). Finally, while the relevance of training (JOBDEGREE) has a small positive coefficient, time since graduation (HDTENURE) is insignificant.[13] Column 1b shows the results of the logit component of the zero-inflated negative binomial model.[14]

In model 2, we include our measures of individuals' motives. The coefficients on these measures reflect the "total effect" of motives and preferences on performance since the specification does not yet include effort, which should play a mediating role. The importance of challenge and independence as well as that of salary have significant positive effects. With a significantly larger coefficient than that for IMP_SAL ($p<0.05$), a one-SD higher score on the challenge measure, IMP_CHAL implies a 19.8% higher expected patent count, while the same

[13] We also have a measure of the respondent's tenure in the current job, potentially reflecting the amount of job-specific human capital (JOBTENURE). When included in addition to the (highly correlated) measure HDTENURE, JOBTENURE has a positive effect on performance, while having a negative effect on innovative effort.

[14]Recall that the logit regression predicts membership in the "never patenting" group, i.e., positive coefficients indicate a lower likelihood of patenting. As expected, Masters and PhDs are more likely to patent than are Bachelors (omitted category) and individuals in basic research, design, and computer applications are less likely to patent than individuals in development.

change in the preference for salary implies a 9.2 % higher expected count. Recall, however, that these estimates are likely to reflect compound effects of both individuals' motives and of the associated unobserved incentives. The positive effect of IMP_SAL on performance is notable given its negative effect on effort. One interpretation is that individuals who care much about salary find ways to use their time more efficiently, e.g., by reducing the time of "unnecessary" tinkering and focusing on producing patentable output. Another finding is that the importance of job security (IMP_SEC) is negatively related to performance, with a one-SD higher score on the job security measure implying an 11.9% lower expected patent count. Note that the effect sizes of some of the measures of motives are considerably larger than those of our measures of experience (HDTENURE, JOBDEGREE) and, in the sample of PhDs, comparable to the effects of ABILITY (see appendix). Although relative magnitudes of the these effects depend strongly on the reliability and validity of measures, these results suggest that individuals' motives may be at least as important for performance as knowledge and experience.

In model 3, we include only our controls and the measure of effort (HRSWORKED). Here, HRSWORKED is positive and highly significant. According to this model, a one-standard deviation higher level of effort (6.6 hours) implies a 12.4% higher expected count of U.S. patent applications. Next, we estimated a model including HRSWORKED as well as the eight motive measures (model 4). Changes in the motive coefficients compared to model 2 (without effort) reflect the extent to which effort mediates the relationship between motives and performance. The mediation effects are small, suggesting that most of the effect of motives on performance occurs through what we call "productivity effects". For example, the coefficient on the importance of challenge remains very large and is equivalent to 18.7% higher expected patent counts for a one SD change in the challenge measure.

As discussed earlier, these results could reflect impacts of motives and incentives on cognitive processes (e.g., recall and creativity) or on intermediate outcomes such as project choice. For example, the positive productivity effects of the importance of challenge and independence would be consistent with positive effects of intrinsic motives on creativity. Similarly, the negative effect of the security motive would be consistent with the argument made above that individuals concerned with job security may also be motivated by a desire to avoid failure in their projects, and that such risk averse individuals may gravitate towards projects and approaches that are more incremental and certain, offer less innovative potential and are thus less likely to result in patents (cf. Dunbar, 1995; Ederer et al., 2008).

Even though our results suggest only a modest role of the preference for salary in affecting innovative performance, they do not imply that actual pay and other extrinsic benefits are not beneficial. In fact, in model 5 (Table 3), where LN_SALARY is included as an additional control, the large, significant coefficient suggests a strong, positive effect of pay on innovative performance. Due to the lack of suitable instruments, we are, however, unable to disentangle the causal nature of this relationship, and salary may be endogenous to the extent that individual performance is serially correlated and those who performed well in the past receive higher base pay in subsequent periods. However, it is also conceivable that sufficiently high levels of pay and financial resources more generally may be beneficial for innovation because they allow individuals to focus on the work of innovation rather than worrying about their livelihoods. Most important for our analysis, the inclusion of LN_SALARY yields only negligible changes in the coefficients of motives.

We hypothesized above that the productivity effects of motives and incentives may vary across types of tasks, and suggested that the productivity effects of motives may be greater in task settings that require more creativity and provide greater autonomy. Column 6 reports estimates for the sample of respondents engaged in basic or applied research (mean USPAPP=2.37) and column 7 reports the estimates for those engaged in development (mean USPAPP=1.67). Our key extrinsic motive, the importance of salary (IMP_SAL), *and* our key intrinsic motive, IMP_CHAL, both have significant, positive impacts on productivity for the respondents engaged in basic or applied research, but neither variable has a significant effect in development. Similarly, the importance of job security has a significantly larger negative effect in basic/applied research than in development. The importance of independence, however, has a stronger effect in development. Our interpretation of these results is that motives generally—whether intrinsic or extrinsic—can have stronger productivity effects in R&D work that is less routinized, more demanding of creative solutions, and where employees have more discretion over the approaches they follow. One surprising result is that, while highly significant in the development subsample, HRSWORKED is insignificant in the basic/applied research subsample. This result may reflect the notion that for research tasks demanding more problem solving and creativity, it is not the time expended beyond the 35 hour lower threshold that has an effect as much as the quality of the mental effort.[15] Alternatively, for upstream research where individual motives matter more, hours at the office may not accurately reflect total effort expended. For example, individuals motivated by intellectual challenge may dedicate substantial time outside of the office to coming up with solutions, etc., rendering a count of hours worked a very noisy measure of the quantity of effort.

[15] Note that the different effects of motives across types of R&D also support our assumption that motives are to a large degree exogenous to performance because any effects of performance on motives should be similarly strong across types of R&D.

6.2.2 Robustness Checks[16]

First, we addressed the concern that our performance measure, the number of patent applications, inaccurately measures innovative output—especially valuable innovations—by estimating performance regressions using granted patents (USPGRT) and, most importantly, commercialized patents (USPCOM). While the effect of effort is reduced in regressions using USPGRT and the effect of the independence motive becomes insignificant in regressions using USPCOM, these analyses generally strengthen our finding of significant effects of effort on performance and of significant productivity effects of motives.

Second, in light of the possibility that our measures of motives may be conflated with respondent ability, we estimated key performance regressions using the PhD subsample for which we have a better measure of ability (rankings of respondents' graduate programs). As expected, ABILITY has a positive association with performance. Moreover, the ABILITY-HRSWORKED interaction is positive and significant. Most importantly, however, the inclusion of this measure has virtually no impact on the coefficient estimates of the motives of intellectual challenge, salary, independence and job security. Finally, to probe whether we may be observing firm-level rather than individual-level effects, our Ph.D. subsample allowed the inclusion of firm fixed effects firms with 5 or more individuals in our sample. The coefficients of many of the measures of the motives are somewhat reduced, suggesting that individuals' motives may differ systematically across firms. However, the productivity effects of the importance of salary, intellectual challenge, independence, and job security remain large and significant.

[16] These and other robustness checks are discussed in more detail in the appendix.

7 Discussion

Our results suggest that researchers' motives matter for innovative effort and performance. First, desires for challenging work and responsibility appear to elicit more effort in R&D. Second, controlling for effort, preferences for challenge, independence, and, to a lesser extent, salary are associated with superior performance, with the effect of challenge being large and easily dominating any other. Moreover, a strong preference for job security is consistently associated with sub-par performance. Interestingly, these productivity effects of motives appear to be much stronger in basic and applied R&D, compared to development.

Our key results are robust across different estimation methods and the inclusion of controls for firm effects as well as individuals' ability and work experience. Unfortunately, the SESTAT data did not provide measures for a number of motives that our interviews suggest may be quite important for those employed in R&D, including the desire to solve practical problems (as distinct from intellectual challenge), and the motive to contribute to the work of a team.

In addition to the desire for income playing a modest role, the two strongest, robust relationships are the positive one between the desire for intellectual challenge and innovative performance and the negative one between the desire for job security and performance. Notwithstanding the psychological research that motivates a good deal of our empirical research, we cannot identify the underlying sources of these effects. One explanation offered by the literature is that these preferences for challenge and security may condition intermediate behaviors, such as the kinds of projects that researchers might select. A second, and not mutually exclusive explanation, is an impact on cognition itself. A third possibility, not discussed above, is that these preferences may be linked to other individual traits affecting innovation. For example, desire for intellectual challenge may indicate that a respondent has a preference for novel experiences, and that tasks providing novelty are consequently pleasurable for such individuals. Work in neuroscience suggests that such pleasurable motivational states elicit hemispheric activity that, in turn, affects individuals' scope of attention and problem-solving capabilities (Friedman & Foerster, 2005; Jung-Beeman et al., 2004). Similarly, those who are concerned with job security may be predisposed to fear or anxiety, and Friedman and Foerster (2005) observe that perceptions of threat elicit distinctive hemispheric activity that tends to suppress creativity.

A potential concern with our empirical results is that our measures for motives are endogenous. We do not have instruments or time series data that would allow one to assess, no less correct for, the possibility. Yet, our corollary analyses, while not directly addressing the concern, tend to mitigate it. [17] Given that this is the first time these strong relationships between individuals' motives and innovative activity have been observed in large sample empirical research on innovation, future study is needed to examine the underlying drivers.

Policy and managerial implications of our findings are several. For managers, the findings highlight the importance of intrinsic motivation for innovative performance. Accordingly, management should consider the returns to the provision of intrinsic benefits, while of course recognizing the associated costs and challenges. Nonpecuniary incentives can provide leverage where pecuniary incentives tend to be less effective, such as when the link between effort and performance is highly uncertain or when agents' behaviors and performance are hard to observe by principals, conditions which are often characteristic of R&D (cf. Alchian & Demsetz, 1972; Ouchi, 1979; Prendergast, 1999). Moreover, individuals engaged in innovation

[17] For example, as noted above, while we find a strong correlation between salary levels and measures of satisfaction with salary, there is no correlation between our measure of the preference for salary (i.e., the salary motive) and salary levels. Moreover, if endogeneity were present, one would then expect to observe similar relationships between motives and performance across the full range of innovative activities, including development, but the observed relationships are largely confined to basic and applied research.

appear to have particularly strong preferences for nonpecuniary benefits, potentially providing such benefits with a very high motivating "power." The challenge of appealing to employees' intrinsic motives is that intrinsic benefits typically cannot be provided directly. Organizations can, however, control them indirectly to some degree, through *facilitating or enabling conditions* such as task assignments, greater autonomy (Deci et al., 1985; Hackman & Oldham, 1976), or supporting scientists' desire to participate in professional communities (cf. Stern, 2004).

Management also needs to recognize, however, that appealing to individuals' motives can occasionally detract from organizational goals. For example, there are cases where individuals pursued research projects out of their own interest, against explicit policies of management. While such projects have sometimes yielded high returns for the employing organization (Katz, 1993; Kidder, 1981), they can also diminish firm performance. Researchers' pursuit of their intrinsic or professional interests can at times detract from their firm's interests, as when the desire for peer recognition motivates an industrial scientist to disseminate research findings that the employer would prefer to keep secret.

