INDIVIDUAL INCENTIVES

AS DRIVERS OF INNOVATIVE PROCESSES AND PERFORMANCE

by

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Department of Business Administration
Duke University

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
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ABSTRACT

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Abstract

Applied economists and strategy scholars have examined a variety of firm-level factors that may explain the level and direction of firms' innovative effort and performance, including firms' profit incentives. Innovation at the firm level, however, should also depend heavily on the nature of the pecuniary and non-pecuniary incentives driving the efforts of those individuals that are responsible for innovative activities within firms. Drawing on research in economics and social psychology, I examine three questions:

1. What are the motives of individuals engaged in firm innovation?
2. How do individuals' motives and incentives affect their innovative effort and performance?
3. How do individuals' motives and incentives differ between entrepreneurial and established firms, and are any such differences associated with differences in innovative effort and performance?

My empirical analysis builds on the National Science Foundation's SESTAT data, which contain survey responses from over 10,000 scientists and engineers employed in U.S. firms. Among others, the data contain measures of individuals' extrinsic, intrinsic, and social motives (e.g., preferences for work benefits such as salary, intellectual challenge, and contribution to society), effort, and innovative performance.

In chapter Two ("What makes them tick – Employee motives and firm innovation"), I develop a formal model of the relationships between individuals' motives and incentives, effort, and innovative performance. Econometric analyses using the SESTAT data suggest that individuals' motives have significant effects upon innovative effort, as well as on innovative performance, controlling for effort. Overall,

intrinsic motives (in particular, intellectual challenge) appear to be more beneficial for innovation than extrinsic motives.

In chapter Three ("Fire in the belly? Individuals' motives and innovative performance in startups and established firms"), I examine differences in motives, effort, and performance between startups and established firms. I find that individuals' extrinsic motives differ significantly between startups and established firms, while their intrinsic motives are surprisingly similar. Startup employees expend more effort and have higher patent application counts than individuals in established firms. Individuals' motives explain only a limited amount of these effort and performance differences across firm types, however, because the intrinsic motives that are most strongly associated with effort and performance differ little between startups and established firms.

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I also want to thank the many other faculty members at Duke and other institutions who have enriched me with countless hours of stimulating discussions, with their honest critical feedback, and by serving as role models and examples. I hope I will become a worthy member of this wonderful academic community.

I am also grateful to my colleagues at Duke who have made my time as a Ph.D. student enjoyable and intellectually stimulating. I thank Abhirup Chakrabarti, Morela Hernandez, Min Li, Shlomi Sher, and Aparna Venkatraman for being a great cohort in times of joy and suffering. I would especially like to thank my more experienced colleagues Jim Emery, Kim-Chi Trinh, and Mike Roach who helped me make the most of my years at Duke by willingly sharing their knowledge and experiences with me. Finally, I thank Long Vo for his patience and support, and for his invaluable help with the editing of this dissertation.

I dedicate this dissertation to my grandmother Christiane Sauermann. I admire her persistence in times of unimaginable hardship, her insatiable thirst for learning and knowledge, and her unconditional and selfless love and care for others.

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1 Prior Research and Dissertation Overview

"…most seemed to view the prospect of stock as a mere sweetener, and most agreed with Ken Holberger, who declared, 'I don't work for money.' "

Tracy Kidder (1981): The soul of a new machine

Innovative processes and performance in firms have important implications for economic firm performance as well as societal welfare. Hence, scholars in the fields of the economics of innovation as well as strategy have pursued various fruitful avenues in explaining the levels and direction of innovative effort of firms and in identifying the firm-level factors that drive superior innovative performance. Innovation at the firm-level, however, should also depend heavily on the level and nature of the efforts of those individuals that are ultimately responsible for innovative activities within firms, including both managerial and non-managerial employees. These individuals respond to a variety of individual-level incentives of a pecuniary as well as non-pecuniary nature. While firm-level profit incentives have received great attention in the innovation and strategy literatures (e.g., Arora & Ceccagnoli, 2006; Christensen, 1997; Cohen, 1995; Schmookler, 1962), the incentives of individuals engaged in firm innovation have been understudied. At the same time, qualitative examples as well as research in other fields suggest that individuals' incentives may have important impacts upon innovation, and that these incentives are of a pecuniary as well as non-pecuniary nature (Amabile, 1996; Katz, 1993; Kidder, 1981; Stephan, 1996; Zuckerman, 1988). The concrete pecuniary and non-pecuniary motives and incentives that drive individuals engaged in firm innovation, as well as the relationships between these motives and incentives and innovative outcomes, however, are poorly understood. To address this gap, I employ an interdisciplinary approach to study the impacts of pecuniary as well as nonpecuniary individual-level motives and incentives on innovative activities, processes and performance in firms. This effort contributes to the literatures on the economics of innovation and firm strategy, in particular to the emerging stream of strategy research examining the "micro-foundations" of firm capabilities and firm performance (e.g., Felin & Foss, 2005; Gavetti, 2005; Rothaermel & Hess, 2007).

While most of the research on micro-foundations has taken a cognitive perspective by examining how cognitive processes at the individual level affect firm-level outcomes (e.g., Gavetti, 2005; Reger & Huff, 1993; Tripsas & Gavetti, 2000), I take a motivational perspective by focusing on the motives and incentives of the individuals engaged in firm innovation. I define individual-level *incentives* as expected pecuniary or non-pecuniary benefits that are contingent upon individuals' employment, effort or performance. Examples include contingent pay, intellectual challenge, and peer recognition. Individual-level *motives* are defined as individuals' preferences over these benefits (e.g., how important are pay and peer recognition to the individual). Using these definitions, I theoretically and empirically examine the following research questions:

1. What are the motives of individuals engaged in firm innovation?
2. How do individuals' motives and incentives affect their innovative effort and performance?
3. How do individuals' motives and incentives differ between entrepreneurial and established firms, and are any such differences associated with differences in innovative effort and performance across firm types?

In examining these questions, I draw on a range of literatures, including economics, social psychology, and organizational behavior. My empirical analyses use data from the Scientists and Engineers Statistical Data System (SESTAT), maintained by the National Science Foundation (National Science Foundation, 2003). This unique data set combines survey data from over 10,000 scientists and engineers employed in private sector firms and includes a wide range of individual-, firm-, and industry-level variables that allow for a detailed analysis of the role of individuals' motives in firm innovation.

Beyond advancing our understanding of innovation and firm performance, my research may yield dividends for both policy and management. For policy makers, a consideration of the motives and incentives of those individuals responsible for advancing technology may contribute to the formulation of labor market policies, intellectual property policies, and policies targeted at university-industry interactions. For management, a better understanding of individual-level motives as well as of the conditions that affect firms' ability to shape individuals' motives and incentives may allow firms to devise organizational systems that result in higher innovative performance and, potentially, a competitive advantage vis-à-vis other firms.

In studying the role of individual-level motives and incentives as drivers of innovative processes and performance, we can draw on prior research that has studied individuals' motivation and incentives in other (non-innovative) contexts. At the same time, it is important to consider how innovative contexts may differ from those other settings. First, the innovation task may be different with respect to task objectives, task structure, and informational conditions. Second, the individuals engaged in innovation may differ from others with respect to their motives. Finally, the relationships between motives, incentives, and performance may be different because of different mediating processes. Of course, the strict distinction between innovative and non-innovative settings is a simplification. Innovation takes place in many parts of the organization and is not confined to "pure" innovation functions such as research and development (R&D) (Damanpour, 1992; Van de Ven, 1986). It is nevertheless useful to consider some of the distinctive features of the (ideal-type) innovation setting and to review some of the existing literature concerning the nature and role of individuals' motives and incentives in innovation. In doing so, my focus will be on organizational settings that are designed explicitly for innovation, such as R&D labs. In addition, I will discuss select research that speaks to individual-level motives and incentives more generally and that may be useful in examining their role in innovative contexts.

1.1 The Nature of the Innovation Task

Innovation tasks are characterized by the goal of the generation of new knowledge and ideas, potentially reflected in new organizational processes, products, or services. This definition thus encompasses both upstream activities such as basic and applied research as well as more downstream activities such as the development of new ideas into marketable products and processes (cf. Dosi, 1988; Stoneman, 1995). Innovation scholars are interested in various aspects of the innovative performance of firms, including quantity (e.g., measured as numbers of patents or new product introductions), quality (e.g., commercial value, citations to patents), and the particular nature of innovations (e.g., radical vs. incremental, different problems that are being solved, etc.).

Compared to other activities such as manufacturing, innovation is typically characterized by higher levels of uncertainty with respect to the underlying production technology and a weaker link between individuals' effort and performance. Moreover, individual employees will often be considerably more expert about the technology in question than management and, given the uncertainty endemic to the outcomes of innovation projects, observable outcomes are not necessarily informative of the level or quality of effort expended by the employee (Dosi, 1988; Hauser, 1998; March, 1991; Ouchi, 1979; Sitkin, Sutcliffe, & Schroeder, 1994). Under these conditions, it is typically difficult and very costly to design incentive systems that rely on monitoring of behaviors or on measurement of individuals' innovative performance (Hauser, 1998; Ouchi, 1979; Prendergast, 1999). As a consequence, R&D labs are settings with some significant delegation of authority to the individual employee. The particular motives and incentives of individual employees — those under the control of management as well as those that are not — may thus have important impacts on innovative activities and performance (Prendergast, 2002). Finally, it has been argued that innovation tasks are typically perceived as very interesting and intellectually challenging, suggesting that individuals may generate relatively large amounts of intrinsic benefits from such tasks or, alternatively, that the cost of effort are lower than in non-innovative settings (Cohen & Sauermann, 2007; Lacetera & Zirulia, 2008; Stephan & Levin, 1992).

Given the particular characteristics of innovative settings, both the nature and the effects of individuals' motives and incentives may differ from those in non-innovative settings.[1] In this dissertation, I explicitly focus on innovative processes and performance as the phenomena of interest and I examine to what extent various types of individual-level motives and incentives explain patterns of innovation within and across firms.

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[1] For example, Lazear (2000) showed that pay-for-performance compensation significantly increased the productivity of employees replacing broken windshields. This does not imply that individual-level pay-for-performance systems in basic research would be similarly effective.

1.2 Individuals' Motives in the Innovation Context

1.2.1 General Characteristics of Individuals' Motives

While organizational theory and economics have advanced our understanding of the particular nature of the innovation task and what it implies for incentive design, other literatures have examined the motives of the individuals engaged in innovation. Before reviewing prior work on the motives of individuals engaged in innovation, however, it is useful to provide some background on the nature of individuals' motives more generally. In doing so, I will draw heavily on research in social psychology and organizational behavior.

As stated above, I define individuals' motives as individuals' preferences over contingent benefits. These preferences can refer to *desired amounts* of such benefits (e.g., how much independence or intellectual challenge does an individual desire) or to the *importance* of those benefits to the individual (e.g., how important is intellectual challenge). While the two kinds of preferences are often highly correlated, they are treated as distinct concepts in the organizational behavior literature (for a more detailed discussion, see Cable & Edwards, 2004). In this dissertation, I will focus on motives regarding the importance of benefits.[2] Another fundamental question regarding motives regards their origins or sources. In particular, are an individual's motives fixed or do they change over time or across contexts? The assumption of exogeneity (and stability) of preferences is routinely made by economists (for an exception, see Bowles, 1998). Some social psychologists also consider preferences for work attributes to be "trait-like", i.e., relatively stable

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[2] This focus on the importance of benefits (vs. desired levels) is primarily a function of data availability in the empirical part of this dissertation. In addition, most prior empirical research regarding scientists' and engineers' motives has also operationalized motives using importance measures (see below).

over time, and several measurement instruments have been developed that are routinely used in empirical work with the implicit assumption of stability of motives (e.g., Amabile, Hill, Hennessey, & Tighe, 1994; Cable & Edwards, 2004; Super, 1964).[3] However, it is also likely that individuals' motives change over time, reflecting different stages in the life cycle and different socioeconomic contexts (Demo, 1992). Moreover, it is also conceivable that individuals' preferences change in response to realized benefits. For example, in an effort to reduce "cognitive dissonance", individuals may rationalize high innovative efforts despite low monetary rewards by reporting that monetary rewards matter little to them (cf. Festinger, 1957). Thus, individuals' motives are partly stable and "trait-like" but may also, to a limited degree, change over time and in response to the particular context. I will revisit this issue in chapter Two.

1.2.2 Typology of Motives and Benefits

Work may potentially provide individuals with a wide range of different benefits, including pay, intellectual challenge, peer recognition, etc. As noted above, work benefits can be contingent upon employment in a particular organization (e.g., fixed wage), upon effort (e.g., hourly wage) or upon performance (e.g., performance-based pay). The number of concrete benefits, and thus of individuals' motives, is virtually unlimited. It is, therefore, useful to find a typology that meaningfully distinguishes between broader classes of motives and incentives. Such a typology can be based on a variety of dimensions, depending on the underlying theoretical perspective and the research questions to be examined.

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[3] Studies explicitly investigating the stability of preferences for job characteristics are rare. Genetic research appears promising in this area; in a small-sample twin study, Keller et al. (1992) found that about 40% of measured variance in work values (their term for preferences for job characteristics) was due to genetic factors.

Many social psychologists have traditionally focused on the source of the benefit and have distinguished extrinsic versus intrinsic benefits and motives. Intrinsic benefits derive from within the individual or task, while extrinsic benefits are only indirect task outcomes that are provided by some external agent or condition (see below). Economists, on the other hand, typically focus on the nature of the benefit and distinguish pecuniary and non-pecuniary benefits (Amabile, 1996; Dasgupta & David, 1994; Gagne & Deci, 2005; Hamilton, 2000; Ryan & Deci, 2000).

Researchers in vocational psychology and related fields have conducted a considerable amount of empirical work to gain a better understanding of the nature and structure of individuals' preferences for work benefits, which are called "work values" in that literature. For example, Elizur et al. (Elizur, Borg, Hunt, & Beck, 1991; Sagie, Elizur, & Koslowsky, 1996) conducted correlational analyses using survey data from individuals in eight countries and identified three broader types of motives which they label instrumental (e.g., importance of pay, security), cognitive (e.g., personal growth and independence), and affective (e.g., recognition). They also distinguish work benefits by the nature of their contingency into benefits that are contingent on membership in the organization or contingent upon performance. Ros et al. (Ros, Schwartz, & Surkiss, 1999) distinguish four types of work values, including intrinsic, extrinsic, social, and prestige. In their discussion of the motives and incentives of scientists, Stephan and Levin (1992) distinguish "gold" (extrinsic benefits), "puzzles" (intrinsic benefits) and "ribbons" (social benefits). Finally, there are other researchers who propose far more detailed distinctions. Donald Super (Super, 1964) developed an influential "work values inventory", which is, with some modifications, still used today by researchers and especially professionals in career counseling (Zytowski, 2006). Types of benefits in these inventories comprise factors such as achievement, creativity, income, lifestyle, challenge, and security. In more recent work, Edwards and Cable identify eight work value dimensions which they label altruism, relationships with others, pay, prestige, security, authority, variety, and autonomy (Cable & Edwards, 2004).

Thus, there are numerous possible ways to classify work benefits and the associated motives, varying in the underlying dimensions that are emphasized and in the level of aggregation. Based on the prior literature and my own interviews[4], I will distinguish work benefits and motives based on two key dimensions: extrinsic vs. intrinsic and social vs. nonsocial (Figure 1). This typology reduces the large number of concrete work benefits and motives into a smaller, more manageable set. At the same time, it acknowledges key differences between work benefits, in particular with respect to the source of the benefit (external vs. internal to the individual) and with respect to the role of a specific social context. I characterize the various types of benefits in the following.

Extrinsic benefits are provided by some external entity such as a market or actor such as an employer, a superior, or a customer. These 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 those which are pecuniary. Examples of extrinsic benefits from R&D include monetary or other tangible rewards such as pay raises, royalty income from patents, research funding, or a paid vacation.

Intrinsic benefits originate within the individual or the activity itself - not the environment - and are often a function of the interaction between characteristics of the activity (e.g., nature of the task) and of the individual (e.g., interest in the

[4] To inform my research, I conducted semi-structured interviews with bench scientists, R&D managers, and academic scientists in Germany and in the U.S.

task).[5] Some intrinsic benefits, such as task enjoyment and intellectual challenge, are realized directly from the process of engaging in certain activities and are thus effort-contingent (Amabile, 1996; Stephan, 1996). Others, such as a feeling of achievement, mastery or self-competence, result directly from task outcomes.

Social benefits encompass intangible benefits that originate from social relations and associated perceptions. Extrinsic social benefits are provided by others, either informally (e.g., social approval, peer recognition) or more formally through institutionalized "award" systems. Social benefits may be derived from a reference group within a focal organization or from others who stand outside of one's organization, as illustrated by the importance that academics often attach to the number of citations that their publications command from other academics. Other social benefits are self-administered. For example, individuals may derive pleasure from contributing to the well-being of individuals with whom they have a social relationship (Fehr & Falk, 2002; Fehr & Fischbacher, 2002). Social incentives may be particularly important in teams or organizations to the extent that members develop a high degree of cohesion and mutual commitment (Alvesson, 2000; Kidder, 1981; Knoke 1990; O'Reilly, 1989; Ouchi, 1979). Indeed, Hamilton et al. (2003) suggest that some of the apparent productivity benefits observed for teams in a production environment may be due to nonpecuniary rewards associated with team membership. To the extent that individuals internalize social benefits, these benefits become intrinsic benefits in that their realization does not then depend on any

[5] This implies that many intrinsic benefits, unlike extrinsic benefits, do not exist independently from a "reference" individual, and a given work attribute may provide an intrinsic benefit in the eyes of one employee but not of another. For example, a particular research project may appear highly interesting to one researcher (and that researcher will derive intrinsic benefits from working on that question), while it appears boring to another. Our understanding of the factors driving individual differences in general levels of curiosity as well as which particular problems individuals find interesting is quite limited (Loewenstein, 1994).

external agents or institutions. Such internalized social benefits also resemble the norms highlighted recently by Akerlof and Kranton (2005).

Nonsocial benefits are benefits that are not tied to a particular social context. For example, to the extent that pay is valued for its purchasing power, it is an extrinsic benefit that is valued regardless of the particular person or group providing that pay. Similarly, intrinsic benefits derived from intellectual challenge or from satisfying curiosity do not require any outside agents and are not contingent on any relationship with the social environment.

This typology of benefits, distinguishing between extrinsic and intrinsic as well as social and nonsocial benefits, is clearly too broad given that each of these still encompasses a heterogeneous set of benefits with potentially unique roles in the innovation process. Moreover, different types of benefits and incentives may be correlated and hard to distinguish empirically. For example, an individual who receives a publicly announced bonus may simultaneously derive extrinsic nonsocial benefits (the actual money), extrinsic social benefits (peer recognition), intrinsic nonsocial benefits (feeling of achievement) and intrinsic social benefits (having contributed to the success of the organization). The broad conceptual distinction across the extrinsic-intrinsic and social-nonsocial dimensions is nevertheless useful to underscore that different motives can apply to R&D employees, and these different motives, in turn, can originate from distinct sources. In the empirical chapters of this dissertation, I will focus on the extrinsic-intrinsic dimension because I have only one measure that captures social motives (contribution to society). This focus is solely due to data availability and does not suggest that social benefits are less important to individuals or that the social-nonsocial distinction is less useful from a theoretical or practical perspective. Indeed, my interviews as well as prior research on the concrete motives and incentives of scientists and engineers suggest that social motives and incentives may be very important (see below).

Figure 1: Typology of Benefits and Motives

	Extrinsic	**Intrinsic**
Social	e.g., peer recognition	e.g., feeling of contributing to society
Nonsocial	e.g., pay	e.g., intellectual challenge

1.2.3 The Motives of Individuals Engaged in Innovation

After this general discussion of motives and incentives, I will review some of the existing work on the motives and incentives of individuals engaged in innovation. Unfortunately, much of that work has been conducted several decades ago or is based on small samples of individuals in very specific contexts.

First, an early body of research in the 1950's, 60's and 70's focused on industrial scientists and engineers and examined the question to what extent the motives and values of these groups of employees conflict with the dominant values of large industrial corporations. Some authors characterized scientists as having a "cosmopolitan" orientation involving professional values such as openness, independence, and the pursuit of knowledge for its own sake, which are at conflict with the dominant values of the modern business enterprise, including hierarchy, conformity, and financial profit. Engineers, while still different from non-professional employees, were said to have a "local" orientation that is more consistent with typical corporate values (Blume, 1974; Gouldner, 1957; Kerr & Von Glinow, 1977; Kornhauser, 1962; Ritti, 1968; Shepard, 1956). Over time, scholars have recognized that these sharp distinctions between "cosmopolitans" and "locals" may be overly simplistic and have instead suggested to view "professionalism" as a continuum (Kerr & Von Glinow, 1977). Even this more refined view, however, viewed scientists and engineers as quite different from "non-professional" employees with regard to their dominant motives and values.

In related exploratory work (Cohen & Sauermann, 2007), I probe potential differences in the motives of professionals versus production workers using more recent data. More specifically, I analyzed data from the General Social Survey (GSS, 2001), which is conducted regularly by the University of Chicago National Opinion Research Center. Among other questions, the survey asks respondents to rank a number of job characteristics according to their importance.[6] According to these data, the importance of nonpecuniary benefits such as the significance of the work and a feeling of accomplishment is larger for scientific and engineering professionals than for production workers.

When interpreting such comparative results, however, we have to consider Badawy's (1973) important observation that the same general benefit (e.g., peer recognition) can take on different concrete expressions and can be obtained in different ways. For example, both scientists and engineers strongly value recognition. For the scientist, however, recognition is typically tied to the broader scientific community, while engineers derive recognition primarily from within the organization. Accordingly, the desire to obtain recognition may drive quite different specific innovative behaviors depending on the particular social reference group from which recognition is sought.

[6] The exact question is “Would you please look at this card and tell me which one thing on this list you would most prefer in a job? Which comes next? Which is third most important? Which is fourth most important?”

To summarize, this stream of early literature suggests that nonpecuniary incentives are particularly important to professionals such as scientists and engineers and that there may be important differences in the values and motives of scientists, engineers, and other employees. It is not clear, however, to what extent the notion of a "conflict" between individuals' professional motives and firms' business goals is still valid in modern innovative organizations. For example, several studies suggest that firms in some science-based industries provide scientists and engineers with the freedom to engage in the professional community (Nelson, 1959b; Stern, 2004) or even explicitly reward them for forming such ties (Henderson, 1994; Henderson & Cockburn, 1994). Firms may benefit from such policies in various ways, including access to academic knowledge and attracting highly qualified individuals at relatively low cost (Henderson & Cockburn, 1994; Stern, 2004). Rather than indicating a fundamental conflict between the values and motives of scientists and the objectives of their employing firms, these studies suggest that firms in science-based industries may actually benefit from the "academic" values of their scientific employees. It is not clear, however, if the same holds true for other industries.

A more recent second stream of research is work on the motives and incentives of open-source software developers. The puzzle here was initially why programmers (who are often employed by firms) would essentially work for free on open source projects. Although there is not yet a consensus about precisely which individual incentives are most important for open source software programmers, a range of incentives have been identified, including the intrinsic pleasure of creating, the social incentive of fulfilling perceived obligations to the community, and reputational gains in the open source community that can yield higher salaries in the future (Hertel, Niedner, & Herrmann, 2003; Lakhani & von Hippel, 2003; Lerner & Tirole, 2002; Roberts, Hann, & Slaughter, 2006). In addition to providing descriptive accounts of the motives of open-source programmers, some authors have begun to examine relationships between these motives and individuals' choices, effort, and performance. For example, Lerner and Tirole (2005) suggest the interesting possibility that the incentive structure of open source programmers may lead to poorer documentation and less attention to user interfaces compared to commercial software. Roberts et al. (2006) found that programmers who are paid or who care a lot about status in the community expend above average effort, while those who are primarily concerned with solving concrete problems or increasing the value of the software actually expend below average effort. Individuals' intrinsic motivation did not significantly affect effort levels.

The work on open-source software is particularly interesting because it is based on recent data and examines an economically important industry. At the same time, most studies are of a descriptive nature and systematic patterns concerning the impact of pecuniary and non-pecuniary motives and incentives on effort and performance have not yet emerged. In addition, it is not clear to what extent studies of individuals in the open source context — with its distinct features — are informative of individuals engaged in innovation more generally.

Third, we can gain qualitative insights about individuals' motives in innovative settings by drawing on numerous case studies. While typically limited to a smaller number of firms and individuals, these cases paint a richer picture of the nature of individuals' motives and of the relationships between various motives, innovative activities, and performance. In addition, such studies may highlight the interactions of individuals' motives with other characteristics of the firm, such as organizational structure, social networks, or managerial decision making. Consider Katz's history of Digital’s Alpha chip (Katz, 1993) as one illustrative example. In the early 1980s, an R&D team within Digital was working on a new microprocessor architecture, code-named PRISM. By late 1987, however, believing that internal development was too slow, Digital canceled the project and decided to adopt an existing design from an external provider in order to quickly gain a foothold in the emerging market. The PRISM team continued to “discreetly” work on the design, however, driven by the vision of building a chip twice as fast as anything available in the industry. Over time, the team convinced Digital’s management of the promise of the PRISM chip and eventually brought it to life as the Alpha chip. Katz (1993) described the Alpha team’s motivation: “They were not preoccupied with their individual careers; they were more interested in having their peers within the engineering community see them as being one of the world’s best design teams. Ambition, promotion and monetary rewards were not the principal driving forces. Recognition and acceptance of their work output by their technical peers, and by society was, for them, the true test of their creative abilities” (p. 17). This case illustrates the power of nonpecuniary individual-level incentives in driving innovative effort, points to the importance of social context both within and outside of the organization, and also shows how individuals' incentives may conflict with the goals stated by management (although the Alpha chip eventually proved to be a great success for the organization).

While the motives and incentives of scientists and engineers employed in firms have received little attention recently, a large body of work in the sociology and economics of science has examined the motives and incentives of scientists employed in academia. This literature has long featured the importance of individual-level motives such as intellectual challenge, curiosity and peer recognition, and, more recently, also pecuniary rewards, in affecting the advance of science (Dasgupta & David, 1994; Merton, 1973; Stephan, 1996; Stephan & Levin, 1992; Zuckerman, 1988). This work may also shed light on the motives of individuals engaged in industrial innovation because many firm employees working in R&D have advanced graduate degrees and participate actively in the scientific community. Supporting the notion of strong "academic" motives on the part of industrial scientists, Stern (2004) recently showed that biological scientists were willing to accept a significant wage discount (about 25%) in return for the option to publish research findings in academic journals. Of course, this finding is entirely consistent with the earlier research on scientists in industry discussed above (e.g., Gouldner, 1957; Kornhauser, 1962).

Overall, several literatures suggest that nonpecuniary motives may be very salient to individuals engaged in firm innovation and that different groups of employees may differ with respect to their dominant motives. However, much of this existing research may be outdated or draws on samples that are small in size and scope. In chapter Two of this dissertation, I exploit the SESTAT 2003 data to examine the structure of the motives of a broad sample of scientists and engineers employed in private-sector firms. More specifically, I provide descriptive data on individuals' preferences for work benefits such as salary, fringe benefits, job security, intellectual challenge, independence, opportunities for advancement, responsibility, and contribution to society. In addition, I examine relationships among these various motives as well as differences in motives across different groups of individuals, e.g., scientists versus engineers.

1.3 The Links between Motives, Incentives, and Innovative Performance

While it is interesting to learn more about the structure of the motives of individuals engaged in innovation, my primary objective is to gain deeper insights into the role of these motives as drivers of innovative processes and performance. Therefore, a key aspect of my work is the examination of the relationships between individuals' motives and incentives, innovative activities, and innovative performance. Prior work in economics, social psychology, and organizational behavior suggests that individuals' motives and incentives may affect performance through various causal channels, and the role of these channels may differ across types of tasks and organizational contexts. At a very aggregate level, we can distinguish two key causal channels. The first channel involves effects of motives and incentives on *overall levels of motivation and effort*. The second channel involves effects of motives and incentives on the *quality and direction of effort*, e.g., via effects on cognitive processes or on choices between alternative activities. I call the latter channel "productivity effects" of motives and incentives. I will review selected prior research on both channels in the following.

From an economics perspective, both channels have been examined in the agency literature. The standard agency model essentially suggests that stronger motives and incentives should lead to higher levels of effort because the expected marginal utility from effort increases (Prendergast, 1999). Until recently, agency theory focused on one type of incentive with the typical characteristics of money. Recently, however, a relatively new stream of literature (sometimes called "behavioral agency theory") has emerged that explicitly considers multiple types of motives and incentives, including those of a nonpecuniary nature such as "respect", "identity" or "intrinsic motivation" (e.g., Akerlof & Kranton, 2005; Besley & Ghatak, 2005; Ellingsen & Johannesson, 2007; Lacetera & Zirulia, 2008; Murdock, 2002). Some of these models incorporate the idea that pecuniary and nonpecuniary motives and incentives may not only have additive effects on some overall level of work motivation, but that they may act as substitutes or complements and that they may affect choices regarding different directions of effort (e.g., engaging in basic vs. applied R&D). With some exceptions (e.g., Cockburn, Henderson, & Stern, 1999;

Frey & Oberholzer-Gee, 1997), however, systematic empirical research complementing this new line of theoretical work is missing.

The organizational behavior literature, on the other hand, has studied the relationships between pecuniary and non-pecuniary motives, incentives, effort, and performance both conceptually and empirically. A well-established class of theoretical models are so-called "expectancy models" that have been used to explain both effort levels and choices between activities (Mitchell, 1974; Porter & Lawler, 1968; VanEerde & Thierry, 1996). While the original model has been refined in various ways, expectancy models essentially state that an individual's motivation to engage in a particular behavior is a function of (1) the expectancy that performing that behavior will lead to performance (Expectancy), (2) the strength of the link between performance and a desired reward (Instrumentality), and (3) the value of that reward to the individual (Valence). Using my definitions introduced earlier, motives (preferences for benefits) would correspond to valence, while incentives (expected benefits) would closely correspond to expectancy and instrumentality. Consistent with the standard agency model, expectancy theory would also suggest a positive relationship between motives and incentives on one hand and motivation, effort, and performance on the other.

Expectancy models as well as the standard agency model can be refined by considering that an individual may respond not only to absolute levels of incentives but also to the congruence between actual incentives and certain standards or aspirations the individual holds with respect to incentives. Such standards can be a function of existing endowments with benefits (e.g., wealth), social comparison processes, or individual-specific preferences regarding desirable amounts of various benefits (see my discussion of motives above) (Cable & Edwards, 2004; Edwards, Caplan, & Harrison, 1998; Pfeffer, 1990; Rice, McFarlin, Hunt, & Near, 1985). This view adds two important considerations to the discussion. First, expected benefits may be evaluated in a relative rather than absolute fashion and the social context may play an important role in shaping individuals' responses to a given incentive. Second, the marginal utility from a given type of incentive may be nonconstant and may even change signs as actual levels deviate from the desired levels (or the "standard" of comparison). While nonconstant marginal utilities are a common feature of the utility functions used in economics, the social psychology literature discussing these issues is much more explicit about the underlying causes and shape of such nonlinearities and has developed sophisticated methods to analyze them (e.g., Edwards, 2002). Studying relative levels of incentives and nonlinear utilities empirically poses considerable challenges with respect to both the quality of measures (e.g., to detect nonlinearities) and the number of constructs that have to be measured (e.g., additional measures of standards).

Empirical studies based on expectancy theory typically show a positive relationship between expectancy, instrumentality, valence and outcomes such as attitudes (e.g., choice intentions) or behaviors (effort and performance). However, the relationships involving attitudes are typically stronger than the relationships involving behaviors. Moreover, while the theory predicts that expectancy, instrumentality, and valence should interact in determining effort and performance, such interactions are not significantly more predictive than the individual components (for a meta-review, see VanEerde & Thierry, 1996). In a meta-analysis of 39 empirical studies examining financial incentives from different theoretical lenses, Jenkins et al. (1998) found that financial incentives were not related to performance quality but had a significant positive relationship with performance quantity. Moreover, the authors found that the latter effect holds for tasks that are "extrinsic, boring, and nonappealing" as well as tasks that were described as "intrinsic, appealing, exciting". Even though the latter category does not include realistic R&D settings, the findings of Jenkins et al. suggest that financial incentives may be effective in increasing the quantity of innovative output in organizations. The results of these studies conducted in social psychology and organizational behavior are consistent with studies by economists that also show significant incentive effects of performance-contingent pay, though typically in non-innovative settings (e.g., Ichniowski, Shaw, & Prennushi, 1997; Larkin, 2006; Lazear, 2000).

While there is considerable empirical evidence that financial incentives may have positive effects on effort or performance, there are literatures that caution against potential negative impacts of financial incentives on intrinsic motivation, an effect that has been described as "motivation undermining" or "motivation crowding-out" (Deci, Koestner, & Ryan, 1999; Deci & Ryan, 1985; Frey & Jegen, 2001; Gneezy & Rustichini, 2000). While there is a large body of evidence that financial incentives can, under certain conditions, undermine intrinsic motivation (for a review, see Deci et al., 1999), the net effect of financial incentives on overall motivation (change in intrinsic motivation + change in extrinsic motivation) and on performance is unclear and presumably highly task-specific. It seems important, therefore, to move from laboratory studies to studies examining the effects of financial (and nonfinancial) incentives using large samples of individuals in various realistic contexts.