For policy makers, our results suggest that policies that encourage educational institutions to strengthen and reinforce intrinsic motivation, including love of challenge, curiosity, etc., may offer social dividends. At the same time, policies that change the incentives of individuals engaged in innovation should be evaluated in light of the complex ways in which such changes may affect not only the rate and direction of research effort, but its productivity as well.[18]

[18] A possible example of such a policy that applies to academic research is the Bayh-Dole Amendment enabling academic institutions to hold patents to their inventions as a matter of course, and the associated awarding of a share of licensing and other income to the academic inventors.

Table 1: Summary Statistics

	Variable	Type	Observations	Mean	Std. Dev.	Min	Max
Dependent variables	uspapp	count	11014	1.19	4.50	0	96
	uspgrt	count	11014	0.60	2.88	0	96
	uspcom	count	11014	0.26	1.76	0	96
	publication	count	11014	0.97	3.67	0	96
	hrsworked	continuous	11014	45.42	6.63	35	96
Motives	Imp. intellectual challenge	4 point	11014	3.64	0.53	1	4
	Imp. benefits	4 point	11014	3.58	0.55	1	4
	Imp. salary	4 point	11014	3.56	0.53	1	4
	Imp. job security	4 point	11014	3.52	0.59	1	4
	Imp. independence	4 point	11014	3.48	0.59	1	4
	Imp. opportunities advancement	4 point	11014	3.35	0.65	1	4
	Imp. responsibility	4 point	11014	3.28	0.63	1	4
	Imp. contribution to society	4 point	11014	3.11	0.73	1	4
Firm level indep. vars.	emsize1	dummy	11014	0.03	0.17	0	1
	emsize2	dummy	11014	0.03	0.18	0	1
	emsize3	dummy	11014	0.09	0.28	0	1
	emsize4	dummy	11014	0.11	0.31	0	1
	emsize5	dummy	11014	0.05	0.22	0	1
	emsize6	dummy	11014	0.13	0.34	0	1
	emsize7	dummy	11014	0.17	0.38	0	1
	emsize8	dummy	11014	0.38	0.48	0	1
	newbus	dummy	11014	0.08	0.28	0	1
Individual level indep. vars	basic R&D	dummy	11014	0.03	0.18	0	1
	applied R&D	dummy	11014	0.20	0.40	0	1
	development	dummy	11014	0.24	0.43	0	1
	design	dummy	11014	0.19	0.39	0	1
	computer apps	dummy	11014	0.33	0.47	0	1
	wa_nonrd	count	11014	1.54	1.47	0	8
	jobdegree	3 point	11014	2.53	0.66	1	3
	hd_bachelor	dummy	11014	0.45	0.50	0	1
	hd_master	dummy	11014	0.24	0.43	0	1
	hd_phd	dummy	11014	0.31	0.46	0	1
	male	dummy	11014	0.80	0.40	0	1
	married	dummy	11014	0.75	0.43	0	1
	children011	count	11014	0.66	0.97	0	9
	hdtenure	continuous	11014	13.27	9.55	supp.*	49
	supervdirect	continuous	11014	1.70	4.90	supp.*	250
	ln_supdir	continuous	11014	0.55	0.80	supp.*	5.53
	govt_nasa	dummy	11014	0.03	0.16	0	1
	govt_dod	dummy	11014	0.12	0.33	0	1
	uscitizen	dummy	11014	0.85	0.36	0	1
	asian	dummy	11014	0.24	0.43	0	1
	black	dummy	11014	0.05	0.21	0	1
	white	dummy	11014	0.71	0.45	0	1
	race_other	dummy	11014	0.06	0.24	0	1
	ability	continuous	2805	3.42	0.77	0.42	4.75
	salary	continuous	11014	83951	37272	supp.*	999996
	ln_salary	continuous	11014	11.25	0.50	6.91	13.82
	satisfaction salary	4 point	11014	3.22	0.69	1	4

Source: Based on NSF (2003): SESTAT restricted-use data file
Note: * Suppressed due to NSF confidentiality restrictions

Table 2: Effort Regressions

	truncreg 1 hrsworked	truncreg 2 hrsworked	truncreg 3 hrsworked
Imp. Salary		-0.409*	-0.481**
		[0.186]	[0.185]
Imp. Benefits		-0.154	-0.138
		[0.185]	[0.184]
Imp. Job Security		-0.283	-0.214
		[0.158]	[0.156]
Imp. Challenge		0.964**	0.874**
		[0.180]	[0.179]
Imp. Independence		0.339*	0.293
		[0.156]	[0.154]
Imp. Advancement		0.017	0.060
		[0.152]	[0.150]
Imp. Responsibility		0.626**	0.584**
		[0.158]	[0.157]
Imp. Contr. Society		-0.149	-0.090
		[0.126]	[0.125]
LN_SALARY			1.887**
			[0.232]
EMSIZE: 1-10	-0.123	-0.345	0.069
	[0.552]	[0.546]	[0.546]
EMSIZE: 11-24	-1.423**	-1.544**	-1.208*
	[0.500]	[0.495]	[0.494]
EMSIZE: 25-99	-0.362	-0.483	-0.279
	[0.338]	[0.336]	[0.334]
EMSIZE: 100-499	-0.427	-0.449	-0.261
	[0.292]	[0.290]	[0.289]
EMSIZE: 500-999	-0.856*	-0.848*	-0.700
	[0.367]	[0.362]	[0.359]
EMSIZE: 1000-4999	-0.640*	-0.644*	-0.547*
	[0.261]	[0.258]	[0.256]
EMSIZE: 5000-24999	-0.426	-0.406	-0.338
	[0.232]	[0.230]	[0.229]
NEWBUS	2.243**	2.204**	2.035**
	[0.334]	[0.330]	[0.327]
IND_NAICS (27)	incl.	incl.	incl.
WAPRI: basic	-0.502	-0.538	-0.430
	[0.483]	[0.477]	[0.474]
WAPRI: applied	0.008	-0.027	-0.042
	[0.257]	[0.255]	[0.253]
WAPRI: design	-0.066	0.000	0.023
	[0.247]	[0.245]	[0.242]
WAPRI: computers	-0.848**	-0.745**	-0.658**
	[0.250]	[0.248]	[0.245]
WA_NONRD	0.938**	0.896**	0.884**
	[0.064]	[0.064]	[0.063]
DEGREE: masters	0.584**	0.494*	0.217
	[0.210]	[0.208]	[0.210]
DEGREE: phd	2.313**	2.041**	1.519**
	[0.245]	[0.244]	[0.253]
HD_FIELD (15)	incl.	incl.	incl.
LN_SUPDIR	1.662**	1.587**	1.438**
	[0.114]	[0.114]	[0.114]
HDTENURE	0.096**	0.106**	0.042
	[0.029]	[0.029]	[0.030]
HDTENURE_SQ	-0.002**	-0.002**	-0.001
	[0.001]	[0.001]	[0.001]
JOBDEGREE	0.467**	0.423**	0.350**
	[0.137]	[0.136]	[0.134]
MALE	0.920**	0.956**	0.802**
	[0.221]	[0.220]	[0.218]
CHILDREN011	-1.159**	-1.097**	-1.098**
	[0.249]	[0.245]	[0.247]
MALE x CHILDREN011	1.143**	1.099**	1.076**
	[0.261]	[0.257]	[0.259]
MARRIED	-0.183	-0.092	-0.113
	[0.213]	[0.211]	[0.209]
USCITIZEN	0.630*	0.724**	0.692*
	[0.278]	[0.276]	[0.274]
RACE (3)	incl.	incl.	incl.
Observations	11014	11014	11014

Robust standard errors in brackets
* significant at 5%; ** significant at 1%

Table 3: Performance Regressions

	Full Sample						Basic/Appl.	Developm.
	zinb	zinb (logit)	zinb	zinb	zinb	zinb	nbreg	nbreg
	1a	1b	2	3	4	5	6	7
	uspapp		**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**
Imp. Salary			0.167*		0.175**	0.158*	0.294**	0.007
			[0.065]		[0.064]	[0.064]	[0.099]	[0.092]
Imp. Benefits			-0.042		-0.041	-0.029	-0.110	-0.027
			[0.071]		[0.071]	[0.070]	[0.102]	[0.091]
Imp. Job Security			-0.213**		-0.200**	-0.202**	-0.332**	-0.186*
			[0.059]		[0.060]	[0.059]	[0.087]	[0.085]
Imp. Challenge			0.342**		0.325**	0.308**	0.452**	0.177
			[0.066]		[0.065]	[0.066]	[0.100]	[0.109]
Imp. Independence			0.174**		0.184**	0.178**	0.127	0.251**
			[0.054]		[0.053]	[0.054]	[0.076]	[0.088]
Imp. Advancement			-0.035		-0.039	-0.041	0.111	-0.047
			[0.053]		[0.053]	[0.053]	[0.079]	[0.089]
Imp. Responsibility			-0.075		-0.085	-0.079	-0.197*	-0.055
			[0.054]		[0.055]	[0.054]	[0.081]	[0.091]
Imp. Contr. Society			-0.034		-0.037	-0.031	-0.002	-0.043
			[0.047]		[0.047]	[0.047]	[0.064]	[0.078]
HRSWORKED				0.018**	0.015**	0.013**	0.009	0.023**
				[0.005]	[0.005]	[0.005]	[0.006]	[0.007]
LN_SALARY						0.277**		
						[0.058]		
EMSIZE: 1-10	0.109	0.773*	0.093	0.164	0.149	0.114	-0.582	-0.209
	[0.277]	[0.385]	[0.280]	[0.285]	[0.288]	[0.285]	[0.320]	[0.334]
EMSIZE: 11-24	-0.208	0.575	-0.189	-0.202	-0.188	-0.222	-0.898**	0.044
	[0.237]	[0.358]	[0.228]	[0.250]	[0.238]	[0.236]	[0.277]	[0.297]
EMSIZE: 25-99	-0.082	0.770**	-0.134	-0.115	-0.152	-0.201	-0.823**	-0.344
	[0.159]	[0.252]	[0.152]	[0.159]	[0.153]	[0.151]	[0.160]	[0.200]
EMSIZE: 100-499	-0.332	0.536*	-0.285	-0.327	-0.281	-0.261	-0.520**	-0.462*
	[0.187]	[0.261]	[0.186]	[0.184]	[0.184]	[0.187]	[0.164]	[0.191]
EMSIZE: 500-999	-0.223	0.484	-0.276	-0.237	-0.288	-0.288	-0.841**	-0.213
	[0.192]	[0.321]	[0.197]	[0.183]	[0.187]	[0.190]	[0.251]	[0.208]
EMSIZE: 1000-4999	-0.321**	-0.05	-0.289**	-0.316**	-0.286**	-0.279**	-0.350*	-0.214
	[0.106]	[0.213]	[0.106]	[0.106]	[0.107]	[0.106]	[0.143]	[0.141]
EMSIZE: 5000-24999	-0.231*	0.11	-0.223*	-0.207	-0.201	-0.186	-0.573**	-0.290*
	[0.106]	[0.187]	[0.103]	[0.108]	[0.105]	[0.104]	[0.114]	[0.122]
NEWBUS	0.023	-0.711*	-0.054	-0.023	-0.082	-0.026	0.020	0.364*
	[0.166]	[0.297]	[0.156]	[0.165]	[0.158]	[0.163]	[0.160]	[0.173]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	0.295	0.786*	0.284	0.314*	0.299	0.292		
	[0.159]	[0.312]	[0.155]	[0.159]	[0.154]	[0.153]		
WAPRI: applied	0.273**	-0.043	0.235**	0.272**	0.234**	0.229*	0.197	
	[0.094]	[0.208]	[0.090]	[0.094]	[0.090]	[0.090]	[0.124]	
WAPRI: design	-0.107	0.605**	-0.101	-0.109	-0.101	-0.084		
	[0.126]	[0.180]	[0.126]	[0.128]	[0.128]	[0.129]		
WAPRI: computers	-0.765**	1.149**	-0.793**	-0.752**	-0.779**	-0.742**		
	[0.179]	[0.225]	[0.173]	[0.179]	[0.173]	[0.178]		
WA_NONRD	-0.009	0.041	-0.003	-0.028	-0.018	-0.022	-0.075*	-0.016
	[0.029]	[0.041]	[0.029]	[0.029]	[0.029]	[0.029]	[0.036]	[0.034]
DEGREE: masters	0.249	-0.466**	0.212	0.256*	0.216	0.204	0.513**	0.443**
	[0.129]	[0.155]	[0.130]	[0.129]	[0.129]	[0.129]	[0.167]	[0.139]
DEGREE: phd	0.875**	-2.030**	0.815**	0.855**	0.799**	0.761**	1.424**	1.581**
	[0.122]	[0.226]	[0.122]	[0.123]	[0.121]	[0.123]	[0.138]	[0.128]
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	0.291**		0.300**	0.263**	0.276**	0.261**	0.383**	0.184**
	[0.040]		[0.039]	[0.041]	[0.040]	[0.039]	[0.063]	[0.059]
HDTENURE	-0.010		-0.010	-0.012	-0.012	-0.021	0.009	-0.005
	[0.013]		[0.012]	[0.013]	[0.012]	[0.013]	[0.018]	[0.018]
HDTENURE_SQ	0.000		0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
JOBDEGREE	0.136*		0.142*	0.141*	0.144*	0.144*	-0.029	0.187*
	[0.060]		[0.057]	[0.059]	[0.057]	[0.057]	[0.084]	[0.080]
MALE	0.595**		0.588**	0.581**	0.577**	0.556**	0.394**	0.564**
	[0.088]		[0.085]	[0.088]	[0.086]	[0.085]	[0.114]	[0.133]
USCITIZEN	0.150		0.163*	0.140	0.156	0.137	-0.093	-0.037
	[0.084]		[0.082]	[0.085]	[0.082]	[0.082]	[0.129]	[0.130]
RACE (3)	incl.		incl.	incl.	incl.	incl.	incl.	incl.
GOVT_DOD		0.785**						
		[0.225]						
GOVT_NASA		0.503						
		[0.363]						
Observations	11014		11014	11014	11014	11014	2586	2690
Chi-square	459.162		526.916	462.118	527.585	531.322	943.516	600.498
df	66		74	67	75	76	72	71

Robust standard errors in brackets
* significant at 5%; ** significant at 1%

References

Akerlof, G. A. & Kranton, R. E. 2005. Identity and the economics of organizations. Journal of Economic Perspectives, 19(1): 9-32.

Alchian, A. A. & Demsetz, H. 1972. Production, Information Costs, and Economic Organization. American Economic Review, 62(5): 777-792.

Amabile, T. 1996. Creativity in context. Boulder, Colo.: Westview Press.

Amabile, T. M. 1993. Motivational synergy: Toward new conceptualizations of intrinsic and extrinsic motivation in the workplace. Human Resource Management Review, 3: 185-201.

Amabile, T. M., Hill, K. G., Hennessey, B. A., & Tighe, E. M. 1994. The Work Preference Inventory - Assessing Intrinsic and Extrinsic Motivational Orientations. Journal of Personality and Social Psychology, 66(5): 950-967.

Besley, T. & Ghatak, M. 2005. Competition and incentives with motivated agents. American Economic Review, 95(3): 616-636.

Cable, D. M. & Edwards, J. R. 2004. Complementary and supplementary fit: A theoretical and empirical integration. Journal of Applied Psychology, 89(5): 822-834.

Camerer, C. & Hogarth, R. M. 1999. The effects of financial incentives in experiments: A review and capital-labor-function framework. Journal of Risk and Uncertainty, 19: 7-42.

Cameron, A. C. & Trivedi, P. K. 1998. Regression analysis of count data. Cambridge, UK ; New York, NY, USA: Cambridge University Press.

Cohen, W. M., Nelson, R. R., & Walsh, J. P. 2000. Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not), NBER Working Paper.

Cohen, W. M. & Sauermann, H. 2007. Schumpeter's Prophecy and Individual Incentives as a Driver of Innovation. In F. Malerba & S. Brusoni (Eds.), Perspectives on Innovation: 73-104: Cambridge University Press.

Dasgupta, P. & David, P. A. 1994. Toward a New Economics of Science. Research Policy, 23(5): 487-521.

Deci, E. L. & Ryan, R. M. 1985. Intrinsic motivation and self-determination in human behavior. New York: Plenum.

Deci, E. L., Koestner, R., & Ryan, R. M. 1999. A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. Psychological Bulletin, 125(6): 627-668.

Dunbar, K. 1995. How scientists really reason: Scientific reasoning in real-world laboratories. In R. J. Sternberg & J. E. Davidson (Eds.), The nature of insight: 365-395. Cambridge, MA: MIT Press.

Ederer, F. & Manso, G. 2008. Are Financial Incentives Detrimental to Innovation, Working Paper.

Festinger, L. 1957. Theory of Cognitive Dissonance: Stanford University Press.

Fox, M. F. 1983. Publication Productivity among Scientists: A Critical Review. Social Studies of Science, 13(2): 285-305.

Frey, B. S. & Jegen, R. 2001. Motivation crowding theory. Journal of Economic Surveys, 15(5): 589-611.

Friedman, R. S. & Foerster, J. 2005. Effects of motivational cues on perceptual asymmetry: Implications for creativity and analytical problem solving. Journal of Personality and Social Psychology, 88(2): 263-275.

Gagne, M. & Deci, E. L. 2005. Self-determination theory and work motivation. Journal of Organizational Behavior, 26(4): 331-362.

Gambardella, A., Harhoff, D., & Verspagen, B. 2006. The value of patents, Working Paper.

George, J. M. 2007. Creativity in organizations. The Academy of Management Annals, 1(1): 439-477.

Goldberger, M. L., Flattau, P., & Maher, B. A. 1995. Research-Doctorate Programs in the United States: Continuity and Change: National Academy Press.

Griliches, Z. 1957. Hybrid Corn: An Exploration in the Economics of Technological Change. Econometrica, 25(4): 501-522.

Hackman, J. R. & Oldham, G. R. 1976. Motivation through the design of work - Test of a theory. Organizational Behavior and Human Performance, 16(2): 250.

Hennessey, B. A. & Amabile, T. M. 1998. Reward, intrinsic motivation, and creativity. American Psychologist, 53(6): 674-675.

Holland, J. L. 1997. Making vocational choices : a theory of vocational personalities and work environments (3rd ed.). Odessa, Fla.: Psychological Assessment Resources.

Holt, K. 1974. Work frustration in engineering departments. R & D Management, 5(1): 17-21.

Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. 2001. The job satisfaction-job performance relationship: A qualitative and quantitative review. Psychological Bulletin, 127(3): 376-407.

Jung-Beeman, M., Bowden, E. M., Haberman, J., Frymiare, J. L., Arambel-Liui, S., Greenblatt, R., Reber, P. J., & Kounios, J. 2004. Neural activity when people solve verbal problems with insight. PLoS Biology, 2(4): 500-510.

Katz, R. 1993. How a Band of Technical Renegades Designed the Alpha-Chip. Research-Technology Management, 36(6): 13-20.

Katz, R. 2004. Motivating professionals in organizations. In R. Katz (Ed.), The human side of managing technological innovation: 3-20. New York: Oxford University Press.

Kidder, T. 1981. The soul of a new machine (1st ed.). Boston: Little, Brown.

Lacetera, N. & Zirulia, L. 2008. Knowledge spillovers, competition, and taste for science in a model of R&D incentive provision, Working Paper.

Lakhani, K. R. & von Hippel, E. 2003. How open source software works: "free" user-to-user assistance. Research Policy, 32(6): 923-943.

Lerner, J. & Tirole, J. 2005. The Economics of Technology Sharing: Open Source and Beyond. Journal of Economic Perspectives, 19(2): 99.

Manners, G., Steger, J. A., & Zimmerer, T. W. 1997. Motivating your R&D staff. Research Technology Management, 40(6): 29-34.

Manso, G. 2006. Motivating innovation. Working Paper.

Merton, R. K. 1973. The sociology of science : Theoretical and empirical investigations. Chicago: University of Chicago Press.

Moorman, R. H. & Podsakoff, P. M. 1992. A Metaanalytic Review and Empirical-Test of the Potential Confounding Effects of Social Desirability Response Sets in Organizational-Behavior Research. Journal of Occupational and Organizational Psychology, 65: 131-149.

Murdock, K. 2002. Intrinsic motivation and optimal incentive contracts. Rand Journal of Economics, 33(4): 650-671.
National Science Board. 2008. Science and Engineering Indicators 2008. Arlington, VA: National Science Foundation.
National Science Foundation, S. R. S. 2003. Scientists and Engineers Statistical Data System (SESTAT), restricted-use data file.
Nelson, R. R. 1959. The simple economics of basic scientific research. Journal of Political Economy, 67(3): 297-306.
Ouchi, W. G. 1979. Conceptual-Framework for the Design of Organizational Control Mechanisms. Management Science, 25(9): 833-848.
Pedhazur, E. J. & Schmelkin, L. P. 1991. Measurement, design, and analysis : an integrated approach. Hillsdale, N.J.: Lawrence Erlbaum Associates.
Pelz, D. C. & Andrews, F. M. 1976. Scientists in organizations : productive climates for research and development (Rev. ed.). Ann Arbor: Institute for Social Research, University of Michigan.
Prendergast, C. 1999. The provision of incentives in firms. Journal of Economic Literature, 37(1): 7-63.
Roberts, J., Hann, I. H., & Slaughter, S. 2006. Understanding the Motivations, Participation, and Performance of Open Source Software Developers: A Longitudinal Study of the Apache Projects. Management Science, 52(7): 984-999.
Ryan, R. M. & Deci, E. L. 2000. Intrinsic and extrinsic motivations: Classic definitions and new directions. Contemporary Educational Psychology, 25(1): 54-67.
Sauermann, H. 2005. Vocational Choice: A Decision Making Perspective. Journal of Vocational Behavior, 66: 273-303.
Sauermann, H. & Cohen, W. 2007. Fire in the belly? Individuals' motives and innovative performance in startups versus established firms, Working Paper.
Schmookler, J. 1962. Economic sources of inventive activity. Journal of Economic History, 22: 1-20.
Schumpeter, J. A. 1934. The theory of economic development; an inquiry into profits, capital, credit, interest, and the business cycle. Cambridge, Mass.,: Harvard University Press.
Schumpeter, J. A. 1942. Capitalism, Socialism and Democracy: Harper & Brothers.
Stephan, P. E. & Levin, S. G. 1992. Striking the Mother Lode in Science: Oxford University Press.
Stephan, P. E. 1996. The economics of science. Journal of Economic Literature, 34(3): 1199-1235.
Stern, S. 2004. Do scientists pay to be scientists? Management Science, 50(6): 835-853.
Wooldridge, J. M. 2001. Econometric Analysis of Cross Section and Panel Data: MIT Press.
Zuckerman, H. 1988. The sociology of science. In N. J. Smelser (Ed.), The Handbook of Sociology: 511-574: Sage.