As suggested above, in addition to affecting overall levels of effort, motives and incentives may also impact the quality or nature of the effort individuals expend ("productivity effects"). First, such effects may arise if the various types of motives and incentives have (potentially different) effects on cognitive processes such as attention, the intensity of brain functions, or creativity. For example, social psychologists have suggested that creativity is enhanced by intrinsic motivation and can be stifled by pecuniary rewards (Amabile, 1996; Amabile, 1993; Hennessey &

Amabile, 1998). Similarly, other researchers argue that motives and incentives may affect the intensity of cognitive effort or individuals' perceptual and conceptual attention (Camerer & Hogarth, 1999; Friedman & Foerster, 2005).

Second, productivity effects may also arise if motives and incentives affect individuals' choices of intermediate behaviors such as knowledge sharing, cooperation, or project selection that may have important implications for innovative performance. For example, cooperation in teams may be more effectively induced by some types of incentives than others. Pecuniary rewards given to individuals may undermine cooperative behaviors, whereas pecuniary rewards given to teams are problematic because of free-rider problems (Alchian & Demsetz, 1972; Prendergast, 1999). Perhaps teamwork is best supported by intrinsic or social rewards where the team members strive for some collective goal and feel mutual obligation (Fehr & Falk, 2002; Osterloh & Frey, 2000). It is conceivable that these productivity effects of motives and incentives are particularly important in the innovation context where work is typically less routinized and prescribed, where teamwork is frequently the norm, and where cognitive processes such as creativity are particularly important (Amabile, 1996; Sitkin et al., 1994). However, studies examining these issues in real settings using larger samples are virtually absent.[7]

In chapter Two of this dissertation, I examine the relationships between scientist and engineers' various motives, their innovative effort, and innovative performance. I also investigate to what extent these relationships differ across different types of innovation, e.g., in basic and applied R&D versus development.

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[7] There are many other processes that may mediate the relationships between motives and incentives on one hand and innovative performance on the other. A complete review of the relevant literature is beyond the scope of this chapter. The important insight is that motives and incentives may affect performance via both overall effort levels and via the quality or direction of that effort.

1.4 Incentive Systems, Innovative Capabilities, and Competitive Advantage

Firms can employ various levers to shape the motives and incentives of innovative employees. In doing so, they have to take into account the particular nature of the innovation task, the nature of individuals' motives, and the systematic relationships between motives, incentives, and innovative performance. Organizations can directly provide some types of incentives to individuals as in the case of contingent pay for patents or social recognition in the form of special honors such as membership in IBM's distinguished group of "IBM Fellows".[8] However, organizations often cannot directly control intrinsic incentives. Intrinsic incentives are typically managed indirectly, through "enabling conditions" such as task assignments or the provision of greater autonomy that allow individuals to realize higher levels of intrinsic benefits (Deci & Ryan, 1985; Hackman & Oldham, 1976). Similarly, social benefits are not always under the control of the organization, notably if the individuals are strongly embedded in a social context external to the organization such as a profession (Alvesson, 2000; Gouldner, 1957, 1958). In that case, employers can provide enabling conditions by allowing their employees to interact more intensively with their professional communities (Hauser, 1998; Henderson & Cockburn, 1994; Stern, 2004).

Systematic empirical studies of the systems of incentives and enabling conditions in innovative firms are rare. The existing work typically focuses on financial incentives such as stock options and pay for performance systems (Lerner & Wulf, 2006; Zenger & Lazzarini, 2004) or focuses on specific contexts such as in

[8] IBM fellows are a very select group of employees that, in addition to the recognition this title involves, also receive broad latitude in identifying and pursuing projects in their area of expertise. For more information, see http://www2.hursley.ibm.com/IBM_Fellows.html (accessed March 30, 2008).

Stern's (2004) work on biologists' freedom to publish. Interestingly, more practice-oriented writers have recognized the importance of a broader set of incentives and enabling conditions and provide rich case evidence of their use in R&D contexts. Manners et al. (1997), for instance, emphasize the importance of creating “excitement” about innovative work and argue that performance per se is immediately exciting and that, while money rarely motivates people, the quest for outstanding results can (p. 33). Other authors provide extensive lists of incentives and rewards that can be used in the R&D setting, ranging from challenging research and time for personal projects over public praise and plaques to special parking and paid education (Koning, 1993; Mower & Wilemon, 1989).

Given the lack of systematic research in this area, it would be important to gain a better descriptive understanding of the various incentive systems used in innovative organizations. From a strategic perspective, however, an even more interesting question is to what extent organizations differ in their use of such systems, why they differ, and if any such differences translate into differences in innovative and financial performance. One potential driver of differences in the incentives organizations provide to their employees are deliberate managerial choices such as those discussed above, e.g., whether to use a pay for performance system or whether to allow scientists to publish. These choices are rather complex because they should take into account, among others, the particular nature of the task, complementary human resource practices, other organizational characteristics, and the motives of the affected individuals. Given these complexities, firms that are able to create a consistency or "fit" between these various factors may indeed enjoy higher performance and, potentially, a competitive advantage (Delery & Doty, 1996; Ichniowski & Shaw, 2003; Lepak & Snell, 2002; Sauermann, 2007).

Another potential driver of differences in incentives across organizations are certain structural characteristics of organizations that either directly affect individuals' incentives or that constrain management's ability to implement certain systems of incentives and enabling conditions. For example, small startup organizations may be resource constrained, limiting their ability to provide certain extrinsic incentives, whereas large established organizations may be characterized by higher levels of bureaucracy, limiting their ability to provide independence and other enabling conditions to their employees (Idson, 1990; Oi & Idson, 1999).

To the extent that organizations differ in their structural characteristics and in the incentives they offer to their employees, prospective employees will tend to self-select based on their preferences and motives (Besley & Ghatak, 2005; Rosen, 1986; Sauermann, 2005). As a consequence, different types of organizations will be characterized by different motives and incentives of their employees which, in turn, may affect the nature and level of innovation observed across organizations. In chapter Three of this dissertation, I take a closer look at differences in incentives and motives across type of organizations and their implications for relative innovative performance. More specifically, I use the SESTAT data to examine whether the motives of individuals employed in startups differ from those of employees in established firms, and to what extent any such differences are related to differences in innovative effort and performance observed between these types of organizations.

2 What Makes Them Tick? Employee Motives and Firm Innovation

2.1 Introduction

Dating from the 1950's and early 1960's, economists such as Jacob Schmookler (1962), Zvi Griliches (1957), Richard Nelson (1959a) and Kenneth 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.

The pecuniary and nonpecuniary motives of individuals may, however, have important effects on firm innovation. Schumpeter's (1934; 1942) writings, for example, suggest a critical role of individuals' pecuniary as well as nonpecuniary incentives for entrepreneurship and innovative activity. Case studies have also illustrated the power of nonpecuniary individual-level incentives for innovation and have shown that these incentives may even dominate competing firm-level incentives (e.g., Katz, 1993; Kidder, 1981). 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 (Hertel et al., 2003; Lakhani & von Hippel, 2003; Lerner & Tirole, 2005).[1]

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[1] While some scholars suggest extrinsic benefits in the form of higher expected future earnings stimulate these efforts (Lerner & Tirole, 2005), other scholars emphasize nonpecuniary

Finally, the sociology and economics of science has long featured the importance of individual-level motives such as intellectual challenge, curiosity and peer recognition, and, more recently, even pecuniary rewards, in affecting the advance of science (Dasgupta & David, 1994; Merton, 1973; Stephan, 1996; Stephan & Levin, 1992; Zuckerman, 1988). Although these literatures suggest an important role of individual-level incentives for innovation, there is a dearth of empirical research on the importance of individual incentives for industrial innovation.

In this paper we examine the motives of individuals employed in industrial R&D and study the impact of those motives on individuals' innovative effort and performance. Drawing from social science broadly, we consider the role of individual-level motives in industrial innovation by developing a simple model of the impact of both pecuniary and nonpecuniary motives on innovation. In our empirical analysis, we first present descriptive data on the motives of over 11,000 scientists and engineers employed in for-profit 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 our key result, we find that individual-level motives, and especially nonpecuniary motives, significantly impact innovative processes and outcomes.

2.2 Incentives and the Economics of Innovation

2.2.1 Why Study Individuals' Incentives?

A key reason to go beyond firm-level incentives to consider the motives of R&D employees to enrich our understanding of the drivers of innovation is that firms'

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benefits such as intrinsic pleasure, ego gratification and peer recognition (Hertel et al., 2003; Lakhani & von Hippel, 2003; Lerner & Tirole, 2005). There is, however, no consensus as to the relative importance of the impact of these different types of benefits and associated motives.

R&D personnel exercise substantial autonomy — arguably more than other types of employees. This autonomy is generally desirable from the firm's perspective since there is typically uncertainty about how to tackle technical challenges and R&D employees are often more expert than management in their particular fields - and almost always more expert about any particular problem at hand. In addition, effort and performance in R&D are hard to observe and measure, further diminishing the effectiveness of conventional control systems (Hauser, 1998; Ouchi, 1979). Thus, R&D labs are settings where there is significant delegation of authority to individual employees (cf. Foss & Laursen, 2005; Prendergast, 2002). As a consequence, the innovative performance of a firm may be affected by the motives of its R&D personnel, especially if those motives are misaligned with the firm's interests, but also if those motives complement the goals of the firm, in which case superior innovative performance should be achievable by the firm at lower cost (cf. Stern, 2004; Teece, 2003).

Although the impact of individual motives on industrial innovation has been little studied empirically - with Stern (2004), Zenger (1994) and Gambardella et al. (2006) the exceptions - economic theorists have considered implications of individual incentives for firm performance more generally. Typically assuming that employees' incentives are pecuniary, that individuals prefer leisure over work, that individuals' incentives are contractible, and that there is information asymmetry between the employee and the employer, economic theorists have considered how firms should structure contracts with individual employees (i.e., agents) to align their behavior as much as possible with the interests of the firm (i.e., the principal) (Gibbons, 1998; Prendergast, 1999). Of late, economic theorists have begun to entertain the implications of agents' nonpecuniary, intrinsic motives for institutional design and performance, highlighting the different impacts of nonpecuniary and pecuniary motives (Akerlof & Kranton, 2005; Besley & Ghatak, 2005; Murdock, 2002). However, with few exceptions, the existing empirical work tends to focus on pecuniary incentives and non-innovative contexts (for a review, see Jenkins et al., 1998; see also Lazear, 2000; Leonard, 1990; Lerner & Wulf, 2006) and has yet to subscribe to a broader notion of individuals' motives and incentives. Such a broader view may be particularly important for industrial R&D since survey data highlight the salience of nonpecuniary motives among R&D personnel. The General Social Survey (GSS) of the University of Chicago's National Opinion Research Center, for example, shows that for scientific and engineering professionals, the nonpecuniary benefits of significance of their work and a feeling of accomplishment are more important than pecuniary benefits, while production workers place a higher emphasis on income (cf. Cohen & Sauermann, 2007).

2.2.2 Employee Incentives and Innovation

2.2.2.1 Definitions

We start from the premise that an individual's motivation to perform a given activity depends upon the expected benefits from engaging in that activity as well as the individual's preferences for these benefits.[2] We refer to benefits that are contingent upon an individuals' employment, effort, or performance as *incentives*. We refer to preferences for contingent work benefits (incentives) as *motives*.[3] We will follow social psychologists' classification of benefits and motives as either extrinsic or intrinsic (e.g., Amabile, 1996; Gagne & Deci, 2005; Ryan & Deci, 2000;

[2] For simplicity, we do not consider factors that are negatively valued by individuals (e.g., punishments). One could easily extend our discussion to include such factors.

[3]Our definitions are very similar to those used by the Merriam-Webster dictionary, which defines a *motive* as "something (as a need or desire) that causes a person to act" and an *incentive* as "an external influence (as an expected reward) inciting to action." (Definition accessed online on 8/21/2006).

Sauermann, 2005). We can further distinguish benefits by the extent to which they originate from social relations and associated perceptions (social vs. nonsocial benefits). We will characterize these different types of benefits and associated motives in turn.

Extrinsic benefits are provided by some environmental entity such as a market or actor such as an employer, a superior, a judging body, or a customer, typically conditional upon an evaluation of an individuals' effort or of the task outcome. These 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 those which are pecuniary. Examples of extrinsic benefits from R&D include monetary or other tangible rewards such as pay raises, royalty income from patents, research funding, or a paid vacation. An extrinsic benefit of a social nature is peer recognition.

Intrinsic benefits originate within the individual or the activity itself - not the environment - and are often a function of the interaction between characteristics of the activity (e.g., challenge of the task) and of the individual (e.g., interest in the task).[4] Some intrinsic benefits, such as task enjoyment and intellectual challenge, are realized directly from the process of engaging in certain activities and are thus effort-contingent (Amabile, 1996; Stephan, 1996). Others, such as a feeling of achievement, mastery or self-competence, result directly from task performance and task outcomes. Intrinsic benefits of a social nature include the good feeling of

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[4] This implies that many intrinsic benefits, unlike extrinsic benefits, do not exist independently from a "reference" individual, and a given work attribute may provide an intrinsic benefit in the eyes of one employee but not of another. For example, a particular research question may appear highly interesting to one researcher (and that researcher will derive intrinsic benefits from working on that question), while it appears boring to another. Our understanding of the factors driving individual differences in general levels of curiosity as well as which particular problems individuals find interesting is quite limited (Loewenstein, 1994).

contributing to the well-being of peers, the success of a team, or the welfare of the broader society.

This typology of benefits, distinguishing primarily between extrinsic and intrinsic benefits, is clearly too broad given that each of these types still encompasses a heterogeneous set of benefits with potentially unique roles in the innovation process. In addition, most activities may result in several different types of benefits, often making it difficult to single out a particular motive as the sole driver. For example, consider scientific competition. It may be driven by extrinsic nonsocial benefits associated with career advancement or financial rewards, extrinsic social benefits in the form of peer recognition, or intrinsic benefits in the form of feelings of superiority and domination. The broad distinction across extrinsic vs. intrinsic, and social vs. nonsocial benefits is nevertheless useful to underscore that different motives can apply to R&D employees, and these different motives, in turn, can originate from distinct sources. Due to data availability, we will focus our attention in this paper primarily on extrinsic vs. intrinsic motives and incentives.

2.2.2.2 Influence of Motives and Incentives on Innovative Effort and Performance

Assuming that R&D employees have some discretion over how much they actually work, stronger extrinsic as well as intrinsic motives and incentives can stimulate individuals to expend higher levels of innovative effort by increasing the marginal utility from effort (see below). One might reasonably assume that the effect of these different motives and associated contingent benefits on effort levels is additive. In this case, one type of incentive may substitute for another, which implies, for example, that firms should be able to pay more intrinsically or socially motivated R&D employees less by allowing them to satisfy these nonpecuniary motives.[5] Indeed, such an inference is suggested by Stern’s (2004) finding that new biology Ph.D.’s taking jobs in pharmaceutical R&D labs were willing to accept, on average, 25% lower salaries if prospective employers allowed them to pursue more academic-like science, publish and participate in the scientific community. Complicating, however, the presumption of simple additivity, experimental work in social psychology suggests an interaction of extrinsic rewards and intrinsic motives; that extrinsic rewards may under certain conditions "crowd-out" intrinsic motivation (Amabile, 1996; Deci et al., 1999; Frey & Jegen, 2001; Wiersma, 1992). Such an interaction would imply, for example, that the net effect of providing an extrinsic reward to an intrinsically motivated individual could be a reduction in effort. Although the psychological mechanisms behind the crowding-out effect remain unclear, and there is only limited evidence of crowding-out in organizational settings (Frey & Jegen, 2001), this effect may be particularly relevant to R&D where intrinsic motives are prominent. [6]

In addition to conditioning the level of innovative effort, individuals' motives and incentives may also affect the nature and quality of that effort, and, in turn, innovative performance. Such "productivity effects" can occur via certain cognitive processes or via other intermediate processes such as the allocation of effort across

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[5]Teece (2003) notes that management may well consider the exploitation of “culture”, at least partly encompassing nonpecuniary incentives, as management “control on the cheap.” He states: “If individuals can be motivated and directed without pecuniary incentives and the exercise of authority, tremendous resource savings can ensue and the innovation processes can avoid the burdens of bureaucracy.” (p. 148)

[6] Different explanations concerning the psychological mechanisms underlying crowding-out have been offered. Some authors suggest that salient contingent rewards reduce perceived self-determination and autonomy, which in turn are important facilitating factors for intrinsic motivation. Others suggest that the presence of pecuniary rewards may be construed as a signal that the task will be devoid of intrinsic or social benefits ("Why would they pay me for a fun job?"), reducing the amount of nonpecuniary benefits actually perceived (Benabou & Tirole, 2003; Deci et al., 1999).

different activities. The effects of motives and incentives on cognitive processes have received a considerable amount of attention in the social psychology literature (Amabile, 1996; Camerer & Hogarth, 1999; Friedman & Foerster, 2005). A review by Camerer and Hogarth (1999) suggests, for example, that pecuniary incentives in laboratory settings have been found to improve some features of individuals' cognition, including memory, recall and simple problem-solving functions. The authors also note, however, that pecuniary incentives can have quite different effects, depending upon the nature of the task at hand, and the capabilities of the individual.

Amabile and colleagues focus on the impact of the nature of motivation on creativity in particular. In early work, they argue that intrinsic motivation may stimulate creativity by supporting riskier and more exploratory thinking while extrinsic rewards may even undercut creativity by focusing individuals' attention on more expedient, and consequently more incremental approaches to solving problems (Amabile, 1996; Amabile, 1993; Hennessey & Amabile, 1998).[7] Thus, the productivity of effort in terms of creative output may differ depending on the degree to which intrinsic or extrinsic motives and incentives dominate. In later work, building on Deci and Ryan (1985) and others, Amabile (1996) extends the model by suggesting that some types of extrinsic rewards can complement intrinsic motivation by providing positive feedback (e.g., idea validation) as well as resources that enable individuals to pursue their initiatives (see also George, 2007).

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[7] Manso (2006) develops an agency-type model that produces similar results. More specifically, he shows that short-term pecuniary incentives motivate agents to "exploit", while long-term pecuniary incentives may motivate agents to "explore" and innovate, even if exploration leads to inferior short-term performance.

Whether Amabile's argument implies that the R&D efforts of those who are more extrinsically motivated will be less productive is, however, unclear because much of what constitutes industrial R&D is actually straightforward and incremental, demanding little novelty (cf. Fox, 1983; Holt, 1974; Rosenberg & Steinmueller, 1988).[8] Thus, one might interpret Amabile's argument to suggest that dominant intrinsic motives and rewards increase the quality of innovative effort especially for those R&D tasks that are more demanding of novel approaches and solutions. At the same time, for those R&D tasks that require expedience and little creativity, dominance of extrinsic motivation may increase innovative performance (cf. Amabile, 1993). Thus, extrinsic rewards may, for example, enhance performance in more downstream R&D tasks that are more straightforward and routinized, such as clinical trials in pharmaceutical research.[9]

In addition to affecting the productivity of effort via cognitive processes, individuals' motives may also affect productivity by driving or inhibiting certain intermediate behaviors. For example, preferences for independence or job security may not only bear on the kinds of jobs individuals prefer, but, in an R&D setting, the kinds of projects and approaches they select, with consequences for performance. More specifically, those individuals who value job security may be more risk-averse, and thus may pursue less risky, proven approaches to solving problems, diminishing

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[8] Moreover, not all creativity researchers see a special role for intrinsic motivation. Some argue that creative products are the result of very ordinary problem-solving processes and do not even require any special creative thinking processes such as "divergent thinking" for which intrinsic motivation might be particularly effective (Weisberg, 2006).

[9] Social psychology research also suggests that the effect of motives and benefits upon the quality of effort may be nonmonotonic. Research on the "choking" effect suggests that extremely high levels of motives and incentives may cause individuals, preoccupied by the reward rather than the task, to become distracted (deflecting attention from otherwise relevant cues and information), or to become self-conscious at the cost of disrupting potentially beneficial automatic cognitive processes (Baumeister, 1984; Lewis & Linder, 1997).

the likelihood of significant advance that may require more exploratory approaches (cf. Amabile & Conti, 1999; Dunbar, 1995; Greve, 2003; Lopes, 1987). This discussion raises the more general point that effort is multi-dimensional and individuals may allocate some total amount of effort to different activities or projects according to their motives and incentives. These effort allocation choices may be an important driver of the quality or productivity of the total amount of effort observed.[10] Unfortunately, our data do not allow us to analyze such effort allocation decisions in more detail.

Overall, the work of social psychologists suggests that motives and incentives may not only affect the level of effort that individuals expend on innovation, but also the productivity of that effort. Moreover, such effects on both the level and the quality of effort may vary, depending on the particular types of individuals' motives and incentives and the nature of the task. Finally, this work also suggests that different types of motives and incentives may not operate independently but may interact, with possibly offsetting effects.

2.3 Model

Drawing on the prior discussion, we develop a simple model to reflect the impact on innovative effort and performance of individuals' preferences for the benefits from innovative work (what we define as their motives) and the associated expected benefits (incentives). In this basic model, we consider the levels and nature of expected benefits as exogenous and do not model individuals' self-selection into

[10] This line of thinking has been discussed in the literature on "multi-tasking" and has also been considered in empirical and theoretical work on R&D (Cockburn et al., 1999; Kerr, 1985; Lacetera & Zirulia, 2008; Prendergast, 1999).

different incentive systems or firms' design of optimal incentive contracts. We will consider self-selection and the implications for our empirical strategy below.[11]

The premise of our model is that an individual expends effort, E, to derive utility, U, from that effort, and that utility is a function of some set of extrinsic and intrinsic benefits. We assume that U is a function of the individual's intensity of preference (or motive), I, for, respectively, extrinsic (B^e) and intrinsic (B^i) benefits, realized benefits, and the cost of effort, such that:

$$U = I^e B^e + I^i B^i - E^2/2 \qquad (1)$$

Thus, we are assuming a simple additive utility function where the benefits are weighted according to their importance to the individual, **I**, a vector the elements of which are I^e, I^i. We also assume, for simplicity, that the marginal utility from extrinsic and intrinsic benefits, respectively, is constant, while overall utility is diminishing in effort.

Realized benefits, B, can have a fixed (employment-contingent) component W, a variable component that depends upon the quantity of effort, E, and a variable component that depends upon innovative output, Q. Thus, the realized levels of extrinsic and intrinsic benefits can be expressed as:[12]

$$B^e = W^e + \alpha^e E + \gamma^e Q \qquad (2)$$

$$B^i = W^i + \alpha^i E + \gamma^i Q \qquad (3)$$

[11] We model self-selection explicitly in a companion paper (Sauermann & Cohen, 2007b).

[12] While we allow all types of benefits to be contingent upon employment, effort, and performance, concrete benefits may be predominantly contingent upon one of these factors. For example, the satisfaction derived from intellectual challenge is primarily effort contingent whereas peer recognition will be predominantly performance contingent.

where α^e, γ^e, α^i, $\gamma^i \geq 0$. The variables α^e and α^i, defined to be elements of the vector, $\boldsymbol{\alpha}$, denote the impact of effort on extrinsic and intrinsic benefits, respectively; γ^e and γ^i, defined to be elements of the vector, $\boldsymbol{\gamma}$, denote the impact of output on extrinsic and intrinsic benefits. These variables can vary across individuals and organizations and are partly a function of managerial policy, although managerial influence may be more direct for some types of benefits than for others. For example, management can directly control contingent extrinsic benefits associated with innovative output such as bonuses, pay raises, promotions, etc. For intrinsic benefits, however, that influence may be achieved more indirectly in the provision of facilitating conditions, through, for example, task assignments (e.g., providing more challenging projects). For the current analysis, we assume the α's and γ's to be exogenous; that is, we do not consider the manager's optimization problem. Substituting equations (2) and (3) into equation (1) yields:

$$U=I^e(W^e+\alpha^e E+\gamma^e Q) + I^i(W^i+\alpha^i E+\gamma^i Q) - E^2/2 \qquad (4)$$

Note that our utility function differs from that typically assumed in agency theory in that, while effort has the conventionally assumed negative impact on utility via positive costs of effort, it may also have an offsetting positive effect via effort contingent extrinsic and, especially, intrinsic benefits. The simple additive form of our model reflects the assumption that different types of motives and incentives do not interact (we will consider such interactions later).

To address the influence of contingent intrinsic and extrinsic benefits and individuals' preferences for these benefits on innovative performance, we assume for simplicity a constant marginal productivity of effort; that a researcher's innovative output, Q, is a multiplicative function of effort and the researcher's productivity, P:[13]

$$Q = PE \qquad (5)$$

Extending prior work on innovative performance that has considered its industry or firm-level determinants (cf. Cohen, 1995), we now also consider individual-level determinants. Accordingly, we assume innovative productivity, P, to be a function of vectors of industry characteristics, $\mathbf{A^1}$ (e.g., technological opportunity), firm characteristics, $\mathbf{A^2}$ (e.g., firm size, resources, etc.), and individual characteristics, $\mathbf{A^3}$ (e.g., ability) such that:

$$P=P(\mathbf{A^1}, \mathbf{A^2}, \mathbf{A^3}, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \mathbf{I}) \qquad (6)$$

The inclusion of the vectors $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}$, and $\mathbf{I}$ as arguments of P in equation (6) also allows extrinsic and intrinsic motives and incentives to affect researcher productivity, in addition to affecting levels of effort. The discussion above, however, suggests that such "productivity effects" of motives and incentives may be quite complex, and differ depending on the nature of the task.

We will now assume that the individual has unbiased expectations of her own productivity and of the links between effort, performance, and contingent benefits.[14]

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[13] Note that productivity, P, is conceptually distinct from performance.

[14] Our model does not explicitly incorporate uncertainty about benefits or time lags in the availability of benefits. We assume that individuals incorporate these factors in the formation of their expectations with respect to benefits from effort and performance. While a detailed discussion of these issues is beyond the scope of this paper, we can offer some interesting conjectures. Generally, it is likely that effort and performance contingent intrinsic and extrinsic benefits differ with respect to the uncertainty and the time lag involved. First, effort

In equilibrium, the individual chooses a level of utility-maximizing effort, E*, taking into account expected benefits from effort itself as well as the effects of her effort upon innovative output, and, in turn, output-contingent benefits. Substituting PE for Q, we can rewrite (4) and solve for E*:

$$dU/dE = I^e\alpha^e + I^e\gamma^e P + I^i\alpha^i + I^i\gamma^i P - E = 0 \tag{7}$$

$$E^* = I^e\alpha^e + I^e\gamma^e P + I^i\alpha^i + I^i\gamma^i P \tag{8}$$

We can now also consider possible negative effects of performance-contingent extrinsic rewards on (effort-contingent) intrinsic benefits ("motivation crowding-out") by modifying (3) to include an interaction between α^i and γ^e, as well as a parameter ρ to indicate the strength of crowding-out:[15]

$$B^i = W^i + \alpha^i E - \rho\alpha^i\gamma^e E + \gamma^i Q, \tag{3a}$$

where $1/\gamma^e \geq \rho \geq 0$. This formulation reflects the idea that the negative impact of extrinsic rewards on intrinsic benefits is stronger in settings where the potential for

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contingent incentives should generally be less uncertain than performance contingent incentives because factors outside of the control of the individual may affect the effort-performance link (e.g., luck). Performance-contingent benefits may also be available later than effort contingent benefits because performance is typically observed much later than effort, especially in innovation. Second, unlike extrinsic benefits, intrinsic benefits are self-administered and do not require that some external party evaluates effort or performance. Therefore, intrinsic benefits should be less uncertain and more immediately available than extrinsic benefits. Thus, assuming that individuals are risk-averse and prefer current over future consumption, we would expect that effort-contingent incentives are more powerful than performance-contingent incentives and intrinsic incentives are more powerful extrinsic incentives, ceteris paribus. These conjectures do not affect our qualitative predictions.

[15] We limit this discussion to possible crowding-out due to performance contingent extrinsic rewards. Crowding-out may also occur due to effort-contingent extrinsic rewards (Deci et al., 1999); the analysis of such effects would be very similar to the one shown here.

intrinsic benefits is large, as well as the idea that crowding-out is due to the performance-contingent nature of extrinsic benefits such as pay (i.e., γ^e) rather than the levels of such benefits per se (i.e., W^e). To consider the possibility of crowding-out, (4) can be rewritten as:

$$U=I^e(W^e+\alpha^e E+\gamma^e Q) + I^i(W^i + \alpha^i E - \rho\alpha^i\gamma^e E + \gamma^i Q) - E^2/2 \qquad (4a)$$

Maximizing (4a) and solving for equilibrium effort yields an expression that allows for crowding-out due to the offering of extrinsic benefits:

$$E^* = I^e\alpha^e + I^e\gamma^e P + I^i\alpha^i - I^i\rho\alpha^i\gamma^e + I^i\gamma^i P \qquad (8a)$$

Equations 8 and 8a yield several hypotheses about the determinants of individuals' innovative effort. First, effort is positively related to the importance an individual assigns to extrinsic and intrinsic benefits (I^e and I^i respectively). Second, higher productivity, P, increases effort because the marginal payoff to effort is higher. Third, zero productivity does not imply zero effort. Due to the effort-contingent nature of some extrinsic and intrinsic benefits, individuals may expend effort even if they expect not to realize any innovative output. Thus, the model allows for individuals who are willing to work at least some amount just for the utility derived from the work itself. Fourth, stronger links between effort and performance on the one hand and intrinsic benefits on the other (i.e., α^i and γ^i) will increase effort. Fifth, equation (8a) suggests that stronger performance-contingent extrinsic benefits (larger γ^e) will negatively moderate the positive effect of I^i to the extent that crowding-out takes place (ρ>0). As a result, a stronger link between performance and extrinsic reward has an ambiguous effect on effort.[16]

In addition to predictions regarding the determinants of effort, our model also suggests predictions with regard to the determinants of innovative performance. Specifically, equation 5 in combination with equation 6 predicts not only a positive effect of effort on performance, but also, controlling for effort, significant effects of intrinsic and extrinsic motives and incentives ("productivity effects").

In the following, we examine the impact of individuals' motives on innovative effort and performance empirically. While our model structures the empirical analysis, data limitations prevent us from conducting a comprehensive test of the model predictions. Thus, we rely upon our model principally as a source of qualitative insights.

2.4 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 is composed of three component surveys: the Survey of Doctorate Recipients (SDR), the National Survey of College Graduates (NSCG), and the National Survey of Recent College Graduates (NSRCG). The sample population includes individuals who have a science,

[16] Taking the derivative of (8a) with respect to γ^e gives $dE^*/d\gamma^e = I^e P - I^i \rho \alpha^i$. This shows that its net effect upon effort depends on the importance of intrinsic and extrinsic benefits (I^e and I^i), productivity, the strength of crowding-out, as well as the degree to which intrinsic benefits derive from effort. Thus, even if crowding-out occurs, the net effect of stronger extrinsic incentives may well be positive, especially if individuals value extrinsic benefits highly, if ability (and thus potential output) is high, if tasks provide few intrinsic benefits to begin with, or if the individual does not care about such benefits. Thus, studies finding positive effects of performance-pay on effort and performance can be entirely consistent with the idea of crowding-out, especially if tasks provide low levels of intrinsic benefits (e.g., windshield installation in Lazear (2000)).

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%.[17]

We focus on a sample of 11,041 SESTAT respondents who possess Bachelors, Masters, or Ph.D. degrees, and are employees of private for-profit firms, which are primarily active in one of the industry groups listed in Table 1. As Table 1 shows, a majority of our sample respondents - 6,049, or 54.9% - work in the manufacturing sector, though a sizable minority - 4,373 or 39.7% - work in services, with 1,496 of these working in R&D services. We only include respondents whose primary work classification is basic research, applied research, development, design, or computer applications; the distribution of respondents across these work types is also shown in Table 1. A notable feature of the distribution across work classifications is that 3,649, or 33.1% of the respondents, work in computer applications. Also, only 381, or 3.5% of the sample, work in basic research, a proportion which is comparable to the share of R&D firms spend on basic research more generally.

We were able to obtain two important additional control variables, firm identities and the school awarding the respondent’s Ph.D. (employed below as a proxy measure for ability), for a subset of our respondents comprised entirely of Ph.D.’s (n=2,805). We use this subsample ("Ph.D.-sample") to conduct a series of robustness checks. A comparison between the full sample and the Ph.D.-sample is provided in Table 2. Apart from the fact that the Ph.D.-sample is comprised entirely

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[17] For more information on the sampling frame, survey administration, etc., please visit http://sestat.nsf.gov/ and http://www.nsf.gov/statistics/survey.cfm. The complete survey instruments are available at http://nsf.gov/statistics/question.cfm.

of Ph.D.'s, the key difference between the two samples is that the Ph.D.-sample has relatively fewer respondents in design and computer applications.

2.5 Measures

Unless otherwise indicated, all measures are constructed from respondents' survey questionnaires and are included in the SESTAT database. Note that missing data on non-critical items was imputed by the NSF. As we show below, the SESTAT data provide some unique measures reflecting extrinsic and intrinsic motives, as well as measures of our two key dependent variables, innovative effort and performance.

Dependent Variables

Quantity of effort: 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).[18] Note that the survey question does not specify a particular location for that work, so individuals should report any applicable hours spent working in their offices as well as at home.

Innovative Performance: 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). Due to this 5-year window, patent counts of individuals who have been in the labor force for less than 5 years are not directly comparable to patent counts for individuals with 5 or more years of experience. Accordingly, we have to adjust for such differences in "exposure time" in our econometric analysis

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[18] Note that this measure reflects total hours worked on R&D as well as on other activities, introducing a possible source of measurement error. The SESTAT data also, however, allow us to control for the other, non-R&D activities in which individuals engage (see below).

(see discussion of estimation issues below). Moreover, patent application output is only an imperfect measure of innovative performance. First, not all inventions are patented (Cohen, Nelson, & Walsh, 2000). We therefore, as discussed below, include several industry- and firm-level variables to control for the likelihood of whether a given invention is patented. Another widely recognized limitation of this measure is that there is enormous variability in the technical importance as well as economic value of patented innovations that should be considered when assessing innovative performance.[19] To assess the robustness of our results in light of this limitation, we also employ the self-reported number of granted patents that have been licensed or resulted in a commercialized product (USPCOM) as an alternative performance measure because commercialized and licensed patents would tend to reflect more valuable inventions. This measure, however, suffers from the limitation of a longer and likely more variable lag between the measure and the actual innovative activity taking place. A third performance measure we use to explore robustness of our results is the self-reported number of patents granted within the prior five years (USPGRT). Finally, we also probe the relationships between our key independent variables and the number of (co-)authored peer-reviewed journal publications that have been published or accepted in the previous five years (PUBLICATION). Given the unclear role of publications in the industry context, however, we use the latter measure only on a purely exploratory basis.

[19] Since they do not identify respondents, the SESTAT data do not allow us to match individuals' patents to patent citations, use of which is one way to control for the importance of inventions.

Independent Variables

Preferences for work benefits (motives): Respondents were asked to rate the importance of six work benefits in response to the following question: "When thinking about a job, how important is each of the following factors to you . . ." Respondents rated the importance of each benefit 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 six work benefits and their associated preference measures are:

- Salary (IMP_SAL)
- Benefits (IMP_BEN) [20]
- Opportunities for advancement (IMP_ADV)
- Intellectual challenge (IMP_CHAL)
- Level of responsibility (IMP_RESP)
- Contribution to society (IMP_SOC).

Preferences for job characteristics: Respondents were also asked to rate the importance of two factors, job security and independence, which do not constitute contingent work benefits but are better thought of as more general job characteristics. As discussed in our review of the psychology literature, preferences for such factors may also have important impacts on innovative outcomes. Although we did not include preferences for general job characteristics in our formal model, we will include these measures into our regressions on an exploratory basis.[21]

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[20] Note that the survey instrument uses the term "benefits" in a more narrow sense (i.e., fringe benefits) than we use it throughout this paper.

[21] One might think of general job characteristics such as independence and job security as benefits that, while not contingent upon effort or performance, are contingent upon

Measurement and coding of these preferences are the same as for the preferences for work benefits discussed above. The two job characteristics are the degree of independence (IMP_IND) and job security (IMP_SEC).

One concern is that self-reported preferences for job benefits and job characteristics such as such as salary, intellectual challenge, and contribution to society may be affected by social desirability bias (SDB). Such bias may occur if individuals try to present themselves in a positive light by giving "desirable" answers (Moorman & Podsakoff, 1992). Typically, one would expect this bias to lead to overstated preferences for socially desirable attributes (e.g., challenging work, contribution to society) and understated preferences for socially less desirable attributes (e.g., pay, security) (Rynes, Gerhart, & Minette, 2004).[22] Such a bias could be problematic for our econometric analysis if it is systematically related to key dependent or independent variables. While we have no reason to suspect such systematic effects, the potential for SDB has to be kept in mind when interpreting our results.

<u>Salary:</u> Respondents reported the amount of their basic annual salary received at their current employer. Respondents were explicitly asked not to include bonuses or overtime compensation. The salary distribution is highly skewed and we

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employment in a particular firm. In a companion paper, we also consider individuals' choices between different types of employers. In that paper, we consequently treat independence and job security as contingent benefits and preferences for these benefits as motives (Sauermann & Cohen, 2007b).

[22] Over 60% of our cases were collected by mail, 28% via computer-assisted telephone interviews, 9% via the internet, and 2% in personal interviews. We checked whether the responses in personal modes (telephone and personal interview) differed from those in impersonal modes (mail, www). We found no significant correlation between survey mode and IMP_SAL; correlations of a personal survey mode with most other preference measures are significant but small, except for somewhat larger correlations with IMP_ADV (r=0.09) and IMP_SOC (r=0.10). Since survey mode was not randomly assigned (telephone interviews and personal interviews were used primarily to obtain data from nonrespondents to the paper survey), it is not clear to what extent these correlations reflect SDB.

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.

Determinants of R&D productivity:

Industry-level determinants

- Industry classification: Dummies for 28 industries (2- to 4-digit NAICS classification) (IND_NAICS). Industry dummies are included to control for differences in technological opportunity and other industry-level conditions affecting R&D productivity. They should also control for cross-industry differences in patent propensities (Cohen et al., 2000).

Firm-level determinants

- Employer firm size: Respondents were asked to estimate the size of their employer in terms of the number of employees in all locations combined, represented by a set of dummy variables as follows: 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. We include employer size to control for organizational resources (e.g., R&D spending).
- Startup status: Dummy = 1 if firm was founded within the last five years (NEWBUS).
- Firm identifiers: Employer names are available for our Ph.D.-sample. [23] 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 Ph.D.-sample (EMPLIDCT5). [24]

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[23] Since the employer names were obtained in verbatim form, we manually recoded the data to eliminate differences in employer names due to misspellings, the use of abbreviations, etc.

Individual-level determinants

- Primary work type: Respondents indicated on which of a list of work activities they spend the most hours during a typical work week (WAPRI, see Table 1).
- Number of non-R&D work activities: Respondents indicated which of a list of 9 non-R&D work activities occupied more than 10% of their time. We summed the number of these activities (WA_NONRD) to control for time spent on non-R&D activities that are not expected to result in patent applications.[25]
- Highest degree: Dummy coding for Bachelors, Masters, and Ph.D. (DEGREE).
- Field of highest degree: Dummy coding for 16 fields (HD_FIELD). [26]
- Ability: For our Ph.D.-sample, we were able to obtain the names of the Ph.D.-granting institution. We matched these institution names and the Ph.D. field to the National Research Council's evaluation of Ph.D. program quality (Goldberger, Flattau, & Maher, 1995). The particular quality measure we use is a survey rating of "program effectiveness in educating research scholars and scientists" (ABILITY). The scale ranges from 0 ("not effective") to 5 ("extremely effective"). While this measure formally captures the quality of an individuals' graduate

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In ambiguous cases, we used additional information such as employer location and employer size to determine whether two respondents had the same or different employers.

[24] We conducted our analyses using sets of dummy variables reflecting varying levels of resolution (e.g., one dummy for each firm with 10 or more individuals (EMPLIDCT10), etc.). Smaller sets of dummies had significantly lower explanatory power than EMPLIDCT5, especially in the performance regressions. Regressions using larger sets of dummies (e.g., EMPLIDCT3) sometimes failed to converge due to the large number of degrees of freedom required. Considering the limited effects of EMPLIDCT5 (see below), it is very unlikely that a higher degree of resolution would change our qualitative findings.

[25] These non-R&D activities included accounting, employee relations, management, production, professional services, sales/marketing, quality management, teaching, other.

[26] These fields include: 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 fields.

education, it is also likely to reflect innate ability to the extent that high-ability individuals self-select or are selected into high-quality Ph.D. programs.[27]

- Time since obtaining highest degree, in years (HDTENURE) and HDTENURE_SQ; serve as measures of field-specific skills and knowledge. In addition, this measure could also capture cohort effects (Stephan, 1996).[28]
- Relevance of education: Extent to which the current work is related to the field of the highest degree, 3-point scale (JOBDEGREE); serves as measure of relevance of the skills and knowledge acquired during academic training.

<u>Additional Control Variables:</u>

- Sensitive research: Two dummy variables indicating whether the individual's work was supported by a contract with / a grant from the U.S. department of defense (GOVT_DOD) or the NASA (GOVT_NASA). We expect that findings resulting from such work are less likely to be disclosed in patent applications.
- Managerial status: natural log of the number of people the respondent supervises directly (LN_SUPDIR).
- Gender dummy (MALE).
- Race dummies: Dummies for Asian, Black, other (White is omitted category) (RACE).
- Citizenship status: Dummy coded 1 for U.S. citizens (USCITIZEN).

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[27] The field definitions used in SESTAT and the fields ranked by the NRC do not match perfectly. When the SESTAT field definitions were broader, we averaged the NRC ratings of relevant programs, using the number of Ph.D.'s in each program at a given institution as weights (cf. Stephan, Sumell, Adams, & Black, 2005b).

[28] 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.

- Marital status dummy (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 under the age of 12. Count of children under the age of 12 living in the same household as the respondent (CHILDREN011). This variable serves as a proxy for time constraints in our effort regressions.

2.6 Descriptive Analysis

In this section, we briefly describe the distribution and structure of individuals' motives and preferences for job characteristics, and we provide summary statistics for other key variables.

2.6.1 Motives and Preferences for Job Characteristics

Table 3 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).[29] The results of these regressions (estimated using ordered probit) are shown in Table 4. 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 Ph.D.'s 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).

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.[30]

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.

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[29] 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.

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

Finally, we examined the relationships among the preferences for work benefits and job characteristics. An exploratory factor analysis (common factor analysis, oblique rotation with oblimin(0) criterion) revealed two factors, as shown in Table 5. 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 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 will focus on the individual preference measures in our subsequent analyses. However, we will also estimate some exploratory regression models using factor-based scores. For that purpose, we computed one factor-based measure EXTRINSIC as the simple average of the three preferences for salary, fringe benefits and job security (Cronbach's alpha = 0.66). The measure INTRINSIC is computed as the simple average of the importance of intellectual challenge, independence, opportunities for advancement, responsibility, and contribution to society (alpha = 0.72). The two measures have a positive correlation of 0.18.

2.6.2 Selected Other Variables

Table 6 presents summary statistics for our measures of performance, quantity of effort, and selected independent variables, and Table 7 presents the correlations. As Table 6 shows, 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. As expected, the average number of commercialized patents, 0.26, is significantly lower than that of patent applications. The average level of effort is 45.4 hours per week. Finally, 45% of the individuals in our sample have a Bachelors as their highest degree, 24% have a Masters and 31% have a Ph.D.

2.7 Specifications

In our econometric analysis, we estimate a series of effort and performance regressions. In the following, we present our benchmark specifications and briefly discuss how they differ from the specifications suggested by our theoretical model, largely due to data limitations.

In the effort regressions, we regress effort (HRSWORKED) on vectors of measures of: 1.) preferences for work benefits (**I**); 2.) variables affecting individuals' average productivity (**P**); 3.) additional control variables (**V**):

$$\text{HRSWORKED}_i = \beta_0 + \beta_1\mathbf{I}^{\mathbf{e}}_i + \beta_2\mathbf{I}^{\mathbf{i}}_i + \beta_3\mathbf{P}_i + \beta_4\mathbf{V}_i + u_{i,} \qquad (9)$$

where u_i is an error term. Contrasting this specification with equation 8 in our theoretical model[31] suggests several important differences that affect the interpretation of our results. First, we do not have measures for the links between effort and performance, on the one hand, and benefits, on the other (i.e., the α's and γ's in our model). While some of these links may be observable (e.g., the slope of a pay-for-performance function), others are not (e.g., the increase in intellectual challenge associated with a task assignment). A lack of measures for these links implies that estimated coefficients of the I's (i.e., motives) reflect a compound effect of the I's and unobserved α's and γ's. Our qualitative predictions for the effects of the I's, however, should still hold as long as the I's and associated α's and γ's 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 the B's and I's, and, as a consequence, the I's and the α's and γ's.

Second, our theoretical model predicts an interaction between the determinants of R&D productivity, P, and individuals' motives (**I**). We estimated multiplicative models, but the interactive terms were never significant. Thus, we focus on the main effects alone, as reflected in (9).

In our performance regressions, building on Amabile's and the work of other psychologists, our full specification entertains the possibility that individuals' motives and preferences for job characteristics may contribute to innovative productivity controlling for effort ("productivity effects"). Accordingly, our specification includes

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[31] Equation (8) is: $E^* = I^e\alpha^e + I^e\gamma^eP + I^i\alpha^i + I^i\gamma^iP$.

our measures of preferences, employee effort, and factors that condition innovative productivity (the arguments of the vector **P**):

$$USPAPP_i = \beta_0 + \beta_1 HRSWORKED_{\mathbf{i}} + \beta_2 \mathbf{I^e}_i + \beta_3 \mathbf{I^i}_i + \beta_4 \mathbf{P}_i + \upsilon_{2i} \qquad (10)$$

For the full sample, we focus our discussion on additive specifications of the performance regressions, since interaction terms including effort and various elements of **P** turned out to be insignificant. Consistent with our model, however, the interaction between effort and ability is significant in the Ph.D.-sample where a better measure of ability (quality of graduate education) is available.

2.8 Estimation Issues

2.8.1 Effort Measure

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, our featured technique is truncated regression. Second, 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 officially required 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 also estimate key effort models using a tobit regression model, with a lower limit of 40 hours. Finally, 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.

2.8.2 Performance Measure

Our second featured dependent variable, the number of U.S. patent applications filed over the prior five years, is a discrete measure of innovative performance and has a skewed distribution. Only 24% of our respondents have one or more patent applications, while roughly 76% did not report any patent applications in the five years prior to the survey. In addition, zero patent counts could be produced by different underlying processes. One possibility is that an individual’s unobserved performance is not sufficient to yield any patents even though the individual is at risk of patenting. Another possibility is that certain individuals are not at risk of patenting, perhaps because patenting is seen by their employers as undesirable due to the information that a patent discloses (cf. Cohen et al., 2000). A family of count models that accounts for both skewed count outcomes and different processes generating zero counts are zero-inflated negative binomial (ZINB) models (Cameron & Trivedi, 1998). ZINB models have been increasingly used in the literature to examine determinants of patenting and publishing behaviors (e.g., Stephan, Shiferaw, Sumell, & Black, 2005a). Estimating a ZINB model amounts to simultaneously estimating two regression models; one is a logit predicting membership in the “always-0” group, and the other one is a negative binomial model for those cases that are not in the “always-0” group. The two regressions can have different independent variables, reflecting the two different underlying processes. In our ZINB models, we excluded several individual-level variables, such as our preference measures, HDTENURE, and LN_SUPDIR from the logit part, 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. In discussing the results of ZINB models, we focus primarily on the negative binomial part, since patents are by assumption not a valid measure of innovative performance in the logit component.

We also had to address the fact that our performance measures are patent counts over a five-year span, but some individuals have a labor market experience of less than five years. We account for this fact by explicitly considering exposure time (ranging from one to five years) in the performance regressions.[32]

2.8.3 Endogeneity

The nature of our data warrants careful consideration of endogeneity. First, as described in the measurement section, our performance measures (e.g., USPAPP) capture performance over a 5-year span, while our key independent variables reflect constructs at the time of the survey. Can we assume that the measured values of the featured independent variables (i.e., motives) are not systematically affected by the performance over the prior five years? The assumption of exogeneity of preferences is routinely made by economists. Perhaps more convincingly, social psychologists typically consider preferences for work attributes to be "trait-like", i.e., relatively stable over time. Several measurement instruments have been developed for such preferences, and they are routinely used in empirical work with the implicit

[32] The adjustment for different exposure times was made by including ln(exposure time) in the model and constraining its coefficient to zero as suggested by Long and Freese (2005).

assumption of stability (e.g., Amabile et al., 1994; Cable & Edwards, 2004).[33] However, it is conceivable that individuals' reported preferences change in response to realized 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, we examined the correlation between the importance of salary (IMP_SAL), the satisfaction with salary,[34] 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 the level of this benefit, the rated importance of the benefit is likely to be largely exogenous.[35]

Another potential source of endogeneity in our performance regressions is 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 expected (performance-contingent)

[33] Studies explicitly investigating the stability of preferences for job characteristics are rare. Genetic research appears promising in this area; in a small-sample twin study, Keller et al. (1992) found that about 40% of measured variance in work values (their term for preferences for job characteristics) was due to genetic factors.

[34] Our respondents also reported their satisfaction with the eight work benefits and job characteristics 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 & Edwards, 2004; Judge, Thoresen, Bono, & Patton, 2001). We thus do not use satisfaction scores as measures of either actual levels of benefits (i.e., B^e, B^i) or the contingent nature of certain benefits (α's and γ's) in our econometric analysis.

[35] This statement may be invalid if realized benefits are extremely low. For example, the importance of salary may increase if salary is so low that the respondent has to worry about paying her bills. An examination of the satisfaction scores indicates that our respondents rated the satisfaction with all 8 benefits/job characteristics above the midpoint (i.e., somewhat or very satisfied), suggesting that effect should not be a problem in our sample.

benefits. While our performance measures capture realized performance, we may still expect endogeneity in our regressions if individuals' expectations with respect to benefits and performance are influenced by their past performance. We examined this possibility by estimating performance regressions using CHILDREN011 and MARRIED as instruments for effort. The results do not reject the null hypothesis of exogeneity of HRSWORKED in any of our performance regressions.[36]

2.9 Results

2.9.1 Effort

Table 8 reports the results of our effort regressions, featuring the truncated regression models. Column 1 shows the results of a regression of HRSWORKED on the productivity and other control variables. In model 2, we add our measures of respondents' preferences for work benefits. Four of the preference measures have significant effects on effort. Our measure of the desire for intellectual challenge (IMP_CHAL) has the strongest positive effect, followed by the importance of responsibility and independence. These positive coefficients are consistent with our model, which predicts that stronger preferences for benefits increase utility from effort and, in turn, optimal effort.[37] What is notable about these results is the dominance of an intrinsic motive - desire for intellectual challenge.

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[36]We tested for potential endogeneity by including the residual from an OLS first-stage effort regression into different specifications of second-stage performance regressions (Wooldridge, 2001). The instruments used in the first stage regression, CHILDREN011 and MALExCHILDREN011, are individually and 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).

[37] As discussed above, to the extent that preferences for these work benefits (i.e., the I vector in our model) are correlated with the unobserved degree to which effort and performance yield those benefits (i.e., the α and γ vectors), the estimated coefficients may reflect not only the impact of the motives or preferences (notably desire for challenge, responsibility and independence), but also partially reflect the α's and γ's.

In addition to these positive effects, we observe a significant negative coefficient for the importance of salary. This negative coefficient is unexpected. A corollary analysis suggests that this result is primarily due to a relatively small number of respondents - less than 1% of our sample - who expend more than average effort, yet rate their preference for salary very low. Thus, there may be some segment of R&D employees who both eschew financial gain yet are very dedicated to their work, much like Kidder’s (1981) “Hardy Boys” at Data General who worked very long hours to develop a new generation of minicomputer while claiming that they “don’t work for the money.” We should, however, not make too much of this result because it is observed only for non-Ph.D.'s (Table 9). Nevertheless, the observed negative relationship between the preference for salary and individuals' effort merits further research, especially because it is not predicted by our model. 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 additional control (model 3). Its inclusion results in slight changes in the coefficients of the measures of some motives and preferences, but the qualitative results remain unchanged. The negative effect of IMP_SAL even becomes somewhat 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.

In model 4, we include the two factor-based scores instead of the 8 individual preference measures. We find that the factor reflecting primarily extrinsic motives (salary, fringe benefits, job security) has a significant negative effect on effort, while the factor reflecting primarily intrinsic motives has a strong positive effect. We are cautious about interpreting these results, however, since the component measures of each score reflect quite different underlying motives, and, as evident in model 2, the effects of the different preference measures vary considerably. While the factor-based measures suggest that intrinsic motives may generally be more positively related to effort than extrinsic motives, we believe that it is useful to look beyond this simple dichotomy and to examine specific types of motives individually. [38]

Re-estimating model 2 using ordered probit and tobit regression suggests that the effects of the importance of challenge, responsibility, and salary are robust (models 5 and 6). However, the effects of the preference for contribution to society and independence appear to be fragile. Model 7 is estimated without individuals who are employed in computer systems design, which is the largest single industry in our sample (for an industry breakdown, see Table 1). Model 8 is estimated using only cases in manufacturing industries. The qualitative results are similar to model 2, with slight changes of the coefficients of the importance of salary and job security.

As discussed above, we were able to obtain two additional sets of measures for a subsample of our data ("Ph.D. - Sample). 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 9, 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 8, model 2). Model 2 is

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[38] In order to address high correlations among the preference measures, we also estimated truncated regression models with one preference measure at a time. All 8 measures are individually significant, with negative effects of the importance of salary, benefits, and job security, and positive effects of the other 5 measures. On the basis of the model reported in Table 8, col. 2, we also tested various subsets of coefficients for joint significance. Testing blocks of coefficients takes correlations between variables within a block into account but, unlike factor-based scores, does not assume a single underlying construct. The measures of the importance of salary, job security, and fringe benefits map 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). Broadening the latter set to include the measures of importance of responsibility and contribution to society (consistent with the results of the factor analysis) also results in a highly significant joint test (Chi2(5)=96.43, p<0.001).

estimated using only non-Ph.D.'s. Model 3 estimates the base line model using the Ph.D.-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-Ph.D. sample, while the coefficient is positive (but insignificant) in the Ph.D. 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 Ph.D.'s. [39] 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 Ph.D. programs expend more effort. Including this ABILITY 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 Ph.D.-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.

Finally, the coefficients of some of our control variables also deserve attention (Table 8, 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 less than individuals without children. Ph.D.'s spend more time on the job than respondents with either Masters or Bachelors degrees. Finally, our firm

[39] A detailed analysis of differences in the effects of motives across degree types using interactions shows three significant effects: For individuals with a master's degree, the preference for contribution to society has a stronger positive effect than for individuals with a bachelor's degree. For Ph.D.'s, 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.

size measures suggest that respondents who work in the very smallest (1-10 employees), and the very largest firms (our omitted category of firms with over 25,000 employees) tend to work more hours, though, controlling for size, respondents who work in new businesses (NEWBUS) work the most hours. We examine differences in motives and effort across firm types in more detail in a companion paper (Sauermann & Cohen, 2007b).

To summarize the results for our featured variables, motives matter, and the strongest, most robust result is that individuals with a strong preference for intellectual challenge expend more effort.

2.9.2 Innovative Performance

2.9.2.1 Main Analyses

Our theoretical model predicts a positive effect of the quantity of effort upon innovative performance. In addition, preferences for work benefits and job characteristics may affect the productivity of innovative effort and thus have an effect on performance even controlling for the quantity of effort ("productivity effects"). We examine these relationships in a series of regressions reported in Table 10. Tables 11 - 13 show additional analyses that examine key issues in more detail and address the robustness of our findings. All models in Table 10 are zero-inflated negative binomial regressions. As discussed above, the ZINB model may be superior to the negative binomial regression model when the dependent count variable is characterized by excess zeroes. Model 1 includes only our control variables. We observe that Ph.D.'s have a significantly larger number of patent applications than non-Ph.D.'s and that individuals who are engaged in applied R&D have more patent than individuals in development (omitted category). Individuals engaged in computer applications/systems design have the lowest number of patent applications. The number of patent applications also increases with the number of subordinates (LN_SUPDIR).[40] Column 1b shows the results of the logit part of the zero-inflated negative binomial model. [41]

In model 2, we include the measures of individuals' preferences. The coefficients on these measures reflect the "total effect" of motives and preferences on performance. The importance of challenge and independence as well as the importance of salary have significant positive effects. Concretely, a one-SD higher score on the challenge measure implies a 19.8% higher expected patent count, while a one-SD higher score on the preference for salary implies a 9.2 % higher expected patent count. The IMP_CHAL coefficient is significantly larger than that of IMP_SAL ($p<0.05$). The positive effect of IMP_SAL on performance is particularly interesting in light of the negative effect this measure had on effort. One interesting 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.[42]

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[40] This result could reflect that individuals with higher performance are more likely to be promoted to managerial positions. However, our interviews suggest that this positive coefficient could also reflect that supervisors/managers are sometimes named on a patent because of cultural norms in organizations or because doing so facilitates the internal process required to file a patent.

[41]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 Ph.D.'s are more likely to patent than are Bachelors (omitted category) and individuals in basic research, design, and computer applications are less likely to be patenters than individuals in development (omitted category). As expected, individuals who receive funding from the Department of Defense are less likely to disclose their work in patents.

[42] One manager in our interviews suggested that individuals with strong pecuniary motives may also be more likely to file for a patent for a given invention. We expect this effect to be relatively small because employees in U.S. firms typically receive only small, if any, payments specifically for patenting. However, to the extent that this effect occurs, the "performance effect" of the salary motive would be biased upwards and the true difference between the effect of IMP_SAL and IMP_CHAL would be even larger than currently estimated.

Another interesting observation is that the importance of job security is negatively related to performance, with a one-SD higher score on the job security measure implying an 11.9% lower expected patent count.

In model 3, we include only our controls and the measure of effort (HRSWORKED). HRSWORKED is positive and highly significant. According to this model, a one-standard deviation (6.6 hours) higher level of effort translates into a 12.4% higher expected count of U.S. patent applications.[43]

Next, we estimated a model including HRSWORKED as well as the eight preference measures (model 4). Changes in the coefficients of preferences compared to model 2 (without effort) reflect the extent to which effort mediates the relationship between motives and performance. The mediation effects are very 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. In model 5, we include the salary measure as an additional control. Resulting changes in the coefficients of motives are negligible, although the coefficient of LN_SALARY is large and significant. Finally, models 6 and 7 examine the relationships between the factor-based measures EXTRINSIC and INTRINSIC and innovative performance. Model 6 suggests that the total effect of EXTRINSIC is slightly negative, while the total effect of INTRINSIC is strong and positive.[44] Including the HRSWORKED measures (model 7) reduces the coefficients somewhat;

[43] It is conceivable that effort has a nonlinear effect on innovative performance: while effort increases performance at lower and medium levels of effort, extremely high working hours could hurt performance (e.g., employees are overworked, stressed out, etc.). We examined this possibility using a quadratic term, but we did not find evidence for a nonlinear effect.

[44] A joint test of the measures IMP_SAL, IMP_BEN, and IMP_SEC in model 2 and 4 is highly significant. A joint test of the other five preferences measures is also highly significant.

the EXTRINSIC measure becomes insignificant, but the positive effect of INTRINSIC remains strong and significant.

What could explain the relatively large effects of individuals' motives on performance, controlling for effort? As discussed earlier, psychological research suggests that motives and incentives may actually affect the nature of mental effort. For example, incentives, including extrinsic ones, may increase attention and affect cognitive functions such as recall (e.g., Camerer & Hogarth, 1999). Amabile and her colleagues suggests that intrinsic motivation, and even certain kinds of supporting extrinsic motivation, may elicit the kind of more exploratory thinking that fosters creativity. We can only speculate about the mechanisms through which preferences for independence and job security affect innovative productivity. While independence is presumably not contingent upon effort or performance, the social psychology literature suggests a strong connection between independence and intrinsic benefits in the sense that independence may enhance the intrinsic benefits individuals can derive from their work (Deci & Ryan, 1985). The observed effect of the preference for independence may thus be closely related to that observed for intellectual challenge. It is also conceivable that individuals who desire more independence in their work will make more use of any available independence to try new things or to explore new ways of doing things, potentially leading to higher innovative productivity. In contrast to the preference for independence, the preference for job security has a significant negative impact on patent output. As discussed earlier, one possible interpretation is that individuals for whom job security is important may be more risk averse and gravitate to projects and approaches that are more incremental and thus subject to less uncertainty, though offering less innovative potential and therefore less likely to be patentable (cf. Dunbar, 1995).

Even though our results suggest only a moderate role of the preference for salary in affecting innovative performance, they do not imply that actual pay and extrinsic benefits more generally are not beneficial. In fact, model 5 in Table 10 suggests that pay is strongly and positively associated with innovative performance. Given the lack of appropriate instruments, we are unable to disentangle the causal nature of this relationship and it may well be that individuals 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 actual innovation task rather than having to worry about sufficient income and resources.[45]

Finally, note that significant productivity effects of motives on performance could theoretically lead to a spurious correlation between motives and effort. More specifically, if individuals are aware of such productivity effects, they may adjust their effort choices accordingly, leading to different optimal effort levels. While this causal path is a theoretical possibility (see also equations 6 and 8), we suggest that it is not the primary cause of the significant relationships between motives and effort observed in our data. First, it is unlikely that individuals are aware of the nature of the productivity effects of motives and incentives ex ante and take them into account in their effort choices (Kahnemann, 1973). Second, such a spurious relationship would imply the same sign for the relationship between a particular motive and effort as well as performance, which is inconsistent with our finding of opposite signs of the salary motive in the effort and performance regressions. Third, as discussed in our

[45] Recognizing this important role of financial resources as enabling factors, the MacArthur Foundation annually awards 20-30 Fellowships of $500,000 each to outstanding individuals in order to "enable recipients to exercise their own creative instincts for the benefit of human society" (see http://www.macfound.org/site/c.lkLXJ8MQKrH/b.959463/, accessed March 25, 2008).

literature review above, there are strong conceptual arguments for a direct causal link between motives, incentives and effort, and several prior studies have established such links empirically (though not for all of the motives we examine in this study).

2.9.2.2 Auxiliary Analyses

Table 11 reports a set of additional analyses using negative binomial regression. Models 1 and 2 are equivalent to the ZINB models 2 and 4 in Table 10 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 models 3 through 6, we examine to what extent the productivity effects of individuals' preferences differ across types of tasks. Amabile’s early conjecture suggests that one might observe a stronger positive effect on performance for our key measure of intrinsic motivation, the importance of intellectual challenge, among those respondents involved in basic and applied research (e.g., drug discovery) versus those involved in development (e.g., clinical trials). The rationale is that if development work is more straightforward, requiring less novelty and creativity than might be demanded in more upstream research, then IMP_CHAL would have less of an effect on the productivity of respondents involved in development. Moreover, if, relative to intrinsic motivation, extrinsic motivation elicits more instrumental, less exploratory ways of thinking, as Amabile suggested, then respondents working in development who are more extrinsically motivated may be more productive.

Column 3 estimates our model for the sample of respondents engaged in basic or applied research and column 4 reports the estimates for those engaged in development. We find that 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 has a significant effect in development. Our interpretation of these results is that motives generally - whether intrinsic or extrinsic - can have stronger productivity effects in the types of R&D work which are less routinized, focused more on problem solving sorts of activities where employees have more latitude about the approaches they follow. Assuming development work is more routinized and controlled, performance may depend less on the quality or nature of effort, largely because more of the work to be done is more straightforward and routinized.[46]

Another result of interest in these two regressions is the notable insignificance of HRSWORKED for the basic/applied research subsample, while HRSWORKED is highly significant in the development subsample. Though not anticipated and perhaps something we should not read too much into, the 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.[47]

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[46] 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 reverse effects of performance on motives would be expected to be similarly strong across types of R&D.

[47] Extending Amabile's (1996) discussion, we also estimated regressions testing whether the *relative* importance of intrinsic and extrinsic benefits has a significant effect, in addition to the main effects of preferences for intrinsic and extrinsic benefits. Using the procedure suggested by Kronmal (1993), we included the inverse of the denominator and added this inverse together with the numerator and the interaction between numerator and the inverse of the denominator into the regression equation. The interaction term reflecting the importance of salary relative to the importance of challenge is insignificant, suggesting that there is no independent effect of the relative strength of extrinsic and intrinsic motives.

In Table 11, 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.[48]

Next, 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 therefore 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.

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[48] 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.

2.9.2.3 Ability and Firm Effects in the Ph.D.-Sample

Our Ph.D.-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 an extensive training in top-academic institutions, for example, could have "academic" values that emphasize nonpecuniary motives (Zuckerman, 1988), as well as better training, the latter allowing them to be more productive. In that case, the observed relationship between motives and performance would be spurious. To rule this out, we add an important measure of ability and training.

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 (i.e., α's and γ's).[49]

Table 12 reports the results of a set of negative binomial regressions using the Ph.D.-sample. Model 1 reproduces the results from model 1 in Table 11 (regression using the full sample), while model 2 estimates the model using only the

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[49] 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.

Ph.D. 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 Ph.D.-sample, while the importance of job security and intellectual challenge have a somewhat smaller effect.[50] 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 an 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 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 Ph.D.-sample show, first, that 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.

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[50] Regressions examining these differences using interaction terms show that the effect of the preference for contribution to society is significantly smaller for Ph.D.'s than for Bachelors (negative interaction), while the effects of the importance of independence are significantly larger (positive interaction).

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 & Cohen, 2007b).