APPENDIX

Motives: Additional Descriptive Analyses

Table 1 above provides summary statistics for the preference measures, ordered from highest to lowest average importance. Note that the means for all preference measures are above three, indicating a high to very high importance of all factors. Respondents rated intellectual challenge as the most important work benefit, followed by fringe benefits, salary, job security, independence, opportunities for advancement, responsibility, and contribution to society.

An interesting question is whether the motives and preferences for job characteristics vary across type of work (e.g., basic research vs. development), type of field, or degree. We would expect such differences if different work settings and tasks offer different kinds of work benefits and if individuals self-select based on their motives and preferences. To examine such differences, we regressed the eight preference measures on three sets of dummy variables: primary type of work (basic research is the omitted category), type of degree (Bachelors is the omitted category), and field of highest degree (engineering fields is the omitted category). [1] The results of these regressions (estimated using ordered probit) are shown in Table A3. All regressions are highly significant, suggesting that there are significant differences in individuals' preferences across degrees, fields, and types of work. With respect to differences across types of degrees, we find that PhDs report a significantly lower importance of extrinsic benefits (salary and fringe benefits) as well as job security than Bachelors, while reporting higher importance of certain intrinsic benefits (challenge, contribution to society, and independence).

[1] Please refer to the measurement section for a list of all fields. For this analysis, we formed three aggregate classes of fields: engineering (omitted), science, and other fields.

Comparisons of individuals' preference across primary types of work show significant differences with respect to some factors but not others (development is the omitted category). We find no differences with respect to preferences for salary, and only small differences with respect to preferences for fringe benefits. Individuals primarily engaged in design and computer applications report significantly lower importance of intellectual challenge, independence, opportunities for advancement, responsibility, and contribution to society than individuals in development. Individuals in basic and applied research report a higher importance of intellectual challenge and contribution to society than those in development.[2]

A comparison of the motives of individuals with science versus engineering degrees shows only small differences (controlling for the primary type of work). Scientists have somewhat stronger preferences for fringe benefits, independence and job security.

Finally, we examined the relationships among the preference measures. An exploratory factor analysis (common factor analysis, oblique rotation with oblimin(0) criterion) revealed two factors, as shown in Table A4. The preferences for responsibility, intellectual challenge, independence, contribution to society, and advancement load on one factor. The preferences for fringe benefits, salary, as well as job security load on a second factor. It is interesting to note that the preference for opportunities for advancement does not load on the same factor as salary and fringe benefits, indicating that the preference for opportunities for advancement may not strictly—or even primarily—reflect a pecuniary motive. Overall, the results of this factor analysis suggest that individuals' preferences are correlated in systematic ways. While some

[2] In interpreting these results, we have to consider the potential for social desirability bias. For example, PhDs could think that they are expected to care more than non- PhDs about intellectual challenge and contribution to society, and their higher importance ratings could reflect an attempt to conform to these expectations.

individuals emphasize extrinsic benefits such as salary and fringe benefits as well as job security, others emphasize intrinsic benefits. However, the correlation between the two extracted factors is positive (r=0.23), suggesting that intrinsic and extrinsic motives are not two opposite ends of a "motivation continuum" but two motivational orientations that can occur within the same individual (see also Amabile et al., 1994).

In some disciplines, it is common to use factor-based scores derived from a factor analysis as new variables in subsequent regression analyses. This method assumes that the component measures capture the same underlying latent construct (Pedhazur & Schmelkin, 1991). We do not make such an assumption and focus on the individual preference measures.

Effort: Additional Analyses

The distributional characteristics of our effort measure (number of hours worked) suggest robustness checks using alternative estimation techniques. First, a large number of respondents (39.8%) reported HRSWORKED of 40 hours per week, while only very few individuals report less than 40 hours. It is conceivable that some of the individuals reporting 40 hours actually work less, but report 40 hours since this is the official work time in many organizations. In this case, 40 hours could be considered the lower limit of a censored distribution. To address this possibility, we estimate key effort models using a Tobit regression model, with a lower limit of 40 hours. Second, many responses are clustered at "round" values such as 40 and 50 hours. To address this issue, we divided the HRSWORKED measure into categories, each spanning 5 hours. Using the resulting measure HRSCAT5 as our new dependent variable, we also estimated effort regressions using ordered probit. The Tobit and ordered probit regression suggests that the effects of the importance of challenge, responsibility, and salary are robust. However, the effects of the preference for contribution to society and independence appear to be fragile.

We also estimated key effort regressions without individuals who are employed in computer systems design, which is the largest single industry in our sample (for an industry breakdown, see Table A1), as well as on the subsample of individuals employed in manufacturing industries. The qualitative results are similar to our benchmark regressions (Table 2), with slight changes of the coefficients of the importance of salary and job security.

Finally, we estimated key regressions using the sample of PhDs, for which we have additional measures. First, we constructed a measure of ability based on the ratings of the quality of the respondent's graduate department. Second, we obtained firm identifiers to control for firm fixed effects. In Table A6, we examine the robustness of our results to the inclusion of these two sets of measures. Model 1 reproduces the results from the full sample (Table 2, model 2). Model 2 is estimated using only non-PhDs. Model 3 estimates the base line model using the PhD-sample. Comparing models 2 and 3, we observe several differences in the effects of motives on effort. More specifically, the negative coefficient of the salary motive is confined to the non-PhD sample, while the coefficient is positive (but insignificant) in the PhD sample. The negative effect of the importance of job security as well as the positive effect of the importance of challenge is larger for the PhDs. [3] In model 4, we include the ABILITY measure. Consistent with our model, the coefficient is positive and highly significant, suggesting that individuals who graduated from higher-ranked PhD programs expend more effort. Including this ABILITY

[3] A detailed analysis of differences in the effects of motives across degree types using interactions shows three significant effects: For individuals with a Masters degree, the preference for contribution to society has a stronger positive effect than for individuals with a Bachelors degree. For PhDs, the effect on effort of the importance of salary is more positive, and the importance of job security is more negative than for individuals with a bachelor's degree.

measure does not significantly change the coefficients of the eight preference measures. Finally, in model 5, we also include one dummy variable for each firm that has 5 or more individuals in our sample. Their inclusion has little impact on the coefficients of our key independent variables. Overall, the results of these analyses using the PhD-sample suggest that including firm identifiers and a better measure of ability in effort regressions does not substantially affect the estimated coefficients of individuals' motives and preferences.

Performance: Additional Analyses

In order to assess the robustness of our results, we re-estimated key performance regressions using negative binomial regression (NBREG) and using different subsets of our sample (Table A7). Models 1 and 2 are equivalent to the ZINB models 2 and 4 in Table 3 and are estimated using the full sample. While the positive effect of effort remains strong and significant, the estimated effect of the importance of salary is insignificant, and the effect of the importance of independence is reduced. The effect of the preference for intellectual challenge, however, is even stronger than in the ZINB models. In model 7, we estimate a negative binomial model using only those cases that have at least one patent application (N=2,637). This regression thus examines the impact of effort and individuals' preferences for individuals who were productive enough to have at least one patent application *and* who were not precluded from patenting (who are not in the "never patent" group predicted by the logit part of the ZINB model). Compared to the reference model (model 2), the effect of effort is reduced. The effect of the importance of salary as well as independence increases. The effect of the importance of challenge is reduced but remains highly significant. The effect of the importance of job security becomes insignificant.[4]

We also estimated performance regressions using only cases from the pharmaceutical and medical device industries (model 8). While the number of cases in this subsample is relatively small (N=769), this analysis is particularly interesting because patents are very effective in these industries and should more closely reflect innovative performance than in other industries (Cohen et al., 2000). Compared to the estimates from the full sample (model 2), we find that the effect of effort becomes insignificant, while the effects of the importance of challenge, job security, and independence increase.

Analyses Employing the PhD Sample

Our PhD-sample, for which we have better measures of individuals' ability as well as firm identifiers, allows us to examine the robustness of our results to two potentially problematic issues. First, the relationship we observe between certain motives and performance may have ability as a common cause. Individuals with greater ability or better training could enjoy intellectual challenge, for example, because they are capable of meeting those challenges. In that case, the observed relationship between desire for challenge and performance would be spurious. To rule this out, we add an important measure of ability and training.

[4] We conducted additional analyses to probe the robustness of our results. First, there are a small number of cases in our sample with a very high number of reported U.S. patent applications. While these cases might be truly exceptional performers, it could also be that a very high count of USPAPP reflects measurement error (e.g., individuals reported lifetime patents) or cases where individuals are named on patents without having directly contributed to the invention. Given the small mean of USPAPP in our sample, such cases could severely impact our estimation results. To assess any such effect, we dropped all respondents reporting more than 20 U.S. patent applications in a 5-year span (77 cases, 0.7% of the full sample). The effect of HRSWORKED is unchanged compared to the reference model. However, the effect of the importance of salary becomes insignificant. The effect of the preference for challenge remains large and highly significant.

Second, our analysis thus far could have failed to control sufficiently for firm characteristics, and there are any number of reasons to expect the impact of motives to be at least partly conditioned by firm effects. Among others, it is conceivable that certain firms command higher levels of resources and also attract individuals with particular sets of motives. Alternatively, firms may have different policies linking performance, for example, to financial rewards, implying an impact of firm effects if there is indeed a correlation between the preference for a given type of benefits and the degree to which that benefit is contingent upon effort or performance within a firm.[5]

Table A8 reports the results of a set of negative binomial regressions using the PhD-sample. Model 1 reproduces the results from model 1 in Table A7 (regression using the full sample), while model 2 estimates the model using only the PhD sample. Comparing the two regressions, we observe that the importance of salary and the importance of independence appear to have a somewhat stronger positive effect in this PhD-sample, while the importance of job security and intellectual challenge have a somewhat smaller effect.[6] In model 3, we add our measure of ability (quality of graduate department). This measures has a significant and economically meaningful positive effect (a one-SD higher ability score translates into a 9.1% higher expected patent count), but its addition to the model has virtually no effect on the preference measures. In model 6, we additionally include our effort measure (HRSWORKED) as well as the interaction between ABILITY and HRSWORKED. As predicted, the interaction term

[5] Also, firms may differ in their propensity to patent, i.e., in the likelihood that a given invention is actually patented. While it is not clear that the latter effect would systematically affect our estimates of the impact of motives on performance, controlling for such effects is certainly desirable.
[6] Regressions examining these differences using interaction terms show that the effect of the preference for contribution to society is significantly smaller for PhDs than for Bachelors (negative interaction), while the effects of the importance of independence are significantly larger (positive interaction).

is significant at the 5% level, suggesting that the productivity of innovative effort increases with the ability of the individual. In model 7, we add a dummy variable for every firm that has 5 or more individuals in our sample. The firm effects are jointly significant and their inclusion also changes the coefficients of some preference measures. More specifically, the coefficients of importance of salary, importance of challenge, and importance of independence are somewhat reduced. Once the firm fixed effects are included, the main effects of effort and ability are insignificant, but the interaction term is highly significant.