2.9.2.4 Alternative Performance Measures

Finally, in addition to using U.S. patent applications, we also estimated performance regressions using alternative measures of innovative performance (Table 13). 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, the reason that we do not, however, feature this measure is, first, 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, as presented in Table 13, 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 13 also shows the results of regressions using peer reviewed publications as dependent variables. This analysis is purely exploratory since publications are likely to measure a different kind of innovative performance than patents and many firms may have policies that discourage the publication of research findings. It is nevertheless interesting to probe the effect of motives on this interesting outcome measure. 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.

2.9.2.5 Performance Regressions: Summary

Our results on the determinants of innovative performance highlight several robust effects of preferences for contingent benefits (i.e., motives), as well as preferences for security and independence, controlling for effort. The effect of the desire for intellectual challenge was robust across all specifications and samples, except when the model was applied only to respondents working in development and design. We also found a positive effect of the preference for salary, though less robust than the effect of intellectual challenge and typically lower in magnitude. Another very robust and intriguing result was that the greater the desire for job security, the lower the respondent’s innovative productivity, and, less robustly, we find the greater the desire for independence, the greater the respondent’s innovative productivity. In our sample limited to Ph.D. respondents, we also observed that the effects of the motives and preferences for job security and independence were robust to the inclusion of an additional measure of ability as well as firm effects.

2.10 Discussion

In this paper, we examine the impact of the motives and incentives of R&D employees on innovative effort and performance. As we know, the goals of firms and their employees may differ. Also, intrinsic incentives loom large for R&D employees; information asymmetry between R&D employees and management is especially acute; and the evaluation of R&D outcomes can be very difficult. This all implies that the motives of R&D employees, and the way in which those motives are managed, can play an important role in affecting innovative processes and performance in firms.

In the first part of this paper, we discussed the nature of individuals' motives and incentives, drawing heavily on research in social psychology and economics. We then presented a simple model that captures various ways in which extrinsic and intrinsic motives and incentives condition individuals' innovative effort, productivity, and output. We examined some of the relationships suggested by this model using NSF survey data on the science and engineering workforce. While the data did not allow a full test of the model, we have gained several insights. We have learned, for example, that R&D employees in industry are characterized by a range of intrinsic and extrinsic motives in their work, and that prominent among these are the desire for intellectually challenging work as well as that for income. We also learned that these motives differ considerably across R&D employees, even after controlling for their fields, their training, and the type of tasks in which they engage. Moreover, these differences appear to matter. A preference for challenging work and responsibility appears to elicit more effort in R&D, and, controlling for effort, preferences for challenge as well as - to a lesser extent - the preference for salary are associated with superior performance. In addition, preferences for job characteristics appear to matter as well: the importance of independence has a positive impact on productivity, while the importance of job security has a negative impact. These results are robust across different estimation methods, and the inclusion of controls for firm effects as well as individual's ability and work experience.

Policy and managerial implications of our findings are several. For managers, the findings highlight the importance of intrinsic motivation for innovative performance.[51] Accordingly, management should explicitly consider the returns to the provision of intrinsic benefits and the associated enabling conditions, while of course recognizing the associated costs and challenges. Nonpecuniary incentives can provide leverage where pecuniary incentives tend to 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). Under these conditions, intrinsic and social extrinsic incentives may be more effective motivators, because they are either contingent on task engagement (some intrinsic benefits) or because they do not require that management be able to observe performance to the extent required for pecuniary incentives (Alvesson, 2000; Osterloh & Frey, 2000; Ouchi, 1979; Prendergast, 2002). Moreover, individuals engaged in innovation appear to have particularly strong preferences for

[51] Intrinsic and social factors may also play an important role in the attraction and retention of highly qualified individuals (cf. Henderson, 1994; Sauermann & Cohen, 2007b; Stern, 2004).

intrinsic and social extrinsic benefits, potentially providing such benefits with a very high motivating "power".

But management also needs to recognize that intrinsic and social extrinsic motives can detract from organizational goals. For example, there are cases where individuals pursued research projects out of their own interest, even against explicit policies of management. While such projects have sometimes yielded high returns for the employing organization (cf. Bartlett & Mohammed, 1995; Katz, 1993; Kidder, 1981), they will often run against the interests of the employer and may have negative impacts on firm performance. Social motives may also conflict with organizational interests. The professional norms of open science and the desire for peer recognition, for example, may motivate an industrial scientist to disseminate important research findings while the employer would benefit from secrecy.

These examples raise the more general point that organizations often cannot control incentives directly. Intrinsic benefits are typically provided indirectly, through *facilitating or enabling conditions* such as task assignments or the provision of greater autonomy that affect the likelihood of the realization of such benefits (Deci & Ryan, 1985; Hackman & Oldham, 1976). Similarly, social benefits are not always under the control of the organization, notably if the individuals are strongly embedded in a social context external to the organization such as a profession (Alvesson, 2000; Gouldner, 1957, 1958), though employers can allow their employees to interact more intensively with their professional communities (Henderson & Cockburn, 1994; Stern, 2004).

For government, 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. Our results also suggest that policies that change the incentives of individuals engaged in innovation should be evaluated in light of the complex ways in which such changes in incentives may affect not only the rate and direction of research effort, but its productivity as well. One such policy was the Bayh-Dole Amendment and related legislation that allowed universities and other institutions receiving public research support to retain patent rights from sponsored research, spawning a rapid acceleration in academic patenting. Although there has been much concern expressed over the growing commercial incentives of academics since the advent of Bayh-Dole, we know little about how stable their motives are, nor how changing the nature of the rewards to academic research might change academics' research activity or productivity.

Finally, for policymakers - as well as managers - our analysis should not be construed as suggesting that there is some ideal R&D employee distinguished by some level, for example, of desire for challenge or income. Following our analysis of productivity effects across different types of R&D, we suspect that superior innovative performance for firms and even academic institutions is best achieved through a mix of individuals with different motives, who are exposed to a range of incentives and broader research and professional environments that will vary across the demands of different tasks.

Our analysis is subject to a number of important qualifications. First, our measures of individuals' preferences are single-item measures, which have a lower reliability than multi-item scales designed to measure the same underlying construct (Nunnally, 1978; Pedhazur & Schmelkin, 1991; Rushton, Brainerd, & Pressley, 1983). Second, to advance our research agenda, we need more complete data on a broader range of motives. On the basis of interviews, we believe, for example, that the social motive of loyalty to project teams may importantly affect effort (cf. Dunbar, 1995; Kidder, 1981), and that the motive of wanting to have an impact importantly drives engineers. We also need better measures on the extent to which various extrinsic and intrinsic work benefits are available in different innovative settings and on the extent to which they are contingent upon innovative effort and performance. Finally, notwithstanding the large body of research assuming relative stability of employees' motives (cf. Amabile et al., 1994; Cable & Edwards, 2004), we must entertain the possibility that R&D employees' motives may vary over time and may even be influenced by previously realized benefits, implying endogeneity. To the degree that this is true, one should view our results as more descriptive.

Despite these limitations, our empirical results suggest that individuals' motives and incentives - pecuniary as well as nonpecuniary - may be important drivers of innovative activity and performance, and that future research could fruitfully examine their effects in more detail.

3 Fire in the Belly? Individuals' Motives and Innovative Performance in Startups and Established Firms

> *"The final hurdle was convincing Steve Wozniak to leave his job at Hewlett-Packard to work full time for Apple. Woz had always enjoyed his job at Hewlett-Packard. HP was legendary among engineers for its commitment to quality design. It seemed crazy to give up a job at HP."*
>
> Freiberger & Swaine (1984): Fire in the Valley, pp. 271/274

Startup firms arguably provide a different work environment than large established firms, especially with respect to the pecuniary and nonpecuniary benefits and rewards available to employees. Several decades ago, Schumpeter (1942) argued that entrepreneurial ventures appealed to a wide range of motives, including not only pecuniary gain, but also the will to create a private kingdom, the will to conquer, to succeed for the sake of success itself, the joy of creating and of getting things done, and exercising one's energy and ingenuity. More recently, it has been suggested that small firms offer more autonomy and higher-powered financial incentives than large firms, and qualitative accounts speak of the excitement and challenge driving individuals in young entrepreneurial ventures (e.g., Freiberger & Swaine, 1984; Zenger, 1994). Large established firms, on the other hand, are often characterized as less exciting and more bureaucratic, while providing higher wages, more fringe benefits, and higher job security (Hamilton, 2000; Oi & Idson, 1999; Schumpeter, 1942). If such differences between startups and established firms exist, we would expect individuals to sort into these types of firms according to their motives and preferences (cf. Besley & Ghatak, 2005; Hwang, Reed, & Hubbard, 1992; Lazear, 2000; Sauermann, 2005). As a result, startups and established firms could be characterized by different mixes of individual-level motives and incentives and possibly different performance (Baumol, Litan, & Schramm, 2007; Cohen & Sauermann, 2007; Schumpeter, 1942; Zenger & Lazzarini, 2004).[1]

In this paper, we compare the motives and incentives between startups and established firms of a particularly important group of employees: those engaged in firms' innovative activities. We also examine the extent to which differences in motives distinguish the innovative effort and performance of these different types of firms. In doing so, we consider not only pecuniary motives such as pay but also nonpecuniary motives such as intellectual challenge, independence, and contribution to society.

While considerable research documents the notion of different work conditions and incentives in startups and established firms, much of the existing empirical evidence is limited to pecuniary benefits such as wages (cf. Brown & Medoff, 2003; Oi & Idson, 1999). Moreover, most of the prior work has been conducted in non-innovative settings and it is not clear to what extent its results are generalizable to innovation. As our quote suggests, for example, Hewlett-Packard, a large established firm, seemed to have offered Steve Wozniak great conditions for his innovative work. With respect to individuals' self-selection into startups versus established firms, there is little empirical research outside of the entrepreneurship literature, which typically focuses on entrepreneurial founders (Amit, MacCrimmon, Zietsma, & Oesch, 2001; Shane, Locke, & Collins, 2003; Wasserman, 2006). Finally, explicitly linking

[1] Schumpeter (1942) was one of the first authors to consider differences in incentives as potential drivers of differences in innovative performance across firm types, although he focused on the incentives of individual entrepreneurs versus those of salaried employees in large industrial corporations. He argued that, as compared to entrepreneurial ventures, large established firms might be disadvantaged in innovation due to the weakening of individual-level incentives associated with bureaucratization, routinization, and the loss of ownership status.

differences in motives and incentives and differences in innovative performance seems particularly important because even if individuals' motives and incentives differ between startups and established firms, they may be functionally equivalent, yielding similar innovative performance. Of course, employees' motives and incentives may not only affect the relative performance of startups versus established firms, but also of different individual firms within each of these categories, suggesting interesting avenues for research on firms' innovative capabilities and competitive advantage (cf. Gottschalg & Zollo, 2007; Sauermann, 2007).

To ground our inquiry, we develop a model of how individuals' self-selection into different firm types conditions the relative incidence of pecuniary and nonpecuniary motives in startups versus established firms, and how those motives may impact and differentiate employees' innovative effort and innovative performance. We subsequently test our model predictions using data from over 9,000 scientists and engineers employed in startups and established firms. Our empirical analysis considers a broad range of motives and incentives, including extrinsic factors such as pay, intrinsic factors such as intellectual challenge and independence, and social factors such as contribution to society. Although certainly incomplete, the particular motives considered include motives that figure prominently in qualitative accounts and in personal discussions with practitioners (e.g., Freiberger & Swaine, 1984; Katz, 1993; Kidder, 1981) yet are typically neglected in the scholarly innovation literature.

3.1 Background and Model

3.1.1 Definitions and Model Overview

The basic premise of our paper is that an individual's work in a particular type of organization potentially provides her with a range of benefits such as pay, intellectual challenge, or a feeling of contributing to society (Sauermann & Cohen, 2007a).[2,3] Work benefits can be contingent upon employment, effort, and performance and we call contingent work benefits *incentives*. Individuals hold relatively stable (trait-like) preferences for these benefits, which we call *motives*.[4] Based on the individual's motives as well as the incentives available in different types of firms, the individual chooses an employing organization as well as utility-maximizing levels of effort. Effort, in combination with factors affecting the innovative productivity of that effort, drives innovative performance. Based on arguments offered by psychologists (e.g., Amabile, 1996; Camerer & Hogarth, 1999), we suggest that the innovative productivity of effort may not only depend on factors such as ability and organizational resources, but also on the particular nature of the motives and incentives underlying that effort.

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[2] In related work, we suggest a typology of benefits and motives that distinguishes them using an extrinsic-intrinsic and a social-nonsocial dimension (Sauermann & Cohen, 2007a). Briefly, extrinsic benefits such as pay and peer recognition are provided by some environmental entity and are indirect outcomes of a task. Intrinsic benefits such as task enjoyment originate within the individual or the activity itself and are often a function of the interaction between characteristics of the individual and of the task. Finally, social benefits are those extrinsic or intrinsic benefits that originate from social relations and associated perceptions (e.g., peer recognition or the feeling to contribute to society).

[3] In line with prior literature, we focus on benefits that are valued positively (e.g., Hwang et al., 1992). Factors for which the individual holds a negative preference can typically be reframed as benefits (e.g., as the absence of such a factor).

[4] The assumption of stability of preferences is in line with much of the research in economics and social psychology. At the same time, there is research suggesting that an individual's preferences may vary over time or across contexts. We will discuss this issue in more detail below.

We begin our model by considering the individual’s utility-maximizing choice of effort for a given set of motives and incentives. We then examine individuals' self-selection into startup versus established firms based on the utility achievable in each firm type from the individual’s optimal effort. Finally, we derive implications for the effort and performance that will be observed in different firm types. Following our development of the model, we draw on prior research in labor economics, organizational theory and organizational behavior to make concrete predictions regarding differences between startups and established firms with respect to selected pecuniary and nonpecuniary motives and incentives as well as innovative effort and performance.

3.1.2 Model

We assume that work provides an individual with k different types of work benefits, B^r with $r = 1…k$, such as pay, intellectual challenge, or contribution to society. Each type of work benefit is potentially comprised of three components, distinguished by their respective sources of contingency. C^r reflects that component of B^r that is contingent upon only whether an individual is employed in a given firm, and is independent of the individual’s effort or performance once employed. For example, one might think of there being a fixed base salary associated with employment in a given firm. Second, $\alpha^r E$ is the component that is contingent upon effort, E, where the variable α^r reflects the degree to which B^r depends upon the individual's quantity of effort, as, for example, when an hourly wage is paid. Third, $\gamma^r Q$ is that component of B^r that depends upon the individual’s innovative performance, Q, where the variable γ^r reflects the degree to which B^r depends on performance. For example, employees may receive a bonus for each invention or patentable technology to which they contribute. Thus:[5]

$$B^r = C^r + \alpha^r E + \gamma^r Q \qquad (1)$$

Note that for any given type of benefit, one or more of these right-hand side terms can be zero. For example, there may be no fixed component of the intrinsic benefit of "task enjoyment" since task enjoyment is experienced only while engaging in the task and is therefore entirely effort contingent (cf. Amabile, 1996).

The employee derives some total utility, U, from a given set of work benefits. We assume a simple additive utility function where each benefit, B^r, is weighted by its importance to the individual, I^r. One can think of the I^r's in equation (2) below as reflecting the intensity of the individual's preferences for the different benefits (i.e., motives). Thus, the utility realized by an individual working for a given firm can be expressed as:

$$U = \sum_{r=1}^{k} I^r(C^r + \alpha^r E + \gamma^r Q) - E^2/2 \qquad (2)$$

In this formulation, we assume that gross utility is linear in its components but the overall returns to effort diminish due to increasing cost of effort.

Innovative output, Q, is a simple multiplicative function of the quantity of effort, E, and the individual's productivity, P:[6]

$$Q = PE \qquad (3)$$

[5] Unless otherwise indicated, all variables are at the level of the individual. We suppress the subscript i for notational convenience.

[6] Note that productivity is conceptually distinct from performance.

We assume innovative productivity, P, to be a function of vectors of industry characteristics, $\mathbf{A^1}$ (e.g., technological opportunity), firm characteristics other than the contingent benefits that they may provide, $\mathbf{A^2}$ (e.g., resources), [7] and individual characteristics, $\mathbf{A^3}$ (e.g., ability). In addition, building on research in social psychology, we consider that the productivity of the individual's effort may also be a function of the underlying motives and incentives driving that effort. The social psychology literature suggests several such "productivity effects" of motives and incentives. First, effort is not only characterized by its quantity (e.g., hours worked), but also by its intensity (e.g., how "hard" someone thinks about a problem). While it will be difficult to actually measure the intensity of effort, especially in complex tasks such as innovation, it will typically have positive effects on productivity (Camerer & Hogarth, 1999). Moreover, unless the task is trivial and requires little thought, the intensity of effort should increase with stronger performance-contingent incentives (cf. Camerer & Hogarth, 1999; Lewis & Linder, 1997).[8] Second, Teresa Amabile (1996) suggests that intrinsically motivated individuals are likely to use more exploratory thought processes that are particularly important in creative and innovative work.[9] Thus, the productivity of individual effort is conditioned not only by industry and firm characteristics as well as by conventional individual-level controls such as ability, but also by the individual's motives and incentives, as expressed by:

$$P = P(\mathbf{A^1}, \mathbf{A^2}, \mathbf{A^3}, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \mathbf{I}) \qquad (4)$$

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[7] Firm characteristics may differ systematically across firm types, e.g., between startups and established firms.

[8] We are assuming that any such effect of incentives on the intensity of effort is more or less automatic, i.e., it is not a conscious decision of the individual (cf. Camerer & Hogarth, 1999; Kahnemann, 1973). Relaxing this assumption should not change our qualitative predictions.

[9] We provide a more detailed discussion of these psychological effects, including potential differences in these effects across types of R&D, elsewhere (Sauermann & Cohen, 2007a).

For the moment, we will assume that the links between effort, performance, and contingent benefits (vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$) are given and that the individual has unbiased expectations of $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}$ and of her own productivity, P. In equilibrium, the individual chooses a level of utility-maximizing effort, E*, taking into account expected benefits from effort itself as well as the effects of her effort upon innovative output, and, in turn, output-contingent benefits. Substituting PE for Q, we can rewrite (2) and solve for E*:

$$U=\sum_{r=1}^{k} I^r(C^r + \alpha^r E + \gamma^r PE) - E^2/2 \tag{5}$$

$$E^* = \sum_{r=1}^{k} (I^r\alpha^r + I^r\gamma^r P) \tag{6}$$

Equation 6 predicts that the optimal quantity of effort is a positive function of the effort and performance contingent incentives represented by $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$, of the individual's motives (**I**), and of the individual's productivity (P). Observed output is

$$Q^* = PE^* \tag{7}$$

We now consider the possibility that incentives and firm-level determinants of an individual's productivity (i.e., **C**, $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}$, and $\mathbf{A^2}$) differ between firm types. To the extent that such differences exist, individuals facing the opportunity to select (or switch) employers will consider these differences in their employer choice.[10] Defining

[10] It is not clear to what extent scientists and engineers correctly anticipate differences in incentives across firm types, but research on employer choice more generally suggests that individuals indeed perceive such differences, in particular, between small and large firms

U_s as the individual's expected utility conditional upon employment in a startup, and U_e as the expected utility conditional upon employment in an established firm, the individual will choose to work for a startup or an established firm depending on which of these are higher, where:

$$U_s = \sum_{r=1}^{k} I^r(C^r_s + \alpha^r_s E_s^* + \gamma^r_s P_s E_s^*) \qquad (8)$$

$$U_e = \sum_{r=1}^{k} I^r(C^r_e + \alpha^r_e E_e^* + \gamma^r_e P_e E_e^*) \qquad (9)$$ [11]

We assume that individuals make this employer decision anticipating that they will optimize the level of effort expended in each type of firm. Substituting for equilibrium effort in (8) and (9), per equation (6) above, yields:

$$U_s = \sum_{r=1}^{k} I^r[C^r_s + \alpha^r_s \Sigma_r (I^r\alpha^r_s + I^r\gamma^r_s P_s) + \gamma^r_s P_s \Sigma_r (I^r\alpha^r_s + I^r\gamma^r_s P_s)] \qquad (10)$$

$$U_e = \sum_{r=1}^{k} I^r[C^r_e + \alpha^r_e \Sigma_r (I^r\alpha^r_e + I^r\gamma^r_e P_e) + \gamma^r_e P_e \Sigma_r (I^r\alpha^r_e + I^r\gamma^r_e P_e)] \qquad (11)$$

(Greenhaus, Sugalski, & Crispin, 1978; Sauermann, 2006). In a review of the behavioral decision making literature on that topic, however, Sauermann (2005) suggests that prospective employees may have better information with respect to certain extrinsic benefits (e.g., salary) than with respect to intrinsic and social benefits available within firms, suggesting that self-selection may be imperfect with respect to non-pecuniary factors in particular.

[11] Note that one may think of higher levels of certain types of benefits in a particular setting as compensating for lower levels of other types benefits in that setting (see the large literature on compensating differentials, e.g., Brown, 1980; Kostiuk, 1990; Rosen, 1986). For the marginal individual, the expected utilities attainable in startups and established firms will be approximately equal.

Thus, our model predicts that higher levels of C^r, α^r, and γ^r in a particular firm type will attract individuals with a strong preference, I^r, for the associated benefit B^r. It is also worth noting that, to the extent that one firm type offers higher-powered performance contingent incentives (γ's) than the other, individuals with higher individual-level productivity are predicted to self-select into that firm type (cf. Lazear, 2000; Zenger & Lazzarini, 2004). Thus, to the extent that startups and established firms indeed differ with respect to the incentives they provide, employee self-selection may lead to systematic differences between startups and established firms in individuals' motives and productivity, which, in turn, may affect relative innovative effort and performance. We now consider these effects on relative effort and performance in startups versus established firms.[12]

Equations (12) and (13) show the optimal effort for the *average* individual employed in a startup and in an established firm, respectively. Note that, due to sorting, startups and established firms may differ not only with respect to contingent benefits, but also with respect to the average employee's motives:

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[12] Our model of organizational choice shares certain general features with established matching models in labor economics. First, we assume that individuals have some expectations regarding available benefits before joining an organization, i.e., employment is at least to some extent a search good (Hwang et al., 1992; McCall, 1990; Nelson, 1970). Second, we assume that individuals can collect information on multiple employment alternatives (offer collection) before making an employment choice (Mortensen, 1986; Stigler, 1962). Finally, we focus on the decision problem of the prospective employee and assume that firms offer standard employment contracts to all individuals (Hwang et al., 1992; Mortensen, 1986). However, the specific context of a decision between two types of organizations, as opposed to a potentially large number of individual employers, allows us to depart from matching models in labor economics in other respects. More specifically, we do not model contract attributes and productivity (i.e., C^r, α^r, γ^r, P) as random variables, but assume that individuals have certain expectations with respect to these attributes, e.g., based on prior experiences in startups and established firms or based on general stereotypes (Sauermann, 2005). Consequently, we can ignore search cost and do not consider "waiting for better offers" (unemployment) as an alternative. We thus assume that employment in at least one of the organizational types will exceed the individual's reservation utility. This assumption seems justified given that we are not interested in unemployment spells or the duration of job search and given that all individuals in our sample have chosen an employer.

$$\bar{E}_s^* = \sum_{r=1}^{k} (\bar{I}^r{}_s \alpha^r{}_s + \bar{I}^r{}_s \gamma^r{}_s \bar{P}_s) \quad (12)$$

$$\bar{E}_e^* = \sum_{r=1}^{k} (\bar{I}^r{}_e \alpha^r{}_e + \bar{I}^r{}_e \gamma^r{}_e \bar{P}_e) \quad (13)$$

These equations suggest that differences in the average effort expended by individuals in startups and established firms could be due to differences in the average levels of I^r, as well as differences in α^r, γ^r, and P across the firm types. Note that differences in the employment-contingent levels of benefits (C^r) do not have a direct impact on optimal effort. However, to the extent that individuals sort based on differences in C^r, such differences may cause differences in *average* I^r across firm types and thus indirectly affect optimal effort in startups versus established firms. For the innovative performance of the average individual in startups and established firms, we obtain:

$$\bar{Q}_s^* = \bar{P}_s \bar{E}_s^* \qquad \text{where } \bar{P}_s = \bar{P}_s\,(\mathbf{A^1}, \mathbf{A^2_s}, \mathbf{\bar{A}^3_s}, \boldsymbol{\alpha_s}, \boldsymbol{\gamma_s}, \mathbf{\bar{I}_s}) \quad (14)$$

$$\bar{Q}_e^* = \bar{P}_e \bar{E}_e^* \qquad \text{where } \bar{P}_e = \bar{P}_e\,(\mathbf{A^1}, \mathbf{A^2_e}, \mathbf{\bar{A}^3_e}, \boldsymbol{\alpha_e}, \boldsymbol{\gamma_e}, \mathbf{\bar{I}_e}) \quad (15)$$

Thus, differences in innovative performance between startups and established firms may reflect differences in individuals' effort as well as differences in the determinants of the productivity of that effort, including individuals' motives and incentives. Different incentives available in startups and established firms may thus affect relative performance in two fundamental ways: by attracting individuals with certain motives (sorting effect) and by affecting the effort and productivity of those individuals once they have joined the organization (cf. Lazear, 2000).

3.1.3 Differences in Incentives across Types of Firms

In the previous section, we developed a model of the general relationships between firm types, individuals' motives and incentives, and innovative effort and performance. We now discuss to what extent concrete pecuniary and nonpecuniary incentives (e.g., pay, intellectual challenge, and independence) are actually expected to differ between startups and established firms.

The incentives available to an individual in a particular organizational setting may be a function of various determinants. Our focus in this paper is on firm-level factors that may lead to systematic differences in $\mathbf{C}$, $\boldsymbol{\alpha}$, and $\boldsymbol{\gamma}$ between startups and established firms. We argue that there are certain structural (i.e., enduring) characteristics of startups and established firms that either directly affect individuals' incentives or that constrain management's ability to provide certain incentives. The most important such constraint may be the scarcity of financial resources in many startups, which may limit management's ability to directly provide extrinsic benefits such as job security and pay or to provide working conditions that allow individuals to realize high levels of intrinsic and social benefits. A second such constraint may be complexities associated with organizational size that may not only limit management's ability to observe individuals' performance (Zenger, 1994) but that also reduce the impact an individual's actions may have on organizational outcomes (the 1/n problem). In both cases, performance-contingent incentives should be weaker, ceteris paribus (Kandel & Lazear, 1992; Prendergast, 1999). Finally, high coordination costs and "bureaucracy" typical of large firms may also constrain management's ability to provide or support certain intrinsic benefits such as a sense of independence or feeling of achievement, though this may not be so clear, as discussed below.

In the following, we provide a more detailed discussion of how these general structural characteristics of firm types may affect the availability of particular types of incentives in startups versus established firms. Our choice of particular incentives to be considered is driven by our priors regarding their importance to individuals as well as by the availability of measures in our data. In our discussion, we will draw on prior work in labor economics, organizational theory, and organizational behavior, which has considered work benefits primarily as a function of two particular characteristics of firm types: organizational size and organizational age. We will suggest, however, that some of the general arguments made in these literatures may not necessarily apply to R&D settings. The results of the following discussion are summarized in Figure 2.

The largest body of research exists with respect to pecuniary benefits, in particular, **pay**. First, the labor economics literature focuses on overall levels of pay as a function of firm size and consistently finds that large firms offer higher wages than small firms (Idson & Feaster, 1990; Levy & Murnane, 1992; Oi & Idson, 1999). As suggested above, one possible explanation is that large firms have more resources and thus can pay higher wages to their employees. Similarly, studies examining the relationships between firm age and wage levels typically find a positive effect of age (Brown & Medoff, 2003). Second, small firms may provide higher-powered pecuniary incentives because they are better able to measure individuals' output and because the link between individual effort and firm performance is more direct in small organizations (Kandel & Lazear, 1992; Zenger, 1994; Zenger & Lazzarini, 2004). Given the higher probability of failure of startups, however, it is not clear whether the expected contingent pay is indeed higher, especially when contingent pay is realized only in the long-term (e.g., in the form of equity stakes). For most individuals, expected total pay (fixed plus contingent) is most likely higher in large established firms (cf. Hamilton, 2000; Oi & Idson, 1999). Brown and Medoff (2003) as well as other researchers also suggest that older and larger firms tend to provide higher levels of **fringe benefits** such as health and pension benefits (Mellow, 1982; Olson, 2002).

Job security is to some extent a function of the survival of the organization and thus contingent upon employment. Research in organizational ecology suggests that firms tend to become more stable over time and survival rates tend to increase, possibly because firms overcome liabilities of newness or small size (Carroll & Hannan, 2000; Freeman, Carroll, & Hannan, 1983; Stinchcombe, 1965). As a result, established firms tend to offer higher levels of job security than young firms (Brown & Medoff, 2003; Evans & Leighton, 1989). In addition, job security may also be contingent on individuals' performance. First, to the extent that individuals' performance affects organizational performance and survival, individual performance will increase job security. Second, sub-par performance may result in the threat of job loss even if the organization survives. If small firms are indeed better able to observe individuals' performance and if individuals' performance in small firms more directly impacts organizational performance (see above), then the performance-contingent element of job security should be stronger in small firms.

We have no strong expectations concerning intrinsic benefits available in different types of firms. To the extent that firm size leads to a higher degree of specialization, larger firms may be able to "provide" more **intellectual challenge** and task enjoyment to their R&D employees by allowing them to focus on tasks (or research questions) that they find particularly interesting, freeing them from work on more routine issues (cf. Lazear, 2005). On the other hand, some authors have argued that task variety has beneficial effects on intrinsic motivation, implying that high specialization may reduce intrinsic benefits (Hackman & Oldham, 1976). Larger firms may also have the resources that enable them to allow their employees to obtain intrinsic rewards by engaging in types of work that may offer less immediate benefit to the firm. However, where active markets for technology exist, as in biotech, even startups may be able to support work that is more upstream and potentially more intrinsically rewarding for their R&D employees.[13] Finally, it should be noted that intrinsic benefits such as task enjoyment and intellectual challenge are rather abstract concepts and take on different concrete forms for different individuals. For example, a biological scientist might find it challenging to discover a new enzyme function, while an electrical engineer might find it similarly challenging to develop a high-quality chip design (cf. Loewenstein, 1994; Ritti, 1968). Thus, even if firms differ in the particular kinds of work and tasks they offer, they could provide their employees with similar levels of intrinsic benefits.

The entrepreneurship literature suggests that the prospect of greater **independence** is one of the key reasons for individuals to become self-employed and to start entrepreneurial ventures (Blanchflower & Oswald, 1998; Hamilton, 2000; Shane et al., 2003). Organizational theorists suggest that older and larger organizations tend to be more bureaucratic and routinized (Donaldson, 1996; Idson, 1990; Ingham, 1970), which may reduce individuals' autonomy and sense of independence. An alleged "conflict" between the professional norms of scientists and engineers, which emphasize autonomy, and the bureaucratic management systems of the large business enterprise received much attention several decades ago (e.g., Kornhauser, 1962; Ritti, 1968). It is not clear, however, if scientists and engineers employed in contemporary established organizations really face lower levels of

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[13] Moreover, Stern (2004) found that new hires of pharmaceutical firms were willing to accept lower pay in order to “do science”, which could suggest that resource-constrained smaller firms may additionally benefit from allowing their employees to "do science".

autonomy than those in small organizations or even in self-employment, since it is typically larger firms that support the more upstream research functions that may lend themselves to greater autonomy. Moreover, firms of a certain size will more typically have the slack resources to allow their personnel the autonomy to pursue own projects that may provide only distant, if any, direct payoffs to the firm. Large, diversified firms may also be better able to find commercialization opportunities for inventions that result from employees' self-directed exploration (cf. Nelson, 1959a).[14]

Another intrinsic benefit that was salient in our discussions with R&D employees, especially engineers of different stripes, is the gratification that comes from the implementation of their solutions to significant problems. This benefit may be thought of more generally as the satisfaction that comes from **having an impact**—on a firm's performance, on technology, or even on society. Again, a priori, it is not clear that large established firms would be more capable at enabling their R&D employees to have an impact, although their larger resources may sometimes be required to successfully bring a product to market. At the same time, R&D employees who feel that they have more autonomy and control over not just what they do, but what is done with the fruits of their labor, may believe that they have a better chance of having an impact in a more entrepreneurial setting. Indeed, Klepper and Sleeper's (2005) discussion of the origins of spin-offs suggests that many of these originated from the frustration of the technologists of larger firms who felt that

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[14] One early example is DuPont, which promised Wallace Carothers, who would subsequently invent Nylon, a substantial amount of autonomy in order to attract him to work for its corporate R&D lab (Hounshell & Smith, 1988). Similarly, several large firms including 3M are known for providing "bootleg time" to their R&D employees in order to work on projects of their own choosing (Bartlett & Mohammed, 1995).

their employers were not exploiting the promise of their ideas and inventions through further development or commercialization.

There are also benefits from R&D—indeed from any job—that potentially have both extrinsic and intrinsic dimensions. Examples include **opportunities for advancement** and **acquiring greater responsibility.** Notwithstanding their extrinsic dimensions, however, there is little reason to believe that large or small firms are more capable of providing either. For example, opportunities for advancement are often limited in small firms due to the small number of hierarchical levels. At the same time, it may be easier for high-performers to achieve high-level positions, especially if performance is observed more easily and rewarded more quickly in small firms due to fewer bureaucratic constraints. Similarly, the level of responsibility may be higher in large organizations where an individual can have a large number of subordinates, but small organizations may offer a wider range of tasks and a wider range of responsibilities.

A key motivation for employees in general, and interviews suggest for R&D employees in particular, are social incentives that can take the form of contributing to smaller groups or teams, or even to society more broadly. Some writers suggest that smaller firms lend themselves well to the development of such ties; that smaller organizations offer more **social incentives** such as friendships with coworkers and managers, recognition for work well done, trust, a "family" feeling, or responsibility for others' well-being (cf. Guzzo & Dickson, 1996; Talacchi, 1960). Indeed, in a recent survey, we found that students expected much higher levels of such social benefits in small firms than in large firms (Sauermann, 2006). On the other hand, it is conceivable that even large organizations are able to organize work in ways that provide these social benefits, i.e., by creating relatively small subunits such as R&D

project teams, which then form the social reference group for their respective members (cf. Gersick, 1988; Sackmann, 1992; Zenger, 1994).

Figure 2 summarizes our predictions regarding differences in selected incentives resulting from resource constraints or other structural characteristics of different firm types. Note that conceptual arguments suggest that some components of certain benefits (i.e., C^r, α^r or γ^r per equation (1)) are zero across all types of firms (indicated by "n/a"). For example, there is no effort-contingent component of fringe benefits. The equal sign ("=") indicates that there are no conceptual arguments suggesting clear differences between firms of varying size or age with respect to the focal benefit. A prediction followed by a question mark ("?") indicates that our priors are weak.

Figure 2: Differences in Incentives between Firm Types

Type of Benefit	**C^r Employment-contingent component**	**α^r Effort-contingent component**	**γ^r Performance-contingent component**
Salary	small<large young<old	=	small>large?
Fringe benefits	small<large	n/a	n/a
Job security	small<large young<old	=	small>large?
Intellectual challenge	n/a	=	n/a
Independence	small>large?	n/a	n/a
Having an impact	n/a	n/a	=
Opportunities for advancement	n/a	=	=
Responsibility	=	n/a	=
Social relationships	small>large?	small>large?	small>large?
Contribution to society	n/a	n/a	=

3.1.4 Predicted Differences in Motives, Effort, and Performance

Building on Figure 2, our model offers a number of specific predictions with regard to sorting based on individuals' motives, as well as potential differences in innovative effort and performance across firm types. For simplicity, we will focus on two firm types that are of particular substantive interest: startups (defined as young and small firms) and large established firms (large and old).

With regard to motives around income, since expected base pay is likely higher in large established firms, and our priors with respect to expected performance contingent pay are more diffuse, we would expect individuals who prefer income more intensively to select employment in larger established firms.[15] We would also expect individuals who have a strong preference for fringe benefits and who care more about job security to self-select into large established firms. Reflecting Figure 2, we have few clear sorting predictions around intrinsic motives. With respect to social motives, individuals who care a lot about social relationships within their firm may prefer startups, though our priors are weak. Finally, high-ability individuals are predicted to prefer firms that offer stronger performance-contingent incentives, which, per Figure 2, would suggest that such individuals (weakly) prefer startups.

Since startups may be characterized by higher-powered effort and performance-contingent incentives (Figure 2), we predict that the average effort in startups may be somewhat higher than in established firms. However, the incentive effect of contingent extrinsic benefits may be partly offset by a lower average preference for these benefits (I^r) in startups (cf. equations 12 and 13).

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[15] If the correlation between C, ɑ, and γ for a particular type of benefit is negative (e.g., higher base pay but lower performance-contingent pay), sorting depends on the relative size of these variables, as well as on P.

Finally, equations 14 and 15 lead us to predict that the innovative performance in startups may be higher, ceteris paribus, due to higher levels of effort and individual ability in startups. Due to the complex nature of potential "productivity effects" of motives, we do not have clear predictions how individuals' motives and incentives may affect the relative productivity of effort in startups versus established firms. However, given that we predict no significant differences in intrinsic motives and incentives across firm types, any productivity differential due to motives will likely result from differences in extrinsic motives.

In the following empirical part of the paper, we test these predictions using micro-data on over 9,000 scientists and engineers employed in startups and established firms. As will be evident in our discussion of the data below, however, we do not possess measures of all the motives and incentives considered above, which has to be kept in mind when interpreting our results.

3.2 Data and Measures

3.2.1 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 is composed of three component surveys: the Survey of Doctorate Recipients (SDR), the National Survey of College Graduates (NSCG), and the National Survey of Recent College Graduates (NSRCG). The sample population includes individuals who have a college degree or higher and who are either working in a science and engineering occupation or who are trained in science and engineering fields. 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%.[16]

We focus on a sample of 9,609 SESTAT respondents who possess a bachelors, masters, or Ph.D. degree and are employees of private for-profit firms in a wide range of industries (Table 14). We only include respondents whose primary type of work is basic research, applied research, development, design, or computer applications / programming / systems development. We were able to obtain additional variables for a subset of our sample (n=2,486). This subsample is comprised entirely of Ph.D.'s ("Ph.D.-sample") and will be used for a series of robustness checks.

3.2.2 Key Dependent and Independent Variables

Firm type: In the SESTAT surveys, respondents were asked to estimate the size of their employer in terms of the number of employees in all locations combined. Respondents indicated one of 8 size classes, which we recoded into a set of dummy variables as follows: 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. Respondents were also asked whether their principal employer came into being as a new business within the past 5 years (NEWBUS=1). To make the results more accessible and easier to interpret, we used the age and size measures to define four dummy coded firm types (FIRMTYPE):

- Startups (NEWBUS=1, EMSIZE<100 employees); STARTUP100 dummy
- Small established firms (NEWBUS=0, EMSIZE<100); ESTAB100 dummy

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[16] For more information on the sampling frame, survey administration, data imputation, etc., please visit http://sestat.nsf.gov/ and http://www.nsf.gov/statistics/survey.cfm. The complete survey instruments are available at http://nsf.gov/statistics/question.cfm. Note that missing data on non-critical items were imputed by the NSF.

- Large young firms (NEWBUS=1, EMSIZE>500)[17]
- Large established firms (NEWBUS=0, EMSIZE>500); ESTAB500 dummy

Throughout our econometric analysis, the STARTUP100 category will generally be our omitted reference group.[18] To gain further insights into the role of organizational size and age, we also re-estimated some of our key models using the size and age measures directly.

Quantity of effort: Respondents reported the number of hours they work in a typical work week (continuous measure). We use this measure as a proxy for the quantity of effort dedicated to innovation (HRSWORKED).[19]

Innovative Performance: Each respondent reported 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). Patent output is only an imperfect measure of innovative performance, because not all inventions are patented (Cohen et al., 2000). We include several industry and individual-level variables to control for the likelihood of whether a given invention is patented. These and other controls are discussed below.

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[17] We will not use the small number of cases (n=198) in the "large young firms" group in subsequent analyses (n=198) because, using the firm identifiers from our limited sample as additional information, we concluded that many firms in this group were large spinoffs from older corporations. In those cases, the reported legal age of the firm differs significantly from the age of the business as an organization, which is the focus of our theoretical discussion. While we do not have the data to examine individuals in "true" young and large firms, such firms would be extremely interesting, because they could be the most successful organizations, i.e., the "Googles". We will discuss the issue of the causality between performance and firm characteristics such as age and size below.

[18] The 5 year age cutoff is primarily a function of data availability. We chose 100 employees as size cutoff for startups because a lower cutoff would reduce the sample of startups considerably, while a cutoff larger than 100 employees would lead to the inclusion of firms that would not generally be considered a "startup". We excluded firms with 100-500 employees to arrive at a clearer distinction of small versus large employers. However, we also estimated our models using different definitions (e.g., less than 500 employees for startups, more than 1000 employees for established firms) with very similar results.

[19] Note that this measure reflects total hours worked on R&D as well as on other activities, introducing a possible source of measurement error. The SESTAT data also, however, allow us to control for the other, non-R&D activities in which individuals engage (see below).

Motives (Preferences for work benefits): Respondents were asked to rate 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 . . .". Respondents rated the importance of each benefit 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 benefits and their respective importance measures are

- Salary (IMP_SAL)
- Benefits (IMP_BEN) [20]
- Job security (IMP_SEC)
- Intellectual challenge (IMP_CHAL)
- Degree of independence (IMP_IND)
- Opportunities for advancement (IMP_ADV)
- Level of responsibility (IMP_RESP)
- Contribution to society (IMP_SOC).

As is apparent from this list of motives, the data do not provide measures of two key motives noted above. First, there is no measure of respondents' desire to have an impact. Second, although we do have a measure of respondent's preference for contributing to society, we do not have a measure of the other key social motive of the desire to contribute to a group or team.

One concern with our preference measures is that self-reported preferences for job benefits such as such as salary, intellectual challenge, and contribution to society may be affected by social desirability bias (SDB). Such bias may occur if

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[20] Note that the survey instrument uses the term "benefits" in a more narrow sense (i.e., fringe benefits) than we use it throughout this paper.

individuals try to present themselves in a positive light by giving "desirable" answers (Moorman & Podsakoff, 1992). Typically, one would expect this bias to lead to overstated preferences for socially desirable attributes (e.g., challenging work, contribution to society) and understated preferences for socially less desirable attributes (e.g., pay, security) (Rynes et al., 2004). Such a bias is unproblematic for our econometric analysis if it similarly affects all individuals. It may, however, affect our results if the extent of SDB is systematically correlated with key independent or dependent variables. Our results have to be interpreted accordingly.

Salary: Respondents reported the amount of their basic annual salary received at their current employer. Respondents were explicitly asked not to include bonuses or overtime compensation. Since the salary distribution is highly skewed, we use its natural log in our econometric analyses (LN_SALARY). Annual base salary is not predicted to have direct impacts upon innovative effort or performance; we therefore use this measure only for auxiliary analyses.

3.2.3 Control Variables

Determinants of productivity:

Industry-level determinants

- Industry classification: Dummies for 28 industries (2- to 4-digit NAICS classification) (IND_NAICS) (see Table 14).

Firm-level determinants

- Firm identifiers: Employer names are available for our Ph.D.-sample. We created one set of dummy variables to control for firm fixed effects for each firm that had at least 5 individuals in our sample (EMPLIDCT5, 118 dummies).[21]

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[21] Since the employer names were obtained in verbatim form, we manually recoded the data to eliminate differences in employer names due to misspellings, the use of abbreviations, etc.

Individual-level determinants

- Primary work type: Respondents indicated on which of a list of work activities they spend the most hours during a typical work week. These activities include basic research, applied research, development, design, and computer applications / programming / systems development (WAPRI dummies).
- Number of non-R&D work activities: Respondents indicated which of a list of 9 non-R&D work activities occupied more than 10% of their time.[22] We summed the number of these activities (WA_NONRD).
- Highest degree: Dummy coding for bachelor, master, Ph.D. (DEGREE).
- Field of highest degree: Dummy coding for 16 fields (HD_FIELD).[23]
- Tenure in principal job, in years (JOBTENURE) and job tenure squared (JOBTENURE_SQ); serve as measures of job-specific skills and knowledge.
- Time since obtaining highest degree, in years (HDTENURE) and HDTENURE_SQ; serve as measures of field-specific skills and knowledge. In addition, this measure could also capture cohort effects (Stephan, 1996).
- Time between earning highest degree and taking the current job (HDTENURE0=HDTENURE-JOBTENURE). This variable is a proxy for the labor market experience of the individual at the time of joining the current firm.

In ambiguous cases, we used additional information such as employer location and employer size to determine whether two respondents had the same or different employers. Overall, 1,464 cases in our limited sample are in firms captured by EMPLIDCT5 dummies.

[22] These activities included accounting, employee relations, management, production, professional services, sales/marketing, quality management, teaching, other.

[23] These fields include: 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 fields.

- Relevance of education: Extent to which the current work is related to the field of the highest degree, 3-point scale (JOBDEGREE); serves as measure of relevance of the skills and knowledge acquired during academic training.
- Ability: For our Ph.D.-sample, we know the names of the institutions granting the highest degree. We matched these institution names and fields of study to the National Research Council's evaluation of Ph.D. program quality (Goldberger et al., 1995). The particular quality measure we use is a survey rating of "program effectiveness in educating research scholars and scientists" (ABILITY). 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 programs.[24]

Additional Control Variables

- Managerial status: natural log of the number of people the respondent supervises directly (LN_SUPDIR).
- Sensitive research: Two dummy variables indicating whether the individual's work was supported by a contract with / a grant from the U.S. Department of Defense (GOVT_DOD) or the NASA (GOVT_NASA). We expect that findings resulting from such work are less likely to be disclosed in patent applications.
- Employer change within the last 2 years, dummy variable (EMPLCHANGE).
- Gender dummy (MALE).

[24] The field definitions used in SESTAT and the fields ranked by the NRC do not match perfectly. When the SESTAT field definitions were broader, we averaged the NRC ratings of relevant programs, using the number of Ph.D.'s in each program at a given institution as weights (cf. Stephan et al., 2005b).

- Race/ethnicity: Dummies for Asian, Black, Hispanics, other (White omitted) (RACE).
- Citizenship status (USCITIZEN).
- Marital status dummy (MARRIED). 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 under the age of 12. Count of children under the age of 12 living in the same household as the respondent (CHILDREN011). This variable serves as a proxy for time constraints in our effort regressions.

3.2.4 Descriptive Statistics

Tables 14 through 17 present selected descriptive statistics and correlations. Table 14 gives an overview of the distribution of cases across firm types and industries. While our data cover a wide range of industries, the preponderance of cases comes from a smaller number of industries including chemicals, pharmaceuticals, semiconductors and electronics, and aerospace. By far the largest industries in our sample are computer systems design and scientific R&D services. Note also that the proportion of individuals employed in startups varies considerably across industries. Overall, our sample includes 572 individuals employed in startups, 1,066 individuals employed in small established firms, and 7,971 individuals employed in large established firms.

Table 15 shows the distributions of EMSIZE and NEWBUS, which are the defining dimensions of our three focal firm types. Table 16 compares the means and standard deviations of key variables across the three firm types. Individuals' motives appear to be quite similar across firm types; only the preferences for salary, fringe benefits, and job security are somewhat stronger in established firms. The means for all motives are in the 3-4 range, indicating that individuals generally consider all eight work benefits to be "somewhat important" or "very important". Effort (HRSWORKED) and Performance (USPAPP) show more substantial differences. More specifically, the average number of hours worked is 47.6 for individuals in startups, 45.5 in small established firms and 45.2 in large established firms. The average number of patent applications is 1.7 in startups, 0.9 in small established firms, and 1.3 in large established firms. Some interesting observations emerge with regard to the composition of the work force in startups versus established firms. First, employees in startups are more likely to have an advanced degree (e.g., Masters or Ph.D.). Second, they have a shorter tenure on the current job (as expected) as well as a somewhat shorter industry experience (time since obtaining their highest degree). However, at the time of starting their current job, individuals in startups had longer industry experience. Finally, employees in startups and established firms show no noticeable difference with respect to the ABILITY measure.

3.3 Model Specifications and Estimation Issues

3.3.1 Model Specifications

Consistent with the structure of our formal model, we estimate three sets of regression models in our econometric analysis: models of an individual's choice of firm type (e.g., startups versus established firms), models of innovative effort, and models of innovative performance. Our model specifications depart from our theoretical model, however, primarily due to the lack of measures of the effort- and performance-contingent benefits available in the different firms ($\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$), which has important implications for the interpretation of our results, as discussed below.

The first set of models examines to what extent individuals self-selected into firm types based on their motives (employer choice regressions). For that purpose, we estimate multinomial logit models with individuals' current employer type (FIRMTYPE) as the dependent variable. As suggested by equations (10) and (11) in our model, the independent variables include measures of individuals' motives (**I**), measures of productivity determinants (**P**), as well as controls (**V**).

$$FIRMTYPE_{\mathbf{i}} = \beta_0 + \beta_1\mathbf{I}_i + \beta_2\mathbf{P}_i + \beta_3\mathbf{V}_i + \upsilon_i \qquad (16)$$

To probe the impact of respondent motives on the relative effort expended by employees in startups and established firms, we begin by estimating the relationship between employment status (i.e., in a startup, small established firm, or a large established firm) and individual effort by including the set of firm type dummies to estimate effort differences across firm types. We then introduce the set of measures reflecting motives to consider the impact of motives on effort, and, in so doing, also examine mediating effect of those motives on the relative effects of firm type on effort. Accordingly, in our effort regressions, we start with an additive model regressing effort (HRSWORKED) on ESTAB100 and ESTAB500, variables affecting individuals' productivity (**P**), and additional control variables (**V**):

$$HRSWORKED_i = \beta_0 + \beta_1 ESTAB100_i + \beta_2 ESTAB500_i + \beta_3\mathbf{P}_i + \beta_4\mathbf{V}_i + \upsilon_i \qquad (17)$$

This regression estimates differences in individuals' effort between startups and established firms. We then add the measures of individuals' motives (**I**):

$$HRSWORKED_{\mathbf{i}} = \beta_0 + \beta_1 ESTAB100 + \beta_2 ESTAB500 + \beta_3\mathbf{I}_i + \beta_4\mathbf{P}_i + \beta_5\mathbf{V}_i + \upsilon_i \qquad (18)$$

The coefficients on the measures of motives estimate their impact on innovative effort. If differences in motives across firm types are responsible for differences in relative innovative effort, then adding measures of motives to the effort regression should lead to a change in the coefficients on ESTAB100 and ESTAB500 (cf. Baron & Kenny, 1986).

Our analysis of **innovative performance** follows a similar strategy. However, we conduct the mediation analysis with respect to individuals' motives, the quantity of effort, and a combination of the two. This strategy allows us to determine to what extent the relative performance observed in startups versus established firms is due to differences in motives, differences in the quantity of effort (which may be partially a function of motives) or both. The fully specified model also allows us to estimate the effects of motives on performance controlling for individuals' effort:

$$USPAPP_i = \beta_0 + \beta_1 ESTAB100_i + \beta_2 ESTAB500_i + \beta_3 HRSWORKED_i + \beta_4 \mathbf{I}_i + \beta_5 \mathbf{P}_i + \beta_6 \mathbf{V}_i + u_i \quad (19)$$

As suggested earlier, our estimating equations depart from our theoretical model primarily due to our lack of measures of contingent benefits ($\boldsymbol{\alpha}$'s and $\boldsymbol{\gamma}$'s). As can be seen from equation 6, this implies that estimated coefficients on the measures of individuals' motives may partly reflect effects of these unobserved variables since they interact with motives (i.e., the $\mathbf{I}$ vector). To the extent that motives and incentives of a particular type r are positively correlated (e.g., due to self-selection), we would still, however, expect the same qualitative effect of motives on effort and performance.[25] This implies, however, that if, say, startups and

[25] Incidentally, most empirical studies concerned with individuals' motivation typically include measures of incentives (i.e., $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$), but lack measures of individuals' motives (e.g., Lach & Schankerman, 2003; Lerner & Wulf, 2006). In this sense, our study provides an interesting complementary perspective. Of course, future research should measure both motives and incentives.

established firms are characterized by systematically different degrees of effort or performance contingency (i.e., different values of $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$), the coefficient estimates of the effects of our motives will differ across firm types. Simply including fixed effects for firm types, as we do in estimating equations (17) through (19), constrain our coefficients on motives to be identical. To reflect the possibility that $\boldsymbol{\alpha}$'s and $\boldsymbol{\gamma}$'s differ between these firm types, we also estimate separate effort and performance regressions for each of our three firm types.

A second way in which our empirical analysis departs from our theoretical model is that the model predicts an interaction between productivity and motives in the effort regressions. Although we estimated such multiplicative models by interacting elements of **I** and **P**, the interaction terms were never significant. Thus, we focus below on the main effects alone, as reflected in (18). Similarly, for the complete sample, we focus our discussion on additive specifications of the performance regressions, since interaction terms including effort and various elements of **P** turned out to be insignificant. Consistent with our model, however, the interaction between effort and ability is significant in the Ph.D.-sample where a good measure of ability (quality of graduate education) is available.

3.3.2 Estimation Issues

3.3.2.1 Distribution of Effort and Performance Measures

The dependent variable in our effort regressions, HRSWORKED, is not distributed normally, and we use different techniques to account for this fact. First, 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, one technique we use is truncated regression. Second, a large number of respondents (38%) reported HRSWORKED of 40 hours per week, while only very few individuals reported 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 officially required work time in many organizations (cf. Heckman, 1993). In this case, 40 hours could be considered the lower limit of a censored distribution. To address this possibility, we estimated our effort regressions using a tobit regression model with a lower limit of 40 hours.

Our measure of individuals' innovative performance, the number of U.S. patent applications filed over the prior five years, is a discrete measure of innovative performance and has a skewed distribution. Only 25% of our respondents have one or more patent applications, while roughly 75% did not report any patent applications in the five years prior to the survey. In addition, zero patent counts could be produced by different underlying processes. One possibility is that an individual's unobserved performance is not high enough to produce a positive patent count, even though the individual is at risk of patenting. Another possibility is that certain individuals are not at risk of patenting, perhaps because patenting is seen by their employers as undesirable due to the information that a patent discloses (Cohen et al., 2000). In order to account for these features of our performance measure, we estimate performance regressions using negative binomial regression (NBREG) as well as zero-inflated negative binomial regression (ZINB). A ZINB regression involves estimating two regression equations. A logit equation predicts membership in an "always 0" group, i.e., a group of individuals who are not at risk of patenting. The second equation estimates the effects of the regressors on performance for those individuals in the "not always 0" group, using a standard negative binomial model (Long & Freese, 2005).[26]

[26] For a more detailed discussion of our ZINB models, see Sauermann & Cohen (2007a).

We also had to address the fact that our performance measure is a count over a five-year span, but some individuals have a labor market experience of less than five years. We account for this fact by explicitly considering exposure time (ranging from one to five years) in the performance regressions.[27]

3.3.2.2 Selection Bias and Endogeneity

Given the nature of our sample, we have to consider potential selection biases at the firm and individual levels. First, it is likely that inventions and particularly patent applications help founding teams in acquiring the necessary resources (in particular, capital) to found and grow a new venture (Hsu & Ziedonis, 2007). Thus, startups that are actually observed in our data are likely to exhibit a higher performance than the average "potential startup" before such a selection effect takes place. To some extent, observed performance in startups would then not reflect an advantage of startups in producing new inventions, but rather a selection process that makes startups with a strong (patented) technology basis more likely to be born and observed in our data; startup status may be partly endogenous to observed innovative performance. We expect that the strength of such a selection bias differs across industries and may be particularly high in industries where patent propensity is high, and where patents strongly influence external capital providers in their investment decisions, as the life sciences (cf. Cohen et al., 2000). The question, of course, is the sensitivity of the mediating effect of motives on relative performance to this selection effect. As a first approach to probing the robustness of our results to such a selection effect, we estimate key regressions also using industry subsamples,

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[27] The adjustment for different exposure times was made by including ln(exposure time) in the model and constraining its coefficient to zero (Long & Freese, 2005).

focusing especially on results for those industry settings where patents are not so essential to starting new ventures, as in R&D services and computer applications.

A second selection effect occurs at the level of the individual. As discussed in our theory section, an individual's employment in a startup or an established firm is not the result of a random assignment but of self-selection by the individual and/or selection by the organization. Accordingly, the ESTAB100 and ESTAB500 variables may be endogenous in our effort and performance regressions to the extent that selection into firm types depends on prior performance or to the extent that unobserved factors drive both individuals' selection into a particular firm type and individuals' innovative effort or performance. With respect to effects of performance on selection, we will exploit our measure EMPLCHANGE (indicating whether a respondent changed employers within the last 2 years) to examine the extent to which individuals' 5-year performance is related to more recent employer choices (assuming that 5-year performance to some extent predates recent employer change). With respect to unobservable factors driving both selection and outcomes, we hope that our large set of control variables, including measures of ability, will account for many of the factors that are typically unobserved in similar research (cf. Ackerberg & Botticini, 2002; Zenger & Lazzarini, 2004). At the same time, we will control for individual-level selection bias in our effort regressions using the methods suggested by Dubin and McFadden (1984) and Lee (1983), which are generalizations of the Heckman selection approach to polychotomous choice. Both methods involve estimating split-sample OLS regressions including adjustment terms that are derived from a first-stage multinomial logit predicting employment in one of the three firm types (for a detailed discussion, see Bourguignon, Fournier, & Gurgand, 2007).

A third potential source of endogeneity is due to the temporal structure of our measures. Individuals' motives are measured at the time of the survey, while two key dependent variables, organizational choice and performance, capture outcomes in time periods prior to the survey. Can we assume that the measured values of motives are serially correlated with their values over the prior 5 years and, more importantly, that they are not systematically affected by prior job choices or by the performance over the prior five years? The assumption of exogeneity of preferences is routinely made by economists. Perhaps more convincingly, social psychologists typically consider preferences for work attributes to be "trait-like", i.e., relatively stable over time. [28] Several measurement instruments have been developed for such preferences, and they are routinely used in empirical work with the implicit assumption of stability (e.g., Amabile et al., 1994; Cable & Edwards, 2004). There is also research, however, suggesting that individuals' expressed preferences may be affected by situational factors, life cycle effects, as well as prior outcomes (Demo, 1992; Festinger, 1957; Payne, Bettman, & Schkade, 1999). For the purpose of our analysis, we assume that individuals' preferences for work benefits are exogenous and stable, at least over the time horizon of our study.[29] We will consider implications of relaxing this assumption in our discussion of the empirical results.

3.4 Results

3.4.1 Self-Selection and Differences in Salary across Firm Types

We estimated a set of multinomial logit models to examine the effect of individuals' motives on the choice of employment in startups versus small and large

[28] Studies explicitly investigating the stability of preferences for job characteristics are rare, however. Genetic research appears promising in this area; in a small-sample twin study, Keller et al. (1992) found that about 40% of measured variance in work values (their term for preferences for job characteristics) was due to genetic factors.

[29] We examine the potential for endogeneity of our preference measures in more detail in another paper based on the same dataset (Sauermann & Cohen, 2007a). While we cannot rule out that measured preferences react to prior outcomes, such effects appear to be limited.

established firms (Table 18). Model 1 predicts individuals' choice of a firm type as a function of industry and individual characteristics as well as the complete set of motives. Note that we also included some characteristics of the current position as controls under the assumption that they were to some extent predictable ex ante and thus potentially influenced organizational choice. According to model 1, individuals with more advanced degrees are more likely to sort into startups (reference category) than into established firms. The same is true for individuals with longer labor market experience at the time of making the organizational choice (HDTENURE0). Married individuals are less likely to join a startup, while males are more likely than females to choose a startup over a large established firm. While the type of R&D does not predict organizational choice, a higher variety of non-R&D tasks (WA_NONRD) predicts employment in startups, consistent with the idea that large firms offer more specialized jobs. With respect to motives, the results of model 1 suggest that individuals who self-select into startups have a significantly lower security motive and a significantly higher advancement motive than individuals who sort into established firms. Individuals with a high preference for fringe benefits are more likely to select into large established firms versus startups. The size effect of the importance of job security is particularly large; according to model 1, a one point increase in this measure increases the relative risk of selection into small established firms (vs. startups) by a factor of 1.5 and into large established firms by a factor of 1.8. In models 2 – 9, we estimate models including only one motive at a time to account for significant correlations between the motives and to get a better picture of differences in motives across firm types. These regressions show that individuals with strong preferences for salary, fringe benefits, and job security strongly prefer large established firms over startups. Individuals with strong preferences for job security also prefer small established firms over startups. Individuals with strong preferences for opportunities for advancement, on the other hand, tend to prefer startups over established firms.

We also estimated a selection model using only the Ph.D.- sample for which we have an additional measure of ability (model 10). The do not show a significant impact of ABILITY on organizational choice, although the signs of the coefficients suggest that lower-ability individuals are somewhat more likely to join small established firms versus startups. Considering all ability measures (e.g., DEGREE, HDTENURE0, ABILITY) together, however, it appears that more educated and more experienced individuals strongly prefer startups over small established firms, and weakly prefer startups over large established firms.

As noted earlier, we have a measure of individuals' basic annual salary (without any contingent elements). This measure allows us to examine individuals' preferences for salary as well as actual salary across different types of firms, giving us a better impression of differences in actual benefits and sorting across firm types. Table 19 shows the results of two sets of regression. In columns 1 and 2, we report the results of ordered probit regressions with the importance of salary as the dependent variable. Consistent with the multinomial logit choice models discussed above, we observe stronger salary motives in large established firms than in startups (model 1). Using the disaggregated firm size and firm age measures, we see that these differences primarily result from stronger salary motives in larger firms, while firm age (NEWBUS) does not appear to have an effect. Models 3 – 6 show the results of OLS and quantile regressions (estimating the conditional median rather than the conditional mean) with log salary as the dependent variable. Salary does not differ between startups and large established firms but is lower in small established firms than in startups. Firm size and age dummies (models 5 and 6) show that salary increases significantly with firm size, consistent with the prior research in labor economics discussed earlier. Interestingly, individuals in young small firms also appear to earn more than individuals in small old firms (significant NEWBUS dummy). Overall, individuals in large firms have significantly stronger salary motives and earn larger salaries, consistent with our argument that individuals self-select into types of organizations according to their motives.[30]

Assuming that our self-selection argument is valid also with respect to benefits other than salary, we can interpret observed differences in motives as reflecting differences in the benefits available in startups versus established firms. The results of our analyses would then suggest that startups and large established firms differ significantly with respect to some of the extrinsic incentives they provide, but differ much less with respect to intrinsic incentives. As suggested by the quote at the beginning of our paper and by our theoretical discussion, it is conceivable that large R&D organizations provide their employees with favorable conditions to satisfy their intrinsic and social goals, despite or maybe even because of their size and age. However, it is also possible that startups and established firms differ with respect to non-pecuniary benefits, but that individuals self-select imperfectly because nonpecuniary benefits are hard to observe from outside the organization and difficult to predict ex ante.

The analyses presented in this section raise an interesting question: if large firms provide more extrinsic benefits (e.g., salary, fringe benefits and job security) and if there are no significant differences with respect to the intrinsic and social benefits, why would any individual decide to work for a small firm? Similarly, if there are no differences in intrinsic benefits across firm types, why do we observe a wage

[30] We also estimated the models in Table 6 using a truncated sample that included only individuals with an annual salary of $ 20,000 or higher. The qualitative results are the same.

premium in large firms? While a thorough discussion of these issues is beyond the scope of this paper, we would like to offer some thoughts. First, it is important to remember that we measure preferences only for a limited set of work benefits. It is conceivable that other benefits such as social relationships on the job, the opportunity to have an impact, or even the opportunity to publish (Stern, 2004) are more readily available in small and young firms and may be important in attracting certain individuals. Second, our salary measure does not capture any contingent components, which may be relatively larger in small and young firms (see our discussion above). Thus, while there are significant differences in salary across firm types, differences in total pay may be smaller. Finally, it is quite possible that many individuals who are currently employed in startups and small established firms would actually prefer to work in large firms but do not have the opportunity to do so because of a limited availability of positions. At the same time, large firms may pay salaries that are above the market-clearing level due to high cost of turnover, because of efficiency wage arguments, etc. While some of these issues have been addressed in the labor economics literature more generally (Oi & Idson, 1999; Rosen, 1986), more research is needed, especially in the innovation context.

3.4.2 Effort

Table 20 reports the results of our benchmark effort regressions. Model 1 includes only the firm type dummies as well as industry dummies. This regression shows that individuals in startups report significantly higher effort than individuals in small and large established firms. Adding individuals' characteristics in model 2 explains some of the "effort advantage" of startups over large established firms, but not of the advantage over small established firms. In model 3, we add motives into the regression model. Several of the motives have significant effects upon effort. The strongest positive effect is estimated for the importance of challenge, followed by the importance of responsibility. Surprisingly, the importance of salary has a significant negative effect on effort. A corollary analysis suggests that this result is primarily due to a relatively small number of respondents - less than 1% of our sample - who expend more than average effort, yet rate their preference for salary very low. Thus, there may be some segment of R&D employees who both eschew financial gain yet are very dedicated to their work, much like Kidder's (1981) "Hardy Boys" at Data General who worked very long hours to develop a new generation of minicomputer while claiming that they "don't work for the money." Nonetheless, we remain cautious about interpreting this negative coefficient on IMP_SAL.[31]

Does the inclusion of individuals' motives change the estimated differences in effort across firm types? Including the measures of motives leads to no discernable reduction in the ESTAB100 and ESTAB500 coefficients. The lack of larger changes appears to be due to the fact that the two motives that affect effort most strongly (intellectual challenge and responsibility) do not differ significantly across firm types (Table 18). Models 4 through 6 in Table 20 include certain subsets of motives in order to detect potentially offsetting effects of different types of motives, but the ESTAB100 and ESTAB500 coefficients remain virtually unchanged.