Overall, our analyses using the PhD-sample show that, first, ability and effort affect performance interactively, as suggested by our formal model. Second, the effects of individuals' motives and preferences for job characteristics are largely independent of ability, ruling out an important alternative explanation for our results. Third, the significant impacts of individuals' motives and preferences for job characteristics persist even with controls for firm fixed effects. At the same time, however, the coefficients of some preference measures change once we control for firm effects, suggesting that firms may differ with respect to the motives and preferences of their employees, which in turn could impact firms' relative innovative performance. We examine this interplay between individual and firm-level effects in more detail in related work (Sauermann et al., 2007).

Alternative Performance Measures

Finally, in addition to using U.S. patent applications, we also estimated performance regressions using alternative measures of innovative performance (Table A9). The most important alternative measure is the number of patents granted over a 5-year span that were licensed or commercialized (USPCOM). The virtue of this measure is that it provides a rough sense of the number of economically important inventions that were patented, thus providing a crude quality threshold for our performance measure, as opposed to the number of patent applications or patents granted, the majority of which are not economically important. As noted above, one reason that we do not feature this measure is that strategic considerations other than value may condition the firm's decision to commercialize an invention. Second, the commercialization introduces a substantial and highly variable time lag between the R&D activity and the observed outcome. Notwithstanding these latter concerns, a number of our results are robust. First, our measure of effort, HRSWORKED, continues to have a positive, significant coefficient. The qualitative results for our featured independent variables also remain robust. Preference for intellectual challenge importantly affects performance. The preference for salary remains positive but is no longer significant. Finally, the effect of the preference for job security remains negative and significant.

Table A9 also shows the results of regressions using peer reviewed publications as dependent variables. The results of models 7 and 8 suggest that effort has a strong positive impact on publication output and that the importance of intellectual challenge continues to have a significant and large positive effect. Interestingly, the importance of job security and the importance of independence do not have significant effects. This analysis is purely exploratory since publications are likely to measure a different kind of innovative performance than patents do, and many firms may have policies that discourage the publication of research findings. More work is needed to understand the drivers of patenting and publishing in industry, and it would be particularly interesting to examine similarities and differences with academic settings.

Appendix: Tables

Table A1: Sample Composition

Industry (IND_NAICS)	Basic Research	Applied Research	Develop-ment	Design	Computer Apps.
21x Mining,Oil,Gas	≤5*	57	49	33	36
22x Utilities	8	37	31	107	91
23x Construction	≤5*	17	15	74	28
311-312 Manufacturing:Food,Bev,Tobacco	8	51	47	26	30
313-316 Manufacturing:Textiles	≤5*	7	16	≤5*	14
3211,337 Manufacturing:Wood,Furniture	≤5*	≤5*	10	≤20*	13
322-323 Manufacturing:Paper,Printing	≤5*	23	32	20	34
324 Manufacturing:Petroleum	≤5*	21	10	22	20
325 Manufacturing:Chemicals ex Pharma	21	206	213	76	55
3254 Pharma	49	239	152	27	71
326 Manufacturing:Plastics,Rubber	≤5*	19	33	27	16
327 Manufacturing:NonmetalMinerals	≤5*	7	23	21	11
331 Manufacturing:PrimaryMetal	≤5*	7	17	26	16
332 Manufacturing:FabricatedMetal	≤5*	10	50	60	19
333 Manufacturing:Machinery	≤5*	43	106	159	101
3341 Manufacturing:Computers	8	51	144	67	156
3342-3343 Manufacturing:Communications,Audio, Video	≤5*	40	89	79	107
3344 Manufacturing:Semiconductors,Electronics	11	90	327	190	263
3345 Manufacturing:Instruments	≤5*	39	96	102	105
335 Manufacturing:HouseholdAppliances,Lighting	≤5*	24	60	41	43
3361-3363 Manufacturing:Auto	8	54	129	140	80
3364 Manufacturing:Aircraft,Aerospace	9	94	210	284	202
3365-3369 Manufacturing:TransportationEquipment	≤5*	≤5*	17	25	18
3391 Manufacturing:MedicalEquipment	6	50	91	50	34
3399 Manufacturing:Misc.	≤5*	5	23	21	23
517 Telecom Services	16	54	83	103	282
5415 Computer Systems Design	38	145	306	205	1,645
5417 Scientific R&D Services	160	805	311	84	136
Total	381	2,205	2,690	2,089	3,649

Source: Based on NSF (2003): SESTAT restricted-use data file
*Counts suppressed due to NSF confidentiality restrictions

Table A2: Comparison of Full Sample and PhD-Sample

	Full Sample		Ph.D.-Sample	
Primary work activity (WAPRI)	**Freq.**	**Percent**	**Freq.**	**Percent**
Basic research	381	3.46	116	4.14
Applied research	2,205	20.02	1,092	38.93
Development	2,690	24.42	933	33.26
Design	2,089	18.97	261	9.3
Computer Apps./Programming	3,649	33.13	403	14.37
Total	11,014	100	2805	100
DEGREE				
Bachelor	4,977	45.19	0	0
Master	2,666	24.21	0	0
PhD	3,371	30.61	2805	100
Total	11,014	100	2805	100

Source: Based on NSF (2003): SESTAT restricted-use data file

Table A3: Differences in Preference Ratings

	1 oprobit **IMP_SAL**	2 oprobit **IMP_BEN**	3 oprobit **IMP_SEC**	4 oprobit **IMP_CHAL**	5 oprobit **IMP_IND**	6 oprobit **IMP_ADV**	7 oprobit **IMP_RESP**	8 oprobit **IMP_SOC**
Basic Research	-0.038	0.115	0.182**	0.149*	0.069	0.180**	0.098	0.248**
	[0.068]	[0.071]	[0.069]	[0.074]	[0.065]	[0.063]	[0.065]	[0.066]
Applied Research	0.012	0.096**	0.032	0.133**	0.089*	0.023	0.015	0.112**
	[0.036]	[0.035]	[0.035]	[0.039]	[0.036]	[0.034]	[0.034]	[0.033]
Design	-0.045	0.002	-0.023	-0.098**	-0.111**	-0.195**	-0.131**	-0.102**
	[0.037]	[0.037]	[0.036]	[0.038]	[0.035]	[0.035]	[0.035]	[0.034]
Computer Apps.	0.001	-0.068*	-0.059	-0.120**	-0.112**	-0.174**	-0.220**	-0.160**
	[0.033]	[0.033]	[0.032]	[0.033]	[0.031]	[0.031]	[0.031]	[0.029]
Masters	-0.029	-0.118**	-0.141**	0.080**	0.02	0.05	0.081**	0.118**
	[0.030]	[0.030]	[0.029]	[0.030]	[0.028]	[0.028]	[0.028]	[0.027]
PhD	-0.311**	-0.408**	-0.362**	0.230**	0.094**	-0.011	0.058*	0.243**
	[0.031]	[0.031]	[0.030]	[0.032]	[0.030]	[0.029]	[0.029]	[0.028]
Field: Science	0.015	0.059*	0.043	0.026	0.055*	-0.047	-0.043	0.054*
	[0.027]	[0.027]	[0.027]	[0.028]	[0.026]	[0.026]	[0.026]	[0.025]
Field: Other	0.054	0.118**	0.035	-0.024	0.125**	-0.079*	-0.009	0.009
	[0.037]	[0.037]	[0.035]	[0.036]	[0.035]	[0.033]	[0.033]	[0.033]
Observations	11014	11014	11014	11014	11014	11014	11014	11014
Chi-square	144.792	209.691	165.321	192.998	99.981	97.677	113.875	313.853
df	8	8	8	8	8	8	8	8

* significant at 5%; ** significant at 1%
Robust standard errors in brackets
Source: Based on NSF (2003): SESTAT restricted-use data file

Table A4: Factor Loadings of Preference Measures

Preference measure	Factor 1	Factor 2	Uniqueness
Importance responsibility	**0.69**	0.02	0.51
Importance intellectual challenge	**0.62**	-0.08	0.64
Importance independence	**0.57**	-0.04	0.68
Importance contribution society	**0.51**	-0.01	0.75
Importance opportunities advancement	**0.49**	0.21	0.67
Importance benefits	0.01	**0.68**	0.54
Importance salary	-0.04	**0.61**	0.63
Importance job security	0.04	**0.51**	0.73