In models 7 and 8, we replace our firm type dummy variables with separate measures of size and age, EMSIZE (a set of dummies representing different size classes) and NEWBUS (a dummy indicating if a firm is younger than six years). This analysis suggests that the effort advantage of startups is primarily associated with

[31] While our model does not predict an effect of basic salary on individuals' effort, we estimated regressions including LN_SALARY as a robustness check. The inclusion of the salary measure results in slight changes in the coefficients of the measures of some motives and preferences, but the qualitative results remain unchanged. 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.

age, rather than size. Size has no clear relationship with effort. Compared to individuals in very small firms (1-10 employees, omitted category), individuals in somewhat larger firms appear to work less, but effort tends to increase with size for larger size classes.

In Table 21, we estimate effort regressions separately for each firm type, thus allowing for the possibility that firm types differ in the (unobserved) contingent benefits they provide ($\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$), implying differences in the coefficient estimates for our motive variables across firm types (models 1-3). For example, if a firm type provides more contingent pay than another, then the salary motive would be predicted to have a higher impact on effort in the former. The results suggest that there are indeed some differences in the effects of motives on effort. First, the independence motive has a large positive impact on effort in startups, but not in established firms. The security motive has a negative impact on effort in startups, but not in established firms. Finally, the responsibility motive is positively related to effort in large established firms, but not in small established firms or startups. While we are not surprised that there are differences in the estimated effects of motives on effort across firm types, the direction of these differences is not readily explained given our priors regarding differences in $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ across firm types (see Figure 2).

These split sample regressions provide another basis for evaluating the role of individuals' motives in distinguishing the effort observed in startups and established firms, taking into account differences in the estimated coefficients of motives. Specifically, we compute the predicted effort levels in startup firms using the values of the motive variables actually observed in these firms, and then replace the startup firm values with the mean values of the motive variables observed in large established firms, and vice versa. The results suggest that mean predicted effort in startups is 45.35 hours using the true motives of startup employees, but drops to

44.58 hours when we assume that startup employees have the motives of the average employee in a large established firm. The predicted effort in a large established firm is 42.58 hours assuming the original motives, but increases to 42.85 hours assuming startup motives. While the directions of these changes suggest that startups enjoy a small effort advantage due to the levels of the motives of their personnel, these effects appear to be very small.[32]

Table 21 also reports a set of robustness checks. First, we estimated the key regressions using tobit regression rather than employing a truncated regression model as above. Again, the qualitative results are unchanged. Second, we estimated key regressions using the Ph.D.-sample for which we have an additional measure of ABILITY. While the ABILITY measure has the predicted positive effect on effort, its addition has only a negligible effect on the ESTAB100 and ESTAB500 coefficients as well as the estimated effects of motives (models 7 and 8).

As suggested earlier, our analysis thus far does not consider that certain unobserved individual-level factors may drive both self-selection into firm types as well as effort and could thus be partly responsible for estimated differences in effort across firm types. To assess the robustness of our results to this possible source of endogeneity, we estimated split sample OLS regressions including adjustment terms derived from a first-stage multinomial logit regression using the methods first proposed by Lee (1983) and Dubin and McFadden (1984) (for a review and comparison of these methods, see Bourguignon et al., 2007). We use individuals'

[32] This approach is a variation of the Oaxaca-Blinder decomposition used frequently in labor economics to identify the factors contributing to observed wage gaps. Generally, differences in a particular outcome such as wages across subsamples can be due to (1) different endowments of independent variables (2) different effects of these variables on the outcome, and (3) unobserved factors that affect both selection into subsamples and outcomes (Idson & Feaster, 1990; Oaxaca & Ransom, 1994). Using that terminology, our analysis focused on (1), i.e., different endowments of motives.

preference for fringe benefits as an instrument in the selection equation (see Table 18). Given that fringe benefits are conditional only upon employment in a particular firm (type), but not on effort, this preference should not have a direct effect upon effort (see also our formal model). Table 22 presents the results of these analyses. Neither the adjustment terms derived using Lee's method (models 3, 6, 9) nor those computed using the Dubin-McFadden method (models 4, 7, and 10) are significant, indicating that our data do not reject the null hypothesis of the absence of unobserved factors that affect both firm choice and effort. Note, however, that the estimated coefficients of motives in the STARTUP100 sample become generally larger when the adjustment terms are included. We attribute this effect primarily to the small number of cases in this subsample (n=572) and to the correlations between our instrument, the preference for fringe benefits, and the preferences for other extrinsic benefits.

To summarize, we find that individuals in startups expend significantly higher effort than individuals in established firms. This effect is associated primarily with firm age, not size. While several types of motives have significant impacts upon effort, the few observed differences in the levels of motives across firm types explain only a negligible share of the effort difference. There are at least two effects related to motives and incentives that could help explain that effort difference, although our data do not allow us to examine them explicitly. First, we do not observe the contingent nature of benefits across firm types (i.e., $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$), but these links may be stronger in startups (cf. Zenger & Lazzarini, 2004) and may thus be responsible for higher levels of effort. Second, as noted above, we lack measures of at least two key motives that might account for greater individual effort: R&D employees' intrinsic motive to have some sort of impact and social motives related to desire for peer recognition or commitment to the team and the firm.

3.4.3 Performance

Table 23 presents our main performance regressions. Model 1 includes only the ESTAB100 and ESTAB500 dummies as well as industry dummies. According to this model, individuals employed in small established firms have 56% lower patent application counts and individuals in large established firms have 26% lower counts than individuals employed in startups. These effects become even larger (58% and 34%, respectively) when we add individual-level controls to the model (model 2). In model 3, we include the effort measure, which leads to a reduction in the coefficients of the firm type dummies. This suggests that some of the performance advantage of startups is due to the higher effort expended by startup employees. In model 4, we add individuals' motives. Comparing this model to model 2 suggests that motives may be responsible for a considerable part of the performance advantage of individuals employed in startups over those employed in established firms. The change in ESTAB100 is significant at the 5% level (chi2(1)=6.28), and the change in the ESTAB500 coefficient is significant at 1% (chi2(1)=9.14). To illustrate the economic significance of the change, the estimated performance advantage of startups over large established firms is reduced from 34% to 24%. Model 5 suggests that, taking differences in motives and effort into account, individuals in startups do not perform better than individuals in large established firms, but still have a significant performance advantage over individuals in small established firms.

Model 5 also suggests that individuals' motives affect performance even controlling for the quantity of effort, which suggests that motives may affect the productivity of effort, as proposed by the social psychological research discussed earlier. More specifically, the challenge and independence motives have significant positive effects, while the security motive has a significant negative effect. The positive effect of the challenge motive is consistent with the idea that intrinsic motivation is particularly beneficial in innovative tasks (e.g., Amabile, 1996). The substantial negative effect of the desire for job security (IMP_SEC) on innovative performance is particularly interesting. We suggest that this measure is closely correlated with individuals' more general risk preferences, for which we have no separate measure. Interpreting IMP_SEC as a proxy for individuals' risk aversion, the negative effect of that measure supports the notion that more risk-averse individuals may choose "safer" projects and approaches that may offer fewer opportunities for significant innovation (Amabile & Conti, 1999; Dunbar, 1995). A somewhat smaller positive effect of the salary motive as well as a slightly negative effect of the responsibility motive are fragile. Models 6 through 8 include the sets of extrinsic, intrinsic, and social motives separately and suggest that the single most important motivational driver of the performance of startups relative to established firms is the security motive, which is much stronger in established firms (see above) but has negative effects on productivity. Recall that the challenge motive, which has the strongest impact on productivity, does not differ substantially between firm types and thus does little to explain differences in performance.[33]

In models 9 and 10, we use the EMSIZE and NEWBUS dummies. These regressions suggest that the "performance advantage" of startups is primarily associated with their young age. Moreover, there appears to be a positive effect of size among larger established firms. Due to this effect, individuals in extremely large

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[33] We also estimated key regressions using zero-inflated negative binomial regression. The results of these regressions suggest that much of the performance disadvantage of individuals in small established firms stems from their being in the "always 0" group (large positive ESTAB100 coefficient in the logit part). The estimated ESTAB100 and ESTAB500 coefficients in the negative binomial parts of the ZINB are generally smaller than those obtained using simple negative binomial regression. The effects of motives on performance, on the other hand, are very similar to those obtained using regular negative binomial regression, the effects of the salary and independence motive appear even stronger. Adding motives into the performance regression eliminates the (small) performance advantage of startups, whereby it is again the security motive that has the largest impact on relative innovative performance.

established firms (25,000+) are somewhat more productive than individuals in small established firms and are almost as productive as individuals in startups. Adding our measures of motives into the regression leads to the expected changes in EMSIZE and NEWBUS coefficients; the NEWBUS coefficient is reduced (though it remains large and significant) while the coefficients on the dummies for larger size classes increase slightly.

In order to probe the robustness of our results to possible selection effects at the firm level, we also estimated key performance regressions separately for certain industries. As discussed above, it is conceivable that startups in some industries are more rigorously selected based on their inventions and, in particular, patent applications. Consistent with such a selection effect, we find that startups have very strong "performance advantage" in the life sciences (pharmaceuticals and medical devices industries), while the performance difference is much weaker in R&D services and computer systems design. Recall also that the share of individuals in startups is much smaller in the pharma industry than in computer systems design (see Table 14), which is consistent with a more intense selection environment. Excluding the life science industries from the sample noticeably reduces the ESTAB500 coefficient (though not the ESTAB100 coefficient), but the coefficient remains significant at 5%. These results suggest that some of the observed performance advantage of startups may be due to a process whereby low-performing (potential) startups are more likely to be selected out either before they are born or in the early stages of startup development. While the estimated performance difference between startups and established firms is reduced when the life sciences are excluded from the sample, the mediation effect of effort and motives persists.[34]

Table 24 reports an additional analysis intended to gain a better understanding of the observed higher patent counts in startups and the robustness of the mediating effect of motives by exploiting the EMPLCHANGE variable (change of employers within the last 2 years). The concern here is one associated with possible measurement error; that the startup performance advantage may reflect individuals joining a startup after they already possess patents, rather than generating patented technologies while employed. Given that patents are counted over a 5-year span, it is likely that at least some of the measured performance of recent job changers originated in a different organization (though not necessarily in a different firm type). We therefore estimated performance regressions dropping cases that have joined their current employer only within the last 2 years of the survey (models 1 and 2). The estimated coefficients of ESTAB100 and ESTAB500 are much smaller than in regressions using the full sample, suggesting that some of the observed "performance advantage" of startups may result from work conducted by individuals before joining or founding the current startup, possibly reflecting selection of high-performers into startups.[35] This conjecture is supported by the coefficients of the EMPLCHANGE variable in split sample regressions (models 3-5). EMPLCHANGE is positively related to performance in startups but negatively related to performance in

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[34] More specifically, the ESTAB500 coefficient is reduced from -0.347 ($p<0.05$) to -0.164 (n.s.) once effort and motives are included into the regression. The ESTAB100 coefficient is reduced from -0.907 ($p<0.01$) to -0.737 ($p<0.01$).

[35] In contrast, dropping individuals who recently changed employers from the sample does not reduce the coefficients of the ESTAB100 and ESTAB500 dummies in the effort regressions (cf. Table 20). Thus, while recent hires may be responsible for some of the "performance advantage" of startups, they do not seem to be responsible for the observed "effort advantage" of startups.

small established firms; it has no effect in large established firms. Assuming that USPAPP partly reflects performance prior to making the employer change, it appears that high-performing individuals tend to join or found startups while low-performing individuals are more likely to join small established firms. It is not entirely clear from our data what attracts high-performers to startups, though high-powered performance contingent incentives as well as unobserved nonpecuniary benefits may be responsible.

Our performance regressions thus far implicitly restricted the effects of motives and effort to be the same in startups and established firms. However, reflecting the possibility of different values of $\boldsymbol{\alpha}$'s and $\boldsymbol{\gamma}$'s (strength of various incentives) across firm types, split sample regressions (Table 24, models 3-5) suggest that some of the effects of effort and motives differ across firm types. Indeed, we observe that the positive effect of the salary motive is confined to large established firms, the negative effect of the security motive is particularly strong in startups, and the challenge motive has its strongest effect in large established firms. There are several potential drivers of such differences, including differences in unobserved incentives as well as differences in the nature of innovation across firm types, which may lead to differences in the productivity effects of motives. For example, the larger negative productivity effect of IMP_SEC (security motive) in startups could be explained if risk aversion reduces individuals' exploratory thinking generally, but especially if the actual amount of uncertainty is high (i.e., in startups).

Similar to our discussion of effort, we can compare predicted patent counts assuming different sets of motives in startups. Given the estimated effects of motives from the split regression using the startup sample (model 3) and the true motives in startups, the predicted average patent count is 2.2 patent applications. Replacing the true startups motives with the average motives of individuals in large established firms reduces that prediction to 1.28 patent applications. This large drop in predicted output is primarily due to the increase in IMP_SEC, which has a particularly strong negative effect in startups. The predicted patent output in large established firms using the original motives is 1.41 and changes only slightly to 1.42 if we use startup motives.

In Table 25, we address the concern that unobserved ability could affect our results (cf. Brown, 1980; Gibbons & Katz, 1992). Using our Ph.D.-sample, for which we have a better measure of ability, we find a positive impact of ABILITY upon performance (model 3). Also, as suggested by our formal model, ability and effort have a positive interactive effect (models 7 and 8). However, adding the ability measure into the regression equations does not lead to substantial changes in the coefficients of ESTAB100 and ESTAB500 (models 1 vs. 3) or of our measures of motives (models 2 vs. 4).[36,37]

To summarize, we find that individuals in startups have higher numbers of patent applications than individuals in established firms. Several factors appear to contribute to this effect. First, individuals in startups are characterized by lower levels of desire for job security, which is negatively associated with innovative performance. Other motives that also have strong productivity effects (in particular, intellectual challenge) vary little across firm types and thus do not appear to affect

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[36] We also estimated selectivity-adjusted performance regressions based on the Lee and Dubin-McFadden approaches (see above). These regressions do not suggest the presence of unobservable factors driving both firm choice and performance. However, these results are based on OLS second-stage regressions, which may be inappropriate for our USPAPP measure. It is not clear to what extent this selection-adjustment generalizes to nonlinear (NBREG or ZINB) second-stage regressions.

[37] We also estimated our key effort and performance regressions using the limited sample and including firm identifiers to control for firm fixed effects (while excluding the firm type dummies). Including the firm identifiers leads to small changes in the estimated effects of motives, potentially reflecting differences in incentives across individual firms, but the qualitative results remain unchanged.

the relative performance observed in startups and established firms. Second, individuals in startups expend more effort, which in turn has positive effects on performance. Third, there may be selection effects in that "potential" startups with a strong technological capability and existing patent applications are more likely to be born and survive. Similarly, startups may attract individuals with more patent applications, rather than "causing" their employees to produce more applications.

3.5 Discussion

In this paper, we examine to what extent individuals' pecuniary and nonpecuniary motives and incentives differ between startups and established firms, and whether any existing differences in individuals' motives and incentives affect the relative effort and innovative performance observed in these firm types.

Drawing on research in economics, social psychology, and management, we first developed a model that captures the relationships between firm types, individuals' motives and incentives, effort, and innovative performance. Using NSF survey data from over 9,000 scientists and engineers employed in startups and established firms across a wide range of industries, we then examined whether individuals' motives differ across firm types and if any such differences affect the relative innovative effort and performance observed. We find that some extrinsic motives, in particular, the importance of salary, job security, and fringe benefits differ between startups and established firms. However, intrinsic and social motives are surprisingly similar. We also observe significant differences in innovative outcomes in startups and established firms. First, we find that the individual effort expended in startups is significantly higher than that expended in established firms. However, this higher level of effort is not explained by the few existing differences in individuals' motives, primarily because the motives that most strongly affect effort (in particular, intellectual challenge) do not vary across firm types. It is conceivable that the effort differential reflects a selection effect in the sense that only startup firms that elicit high levels of effort from their employees can overcome the obstacles associated with startup emergence and survival; however, we are unable to explicitly test this possibility. Second, we find that individuals in startups have more patent applications than individuals in established firms. This effect is primarily associated with firm age rather than size. Firm size, however, appears to have positive effects on performance among larger firms, such that individuals in extremely large firms are almost as productive as those in startups. Our analysis suggests that the observed "performance advantage" of startups may be due to three factors. First, individuals in startups are characterized by lower levels of desire for job security, which is negatively associated with innovative performance. Rather than positing a causal relationship between the desire for job security and performance, we suspect that the desire for job security is closely correlated with, and thus proxies for, more general risk aversion, which may affect innovative behaviors and performance (Amabile & Conti, 1999; Dunbar, 1995). Second, individuals in startups expend more effort, which in turn has positive effects on performance. Third, there may be selection effects at the firm as well as individual level. More specifically, "potential" startups with strong technologies are more likely to be born and survive. Similarly, startups may attract individuals with more patent applications, rather than "causing" their employees to produce more applications. To the extent that these selection effects are responsible for observed performance differences, our results do not imply that startups are "better" at innovation than established firms.

As discussed earlier, notwithstanding the large body of research assuming stability of employees' motives (cf. Amabile et al., 1994; Cable & Edwards, 2004), we must entertain the possibility that R&D employees’ motives may themselves be influenced by prior choices or previously realized benefits, implying endogeneity of motives. To the degree that this is true, one should view our results as more descriptive. Like most prior work relating organizational characteristics to performance, we also have to consider that organizational characteristics such as firm size and firm age may be endogenous with respect to performance. It is likely that firms with exceptional performance grow faster than others and have higher odds of survival, and that firm size and age are thus partly a function of performance. A third limitation of our study is the lack of measures of contingent benefits (α's and γ's in our model) and of additional motives that may be particularly important to individuals engaged in R&D (e.g., achievement, peer recognition, and other group-level social motives). We expect that including such measures would explain more of the variance in effort and performance across individuals, as well as across firm types.

Despite the preliminary nature of some of our findings, there are potentially important implications for firm policy. Regarding limited differences in motives across firm types are consistent with the idea that startups and established firms have similar opportunities to provide intrinsic benefits such as intellectual challenge and independence but face different (resource) constraints in the provision of extrinsic incentives such as pecuniary income and job security. Interestingly, potential advantages of established firms in providing pecuniary benefits do not appear to translate in a relative performance advantage; indeed, our results suggest that attracting individuals with strong preferences for job security may even have detrimental effects on innovative effort and performance. A very interesting implication of our findings is that the general perception that startups provide little job security may limit their ability to attract a large labor pool, but it may actually be beneficial to the extent that it leads less risk-averse individuals to self-select into startups.[38] At the same time, large established firms that employ more risk-averse individuals may be able to increase innovative performance by explicitly encouraging exploratory behaviors and by buffering individuals from the inevitable downside of risky projects (cf. Manso, 2006; O'Reilly, 1989; Sitkin et al., 1994). More generally, it is likely that mangers can, within certain constraints imposed by structural characteristics of their organizations, strategically influence the motives and incentives of their R&D personnel. Our results suggest that intrinsic motives and incentives are especially beneficial for innovation and may deserve particular attention, even though they may be more difficult to "manage" than conventional pecuniary incentives such as pay. Along with the analysis of related papers, our results also suggest that the pecuniary and nonpecuniary motives and incentives of R&D employees, and their management by the firm, may contribute importantly to firms' innovative capabilities. Considering individuals' incentives and firm's incentive systems may thus be particularly important for practitioners and scholars interested in factors that distinguish the innovative performance of firms (cf. Gottschalg & Zollo, 2007; Henderson & Cockburn, 1994; Sauermann, 2007; Sauermann & Cohen, 2007a).

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[38] In a recent survey of job searchers, we asked science and engineering graduate students which aspect they would dislike most about employment in startups. The by far most frequent response to this open ended question was a version of "lack of job security".

4 Summary and Discussion

In this dissertation, I examined individuals' motives and incentives as drivers of innovative effort and performance. In chapter One, I reviewed existing literature on individuals' motives and incentives in innovation. I also reviewed select research on incentives conducted in other areas including economics, sociology, organizational theory, and social psychology to inform my study. Chapter One also provides the definitions of motives and incentives used throughout this dissertation as well as a useful typology distinguishing benefits and motives along two dimensions, extrinsic-intrinsic and social-nonsocial.

In chapter Two, I first developed a basic model of the impact of extrinsic and intrinsic incentives on individuals' innovative effort and performance. Using a survey-based data set (SESTAT 2003), I then presented descriptive data on the motives salient to personnel in industrial R&D and test predictions derived from my model. In doing so, I controlled for a wide range of other variables at the individual, firm, and industry level that have been considered in prior innovation research. I found that individuals engaged in industrial R&D have strong extrinsic and intrinsic motives and that there are systematic differences in these motives across types of individuals and work settings. Motives have significant effects upon innovative effort and performance. These effects vary significantly, however, depending on the particular kind of motive (e.g., intellectual challenge vs. pay). I also found that intrinsic and extrinsic motives affect innovative performance even when controlling for effort, suggesting that motives affect not only the quantity of effort individuals exert, but also the innovative productivity of that effort. Overall, intrinsic motives (in particular, intellectual challenge) appear to be more beneficial for innovation than extrinsic motives (e.g., pay), with a one-SD higher score on the challenge motive implying a 19.8% higher expected count of patent applications.

In chapter Three, I examined to what extent the pecuniary and nonpecuniary motives of R&D employees differ between startups and established firms and whether any such differences in motives affect the relative innovative effort and performance observed in startups and established firms. I first developed a formal model of the relationships between firm types, individuals' motives and incentives, effort, and innovative performance. Based on NSF survey data from over 9,000 scientists and engineers (SESTAT 2003), I find that individuals' pecuniary motives, such as their desire for pay and job security, differ significantly between startups and established firms, while their nonpecuniary motives, such as their desire for intellectual challenge and independence, are surprisingly similar. Individuals employed in startups expend significantly more effort than individuals in small and large established firms. Moreover, startup employees have almost twice as many patent applications as individuals in small established firms and about 35% higher patent application counts than individuals in large established firms. While I cannot explain the "effort advantage" of startups, three factors appear to account for their "performance advantage." First, individuals in startups are characterized by lower levels of desire for job security (perhaps reflecting risk-aversion), which is negatively associated with innovative performance. Second, individuals in startups expend more effort, which in turn has positive effects on performance. Third, there may be selection effects in that "potential" startups with a strong technological capability and existing patent applications are more likely to be born and survive. Startups may also attract individuals with more patent applications, rather than "causing" their employees to produce more applications.

Several limitations of this study have to be kept in mind. First, my measures of motives are limited to a set of 8 measures, capturing individuals' preferences for salary, job security, fringe benefits, intellectual challenge, independence, opportunities for advancement, responsibility, and contribution to society. While the range of motives considered is more comprehensive than what is typically considered in the innovation literature, my interviews as well as prior research suggest that some additional motives may play an important role, including the desire to achieve something, to have an impact, as well as social motives related to helping one's peers and contributing to the organization's success. While I do not believe that a lack of measures of these motives leads to significant biases in my empirical results, having such measures might significantly increase our understanding of the drivers of innovation. I also suspect that some of these motives may play a particularly important role in distinguishing individuals' effort and performance in startups and established firms. Second, my measures of individuals' preferences are single-item measures, which typically have a lower reliability than scales designed to measure the same underlying construct using multiple items. With only a single item for each construct, the reliability of measures cannot be estimated and it is not clear how much true relationships are attenuated in the data due to measurement error (Nunnally, 1978; Pedhazur & Schmelkin, 1991; Rushton et al., 1983). The use of the two factor-based scores EXTRINSIC and INTRINSIC in chapter 2 partly addresses this limitation but implicitly makes the questionable assumption that the items underlying each of these scores measure the same construct. A third limitation of this research is that I do not have direct measures of individuals' incentives, i.e., of the contingent benefits that are available to the individuals in my sample. As discussed in chapter 2, this may under certain conditions cause the estimated coefficients of motives to reflect joint effects of motives and incentives of a particular type (e.g., intellectual challenge). However, such a bias would not affect the qualitative insights gained in this study – in fact, it is exactly these combined effects of motives and incentives that ultimately drive innovative effort and performance and that are relevant from a managerial and policy perspective. A fourth limitation of this study is that I cannot make clear inferences regarding the causality of the observed relationships between the key variables. Longitudinal data or instrumental variables would be needed to disentangle these relationships. However, my theoretical discussion suggests clear mechanisms by which motives may impact individuals' effort and innovative performance. In addition, several auxiliary analyses suggest that any bias due to endogeneity of the measured motives should be limited. Even without an unambiguous result regarding the underlying causality, the observed strong relationship between individuals' motives, in particular the challenge motive, and innovative effort and performance is intriguing and suggests that future innovation research may benefit from considering a broader range of pecuniary as well as nonpecuniary motives and incentives.

Finally, this research has used primarily patent applications as measures of innovative performance. As discussed in chapter Two, patents are an imperfect measure of innovation and may vary in their validity across types of innovation and industrial settings. I have tried to mitigate some of these concerns by estimating key regressions using select subsamples as well as alternative performance measures including commercialized patents and scientific publications. It would nevertheless be desirable to replicate and extent this research using additional measures of innovative performance.

Despite these limitations, this dissertation makes several contributions. First, the literature on the economics of innovation has typically focused on firm-level profit incentives for innovation. I hope to contribute to that literature by explicitly considering the motives and incentives of individuals engaged in innovative activities. Moreover, drawing on prior research in social psychology and organizational behavior, I do not only consider pecuniary, but also nonpecuniary motives and incentives. My empirical research suggests that attention to individuals' pecuniary as well as nonpecuniary motives and incentives may significantly increase our understanding of innovation in firms.

My research contributes to the strategy literature by drawing attention to individuals' motives and incentives as a factor that may significantly affect firms' innovative performance. While I have shown that individuals' motives may play a role in distinguishing the innovative performance of firm types (e.g., startups versus established firms), it is likely that they may also affect the relative innovative performance of different firms (see below).

Finally, I hope that my work will also be of interest to scholars in the areas of social psychology and organizational behavior. While these literatures have considered individuals' motives and incentives for many years, I analyze an unusually large data set that shows a significant role of individuals' motives in an important natural context. Moreover, I relate motives to tangible and economically relevant outcomes such as patent applications, thereby extending the list of outcomes typically considered in those literatures.

I see several interesting future areas of research on the role of individuals' motives and incentives in the innovation context. First, it seems important to consider the role of individuals' motives and incentives in shaping firms' innovative capabilities, and capabilities more generally. I examine these issues in more detail elsewhere (Sauermann, 2007). While the literature on organizational capabilities typically focuses on knowledge and organizational processes, I suggest that individuals' incentives should be considered as a critical third component of organizational capabilities generally, and of innovative capabilities in particular. In essence, I argue that individual-level incentives are needed to "turn knowledge into action" by motivating individuals to make use of existing knowledge and to develop new knowledge. Drawing on the literatures in economics, strategy, organizational theory, and social psychology, I discuss the relationships between various types of knowledge, individuals' incentives, and organizational processes and I propose a basic model of organizational capabilities as consisting of these three components. I derive several testable propositions and illustrate my discussion using recent empirical research on innovation. I also suggest that considering individuals' incentives as a component of organizational capabilities may not only increase our understanding of the micro-foundations of organizational capabilities, but may also increase our understanding of the conditions under which such capabilities may be the source of a sustainable competitive advantage.

Second, a better understanding is needed of how concretely firms can and do "manage" individuals' various motives and incentives, especially those of an intrinsic and social nature. Firm policies targeted at individuals' motives and incentives may concern aspects of personnel selection (e.g., selection based on individuals' motives) as well as aspects regarding incentive systems within firms. With respect to the latter, incentives may be provided directly (e.g., contingent pay), but also indirectly via "enabling conditions", as discussed earlier.

Firms may face several challenges in efficiently using these levers. First, managers are likely to have difficulty assessing individuals' motives. Heath (1999) for example, suggests that managers are likely to underestimate the importance of intrinsic incentives while overestimating the role of extrinsic incentives because extrinsic incentives are more salient and visible to outsiders. On the other hand, the motives and preferences as self-reported by employees may suffer from social desirability bias (Rynes et al., 2004). Second, while nonpecuniary incentives may cause smaller direct financial costs to firms, it is not clear what the total costs are of providing certain intrinsic and social incentives or enabling conditions. On the one hand, there is Stern's (2004) finding that biologists employed in private firms who are allowed to publish are willing to accept significantly lower salaries than biologists who are not allowed to publish, suggesting that firms may benefit from substantial savings in return for providing employees with opportunities to realize nonpecuniary benefits such as peer recognition or social relationships within the scientific community. On the other hand, the early example of DuPont, which had to provide famed chemist Wallace Carothers with an extensive laboratory and great independence to attract him, suggests that the cost associated with satisfying employee's nonpecuniary motives may be substantial (Hounshell & Smith, 1988). This discussion raises the more general question how rents are distributed when individuals realize utility from nonpecuniary benefits. Does strong competition for highly educated employees allow them to get compensated "twice" for their efforts, in the form of both high salaries and substantial nonpecuniary benefits (Baumol, 2005)? Or do firms realize net financial gains from employing intrinsically motivated employees? These questions essentially concern the "individual-level appropriability" of pecuniary and nonpecuniary returns from innovation (Cohen & Sauermann, 2007).

Finally, it is important to consider how individuals' motives and incentives influence, and are influenced by, other characteristics of the organization such as organizational structure or decision making processes. For example, the rules and processes by which firms make decisions regarding the selection of inventions for commercialization may have important impacts on individuals' incentives but may also be affected by the motives and incentives of the individuals involved.

Appendix for Chapter 2

Table 1: 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 2: Comparison of Full Sample and Ph.D.-Sample

Primary work activity (WAPRI)	Full Sample Freq.	Full Sample Percent	Ph.D.-Sample Freq.	Ph.D.-Sample 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 3: Importance of Work Benefits (4-Point Scale)

Preference measure	Observations	Mean	Std. Dev.	Min	Max
Importance intellectual challenge	11014	3.64	0.53	1	4
Importance benefits	11014	3.58	0.55	1	4
Importance salary	11014	3.56	0.53	1	4
Importance job security	11014	3.52	0.59	1	4
Importance independence	11014	3.48	0.59	1	4
Importance opportunities advancement	11014	3.35	0.65	1	4
Importance responsibility	11014	3.28	0.63	1	4
Importance contribution to society	11014	3.11	0.73	1	4

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

Table 4: 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 5: 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 6: Summary Statistics for Selected Variables

	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
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 7: 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 8: Effort Regressions

	Full Sample						comp=0	manuf=1
	truncreg	truncreg	truncreg	truncreg	oprobit	tobit	truncreg	truncreg
	1	2	3	4	5	6	7	8
	hrsworked	**hrsworked**	**hrsworked**	**hrsworked**	**hrscat5**	**hrsworked**	**hrsworked**	**hrsworked**
Imp. Salary		-0.409*	-0.481**		-0.052*	-0.493*	-0.311	-0.423
		[0.186]	[0.185]		[0.023]	[0.205]	[0.199]	[0.242]
Imp. Benefits		-0.154	-0.138		-0.023	-0.194	-0.069	-0.116
		[0.185]	[0.184]		[0.024]	[0.209]	[0.206]	[0.245]
Imp. Job Security		-0.283	-0.214		-0.027	-0.327	-0.414*	-0.476*
		[0.158]	[0.156]		[0.020]	[0.175]	[0.173]	[0.210]
Imp. Challenge		0.964**	0.874**		0.154**	1.298**	0.851**	0.737**
		[0.180]	[0.179]		[0.024]	[0.210]	[0.193]	[0.224]
Imp. Independence		0.339*	0.293		0.027	0.399*	0.295	0.144
		[0.156]	[0.154]		[0.020]	[0.183]	[0.167]	[0.192]
Imp. Advancement		0.017	0.060		0.004	-0.018	0.034	0.098
		[0.152]	[0.150]		[0.020]	[0.174]	[0.162]	[0.194]
Imp. Responsibility		0.626**	0.584**		0.086**	0.673**	0.632**	0.701**
		[0.158]	[0.157]		[0.021]	[0.186]	[0.170]	[0.203]
Imp. Contr. Society		-0.149	-0.090		-0.036*	-0.315*	-0.103	-0.184
		[0.126]	[0.125]		[0.016]	[0.144]	[0.132]	[0.154]
Factor Extrinsic				-0.929**				
				[0.202]				
Factor Intrinsic				1.708**				
				[0.205]				
LN_SALARY			1.887**					
			[0.232]					
EMSIZE: 1-10	-0.123	-0.345	0.069	-0.316	-0.100	-0.828	0.034	0.665
	[0.552]	[0.546]	[0.546]	[0.547]	[0.072]	[0.582]	[0.720]	[0.961]
EMSIZE: 11-24	-1.423**	-1.544**	-1.208*	-1.537**	-0.203**	-2.025**	-1.240*	-1.384
	[0.500]	[0.495]	[0.494]	[0.497]	[0.064]	[0.564]	[0.632]	[0.824]
EMSIZE: 25-99	-0.362	-0.483	-0.279	-0.457	-0.064	-0.759*	-0.153	0.348
	[0.338]	[0.336]	[0.334]	[0.336]	[0.042]	[0.374]	[0.398]	[0.504]
EMSIZE: 100-499	-0.427	-0.449	-0.261	-0.449	-0.046	-0.401	-0.201	-0.130
	[0.292]	[0.290]	[0.289]	[0.291]	[0.037]	[0.328]	[0.308]	[0.375]
EMSIZE: 500-999	-0.856*	-0.848*	-0.700	-0.859*	-0.083	-0.841	-0.684	-0.267
	[0.367]	[0.362]	[0.359]	[0.362]	[0.048]	[0.434]	[0.393]	[0.458]
EMSIZE: 1000-4999	-0.640*	-0.644*	-0.547*	-0.619*	-0.068*	-0.664*	-0.570*	-0.360
	[0.261]	[0.258]	[0.256]	[0.259]	[0.033]	[0.301]	[0.271]	[0.318]
EMSIZE: 5000-24999	-0.426	-0.406	-0.338	-0.422	-0.040	-0.434	-0.183	-0.024
	[0.232]	[0.230]	[0.229]	[0.230]	[0.030]	[0.274]	[0.239]	[0.278]
NEWBUS	2.243**	2.204**	2.035**	2.204**	0.301**	2.732**	1.808**	1.465**
	[0.334]	[0.330]	[0.327]	[0.331]	[0.043]	[0.369]	[0.389]	[0.487]
IND_NAICS (27)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	-0.502	-0.538	-0.430	-0.534	-0.111	-0.994	-0.908	-1.004
	[0.483]	[0.477]	[0.474]	[0.481]	[0.062]	[0.553]	[0.475]	[0.698]
WAPRI: applied	0.008	-0.027	-0.042	-0.010	-0.024	-0.192	-0.125	-0.310
	[0.257]	[0.255]	[0.253]	[0.255]	[0.033]	[0.293]	[0.256]	[0.316]
WAPRI: design	-0.066	0.000	0.023	0.011	-0.002	0.084	-0.036	-0.019
	[0.247]	[0.245]	[0.242]	[0.245]	[0.033]	[0.293]	[0.252]	[0.274]
WAPRI: computers	-0.848**	-0.745**	-0.658**	-0.743**	-0.120**	-1.028**	-0.751**	-0.734*
	[0.250]	[0.248]	[0.245]	[0.248]	[0.032]	[0.282]	[0.273]	[0.313]
WA_NONRD	0.938**	0.896**	0.884**	0.889**	0.120**	1.065**	0.909**	0.868**
	[0.064]	[0.064]	[0.063]	[0.064]	[0.008]	[0.070]	[0.067]	[0.077]
DEGREE: masters	0.584**	0.494*	0.217	0.519*	0.072**	0.699**	0.439	0.645*
	[0.210]	[0.208]	[0.210]	[0.209]	[0.027]	[0.244]	[0.225]	[0.259]
DEGREE: phd	2.313**	2.041**	1.519**	2.068**	0.267**	2.367**	1.860**	2.083**
	[0.245]	[0.244]	[0.253]	[0.244]	[0.032]	[0.277]	[0.261]	[0.314]
HD_FIELD (15)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	1.662**	1.587**	1.438**	1.594**	0.206**	1.827**	1.534**	1.356**
	[0.114]	[0.114]	[0.114]	[0.113]	[0.015]	[0.126]	[0.123]	[0.140]
HDTENURE	0.096**	0.106**	0.042	0.110**	0.015**	0.130**	0.103**	0.081*
	[0.029]	[0.029]	[0.030]	[0.029]	[0.004]	[0.035]	[0.030]	[0.036]
HDTENURE_SQ	-0.002**	-0.002**	-0.001	-0.003**	-0.000**	-0.003**	-0.002**	-0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]
JOBDEGREE	0.467**	0.423**	0.350**	0.417**	0.056**	0.492**	0.286	0.354*
	[0.137]	[0.136]	[0.134]	[0.136]	[0.018]	[0.157]	[0.150]	[0.178]
MALE	0.920**	0.956**	0.802**	0.980**	0.148**	1.173**	0.951**	1.021**
	[0.221]	[0.220]	[0.218]	[0.220]	[0.029]	[0.249]	[0.237]	[0.296]
CHILDREN011	-1.159**	-1.097**	-1.098**	-1.120**	-0.168**	-1.268**	-0.989**	-1.254**
	[0.249]	[0.245]	[0.247]	[0.245]	[0.032]	[0.260]	[0.279]	[0.384]
MALE x CHILDREN011	1.143**	1.099**	1.076**	1.113**	0.171**	1.332**	0.955**	1.270**
	[0.261]	[0.257]	[0.259]	[0.258]	[0.033]	[0.275]	[0.292]	[0.394]
MARRIED	-0.183	-0.092	-0.113	-0.103	-0.001	-0.010	-0.093	-0.195
	[0.213]	[0.211]	[0.209]	[0.211]	[0.027]	[0.241]	[0.225]	[0.267]
USCITIZEN	0.630*	0.724**	0.692*	0.773**	0.110**	1.201**	0.368	0.464
	[0.278]	[0.276]	[0.274]	[0.277]	[0.035]	[0.301]	[0.309]	[0.377]
RACE (3)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	11014	11014	11014	11014	11014	11014	8675	6049

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

Table 9: Effort Regressions (Ph.D. – 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 10: Performance Regressions

	zinb	zinb (logit)	zinb	zinb	zinb	zinb	zinb	zinb
	1a	1b	2	3	4	5	6	7
	uspapp		**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**
Imp. Salary			0.167*		0.175**	0.158*		
			[0.065]		[0.064]	[0.064]		
Imp. Benefits			-0.042		-0.041	-0.029		
			[0.071]		[0.071]	[0.070]		
Imp. Job Security			-0.213**		-0.200**	-0.202**		
			[0.059]		[0.060]	[0.059]		
Imp. Challenge			0.342**		0.325**	0.308**		
			[0.066]		[0.065]	[0.066]		
Imp. Independence			0.174**		0.184**	0.178**		
			[0.054]		[0.053]	[0.054]		
Imp. Advancement			-0.035		-0.039	-0.041		
			[0.053]		[0.053]	[0.053]		
Imp. Responsibility			-0.075		-0.085	-0.079		
			[0.054]		[0.055]	[0.054]		
Imp. Contr. Society			-0.034		-0.037	-0.031		
			[0.047]		[0.047]	[0.047]		
Factor Extrinsic							-0.156*	-0.132
							[0.073]	[0.073]
Factor Intrinsic							0.293**	0.269**
							[0.073]	[0.074]
HRSWORKED				0.018**	0.015**	0.013**		0.016**
				[0.005]	[0.005]	[0.005]		[0.005]
LN_SALARY						0.277**		
						[0.058]		
EMSIZE: 1-10	0.109	0.773*	0.093	0.164	0.149	0.114	0.083	0.135
	[0.277]	[0.385]	[0.280]	[0.285]	[0.288]	[0.285]	[0.281]	[0.287]
EMSIZE: 11-24	-0.208	0.575	-0.189	-0.202	-0.188	-0.222	-0.208	-0.204
	[0.237]	[0.358]	[0.228]	[0.250]	[0.238]	[0.236]	[0.234]	[0.245]
EMSIZE: 25-99	-0.082	0.770**	-0.134	-0.115	-0.152	-0.201	-0.124	-0.146
	[0.159]	[0.252]	[0.152]	[0.159]	[0.153]	[0.151]	[0.154]	[0.155]
EMSIZE: 100-499	-0.332	0.536*	-0.285	-0.327	-0.281	-0.261	-0.335	-0.331
	[0.187]	[0.261]	[0.186]	[0.184]	[0.184]	[0.187]	[0.185]	[0.183]
EMSIZE: 500-999	-0.223	0.484	-0.276	-0.237	-0.288	-0.288	-0.219	-0.232
	[0.192]	[0.321]	[0.197]	[0.183]	[0.187]	[0.190]	[0.200]	[0.189]
EMSIZE: 1000-4999	-0.321**	-0.05	-0.289**	-0.316**	-0.286**	-0.279**	-0.300**	-0.297**
	[0.106]	[0.213]	[0.106]	[0.106]	[0.107]	[0.106]	[0.107]	[0.107]
EMSIZE: 5000-24999	-0.231*	0.11	-0.223*	-0.207	-0.201	-0.186	-0.232*	-0.211*
	[0.106]	[0.187]	[0.103]	[0.108]	[0.105]	[0.104]	[0.105]	[0.107]
NEWBUS	0.023	-0.711*	-0.054	-0.023	-0.082	-0.026	-0.019	-0.052
	[0.166]	[0.297]	[0.156]	[0.165]	[0.158]	[0.163]	[0.161]	[0.161]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: basic	0.295	0.786*	0.284	0.314*	0.299	0.292	0.289	0.306
	[0.159]	[0.312]	[0.155]	[0.159]	[0.154]	[0.153]	[0.158]	[0.157]
WAPRI: applied	0.273**	-0.043	0.235**	0.272**	0.234**	0.229*	0.270**	0.268**
	[0.094]	[0.208]	[0.090]	[0.094]	[0.090]	[0.090]	[0.093]	[0.093]
WAPRI: design	-0.107	0.605**	-0.101	-0.109	-0.101	-0.084	-0.102	-0.104
	[0.126]	[0.180]	[0.126]	[0.128]	[0.128]	[0.129]	[0.125]	[0.127]
WAPRI: computers	-0.765**	1.149**	-0.793**	-0.752**	-0.779**	-0.742**	-0.731**	-0.723**
	[0.179]	[0.225]	[0.173]	[0.179]	[0.173]	[0.178]	[0.181]	[0.180]
WA_NONRD	-0.009	0.041	-0.003	-0.028	-0.018	-0.022	-0.017	-0.033
	[0.029]	[0.041]	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]
DEGREE: masters	0.249	-0.466**	0.212	0.256*	0.216	0.204	0.257*	0.262*
	[0.129]	[0.155]	[0.130]	[0.129]	[0.129]	[0.129]	[0.131]	[0.130]
DEGREE: phd	0.875**	-2.030**	0.815**	0.855**	0.799**	0.761**	0.864**	0.847**
	[0.122]	[0.226]	[0.122]	[0.123]	[0.121]	[0.123]	[0.124]	[0.124]
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
LN_SUPDIR	0.291**		0.300**	0.263**	0.276**	0.261**	0.280**	0.256**
	[0.040]		[0.039]	[0.041]	[0.040]	[0.039]	[0.040]	[0.040]
HDTENURE	-0.010		-0.010	-0.012	-0.012	-0.021	-0.007	-0.009
	[0.013]		[0.012]	[0.013]	[0.012]	[0.013]	[0.013]	[0.013]
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]	[0.000]
JOBDEGREE	0.136*		0.142*	0.141*	0.144*	0.144*	0.147*	0.149*
	[0.060]		[0.057]	[0.059]	[0.057]	[0.057]	[0.059]	[0.059]
MALE	0.595**		0.588**	0.581**	0.577**	0.556**	0.603**	0.590**
	[0.088]		[0.085]	[0.088]	[0.086]	[0.085]	[0.088]	[0.088]
USCITIZEN	0.150		0.163*	0.140	0.156	0.137	0.165	0.156
	[0.084]		[0.082]	[0.085]	[0.082]	[0.082]	[0.084]	[0.085]
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	11014	11014
Chi-square	459.162		526.916	462.118	527.585	531.322	478.09	477.568
df	66		74	67	75	76	68	69

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

Table 11: 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 12: Performance Regressions (Ph.D.-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 13: Alternative Performance Measures

	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg	nbreg
	1	2	3	4	5	6	7	8
	uspapp	**uspapp**	**uspgrt**	**uspgrt**	**uspcom**	**uspcom**	**publication**	**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

Appendix for Chapter 3

Note: All Tables are based on NSF (2003): SESTAT restricted-use data file

Table 14: Firm Type Distribution across Industries

IND_NAICS	STARTUP100	ESTAB100	ESTAB500
21x Mining,Oil,Gas	≤5	14	150
22x Utilities	≤5	7	243
23x Construction	≤5	37	57
311-312 Manufacturing:Food,Bev,Tobacco	≤5	≤5	146
313-316 Manufacturing:Textiles	≤5	≤5	34
3211,337 Manufacturing:Wood,Furniture	≤5	≤5	29
322-323 Manufacturing:Paper,Printing	≤5	≤5	88
324 Manufacturing:Petroleum	≤5	≤5	68
325 Manufacturing:Chemicals ex Pharma	8	31	481
3254 Pharma	14	32	436
326 Manufacturing:Plastics,Rubber	≤5	≤5	77
327 Manufacturing:NonmetalMinerals	≤5	9	39
331 Manufacturing:PrimaryMetal	≤5	≤5	41
332 Manufacturing:FabricatedMetal	≤5	18	80
333 Manufacturing:Machinery	12	54	279
3341 Manufacturing:Computers	8	18	362
3342-3343 Manufacturing:Communications,	22	23	236
3344 Manufacturing:Semiconductors,Electronics	48	60	678
3345 Manufacturing:Instruments	9	34	260
335 Manufacturing:HouseholdAppliances,Lighting	6	11	123
3361-3363 Manufacturing:Auto	≤5	9	362
3364 Manufacturing:Aircraft,Aerospace	≤5	15	759
3365-3369 Manufacturing:TransportationEquipment	≤5	≤5	60
3391 Manufacturing:MedicalEquipment	17	18	156
3399 Manufacturing:Misc.	≤5	13	41
517 Telecom Services	19	16	457
5415 Computer Systems Design	240	422	1,299
5417 Scientific R&D Services	132	197	930
Total	572	1,066	7,971

Note: Counts <5 suppressed due to NSF confidentiality restrictions.

Table 15: EMSIZE and NEWBUS Distributions

	NEWBUS		
EMSIZE	0	1	Total
1-10	183	160	343
11-24	217	137	354
25-99	666	275	941
500-999	555	0	555
1000-4999	1,435	0	1,435
5000-24999	1,873	0	1,873
>25000	4,108	0	4,108
Total	9,037	572	9,609

Table 16: Variable Means and Standard Deviations by Firm Type

	Variable	Obs	Mean	Std. Dev.
STARTUP100	IMP_SAL	572	3.476	0.599
	IMP_BEN	572	3.420	0.639
	IMP_SEC	572	3.271	0.706
	IMP_CHAL	572	3.708	0.510
	IMP_IND	572	3.535	0.583
	IMP_ADV	572	3.413	0.681
	IMP_RESP	572	3.346	0.609
	IMP_SOC	572	3.122	0.750
	HRSWORKED	572	47.621	7.918
	USPAPP	572	1.684	5.699
	WAPRI: basic	572	0.042	0.201
	WAPRI: applied	572	0.234	0.424
	WAPRI: development	572	0.231	0.422
	WAPRI: design	572	0.093	0.290
	WAPRI: computers	572	0.400	0.490
	DEGREE: masters	572	0.245	0.430
	DEGREE: phd	572	0.404	0.491
	HDTENURE	572	11.101	8.617
	JOBTENURE	572	1.738	1.418
	LN_SUPDIR	572	0.575	0.729
	ABILITY	191	3.470	0.844
ESTAB100	IMP_SAL	1066	3.508	0.554
	IMP_BEN	1066	3.483	0.597
	IMP_SEC	1066	3.442	0.651
	IMP_CHAL	1066	3.681	0.505
	IMP_IND	1066	3.523	0.586
	IMP_ADV	1066	3.312	0.695
	IMP_RESP	1066	3.303	0.678
	IMP_SOC	1066	3.146	0.772
	HRSWORKED	1066	45.456	7.042
	USPAPP	1066	0.853	4.725
	WAPRI: basic	1066	0.046	0.210
	WAPRI: applied	1066	0.178	0.383
	WAPRI: development	1066	0.211	0.408
	WAPRI: design	1066	0.193	0.395
	WAPRI: computers	1066	0.371	0.483
	DEGREE: masters	1066	0.205	0.404
	DEGREE: phd	1066	0.299	0.458
	HDTENURE	1066	13.811	9.843
	JOBTENURE	1066	5.267	5.601
	LN_SUPDIR	1066	0.626	0.804
	ABILITY	253	3.412	0.764
ESTAB500	IMP_SAL	7971	3.568	0.520
	IMP_BEN	7971	3.606	0.530
	IMP_SEC	7971	3.556	0.570
	IMP_CHAL	7971	3.633	0.531
	IMP_IND	7971	3.479	0.590
	IMP_ADV	7971	3.348	0.646
	IMP_RESP	7971	3.275	0.629
	IMP_SOC	7971	3.104	0.729
	HRSWORKED	7971	45.240	6.435
	USPAPP	7971	1.250	4.408
	WAPRI: basic	7971	0.032	0.176
	WAPRI: applied	7971	0.203	0.402
	WAPRI: development	7971	0.250	0.433
	WAPRI: design	7971	0.195	0.396
	WAPRI: computers	7971	0.320	0.467
	DEGREE: masters	7971	0.247	0.432
	DEGREE: phd	7971	0.305	0.460
	HDTENURE	7971	13.459	9.561
	JOBTENURE	7971	7.689	7.761
	LN_SUPDIR	7971	0.535	0.810
	ABILITY	2042	3.408	0.760

Table 17: Correlations

		1	2	3	4	5	6	7	8	9	10
1	STARTUP100	1									
2	ESTAB100	-0.0889*	1								
3	ESTAB500	-0.5550*	-0.7792*	1							
4	IMP_SAL	-0.0381*	-0.0315*	0.0503*	1						
5	IMP_BEN	-0.0741*	-0.0631*	0.0993*	0.5022*	1					
6	IMP_SEC	-0.1082*	-0.0502*	0.1100*	0.2948*	0.4232*	1				
7	ImP_CHAL	0.0312*	0.0257	-0.0411*	-0.0042	0.0531*	0.0257	1			
8	IMP_IND	0.0203	0.021	-0.0303*	0.0360*	0.0816*	0.0555*	0.3770*	1		
9	IMP_ADV	0.0248	-0.0193	0.0005	0.1999*	0.1907*	0.1978*	0.3337*	0.2281*	1	
10	IMP_RESP	0.0255	0.0117	-0.0258	0.1039*	0.1046*	0.0964*	0.4307*	0.4369*	0.4533*	1
11	IMP_SOC	0.0043	0.0176	-0.0174	-0.0142	0.0964*	0.1138*	0.3170*	0.3080*	0.2668*	0.3546*
12	USPAPP	0.0251	-0.0295*	0.0089	-0.0204	-0.0398*	-0.0598*	0.0717*	0.0506*	0.0186	0.0248
13	HRSWORKED	0.0841*	0.0027	-0.0552*	-0.0520*	-0.0405*	-0.0599*	0.1190*	0.0814*	0.0441*	0.1050*
14	Basic R.	0.0107	0.0228	-0.0257	-0.0085	0.0082	0.0202	0.0223	0.021	0.0416*	0.0255
15	Applied R.	0.0204	-0.0207	0.0045	-0.0292*	-0.0073	-0.022	0.0860*	0.0659*	0.0405*	0.0435*
16	Development	-0.008	-0.0274*	0.0279*	-0.0136	-0.023	-0.0132	0.0234	0.0187	0.0388*	0.0481*
17	Design	-0.0619*	0.0038	0.0357*	0.0044	0.0243	0.0159	-0.0389*	-0.0402*	-0.0375*	-0.0101
18	Computers	0.0373*	0.0307*	-0.0491*	0.0369*	0.0038	0.0098	-0.0709*	-0.0479*	-0.0548*	-0.0824*
19	Masters	0.0013	-0.0306*	0.0248	0.0319*	0.0181	-0.0006	-0.0153	-0.0162	0.0139	0.0117
20	PhD	0.0509*	-0.0085	-0.0249	-0.1058*	-0.1238*	-0.1009*	0.1009*	0.0586*	0.0179	0.0401*
21	HDTENURE	-0.0594*	0.0168	0.0234	-0.0488*	-0.0078	-0.0353*	-0.0571*	0.0158	-0.2748*	-0.0968*
22	JOBTENURE	-0.1793*	-0.0850*	0.1838*	-0.0303*	0.0397*	0.0300*	-0.0542*	0.0205	-0.1729*	-0.0653*
23	MALE	0.0247	0.0541*	-0.0607*	-0.0105	-0.0555*	-0.0531*	-0.0227	-0.0515*	-0.0555*	-0.0442*
24	MARRIED	-0.0309*	-0.0146	0.0316*	0.0249	0.0509*	0.0326*	-0.0381*	-0.0183	-0.0419*	-0.0163

* significant at 1%

		11	12	13	14	15	16	17	18	19	20	21	22	23
11	IMP_SOC	1												
12	USPAPP	0.0263*	1											
13	HRSWORKED	0.0530*	0.1049*	1										
14	Basic R.	0.0528*	0.0103	-0.0164	1									
15	Applied R.	0.0928*	0.1467*	0.0622*	-0.0947*	1								
16	Development	0.0323*	0.0641*	0.0544*	-0.1071*	-0.2859*	1							
17	Design	-0.0410*	-0.0439*	-0.0114	-0.0909*	-0.2427*	-0.2745*	1						
18	Computers	-0.0950*	-0.1511*	-0.0870*	-0.1323*	-0.3534*	-0.3997*	-0.3393*	1					
19	Masters	-0.0043	-0.0800*	-0.0334*	-0.0131	-0.0952*	-0.0082	0.0183	0.0786*	1				
20	PhD	0.1259*	0.2596*	0.1215*	0.0358*	0.3269*	0.1174*	-0.1589*	-0.2677*	-0.3796*	1			
21	HDTENURE	-0.0223	0.0223	0.0288*	-0.0299*	-0.0223	-0.0079	0.0511*	-0.0047	-0.0718*	-0.0303*	1		
22	JOBTENURE	-0.013	0.0492*	-0.0271*	-0.0117	0.0176	0.0149	0.0636*	-0.0770*	-0.0029	-0.0317*	0.5247*	1	
23	MALE	-0.0866*	0.0715*	0.0634*	-0.0503*	-0.0492*	0.0393*	0.0661*	-0.0294*	-0.0331*	0.0370*	0.1353*	0.0854*	1
24	MARRIED	0.0155	0.0417*	0.0129	-0.0312*	0.0152	0.0188	0.0036	-0.0211	0.0289*	0.0873*	0.1936*	0.1062*	0.1312*

Table 18: Organizational Choice (STARTUP100 is Omitted Category)

	Full Sample									
	1		2		3		4		5	
	mlogit		mlogit		mlogit		mlogit		mlogit	
	EST100	EST500	EST100	EST500	EST100	EST500	EST100	EST500	EST100	EST500
Imp. Salary	0.069	0.051	0.114	0.304**						
	[0.120]	[0.105]	[0.103]	[0.091]						
Imp. Benefits	-0.048	0.220*			0.123	0.457**				
	[0.112]	[0.096]			[0.090]	[0.078]				
Imp. Job Security	0.407**	0.599**					0.358**	0.642**		
	[0.093]	[0.079]					[0.080]	[0.068]		
Imp. Intel. Challenge	0.006	-0.067							-0.059	-0.166
	[0.131]	[0.116]							[0.112]	[0.099]
Imp. Independence	0.041	-0.042								
	[0.108]	[0.093]								
Imp. Advancement	-0.348**	-0.276**								
	[0.104]	[0.091]								
Imp. Responsibility	-0.067	-0.106								
	[0.107]	[0.092]								
Imp. Contr. Society	0.180*	0.105								
	[0.086]	[0.074]								
ABILITY										
IND_NAICS (27)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD (15)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied	-0.355	0.048	-0.363	0.026	-0.368	0.025	-0.364	0.047	-0.35	0.045
	[0.289]	[0.256]	[0.281]	[0.246]	[0.283]	[0.250]	[0.288]	[0.253]	[0.280]	[0.245]
WAPRI: development	-0.155	0.115	-0.17	0.076	-0.168	0.093	-0.156	0.117	-0.159	0.087
	[0.294]	[0.262]	[0.286]	[0.251]	[0.287]	[0.255]	[0.293]	[0.259]	[0.284]	[0.250]
WAPRI: design	0.407	0.449	0.398	0.433	0.396	0.439	0.433	0.487	0.4	0.426
	[0.323]	[0.293]	[0.316]	[0.284]	[0.317]	[0.287]	[0.323]	[0.290]	[0.314]	[0.282]
WAPRI: computers	-0.175	0.167	-0.176	0.16	-0.177	0.171	-0.155	0.209	-0.166	0.164
	[0.297]	[0.267]	[0.290]	[0.257]	[0.291]	[0.260]	[0.297]	[0.264]	[0.288]	[0.255]
WA_NONRD	0.006	-0.142**	-0.011	-0.163**	-0.01	-0.163**	-0.007	-0.157**	-0.008	-0.157**
	[0.040]	[0.035]	[0.038]	[0.034]	[0.038]	[0.034]	[0.039]	[0.034]	[0.038]	[0.034]
DEGREE: Masters	-0.407**	-0.132	-0.413**	-0.172	-0.416**	-0.166	-0.379**	-0.12	-0.421**	-0.182
	[0.143]	[0.123]	[0.142]	[0.122]	[0.142]	[0.122]	[0.142]	[0.122]	[0.142]	[0.122]
DEGREE: PhD	-0.506**	-0.320*	-0.542**	-0.438**	-0.530**	-0.390**	-0.461**	-0.329*	-0.546**	-0.456**
	[0.157]	[0.134]	[0.157]	[0.134]	[0.157]	[0.135]	[0.155]	[0.133]	[0.156]	[0.134]
HDTENURE0	-0.044**	-0.104**	-0.041*	-0.102**	-0.042*	-0.103**	-0.041*	-0.101**	-0.041*	-0.102**
	[0.017]	[0.014]	[0.017]	[0.015]	[0.017]	[0.015]	[0.017]	[0.015]	[0.017]	[0.015]
HDTENURE0_SQ	0.001	0.002**	0.001	0.002**	0.001	0.002**	0.001	0.002**	0.001	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
LN_SUPDIR	0.138*	0.146*	0.111	0.113*	0.111	0.111	0.117	0.120*	0.111	0.113*
	[0.067]	[0.059]	[0.066]	[0.057]	[0.066]	[0.057]	[0.066]	[0.058]	[0.066]	[0.057]
JOBDEGREE	0.013	-0.153	0.028	-0.142	0.03	-0.14	0.023	-0.149	0.032	-0.131
	[0.093]	[0.081]	[0.092]	[0.080]	[0.092]	[0.080]	[0.092]	[0.080]	[0.092]	[0.080]
MALE	0.13	-0.432**	0.107	-0.461**	0.115	-0.432**	0.116	-0.437**	0.109	-0.459**
	[0.153]	[0.129]	[0.152]	[0.128]	[0.152]	[0.129]	[0.153]	[0.129]	[0.152]	[0.128]
MARRIED	0.449**	0.695**	0.488**	0.762**	0.488**	0.742**	0.467**	0.728**	0.494**	0.772**
	[0.131]	[0.112]	[0.129]	[0.110]	[0.129]	[0.111]	[0.130]	[0.111]	[0.129]	[0.110]
CHILDREN011	-0.189	-0.146	-0.189	-0.142	-0.199	-0.151	-0.191	-0.143	-0.193	-0.147
	[0.168]	[0.132]	[0.171]	[0.137]	[0.174]	[0.139]	[0.169]	[0.133]	[0.172]	[0.137]
MALE x CHILDREN	-0.037	-0.072	-0.032	-0.066	-0.023	-0.063	-0.033	-0.068	-0.025	-0.052
	[0.174]	[0.138]	[0.177]	[0.142]	[0.179]	[0.144]	[0.174]	[0.138]	[0.177]	[0.142]
USCITIZEN	0.164	0.292*	0.221	0.346**	0.222	0.345**	0.228	0.357**	0.211	0.320*
	[0.156]	[0.132]	[0.152]	[0.127]	[0.153]	[0.127]	[0.153]	[0.128]	[0.154]	[0.128]
RACE (4)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	9609	9609	9609	9609	9609	9609	9609	9609	9609	9609
df	137		123		123		123		123	

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

Table 18 (cont.)

	Full Sample								PhD Sample	
	6		7		8		9		10	
	mlogit		mlogit		mlogit		mlogit		mlogit	
	EST100	EST500	EST100	EST500	EST100	EST500	EST100	EST500	EST100	EST500
Imp. Salary									-0.158	0.245
									[0.225]	[0.192]
Imp. Benefits									-0.042	0.105
									[0.210]	[0.167]
Imp. Job Security									0.406*	0.888**
									[0.167]	[0.136]
Imp. Intel. Challenge									0.055	0.063
									[0.280]	[0.243]
Imp. Independence	0.008	-0.098							-0.07	-0.087
	[0.094]	[0.081]							[0.218]	[0.179]
Imp. Advancement			-0.233*	-0.15					-0.375*	-0.364*
			[0.092]	[0.080]					[0.187]	[0.163]
Imp. Responsibility					-0.092	-0.150*			-0.077	-0.13
					[0.088]	[0.074]			[0.201]	[0.171]
Imp. Contr. Society							0.139	0.07	0.161	0.093
							[0.078]	[0.067]	[0.180]	[0.146]
ABILITY									-0.115	0.017
									[0.140]	[0.118]
IND_NAICS (27)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.		
HD_FIELD (15)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.		
WAPRI: applied	-0.35	0.045	-0.358	0.042	-0.353	0.041	-0.345	0.047	-0.441	-0.172
	[0.280]	[0.245]	[0.280]	[0.245]	[0.280]	[0.245]	[0.280]	[0.245]	[0.499]	[0.443]
WAPRI: development	-0.158	0.089	-0.172	0.088	-0.16	0.089	-0.154	0.093	-0.214	-0.109
	[0.284]	[0.249]	[0.284]	[0.250]	[0.284]	[0.250]	[0.284]	[0.250]	[0.527]	[0.464]
WAPRI: design	0.405	0.431	0.378	0.427	0.397	0.429	0.416	0.446	-0.304	-0.186
	[0.314]	[0.281]	[0.314]	[0.281]	[0.314]	[0.281]	[0.314]	[0.282]	[0.624]	[0.542]
WAPRI: computers	-0.16	0.175	-0.191	0.167	-0.171	0.166	-0.147	0.186	-0.31	-0.394
	[0.287]	[0.254]	[0.287]	[0.255]	[0.287]	[0.255]	[0.288]	[0.255]	[0.579]	[0.505]
WA_NONRD	-0.01	-0.158**	0.001	-0.153**	-0.005	-0.154**	-0.014	-0.163**	0.119	-0.08
	[0.038]	[0.034]	[0.039]	[0.034]	[0.038]	[0.034]	[0.038]	[0.034]	[0.082]	[0.072]
DEGREE: Masters	-0.420**	-0.187	-0.435**	-0.196	-0.421**	-0.185	-0.430**	-0.192		
	[0.142]	[0.121]	[0.142]	[0.122]	[0.142]	[0.121]	[0.142]	[0.122]		
DEGREE: PhD	-0.551**	-0.463**	-0.572**	-0.482**	-0.549**	-0.467**	-0.563**	-0.476**		
	[0.156]	[0.134]	[0.156]	[0.134]	[0.156]	[0.134]	[0.157]	[0.134]		
HDTENURE0	-0.041*	-0.102**	-0.044**	-0.104**	-0.042*	-0.102**	-0.041*	-0.102**	0.004	-0.095**
	[0.017]	[0.015]	[0.017]	[0.015]	[0.017]	[0.015]	[0.017]	[0.015]	[0.037]	[0.030]
HDTENURE0_SQ	0.001	0.002**	0.001	0.002**	0.001	0.002**	0.001	0.002**	-0.001	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
LN_SUPDIR	0.109	0.109	0.12	0.116*	0.115	0.118*	0.103	0.105	0.11	0.033
	[0.065]	[0.056]	[0.066]	[0.057]	[0.066]	[0.057]	[0.065]	[0.056]	[0.133]	[0.116]
JOBDEGREE	0.031	-0.132	0.033	-0.132	0.032	-0.131	0.022	-0.138	-0.122	-0.337*
	[0.092]	[0.080]	[0.092]	[0.080]	[0.092]	[0.080]	[0.092]	[0.080]	[0.191]	[0.162]
MALE	0.113	-0.461**	0.106	-0.457**	0.106	-0.463**	0.129	-0.446**	-0.124	-0.602*
	[0.152]	[0.128]	[0.152]	[0.128]	[0.152]	[0.128]	[0.152]	[0.128]	[0.308]	[0.248]
MARRIED	0.493**	0.772**	0.489**	0.774**	0.493**	0.773**	0.490**	0.773**	0.641*	0.783**
	[0.129]	[0.110]	[0.129]	[0.110]	[0.129]	[0.110]	[0.129]	[0.110]	[0.262]	[0.212]
CHILDREN011	-0.191	-0.145	-0.193	-0.143	-0.192	-0.146	-0.188	-0.141	-0.134	-0.196
	[0.172]	[0.137]	[0.171]	[0.136]	[0.171]	[0.136]	[0.173]	[0.138]	[0.310]	[0.224]
MALE x CHILDREN	-0.027	-0.056	-0.023	-0.057	-0.025	-0.054	-0.033	-0.061	-0.202	0.017
	[0.177]	[0.141]	[0.176]	[0.141]	[0.176]	[0.141]	[0.178]	[0.142]	[0.321]	[0.233]
USCITIZEN	0.214	0.334**	0.158	0.297*	0.207	0.321*	0.231	0.343**	0.485	0.406
	[0.153]	[0.127]	[0.155]	[0.129]	[0.153]	[0.127]	[0.153]	[0.127]	[0.327]	[0.240]
RACE (4)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.		
Observations	9609	9609	9609	9609	9609	9609	9609	9609	2486	2486
df	123		123		123		123		123	