Source: Based on NSF (2003): SESTAT restricted-use data file

Table A5: Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	USPAPP	1														
2	USPGRT	0.7958*	1													
3	USPCOM	0.5951*	0.7831*	1												
4	HRSWORKED	0.1039*	0.0713*	0.0517*	1											
5	IMP_SAL	-0.0206	-0.0308*	-0.0126	-0.0444*	1										
6	IMP_BEN	-0.0380*	-0.0397*	-0.023	-0.0339*	0.4990*	1									
7	IMP_SEC	-0.0553*	-0.0388*	-0.0345*	-0.0549*	0.2879*	0.4206*	1								
8	IMP_CHAL	0.0682*	0.0489*	0.0322*	0.1151*	-0.0005	0.0600*	0.0334*	1							
9	IMP_IND	0.0491*	0.0398*	0.0229	0.0828*	0.0357*	0.0875*	0.0593*	0.3768*	1						
10	IMP_ADV	0.0187	-0.0086	-0.0074	0.0447*	0.2006*	0.2004*	0.2052*	0.3336*	0.2278*	1					
11	IMP_RESP	0.0282*	0.0117	0.0104	0.1060*	0.1039*	0.1098*	0.1026*	0.4342*	0.4391*	0.4506*	1				
12	IMP_SOC	0.0285*	0.0106	-0.0019	0.0466*	-0.0139	0.0987*	0.1143*	0.3173*	0.3064*	0.2668*	0.3550*	1			
13	EMSIZE1	-0.0010	0.0005	-0.0008	0.0425*	-0.0388*	-0.0810*	-0.0731*	0.0172	0.0296*	-0.0133	0.0074	0.0001	1		
14	EMSIZE8	0.0350*	0.0272*	0.0056	0.0015	0.0101	0.0494*	0.0415*	-0.0007	-0.0079	-0.0084	-0.0051	0.0086	-0.1389*	1	
15	NEWBUS	0.0148	-0.0084	-0.0042	0.0795*	-0.0319*	-0.0640*	-0.0926*	0.0211	0.0062	0.0328*	0.0140	0.0022	0.2458*	-0.1935*	1
16	WAPRI: basic	0.0107	0.0094	-0.0125	-0.0090	-0.0084	0.0119	0.0258*	0.0273*	0.0197	0.0403*	0.0293*	0.0499*	0.0093	-0.0315*	0.0064
17	WAPRI: applied	0.1488*	0.1070*	0.0422*	0.0609*	-0.0286*	-0.0033	-0.0178	0.0838*	0.0642*	0.0405*	0.0470*	0.0984*	0.0078	0.0201	0.0147
18	WAPRI: develop.	0.0610*	0.0590*	0.0655*	0.0566*	-0.0118	-0.0218	-0.0128	0.0244	0.0192	0.0427*	0.0481*	0.0334*	-0.0159	0.0122	0.0106
19	WAPRI: design	-0.0445*	-0.0280*	-0.0120	-0.0090	0.0016	0.0188	0.0117	-0.0416*	-0.0406*	-0.0399*	-0.0155	-0.0478*	-0.0368*	0.0023	-0.0628*
20	WAPRI: comp. apps	-0.1492*	-0.1251*	-0.0808*	-0.0925*	0.0370*	0.0024	0.0070	-0.0695*	-0.0459*	-0.0558*	-0.0824*	-0.0937*	0.0350*	-0.0179	0.0277*
21	WA_NONRD	0.0162	0.0273*	0.0262*	0.2223*	0.0216	0.0349*	0.0126	0.0506*	0.0695*	0.1114*	0.1390*	0.0772*	0.0468*	-0.0606*	0.0126
22	JOBDEGREE	0.0337*	0.0209	0.0207	0.0346*	0.0321*	0.0323*	0.0404*	0.0569*	0.0337*	0.0687*	0.0718*	0.0691*	0.0147	0.0053	-0.0122
23	HD: bachelor	-0.1712*	-0.1349*	-0.0758*	-0.0852*	0.0736*	0.0998*	0.0985*	-0.0855*	-0.0442*	-0.0274*	-0.0488*	-0.1127*	-0.0091	-0.0501*	-0.0465*
24	HD: master	-0.0773*	-0.0596*	-0.0256*	-0.0337*	0.0347*	0.0150	-0.0002	-0.0107	-0.0115	0.0112	0.0137	-0.0033	-0.0114	0.0311*	0.0006
25	HD: PHD	0.2568*	0.2010*	0.1056*	0.1234*	-0.1117*	-0.1217*	-0.1062*	0.1023*	0.0584*	0.0192	0.0400*	0.1248*	0.0204	0.0252*	0.0497*
26	HDTENURE	0.0208	0.0656*	0.0465*	0.0283*	-0.0530*	-0.0120	-0.0382*	-0.0592*	0.0160	-0.2777*	-0.0949*	-0.0237	0.018	0.008	-0.0697*
27	LN_SUPDIR	0.1149*	0.0994*	0.0770*	0.2517*	-0.0151	-0.0014	-0.0361*	0.0742*	0.0511*	0.0699*	0.1156*	0.0759*	0.0155	-0.0195	0.0069
28	LN_SALARY	0.1469*	0.1360*	0.0919*	0.1695*	-0.0085	-0.0379*	-0.0830*	0.0566*	0.0487*	-0.0802*	0.0175	-0.0164	-0.0288*	0.0844*	0.0129
29	Satisfaction Salary	0.0177	0.0110	0.0008	0.0082	-0.0019	0.0369*	0.0347*	0.0758*	0.0593*	-0.0693*	0.0346*	0.0350*	-0.0217	0.0757*	-0.0297*
30	ABILITY	0.0589*	0.0293	-0.0090	0.0726*	-0.0507*	-0.0455	-0.0759*	0.0340	-0.0318	-0.0396	-0.0442	-0.0581*	-0.0510*	-0.0144	0.0199
31	MALE	0.0644*	0.0601*	0.0437*	0.0653*	-0.0143	-0.0519*	-0.0590*	-0.0221	-0.0459*	-0.0510*	-0.0399*	-0.0852*	0.0359*	-0.0372*	0.0231
32	MARRIED	0.0451*	0.0434*	0.0277*	0.0165	0.0203	0.0470*	0.0264*	-0.0368*	-0.0206	-0.0439*	-0.0121	0.0156	-0.0185	-0.0027	-0.0314*
33	CHILDREN011	0.0325*	0.0269*	0.0220	0.0056	0.0410*	0.0501*	0.0255*	-0.0171	-0.0176	0.0258*	0.0021	0.0160	-0.0059	-0.0174	0.0165

* significant at 1%

		16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
16	WAPRI: basic	1																
17	WAPRI: applied	-0.0947*	1															
18	WAPRI: develop.	-0.1076*	-0.2844*	1														
19	WAPRI: design	-0.0916*	-0.2421*	-0.2750*	1													
20	WAPRI: comp. apps	-0.1332*	-0.3522*	-0.4001*	-0.3405*	1												
21	WA_NONRD	-0.007	0.0389*	0.0629*	0.0385*	-0.1199*	1											
22	JOBDEGREE	0.0247*	0.0825*	0.0537*	0.0288*	-0.1528*	0.0104	1										
23	HD: bachelor	-0.0181	-0.2172*	-0.1068*	0.1396*	0.1729*	0.0578*	-0.0124	1									
24	HD: master	-0.0177	-0.0963*	-0.0055	0.0126	0.0832*	-0.0129	0.0744*	-0.5131*	1								
25	HD: PHD	0.0360*	0.3240*	0.1205*	-0.1625*	-0.2640*	-0.0505*	-0.0558*	-0.6030*	-0.3753*	1							
26	HDTENURE	-0.0297*	-0.0219	-0.0039	0.0530*	-0.0104	0.0133	-0.1052*	0.0870*	-0.0715*	-0.0276*	1						
27	LN_SUPDIR	-0.0058	0.0817*	0.0564*	0.0091	-0.1263*	0.3966*	0.0504*	-0.0962*	-0.0352*	0.1366*	0.0836*	1					
28	LN_SALARY	-0.0412*	0.0540*	0.0477*	-0.0277*	-0.0504*	0.0287*	0.0403*	-0.2017*	0.0326*	0.1875*	0.2613*	0.1927*	1				
29	Satisfaction Salary	-0.0077	0.0340*	-0.0064	-0.0202	-0.0032	-0.023	0.0403*	0.0033	-0.011	0.0067	0.0650*	0.0520*	0.1925*	1			
30	ABILITY	0.0172	0.0413	0.0041	-0.0231	-0.0536*	-0.0227	-0.0453	.	.	.	0.0328	-0.0139	0.0849*	0.0540*	1		
31	MALE	-0.0495*	-0.0530*	0.0329*	0.0663*	-0.021	0.0063	0.0269*	-0.0077	-0.0297*	0.0359*	0.1294*	0.0723*	0.1382*	-0.021	-0.0215	1	
32	MARRIED	-0.0368*	0.016	0.0202	-0.0013	-0.0168	0.0225	0.0217	-0.1086*	0.0330*	0.0866*	0.1944*	0.0836*	0.1279*	0.0225	-0.0675*	0.1260*	1
33	CHILDREN011	-0.0081	-0.019	0.0131	-0.0105	0.016	0.0241	0.0154	-0.0338*	-0.0022	0.0386*	-0.1285*	0.0645*	0.0480*	-0.0055	0.0033	0.0646*	0.3395*

* significant at 1%

Table A6: Effort Regressions (PhD – Sample)

	Full Sample	PHD=0		Phd-Sample	
	truncreg	truncreg	truncreg	truncreg	truncreg
	1	2	3	4	5
	hrsworked	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**
Imp. Salary	-0.409*	-0.662**	0.400	0.408	0.569
	[0.186]	[0.211]	[0.391]	[0.389]	[0.382]
Imp. Benefits	-0.154	-0.227	-0.187	-0.175	-0.294
	[0.185]	[0.210]	[0.369]	[0.368]	[0.360]
Imp. Job Security	-0.283	-0.021	-0.688*	-0.640*	-0.668*
	[0.158]	[0.180]	[0.315]	[0.314]	[0.300]
Imp. Challenge	0.964**	0.773**	1.546**	1.470**	1.550**
	[0.180]	[0.203]	[0.378]	[0.377]	[0.366]
Imp. Independence	0.339*	0.363*	0.149	0.178	0.070
	[0.156]	[0.175]	[0.339]	[0.337]	[0.323]
Imp. Advancement	0.017	0.081	0.028	0.028	0.099
	[0.152]	[0.169]	[0.315]	[0.314]	[0.306]
Imp. Responsibility	0.626**	0.525**	0.566	0.593	0.450
	[0.158]	[0.180]	[0.325]	[0.323]	[0.310]
Imp. Contr. Society	-0.149	-0.143	0.012	0.045	0.020
	[0.126]	[0.143]	[0.264]	[0.263]	[0.249]
ABILITY				0.704**	0.645**
				[0.217]	[0.208]
EMPLIDCT5 (122)					incl.
EMSIZE: 1-10	-0.345	-0.618	0.237	0.445	1.940
	[0.546]	[0.633]	[1.122]	[1.121]	[1.184]
EMSIZE: 11-24	-1.544**	-1.931**	-0.756	-0.766	0.839
	[0.495]	[0.583]	[0.933]	[0.933]	[1.023]
EMSIZE: 25-99	-0.483	-0.742	0.252	0.229	1.702*
	[0.336]	[0.387]	[0.679]	[0.677]	[0.819]
EMSIZE: 100-499	-0.449	-0.564	-0.616	-0.617	0.794
	[0.290]	[0.344]	[0.576]	[0.578]	[0.753]
EMSIZE: 500-999	-0.848*	-0.839*	-0.518	-0.431	1.659
	[0.362]	[0.415]	[0.833]	[0.832]	[0.948]
EMSIZE: 1000-4999	-0.644*	-0.661*	-0.792	-0.843	0.607
	[0.258]	[0.296]	[0.518]	[0.517]	[0.670]
EMSIZE: 5000-24999	-0.406	-0.440	-0.454	-0.437	0.616
	[0.230]	[0.264]	[0.480]	[0.478]	[0.540]
NEWBUS	2.204**	1.967**	2.815**	2.766**	2.664**
	[0.330]	[0.400]	[0.634]	[0.635]	[0.637]
IND_NAICS (27)	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	-0.538	-1.440*	1.495	1.448	1.735
	[0.477]	[0.580]	[0.912]	[0.912]	[0.901]
WAPRI: applied	-0.027	0.001	0.044	0.008	-0.076
	[0.255]	[0.357]	[0.404]	[0.403]	[0.388]
WAPRI: design	0.000	-0.083	-0.239	-0.193	-0.230
	[0.245]	[0.275]	[0.590]	[0.590]	[0.582]
WAPRI: computers	-0.745**	-0.733**	-0.988	-0.919	-0.900
	[0.248]	[0.274]	[0.620]	[0.615]	[0.571]
WA_NONRD	0.896**	0.834**	1.006**	1.011**	1.001**
	[0.064]	[0.074]	[0.125]	[0.124]	[0.122]
DEGREE: masters	0.494*	0.471*			
	[0.208]	[0.208]			
DEGREE: phd	2.041**				
	[0.244]				
HD_FIELD (15)	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	1.587**	1.365**	1.915**	1.928**	1.924**
	[0.114]	[0.132]	[0.229]	[0.229]	[0.221]
HDTENURE	0.106**	0.074*	0.180*	0.174*	0.169*
	[0.029]	[0.032]	[0.072]	[0.072]	[0.070]
HDTENURE_SQ	-0.002**	-0.002*	-0.004*	-0.004*	-0.004*
	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]
JOBDEGREE	0.423**	0.408*	0.253	0.297	0.115
	[0.136]	[0.162]	[0.280]	[0.280]	[0.272]
MALE	0.956**	0.922**	0.574	0.625	0.781
	[0.220]	[0.241]	[0.506]	[0.502]	[0.471]
CHILDREN011	-1.097**	-0.530*	-2.833**	-2.875**	-3.019**
	[0.245]	[0.255]	[0.544]	[0.544]	[0.532]
MALE x CHILDREN011	1.099**	0.709**	2.506**	2.529**	2.634**
	[0.257]	[0.271]	[0.572]	[0.571]	[0.558]
MARRIED	-0.092	-0.017	-0.248	-0.151	0.014
	[0.211]	[0.237]	[0.460]	[0.457]	[0.431]
USCITIZEN	0.724**	1.078**	-0.153	-0.219	-0.247
	[0.276]	[0.350]	[0.523]	[0.522]	[0.499]
RACE (3)	incl.	incl.	incl.	incl.	incl.
Observations	11014	7643	2805	2805	2805

Robust standard errors in brackets

* significant at 5%; ** significant at 1%

Source: Based on NSF (2003): SESTAT restricted-use data file

Table A7: Performance Regressions: Auxiliary Analyses

	Full Sample		Basic/Appl.	Developm.	Design	Compapp.	uspapp>0	Pharmed
	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg
	1	2	3	4	5	6	7	8
	uspapp	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**
Imp. Salary	0.088	0.102	0.294**	0.007	0.169	-0.193	0.137**	0.204
	[0.073]	[0.072]	[0.099]	[0.092]	[0.144]	[0.165]	[0.053]	[0.176]
Imp. Benefits	-0.022	-0.019	-0.110	-0.027	-0.065	0.238	-0.010	-0.226
	[0.075]	[0.074]	[0.102]	[0.091]	[0.151]	[0.156]	[0.057]	[0.177]
Imp. Job Security	-0.268**	-0.255**	-0.332**	-0.186*	-0.460**	-0.393**	-0.090	-0.298*
	[0.059]	[0.059]	[0.087]	[0.085]	[0.130]	[0.133]	[0.054]	[0.145]
Imp. Challenge	0.394**	0.373**	0.452**	0.177	0.173	0.852**	0.152**	0.585**
	[0.070]	[0.069]	[0.100]	[0.109]	[0.146]	[0.173]	[0.053]	[0.190]
Imp. Independence	0.114*	0.123*	0.127	0.251**	-0.087	0.106	0.167**	0.338*
	[0.058]	[0.057]	[0.076]	[0.088]	[0.135]	[0.147]	[0.045]	[0.155]
Imp. Advancement	-0.041	-0.048	0.111	-0.047	-0.097	-0.018	0.012	-0.159
	[0.057]	[0.056]	[0.079]	[0.089]	[0.123]	[0.140]	[0.045]	[0.153]
Imp. Responsibility	-0.071	-0.085	-0.197*	-0.055	0.097	-0.214	-0.057	-0.327*
	[0.058]	[0.058]	[0.081]	[0.091]	[0.131]	[0.140]	[0.048]	[0.166]
Imp. Contr. Society	0.019	0.019	-0.002	-0.043	0.128	-0.152	-0.049	0.165
	[0.049]	[0.050]	[0.064]	[0.078]	[0.097]	[0.104]	[0.043]	[0.120]
HRSWORKED		0.019**	0.009	0.023**	0.026*	0.025*	0.009*	-0.006
		[0.005]	[0.006]	[0.007]	[0.011]	[0.011]	[0.004]	[0.011]
EMSIZE: 1-10	-0.321	-0.283	-0.582	-0.209	0.099	-0.451	0.031	0.493
	[0.203]	[0.202]	[0.320]	[0.334]	[0.531]	[0.417]	[0.200]	[0.499]
EMSIZE: 11-24	-0.533**	-0.509*	-0.898**	0.044	0.156	-1.810**	-0.152	0.030
	[0.197]	[0.202]	[0.277]	[0.297]	[0.402]	[0.429]	[0.200]	[0.522]
EMSIZE: 25-99	-0.523**	-0.526**	-0.823**	-0.344	-0.368	-0.550*	-0.148	0.583
	[0.124]	[0.124]	[0.160]	[0.200]	[0.274]	[0.270]	[0.102]	[0.316]
EMSIZE: 100-499	-0.571**	-0.561**	-0.520**	-0.462*	-0.582*	-1.408**	-0.197	-0.370
	[0.132]	[0.130]	[0.164]	[0.191]	[0.239]	[0.268]	[0.116]	[0.283]
EMSIZE: 500-999	-0.439**	-0.433**	-0.841**	-0.213	-0.452	-0.381	-0.193	0.006
	[0.142]	[0.139]	[0.251]	[0.208]	[0.309]	[0.310]	[0.142]	[0.353]
EMSIZE: 1000-4999	-0.269**	-0.256**	-0.350*	-0.214	-0.154	-0.380	-0.169*	0.152
	[0.092]	[0.092]	[0.143]	[0.141]	[0.202]	[0.213]	[0.075]	[0.243]
EMSIZE: 5000-24999	-0.210*	-0.191	-0.573**	-0.290*	0.440*	-0.134	-0.141	-0.396
	[0.104]	[0.105]	[0.114]	[0.122]	[0.210]	[0.238]	[0.072]	[0.223]
NEWBUS	0.287*	0.239	0.020	0.364*	0.395	0.572*	-0.012	0.185
	[0.122]	[0.123]	[0.160]	[0.173]	[0.287]	[0.285]	[0.102]	[0.275]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	-0.106	-0.085					0.148	0.854*
	[0.139]	[0.138]					[0.115]	[0.333]
WAPRI: applied	0.201*	0.201*	0.197				0.187**	0.609**
	[0.081]	[0.080]	[0.124]				[0.064]	[0.201]
WAPRI: design	-0.352**	-0.346**					-0.027	-0.381
	[0.106]	[0.106]					[0.090]	[0.319]
WAPRI: computers	-1.300**	-1.286**					-0.417**	-1.713**
	[0.109]	[0.109]					[0.097]	[0.349]
WA_NONRD	-0.045	-0.060*	-0.075*	-0.016	-0.204**	-0.011	0.009	-0.102
	[0.024]	[0.025]	[0.036]	[0.034]	[0.059]	[0.060]	[0.021]	[0.068]
DEGREE: masters	0.469**	0.471**	0.513**	0.443**	0.794**	0.246	0.128	0.160
	[0.097]	[0.097]	[0.167]	[0.139]	[0.178]	[0.167]	[0.082]	[0.257]
DEGREE: phd	1.580**	1.560**	1.424**	1.581**	1.912**	2.002**	0.455**	0.912**
	[0.084]	[0.085]	[0.138]	[0.128]	[0.199]	[0.198]	[0.068]	[0.234]
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	0.298**	0.272**	0.383**	0.184**	0.374**	0.093	0.116**	0.474**
	[0.041]	[0.041]	[0.063]	[0.059]	[0.082]	[0.099]	[0.033]	[0.126]
HDTENURE	-0.006	-0.008	0.009	-0.005	0.007	-0.050	-0.036**	0.074*
	[0.013]	[0.013]	[0.018]	[0.018]	[0.024]	[0.028]	[0.011]	[0.033]
HDTENURE_SQ	0.000	0.000	0.000	0.000	0.000	0.001	0.001**	-0.002*
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
JOBDEGREE	0.215**	0.214**	-0.029	0.187*	0.434**	0.391**	0.006	-0.121
	[0.058]	[0.057]	[0.084]	[0.080]	[0.112]	[0.133]	[0.047]	[0.135]
MALE	0.664**	0.651**	0.394**	0.564**	1.016**	1.030**	0.267**	0.781**
	[0.084]	[0.085]	[0.114]	[0.133]	[0.231]	[0.220]	[0.074]	[0.196]
USCITIZEN	0.146	0.140	-0.093	-0.037	0.272	0.662**	0.132	-0.013
	[0.091]	[0.090]	[0.129]	[0.130]	[0.222]	[0.232]	[0.074]	[0.249]
RACE (3)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	11014	11014	2586	2690	2089	3649	2637	769
Chi-square	2672.705	2732.524	943.516	600.498	850.215	20956.11	524.884	
df	74	75	72	71	71	71	75	48
alphaest	4.014	3.991	2.568	3.269	5.503	7.966	0.656	2.695

Robust standard errors in brackets
* significant at 5%; ** significant at 1%
Source: Based on NSF (2003): SESTAT restricted-use data file

Table A8: Performance Regressions (PhD-Sample)

	Full Sample	PhD Sample					
	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg
	1	2	3	4	5	6	7
	uspapp	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**
Imp. Salary	0.088	0.263**	0.266**		0.257**	0.257**	0.180*
	[0.073]	[0.080]	[0.080]		[0.080]	[0.080]	[0.078]
Imp. Benefits	-0.022	-0.074	-0.080		-0.070	-0.076	-0.043
	[0.075]	[0.085]	[0.085]		[0.084]	[0.084]	[0.082]
Imp. Job Security	-0.268**	-0.198*	-0.184*		-0.185*	-0.167*	-0.185*
	[0.059]	[0.079]	[0.079]		[0.081]	[0.080]	[0.074]
Imp. Challenge	0.394**	0.288**	0.281**		0.273**	0.271**	0.227**
	[0.070]	[0.083]	[0.083]		[0.083]	[0.083]	[0.079]
Imp. Independence	0.114*	0.319**	0.322**		0.326**	0.326**	0.292**
	[0.058]	[0.067]	[0.068]		[0.067]	[0.068]	[0.066]
Imp. Advancement	-0.041	0.013	0.019		0.023	0.031	0.062
	[0.057]	[0.068]	[0.068]		[0.067]	[0.067]	[0.063]
Imp. Responsibility	-0.071	-0.117	-0.110		-0.131	-0.132	-0.115
	[0.058]	[0.069]	[0.069]		[0.070]	[0.070]	[0.064]
Imp. Contr. Society	0.019	-0.126*	-0.126*		-0.133*	-0.126*	-0.088
	[0.049]	[0.059]	[0.061]		[0.060]	[0.060]	[0.056]
HRSWORKED				0.016**	0.014**	0.011*	0.006
				[0.005]	[0.005]	[0.005]	[0.005]
ABILITY			0.114*			0.106*	0.075
			[0.052]			[0.052]	[0.047]
HRS x ABILITY						0.014*	0.017**
						[0.006]	[0.006]
Employer ID's							incl.
EMSIZE: 1-10	-0.321	0.093	0.145	0.113	0.132	0.161	0.351
	[0.203]	[0.323]	[0.326]	[0.305]	[0.330]	[0.325]	[0.334]
EMSIZE: 11-24	-0.533**	-0.178	-0.181	-0.103	-0.152	-0.147	0.057
	[0.197]	[0.272]	[0.266]	[0.293]	[0.281]	[0.273]	[0.284]
EMSIZE: 25-99	-0.523**	-0.247	-0.251	-0.198	-0.255	-0.265	-0.071
	[0.124]	[0.136]	[0.136]	[0.144]	[0.137]	[0.138]	[0.176]
EMSIZE: 100-499	-0.571**	-0.257	-0.252	-0.245	-0.246	-0.240	-0.104
	[0.132]	[0.160]	[0.161]	[0.169]	[0.159]	[0.161]	[0.189]
EMSIZE: 500-999	-0.439**	-0.455	-0.446	-0.435	-0.479*	-0.463*	-0.105
	[0.142]	[0.236]	[0.236]	[0.223]	[0.218]	[0.221]	[0.209]
EMSIZE: 1000-4999	-0.269**	-0.196	-0.211	-0.169	-0.188	-0.191	-0.116
	[0.092]	[0.121]	[0.121]	[0.125]	[0.121]	[0.121]	[0.140]
EMSIZE: 5000-24999	-0.210*	-0.222*	-0.233*	-0.220*	-0.216*	-0.227*	-0.074
	[0.104]	[0.098]	[0.098]	[0.101]	[0.099]	[0.098]	[0.119]
NEWBUS	0.287*	0.171	0.157	0.191	0.128	0.118	0.122
	[0.122]	[0.157]	[0.156]	[0.169]	[0.157]	[0.155]	[0.153]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	-0.106	0.202	0.180	0.180	0.206	0.192	0.346*
	[0.139]	[0.170]	[0.168]	[0.173]	[0.171]	[0.170]	[0.171]
WAPRI: applied	0.201*	0.243**	0.225*	0.304**	0.239**	0.227*	0.284**
	[0.081]	[0.092]	[0.092]	[0.098]	[0.092]	[0.092]	[0.089]
WAPRI: design	-0.352**	-0.229	-0.234	-0.176	-0.222	-0.219	-0.092
	[0.106]	[0.146]	[0.146]	[0.154]	[0.147]	[0.146]	[0.136]
WAPRI: computers	-1.300**	-1.129**	-1.129**	-1.075**	-1.101**	-1.106**	-1.001**
	[0.109]	[0.150]	[0.149]	[0.157]	[0.151]	[0.151]	[0.135]
WA_NONRD	-0.045	0.005	0.001	0.001	-0.008	-0.009	0.006
	[0.024]	[0.035]	[0.034]	[0.036]	[0.035]	[0.035]	[0.035]
DEGREE: masters	0.469**						
	[0.097]						
DEGREE: phd	1.580**						
	[0.084]						
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	0.298**	0.275**	0.277**	0.233**	0.250**	0.258**	0.289**
	[0.041]	[0.052]	[0.052]	[0.054]	[0.051]	[0.051]	[0.050]
HDTENURE	-0.006	-0.009	-0.010	-0.010	-0.010	-0.010	0.003
	[0.013]	[0.017]	[0.017]	[0.019]	[0.017]	[0.018]	[0.016]
HDTENURE_SQ	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]
JOBDEGREE	0.215**	0.013	0.021	-0.007	0.012	0.020	0.040
	[0.058]	[0.063]	[0.064]	[0.068]	[0.064]	[0.064]	[0.063]
MALE	0.664**	0.392**	0.399**	0.387**	0.380**	0.385**	0.400**
	[0.084]	[0.100]	[0.100]	[0.106]	[0.100]	[0.101]	[0.102]
USCITIZEN	0.146	0.149	0.138	0.124	0.142	0.124	0.043
	[0.091]	[0.108]	[0.108]	[0.118]	[0.109]	[0.109]	[0.106]
RACE (3)	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	11014	2805	2805	2805	2805	2805	2805
Chi-square	2672.705	1669.722	1657.054	1575.238	1683.641	1768.159	9122.042
df	74	71	72	64	72	74	196
alphaest	4.014	2.434	2.425	2.518	2.42	2.404	2.053

Robust standard errors in brackets

* significant at 5%; ** significant at 1%

Source: Based on NSF (2003): SESTAT restricted-use data file

Table A9: Alternative Performance Measures

	nbreg 1 uspapp	nbreg 2 uspapp	nbreg 3 uspgrt	nbreg 4 uspgrt	nbreg 5 uspcom	nbreg 6 uspcom	nbreg 7 publication	nbreg 8 publication
Imp. Salary	0.088	0.102	0.047	0.051	0.094	0.104	-0.052	-0.025
	[0.073]	[0.072]	[0.069]	[0.069]	[0.085]	[0.085]	[0.073]	[0.072]
Imp. Benefits	-0.022	-0.019	0.010	0.012	0.032	0.030	-0.178*	-0.196*
	[0.075]	[0.074]	[0.069]	[0.069]	[0.089]	[0.089]	[0.083]	[0.085]
Imp. Job Security	-0.268**	-0.255**	-0.238**	-0.231**	-0.291**	-0.282**	0.038	0.063
	[0.059]	[0.059]	[0.062]	[0.063]	[0.079]	[0.080]	[0.062]	[0.061]
Imp. Challenge	0.394**	0.373**	0.349**	0.339**	0.401**	0.382**	0.277**	0.254**
	[0.070]	[0.069]	[0.080]	[0.080]	[0.106]	[0.106]	[0.082]	[0.081]
Imp. Independence	0.114*	0.123*	0.211**	0.214**	0.173*	0.179*	0.001	0.012
	[0.058]	[0.057]	[0.067]	[0.066]	[0.086]	[0.086]	[0.083]	[0.079]
Imp. Advancement	-0.041	-0.048	-0.165**	-0.165**	-0.197**	-0.193*	-0.032	-0.053
	[0.057]	[0.056]	[0.061]	[0.061]	[0.076]	[0.076]	[0.063]	[0.063]
Imp. Responsibility	-0.071	-0.085	-0.126	-0.131*	-0.049	-0.056	-0.035	-0.050
	[0.058]	[0.058]	[0.065]	[0.065]	[0.082]	[0.082]	[0.068]	[0.070]
Imp. Contr. Society	0.019	0.019	-0.012	-0.016	-0.023	-0.032	0.015	0.020
	[0.049]	[0.050]	[0.056]	[0.056]	[0.074]	[0.075]	[0.058]	[0.059]
HRSWORKED		0.019**		0.011*		0.017**		0.029**
		[0.005]		[0.005]		[0.006]		[0.006]
EMSIZE: 1-10	-0.321	-0.283	-0.197	-0.181	-0.095	-0.070	0.576	0.521
	[0.203]	[0.202]	[0.194]	[0.194]	[0.232]	[0.237]	[0.371]	[0.337]
EMSIZE: 11-24	-0.533**	-0.509*	-0.368	-0.345	-0.233	-0.223	0.125	0.168
	[0.197]	[0.202]	[0.238]	[0.242]	[0.229]	[0.229]	[0.178]	[0.176]
EMSIZE: 25-99	-0.523**	-0.526**	-0.427**	-0.420**	-0.231	-0.221	-0.280*	-0.268*
	[0.124]	[0.124]	[0.147]	[0.147]	[0.181]	[0.182]	[0.128]	[0.126]
EMSIZE: 100-499	-0.571**	-0.561**	-0.535**	-0.522**	-0.311*	-0.285	-0.407**	-0.362**
	[0.132]	[0.130]	[0.119]	[0.119]	[0.149]	[0.149]	[0.102]	[0.104]
EMSIZE: 500-999	-0.439**	-0.433**	-0.397*	-0.387*	-0.188	-0.183	-0.142	-0.108
	[0.142]	[0.139]	[0.163]	[0.163]	[0.189]	[0.187]	[0.157]	[0.153]
EMSIZE: 1000-4999	-0.269**	-0.256**	-0.262*	-0.255*	-0.072	-0.064	-0.109	-0.081
	[0.092]	[0.092]	[0.105]	[0.105]	[0.137]	[0.137]	[0.106]	[0.107]
EMSIZE: 5000-24999	-0.210*	-0.191	-0.241*	-0.233*	-0.074	-0.060	0.104	0.141
	[0.104]	[0.105]	[0.097]	[0.097]	[0.127]	[0.128]	[0.151]	[0.153]
NEWBUS	0.287*	0.239	0.028	0.003	-0.054	-0.099	0.104	0.049
	[0.122]	[0.123]	[0.131]	[0.132]	[0.166]	[0.170]	[0.131]	[0.128]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	-0.106	-0.085	0.014	0.027	-0.772**	-0.754**	0.761**	0.778**
	[0.139]	[0.138]	[0.163]	[0.164]	[0.241]	[0.247]	[0.149]	[0.152]
WAPRI: applied	0.201*	0.201*	0.147	0.148	-0.115	-0.118	0.423**	0.419**
	[0.081]	[0.080]	[0.088]	[0.088]	[0.116]	[0.117]	[0.078]	[0.079]
WAPRI: design	-0.352**	-0.346**	-0.424**	-0.425**	-0.594**	-0.605**	-0.239*	-0.246*
	[0.106]	[0.106]	[0.107]	[0.107]	[0.125]	[0.126]	[0.117]	[0.116]
WAPRI: computers	-1.300**	-1.286**	-1.408**	-1.403**	-1.373**	-1.369**	-0.787**	-0.752**
	[0.109]	[0.109]	[0.130]	[0.129]	[0.157]	[0.154]	[0.136]	[0.134]
WA_NONRD	-0.045	-0.060*	-0.007	-0.016	0.021	0.007	0.031	0.002
	[0.024]	[0.025]	[0.026]	[0.026]	[0.031]	[0.031]	[0.028]	[0.028]
DEGREE: masters	0.469**	0.471**	0.523**	0.520**	0.398**	0.392**	0.446**	0.433**
	[0.097]	[0.097]	[0.109]	[0.108]	[0.135]	[0.134]	[0.131]	[0.134]
DEGREE: phd	1.580**	1.560**	1.600**	1.586**	1.302**	1.282**	1.774**	1.724**
	[0.084]	[0.085]	[0.100]	[0.101]	[0.125]	[0.127]	[0.111]	[0.111]
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	0.298**	0.272**	0.326**	0.310**	0.378**	0.349**	0.279**	0.241**
	[0.041]	[0.041]	[0.046]	[0.046]	[0.057]	[0.057]	[0.050]	[0.051]
HDTENURE	-0.006	-0.008	0.092**	0.091**	0.115**	0.114**	-0.145**	-0.148**
	[0.013]	[0.013]	[0.015]	[0.015]	[0.019]	[0.019]	[0.011]	[0.011]
HDTENURE_SQ	0.000	0.000	-0.002**	-0.002**	-0.002**	-0.002**	0.003**	0.003**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
JOBDEGREE	0.215**	0.214**	0.202**	0.201**	0.239**	0.235**	0.341**	0.332**
	[0.058]	[0.057]	[0.062]	[0.062]	[0.079]	[0.078]	[0.057]	[0.058]
MALE	0.664**	0.651**	0.770**	0.764**	0.711**	0.702**	0.210*	0.188
	[0.084]	[0.085]	[0.095]	[0.096]	[0.126]	[0.127]	[0.095]	[0.097]
USCITIZEN	0.146	0.140	0.082	0.078	0.043	0.029	-0.709**	-0.715**
	[0.091]	[0.090]	[0.110]	[0.109]	[0.143]	[0.145]	[0.122]	[0.122]
RACE (3)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	11014	11014	11014	11014	11014	11014	11014	11014
Chi-square	2672.705	2732.524	1987.484	2012.722	1081.814	1107.347	3023.609	3204.696
df	74	75	74	75	74	75	74	75
alphaest	4.014	3.991	4.499	4.491	6.841	6.811	3.431	3.362

Robust standard errors in brackets

* significant at 5%; ** significant at 1%

Source: Based on NSF (2003): SESTAT restricted-use data file