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

Table 19: Importance of Salary and Actual Base Salary Levels

	oprobit	oprobit	ols	qreg	ols	qreg
	1	2	3	4	5	6
	IMP_SAL	**IMP_SAL**	**LN_SALARY**	**LN_SALARY**	**LN_SALARY**	**LN_SALARY**
ESTAB100	0.087		-0.075	-0.101**		
	[0.067]		[0.049]	[0.015]		
ESTAB500	0.211**		0.064	0.013		
	[0.059]		[0.044]	[0.013]		
EMSIZE: 11-24		0.019			0.192*	0.057**
		[0.097]			[0.081]	[0.019]
EMSIZE: 25-99		0.185*			0.258**	0.114**
		[0.082]			[0.077]	[0.016]
EMSIZE: 500-999		0.208*			0.273**	0.146**
		[0.093]			[0.076]	[0.019]
EMSIZE: 1000-4999		0.250**			0.322**	0.189**
		[0.085]			[0.073]	[0.017]
EMSIZE: 5000-24999		0.266**			0.333**	0.188**
		[0.083]			[0.072]	[0.017]
EMSIZE: 25000+		0.238**			0.368**	0.227**
		[0.081]			[0.070]	[0.016]
NEWBUS		-0.060			0.107*	0.106**
		[0.068]			[0.045]	[0.014]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied	0.057	0.060	0.091*	0.066**	0.087*	0.061**
	[0.075]	[0.075]	[0.044]	[0.017]	[0.044]	[0.015]
WAPRI: development	0.040	0.044	0.076	0.056**	0.074	0.050**
	[0.075]	[0.075]	[0.043]	[0.017]	[0.043]	[0.015]
WAPRI: design	0.015	0.018	0.036	0.050**	0.032	0.046**
	[0.078]	[0.078]	[0.047]	[0.018]	[0.046]	[0.016]
WAPRI: computers	0.046	0.049	0.016	0.028	0.015	0.021
	[0.076]	[0.076]	[0.045]	[0.017]	[0.044]	[0.016]
WA_NONRD	0.010	0.011	0.011*	0.000	0.012*	0.001
	[0.010]	[0.010]	[0.005]	[0.002]	[0.005]	[0.002]
DEGREE: masters	-0.075*	-0.077*	0.122**	0.144**	0.118**	0.141**
	[0.034]	[0.034]	[0.020]	[0.007]	[0.020]	[0.007]
DEGREE: phd	-0.294**	-0.293**	0.262**	0.347**	0.259**	0.338**
	[0.037]	[0.037]	[0.020]	[0.008]	[0.020]	[0.008]
HDTENURE	0.003	0.003	0.034**	0.028**	0.034**	0.028**
	[0.005]	[0.005]	[0.003]	[0.001]	[0.003]	[0.001]
HDTENURE_SQ	0.000	0.000	-0.001**	-0.000**	-0.001**	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
JOBTENURE	-0.018**	-0.017**	0.002	0.002	0.002	0.002
	[0.006]	[0.006]	[0.003]	[0.001]	[0.003]	[0.001]
JOBTENURE_SQ	0.001*	0.001*	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
JOBDEGREE	0.061**	0.063**	0.017	0.027**	0.020	0.026**
	[0.022]	[0.022]	[0.012]	[0.005]	[0.012]	[0.004]
LN_SUPDIR	-0.011	-0.011	0.064**	0.066**	0.063**	0.066**
	[0.018]	[0.018]	[0.012]	[0.004]	[0.012]	[0.004]
EMPLCHANGE	-0.042	-0.043	0.033	0.033**	0.033	0.033**
	[0.039]	[0.039]	[0.023]	[0.009]	[0.023]	[0.008]
MALE	0.023	0.025	0.070**	0.039**	0.074**	0.047**
	[0.033]	[0.033]	[0.018]	[0.008]	[0.018]	[0.007]
MARRIED	0.102**	0.101**	-0.008	0.004	-0.009	0.006
	[0.033]	[0.033]	[0.018]	[0.007]	[0.018]	[0.007]
CHILDREN011	0.033*	0.034*	-0.002	0.012**	-0.002	0.014**
	[0.015]	[0.015]	[0.013]	[0.003]	[0.013]	[0.003]
USCITIZEN	-0.063	-0.064	0.066*	0.006	0.064*	0.001
	[0.042]	[0.042]	[0.029]	[0.009]	[0.029]	[0.008]
RACE (4)	incl.	incl.	incl.	incl.	incl.	incl.
Observations	9609	9609	9609	9609	9609	9609
Chi-square	326.333	333.686				
df	66	71		66		71
Quantile (Median)				11.29		11.29
R-squared			0.093		0.097	

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

Table 20: Effort Regressions

	truncreg 1 hrsworked	truncreg 2 hrsworked	truncreg 3 hrsworked	truncreg 4 hrsworked	truncreg 5 hrsworked	truncreg 6 hrsworked	truncreg 7 hrsworked	truncreg 8 hrsworked
ESTAB100	-2.740**	-2.646**	-2.554**	-2.598**	-2.620**	-2.665**		
	[0.516]	[0.470]	[0.463]	[0.468]	[0.466]	[0.470]		
ESTAB500	-2.939**	-2.071**	-1.851**	-1.964**	-1.987**	-2.077**		
	[0.437]	[0.405]	[0.397]	[0.402]	[0.400]	[0.405]		
Imp. Salary			-0.501*	-0.499*				-0.508*
			[0.202]	[0.202]				[0.202]
Imp. Benefits			-0.184	-0.062				-0.184
			[0.202]	[0.203]				[0.202]
Imp. Job Security			-0.254	-0.198				-0.253
			[0.171]	[0.171]				[0.170]
Imp. Intel. Challenge			0.952**		1.007**			0.939**
			[0.191]		[0.190]			[0.191]
Imp. Independence			0.272		0.262			0.277
			[0.165]		[0.164]			[0.165]
Imp.Advancement			-0.005		-0.164			-0.005
			[0.163]		[0.159]			[0.163]
Imp. Responsibility			0.596**		0.569**			0.595**
			[0.168]		[0.167]			[0.168]
Imp. Contr. Society			0.005			0.412**		0.001
			[0.134]			[0.124]		[0.133]
EMSIZE: 11-24							-1.497*	-1.394*
							[0.683]	[0.674]
EMSIZE: 25-99							-0.261	-0.149
							[0.591]	[0.584]
EMSIZE: 500-999							-0.379	-0.177
							[0.660]	[0.653]
EMSIZE: 1000-4999							-0.263	-0.038
							[0.609]	[0.603]
EMSIZE: 5000-24999							-0.016	0.228
							[0.601]	[0.595]
EMSIZE: 25000+							0.442	0.65
							[0.590]	[0.585]
NEWBUS							2.654**	2.575**
							[0.479]	[0.471]
IND_NAICS (27)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD (15)		incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied		0.82	0.819	0.824	0.809	0.842	0.808	0.807
		[0.517]	[0.509]	[0.516]	[0.511]	[0.517]	[0.516]	[0.508]
WAPRI: development		0.685	0.728	0.682	0.728	0.714	0.687	0.729
		[0.519]	[0.511]	[0.518]	[0.512]	[0.519]	[0.519]	[0.510]
WAPRI: design		0.571	0.682	0.564	0.674	0.615	0.582	0.691
		[0.535]	[0.526]	[0.534]	[0.528]	[0.535]	[0.534]	[0.525]
WAPRI: computers		-0.124	0.031	-0.125	0.017	-0.071	-0.122	0.033
		[0.530]	[0.521]	[0.529]	[0.523]	[0.530]	[0.529]	[0.521]
WA_NONRD		1.015**	0.969**	1.017**	0.974**	1.003**	1.014**	0.969**
		[0.069]	[0.069]	[0.069]	[0.069]	[0.069]	[0.069]	[0.069]
DEGREE: masters		0.699**	0.605**	0.661**	0.646**	0.687**	0.652**	0.560*
		[0.223]	[0.221]	[0.223]	[0.222]	[0.222]	[0.224]	[0.222]
DEGREE: phd		2.489**	2.196**	2.378**	2.325**	2.441**	2.424**	2.134**
		[0.263]	[0.262]	[0.264]	[0.260]	[0.263]	[0.263]	[0.262]
HDTENURE		0.120**	0.131**	0.122**	0.125**	0.121**	0.122**	0.133**
		[0.034]	[0.034]	[0.034]	[0.034]	[0.034]	[0.034]	[0.034]
HDTENURE_SQ		-0.002*	-0.003**	-0.002*	-0.002**	-0.002*	-0.002*	-0.003**
		[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
JOBTENURE		-0.129**	-0.127**	-0.132**	-0.125**	-0.131**	-0.133**	-0.132**
		[0.040]	[0.040]	[0.040]	[0.040]	[0.040]	[0.040]	[0.039]
JOBTENURE_SQ		0.003*	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*
		[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
JOBDEGREE		0.468**	0.430**	0.488**	0.409**	0.441**	0.471**	0.435**
		[0.146]	[0.144]	[0.145]	[0.145]	[0.146]	[0.145]	[0.144]
LN_SUPDIR		1.646**	1.566**	1.640**	1.583**	1.631**	1.650**	1.570**
		[0.121]	[0.121]	[0.121]	[0.121]	[0.121]	[0.121]	[0.121]
EMPLCHANGE		-0.278	-0.247	-0.297	-0.232	-0.277	-0.256	-0.227
		[0.260]	[0.257]	[0.259]	[0.258]	[0.260]	[0.260]	[0.257]
MALE		0.835**	0.897**	0.830**	0.909**	0.889**	0.852**	0.913**
		[0.237]	[0.236]	[0.237]	[0.236]	[0.237]	[0.236]	[0.235]
MARRIED		-0.242	-0.141	-0.204	-0.189	-0.239	-0.238	-0.137
		[0.227]	[0.225]	[0.226]	[0.226]	[0.227]	[0.226]	[0.224]
CHILDREN011		-1.222**	-1.153**	-1.222**	-1.155**	-1.212**	-1.214**	-1.147**
		[0.275]	[0.271]	[0.274]	[0.272]	[0.274]	[0.273]	[0.269]
MALE x CHILDREN		1.200**	1.145**	1.212**	1.131**	1.181**	1.197**	1.143**
		[0.287]	[0.284]	[0.287]	[0.284]	[0.287]	[0.286]	[0.282]
USCITIZEN		0.813**	0.914**	0.791**	0.914**	0.863**	0.785**	0.884**
		[0.300]	[0.298]	[0.300]	[0.298]	[0.300]	[0.300]	[0.298]
RACE (4)		incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	9609	9609	9609	9609	9609	9609	9609	9609
Chi-square	265.126	1024.605	1106.059	1038.081	1085.048	1028.645	1032.611	1114.492
df	29	67	75	70	71	68	72	80

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

Table 21: Auxiliary Effort Regressions

	STARTUP100	ESTAB100	ESTAB500	Full Sample		PhD Sample		
	truncreg	truncreg	truncreg	tobit	tobit	truncreg	truncreg	truncreg
	1	2	3	4	5	6	7	8
	hrsworked	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**
ESTAB100				-3.303**	-3.187**	-2.799**	-2.638**	-2.569**
				[0.508]	[0.506]	[0.899]	[0.884]	[0.883]
ESTAB500				-2.356**	-2.094**	-3.010**	-2.659**	-2.621**
				[0.438]	[0.438]	[0.704]	[0.697]	[0.696]
Imp. Salary	-1.462	-0.854	-0.351		-0.570**		0.091	0.112
	[0.919]	[0.701]	[0.207]		[0.220]		[0.429]	[0.426]
Imp. Benefits	0.477	-0.481	-0.223		-0.231		-0.126	-0.121
	[0.846]	[0.610]	[0.217]		[0.225]		[0.405]	[0.402]
Imp. Job Security	-1.786*	-0.208	-0.042		-0.298		-0.629	-0.571
	[0.714]	[0.540]	[0.181]		[0.188]		[0.341]	[0.340]
Imp. Intel. Challenge	1.567	1.538*	0.807**		1.313**		1.281**	1.188**
	[0.816]	[0.708]	[0.201]		[0.226]		[0.406]	[0.405]
Imp. Independence	2.089**	0.592	0.048		0.348		0.111	0.151
	[0.796]	[0.557]	[0.173]		[0.196]		[0.367]	[0.365]
Imp.Advancement	-0.119	-0.165	0.037		-0.036		0.063	0.063
	[0.722]	[0.515]	[0.170]		[0.186]		[0.341]	[0.338]
Imp. Responsibility	-0.315	-0.223	0.760**		0.634**		0.67	0.696*
	[0.838]	[0.492]	[0.177]		[0.199]		[0.346]	[0.344]
Imp. Contr. Society	-0.027	-0.4	0.045		-0.15		0.032	0.052
	[0.594]	[0.440]	[0.142]		[0.154]		[0.288]	[0.287]
ABILITY								0.821**
								[0.236]
IND_NAICS (27)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD (15)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied	-1.768	0.92	0.978	1.086	1.065	-0.779	-0.933	-0.964
	[2.422]	[1.530]	[0.540]	[0.596]	[0.593]	[0.954]	[0.925]	[0.926]
WAPRI: development	-2.161	1.324	0.806	1.145	1.183*	-0.867	-0.945	-0.931
	[2.560]	[1.538]	[0.536]	[0.600]	[0.597]	[0.991]	[0.960]	[0.961]
WAPRI: design	-2.07	-0.554	0.947	1.134	1.246*	-1.823	-1.782	-1.739
	[2.799]	[1.539]	[0.554]	[0.623]	[0.620]	[1.119]	[1.088]	[1.089]
WAPRI: computers	-3.809	-1.12	0.383	0.029	0.184	-1.948	-1.896	-1.812
	[2.549]	[1.527]	[0.552]	[0.608]	[0.605]	[1.169]	[1.136]	[1.133]
WA_NONRD	1.193**	0.520**	0.981**	1.184**	1.138**	1.174**	1.097**	1.104**
	[0.290]	[0.202]	[0.075]	[0.075]	[0.075]	[0.140]	[0.136]	[0.135]
DEGREE: masters	2.267*	1.424	0.431	0.915**	0.802**			
	[1.152]	[0.777]	[0.230]	[0.262]	[0.262]			
DEGREE: phd	4.574**	2.312*	1.912**	2.852**	2.516**			
	[1.341]	[0.901]	[0.275]	[0.294]	[0.297]			
HDTENURE	0.429**	0.13	0.115**	0.132**	0.144**	0.209*	0.227**	0.222**
	[0.154]	[0.103]	[0.036]	[0.040]	[0.040]	[0.084]	[0.084]	[0.084]
HDTENURE_SQ	-0.010*	-0.004	-0.002*	-0.003*	-0.003**	-0.004	-0.005*	-0.005*
	[0.005]	[0.003]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]
JOBTENURE	0.821	0.044	-0.133**	-0.115*	-0.111*	-0.172	-0.174	-0.177
	[0.659]	[0.162]	[0.041]	[0.047]	[0.047]	[0.093]	[0.092]	[0.091]
JOBTENURE_SQ	-0.243*	0.002	0.003*	0.002	0.002	0.005	0.005	0.005
	[0.106]	[0.006]	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]
JOBDEGREE	1.083	0.005	0.430**	0.512**	0.474**	0.474	0.414	0.473
	[0.693]	[0.505]	[0.150]	[0.169]	[0.169]	[0.298]	[0.295]	[0.293]
LN_SUPDIR	1.972**	2.023**	1.443**	1.917**	1.831**	2.062**	1.942**	1.963**
	[0.628]	[0.397]	[0.128]	[0.135]	[0.134]	[0.247]	[0.251]	[0.250]
EMPLCHANGE	-0.798	0.017	-0.072	-0.338	-0.294	0.395	0.423	0.414
	[0.965]	[0.838]	[0.284]	[0.301]	[0.300]	[0.498]	[0.491]	[0.488]
MALE	1.489	0.911	0.906**	1.059**	1.110**	0.176	0.256	0.305
	[1.237]	[0.913]	[0.242]	[0.267]	[0.266]	[0.566]	[0.564]	[0.560]
MARRIED	-2.336*	0.244	-0.013	-0.128	-0.004	0.011	0.034	0.146
	[1.010]	[0.715]	[0.240]	[0.260]	[0.259]	[0.509]	[0.502]	[0.498]
CHILDREN011	0.668	-2.741*	-1.176**	-1.437**	-1.355**	-3.054**	-2.921**	-2.960**
	[1.037]	[1.170]	[0.260]	[0.281]	[0.280]	[0.596]	[0.592]	[0.590]
MALE x CHILDREN	-0.209	2.521*	1.188**	1.433**	1.376**	2.717**	2.590**	2.610**
	[1.085]	[1.204]	[0.277]	[0.297]	[0.296]	[0.626]	[0.621]	[0.619]
USCITIZEN	0.332	2.782**	0.753*	1.298**	1.410**	-0.046	0.022	-0.032
	[1.031]	[1.014]	[0.321]	[0.326]	[0.326]	[0.558]	[0.559]	[0.558]
RACE (4)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Observations	572	1066	7971	9609	9609	2486	2486	2486
Chi-square		288.756	862.052	1466.887	1577.187	404.996	441.325	447.167
df		73	73	67	75	64	72	73

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

Table 22: Effort Models with Selection Adjustment

	Full Sample	STARTUP100			ESTAB100			ESTAB500		
	OLS	OLS	Lee	DMF	OLS	LEE	DMF	OLS	LEE	DMF
	1	2	3	4	5	6	7	8	9	10
	hrsworked	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**	**hrsworked**
IMP_SAL	-0.387*	-1.225	-1.496*	-1.930**	-0.62	-0.573	-0.57	-0.268	-0.313*	-0.315*
	[0.152]	[0.780]	[0.705]	[0.697]	[0.522]	[0.428]	[0.437]	[0.157]	[0.140]	[0.140]
IMP_BEN	-0.124	0.369			-0.328			-0.164		
	[0.153]	[0.714]			[0.460]			[0.165]		
IMP_SEC	-0.238	-1.431*	-3.474	-5.170**	-0.18	0.121	0.175	-0.025	0.027	0.019
	[0.131]	[0.605]	[2.097]	[1.910]	[0.407]	[0.423]	[0.593]	[0.138]	[0.149]	[0.149]
IMP_CHAL	0.656**	1.061	1.226	1.374	1.026*	0.85	0.862	0.569**	0.552**	0.553**
	[0.137]	[0.624]	[0.724]	[0.721]	[0.488]	[0.498]	[0.500]	[0.146]	[0.152]	[0.152]
IMP_IND	0.204	1.606*	1.687**	1.748**	0.446	0.277	0.275	0.026	0.005	0.007
	[0.120]	[0.638]	[0.640]	[0.642]	[0.394]	[0.420]	[0.423]	[0.129]	[0.134]	[0.134]
IMP_ADV	0.009	-0.062	1.042	1.51	-0.142	0.079	0.036	0.024	0.005	0.006
	[0.122]	[0.629]	[1.158]	[1.102]	[0.381]	[0.393]	[0.412]	[0.129]	[0.130]	[0.139]
IMP_RESP	0.453**	-0.184	0.187	0.65	-0.155	-0.261	-0.256	0.574**	0.558**	0.560**
	[0.125]	[0.725]	[0.769]	[0.776]	[0.361]	[0.397]	[0.404]	[0.133]	[0.138]	[0.137]
IMP_SOC	-0.003	-0.036	-0.462	-0.656	-0.284	-0.489	-0.474	0.035	0.027	0.027
	[0.099]	[0.506]	[0.649]	[0.661]	[0.327]	[0.330]	[0.336]	[0.107]	[0.106]	[0.110]
λ(STARTUP100)			8.302				0.167			-0.344
			[7.886]				[3.096]			[1.429]
λ(ESTAB100)				4.176		-5.209				-0.43
				[6.615]		[3.032]				[1.625]
λ(ESTAB500)				-10.196			2.224		1.217	
				[6.138]			[3.218]		[1.055]	
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied	0.629	-1.175	-0.971	-1.428	0.632	1.374	1.331	0.724	0.784	0.779
	[0.371]	[2.097]	[1.667]	[1.730]	[1.160]	[1.174]	[1.181]	[0.392]	[0.412]	[0.424]
WAPRI: development	0.542	-1.465	-1.538	-1.978	0.891	1.317	1.303	0.583	0.631	0.627
	[0.372]	[2.194]	[1.712]	[1.734]	[1.153]	[1.133]	[1.143]	[0.389]	[0.411]	[0.416]
WAPRI: design	0.478	-1.201	-2.642	-3.603	-0.479	-0.587	-0.556	0.689	0.721	0.719
	[0.383]	[2.423]	[2.352]	[2.381]	[1.139]	[1.171]	[1.202]	[0.402]	[0.425]	[0.425]
WAPRI: computers	0.044	-2.751	-3.096	-3.856*	-0.827	-0.185	-0.201	0.279	0.348	0.342
	[0.376]	[2.166]	[1.743]	[1.799]	[1.135]	[1.186]	[1.208]	[0.397]	[0.419]	[0.426]
WA_NONRD	0.751**	0.955**	0.950**	0.952**	0.399**	0.396**	0.393**	0.768**	0.767**	0.767**
	[0.053]	[0.260]	[0.238]	[0.238]	[0.153]	[0.148]	[0.148]	[0.059]	[0.053]	[0.053]
DEGREE: masters	0.472**	1.811	2.398*	2.284	1.022	1.748*	1.705*	0.326	0.361*	0.357
	[0.161]	[0.954]	[1.061]	[1.183]	[0.549]	[0.712]	[0.716]	[0.170]	[0.178]	[0.196]
DEGREE: phd	1.686**	3.550**	4.685**	5.042**	1.734**	2.378**	2.323**	1.458**	1.493**	1.491**
	[0.195]	[1.115]	[1.486]	[1.543]	[0.671]	[0.718]	[0.724]	[0.207]	[0.202]	[0.221]
HDTENURE	0.097**	0.319*	0.656	0.954**	0.092	-0.004	-0.009	0.085**	0.070*	0.072*
	[0.025]	[0.131]	[0.340]	[0.320]	[0.075]	[0.096]	[0.113]	[0.027]	[0.030]	[0.030]
HDTENURE_SQ	-0.002**	-0.008	-0.013*	-0.017**	-0.003	-0.001	-0.001	-0.002*	-0.001	-0.002
	[0.001]	[0.004]	[0.006]	[0.006]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
JOBTENURE	-0.108**	0.704	0.502	0.345	0.037	0.105	0.109	-0.099**	-0.088**	-0.089**
	[0.027]	[0.395]	[0.488]	[0.484]	[0.100]	[0.109]	[0.120]	[0.029]	[0.030]	[0.030]
JOBTENURE_SQ	0.002**	-0.174**	-0.179*	-0.188*	0.001	0.001	0.001	0.002*	0.002*	0.002*
	[0.001]	[0.057]	[0.078]	[0.078]	[0.004]	[0.004]	[0.004]	[0.001]	[0.001]	[0.001]
JOBDEGREE	0.319**	0.887	1.293	1.794**	0.029	-0.308	-0.315	0.317**	0.285*	0.288*
	[0.106]	[0.569]	[0.671]	[0.678]	[0.362]	[0.396]	[0.410]	[0.112]	[0.118]	[0.119]
LN_SUPDIR	1.246**	1.693**	1.447*	1.379*	1.496**	1.268**	1.292**	1.168**	1.156**	1.158**
	[0.098]	[0.560]	[0.586]	[0.605]	[0.313]	[0.331]	[0.330]	[0.105]	[0.093]	[0.098]
MALE	0.627**	1.026	2.161	3.820*	0.524	-0.615	-0.64	0.642**	0.546**	0.556**
	[0.169]	[1.005]	[1.436]	[1.563]	[0.648]	[0.917]	[0.977]	[0.177]	[0.196]	[0.208]
MARRIED	-0.131	-1.784*	-4.093	-5.855**	0.159	0.518	0.579	-0.014	0.062	0.055
	[0.167]	[0.846]	[2.363]	[2.176]	[0.517]	[0.554]	[0.675]	[0.180]	[0.192]	[0.192]
CHILDREN011	-0.772**	0.497	1.042	1.367	-1.640*	-1.531*	-1.510*	-0.813**	-0.817**	-0.816**
	[0.178]	[0.896]	[1.044]	[1.048]	[0.649]	[0.716]	[0.720]	[0.174]	[0.179]	[0.180]
MALExCHILDREN	0.780**	-0.154	0.085	0.187	1.481*	1.458	1.404	0.824**	0.811**	0.812**
	[0.190]	[0.939]	[0.970]	[0.958]	[0.684]	[0.745]	[0.752]	[0.189]	[0.191]	[0.191]
USCITIZEN	0.680**	0.203	-0.679	-1.391	1.840**	2.048**	2.081**	0.570*	0.604**	0.600**
	[0.219]	[0.896]	[1.196]	[1.150]	[0.674]	[0.673]	[0.696]	[0.239]	[0.226]	[0.226]
RACE	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	40.646**	23.745**	8.707	-0.47	41.651**	52.071**	50.296**	40.333**	39.806**	39.847**
	[1.134]	[6.265]	[16.157]	[13.311]	[3.956]	[7.205]	[6.745]	[1.197]	[1.185]	[1.179]
Observations	9609	572	572	572	1066	1066	1066	7971	7971	7971
R-squared	0.145	0.291	0.293	0.298	0.187	0.189	0.189	0.144	0.144	0.144

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

Table 23: Performance Regressions

	NBREG	NBREG	NBREG	NBREG	NBREG	NBREG	NBREG	NBREG	NBREG	NBREG
	1	2	3	4	5	6	7	8	9	10
	uspapp	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**
ESTAB100	-0.837**	-0.870**	-0.791**	-0.750**	-0.701**	-0.759**	-0.856**	-0.864**		
	[0.176]	[0.168]	[0.168]	[0.163]	[0.165]	[0.164]	[0.165]	[0.168]		
ESTAB500	-0.308*	-0.424**	-0.348*	-0.274*	-0.231	-0.297*	-0.388**	-0.419**		
	[0.137]	[0.139]	[0.136]	[0.132]	[0.134]	[0.132]	[0.136]	[0.138]		
IMP_SAL				0.117	0.132*	0.072				0.121
				[0.068]	[0.067]	[0.068]				[0.068]
IMP_BEN				0.02	0.015	0.059				0.02
				[0.066]	[0.066]	[0.069]				[0.067]
IMP_SEC				-0.311**	-0.294**	-0.330**				-0.313**
				[0.058]	[0.059]	[0.059]				[0.058]
IMP_CHAL				0.452**	0.433**		0.456**			0.444**
				[0.072]	[0.071]		[0.071]			[0.072]
IMP_IND				0.146*	0.156**		0.155*			0.145*
				[0.061]	[0.060]		[0.061]			[0.061]
IMP_ADV				-0.062	-0.068		-0.089			-0.059
				[0.057]	[0.057]		[0.055]			[0.057]
IMP_RESP				-0.11	-0.122*		-0.109			-0.106
				[0.061]	[0.061]		[0.061]			[0.060]
IMP_SOC				-0.002	-0.004			0.052		-0.008
				[0.051]	[0.051]			[0.047]		[0.051]
HRSWORKED			0.021**		0.017**					
			[0.005]		[0.005]					
EMSIZE: 11-24									-0.242	-0.161
									[0.243]	[0.245]
EMSIZE: 25-99									-0.145	-0.164
									[0.215]	[0.209]
EMSIZE: 500-999									0.079	0.083
									[0.251]	[0.243]
EMSIZE: 1000-4999									0.174	0.228
									[0.226]	[0.221]
EMSIZE: 5000-24999									0.231	0.281
									[0.228]	[0.222]
EMSIZE: 25000+									0.423	0.446*
									[0.219]	[0.214]
New Business									0.834**	0.712**
									[0.175]	[0.167]
IND_NAICS(27)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD (15)		incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied		0.279*	0.255	0.247	0.229	0.265	0.269	0.283*	0.27	0.24
		[0.142]	[0.142]	[0.135]	[0.135]	[0.137]	[0.138]	[0.142]	[0.142]	[0.135]
WAPRI: development		0.064	0.04	0.074	0.054	0.063	0.079	0.068	0.07	0.081
		[0.147]	[0.147]	[0.140]	[0.140]	[0.143]	[0.143]	[0.147]	[0.147]	[0.141]
WAPRI: design		-0.273	-0.284	-0.245	-0.253	-0.275	-0.239	-0.267	-0.256	-0.231
		[0.169]	[0.171]	[0.162]	[0.164]	[0.164]	[0.166]	[0.169]	[0.168]	[0.161]
WAPRI: computers		-1.260**	-1.265**	-1.238**	-1.241**	-1.246**	-1.250**	-1.247**	-1.249**	-1.225**
		[0.166]	[0.166]	[0.158]	[0.158]	[0.162]	[0.162]	[0.165]	[0.167]	[0.159]
WA_NONRD		-0.04	-0.060*	-0.038	-0.053*	-0.036	-0.04	-0.041	-0.039	-0.037
		[0.025]	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]	[0.025]
DEGREE: masters		0.442**	0.441**	0.408**	0.408**	0.421**	0.427**	0.445**	0.432**	0.395**
		[0.102]	[0.102]	[0.100]	[0.100]	[0.101]	[0.101]	[0.102]	[0.103]	[0.100]
DEGREE: phd		1.600**	1.572**	1.527**	1.506**	1.583**	1.541**	1.601**	1.583**	1.508**
		[0.090]	[0.090]	[0.088]	[0.089]	[0.090]	[0.088]	[0.089]	[0.090]	[0.088]
HDTENURE		-0.023	-0.025	-0.023	-0.025	-0.022	-0.025	-0.023	-0.022	-0.022
		[0.015]	[0.015]	[0.014]	[0.014]	[0.015]	[0.014]	[0.015]	[0.015]	[0.014]
HDTENURE_SQ		0.001	0.001	0	0	0	0	0.001	0.001	0
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
JOBTENURE		0.035*	0.034*	0.036*	0.036*	0.037*	0.033*	0.035*	0.031*	0.033*
		[0.015]	[0.015]	[0.014]	[0.014]	[0.015]	[0.014]	[0.015]	[0.015]	[0.014]
JOBTENURE_SQ		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
JOBDEGREE		0.196**	0.195**	0.199**	0.197**	0.226**	0.172**	0.194**	0.204**	0.205**
		[0.061]	[0.061]	[0.058]	[0.058]	[0.059]	[0.060]	[0.061]	[0.060]	[0.058]
LN_SUPDIR		0.245**	0.215**	0.255**	0.232**	0.245**	0.256**	0.244**	0.253**	0.261**
		[0.043]	[0.044]	[0.042]	[0.043]	[0.043]	[0.042]	[0.043]	[0.043]	[0.042]
EMPLCHANGE		-0.049	-0.054	-0.039	-0.043	-0.058	-0.033	-0.048	-0.037	-0.029
		[0.092]	[0.093]	[0.090]	[0.091]	[0.091]	[0.091]	[0.092]	[0.092]	[0.090]
GOVT_DOD		-0.266*	-0.243	-0.269*	-0.250*	-0.275*	-0.259*	-0.261*	-0.267*	-0.272*
		[0.126]	[0.126]	[0.124]	[0.125]	[0.124]	[0.126]	[0.125]	[0.125]	[0.123]
GOVT_NASA		-0.397*	-0.400*	-0.427*	-0.427*	-0.410*	-0.409*	-0.403*	-0.385	-0.411*
		[0.201]	[0.196]	[0.203]	[0.198]	[0.199]	[0.208]	[0.202]	[0.200]	[0.200]
MALE		0.718**	0.702**	0.711**	0.698**	0.700**	0.730**	0.721**	0.729**	0.719**
		[0.087]	[0.088]	[0.085]	[0.086]	[0.086]	[0.086]	[0.087]	[0.086]	[0.084]
USCITIZEN		0.043	0.033	0.065	0.058	0.035	0.076	0.047	0.053	0.071
		[0.099]	[0.098]	[0.097]	[0.096]	[0.098]	[0.098]	[0.100]	[0.098]	[0.095]
RACE (4)		incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-2.101**	-4.396**	-5.373**	-5.673**	-6.448**	-4.003**	-5.955**	-4.565**	-5.137**	-6.272**
	[0.310]	[0.418]	[0.448]	[0.548]	[0.562]	[0.486]	[0.507]	[0.437]	[0.449]	[0.571]
Observations	9609	9609	9609	9609	9609	9609	9609	9609	9609	9609
Chi-square	504.594	2076.911	2142.553	2372.628	2401.291	2194.149	2262.419	2099.321	2131.783	2389.738
df	29	66	67	74	75	69	70	67	71	79
pseudoR2	0.03	0.104	0.105	0.109	0.11	0.106	0.107	0.104	0.104	0.11
alphaest	6.904	4.054	4.025	3.913	3.892	3.997	3.967	4.053	4.029	3.889

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

Table 24: Auxiliary Performance Regressions

	EMPLCHANGE==0		STARTUP100	ESTAB100	ESTAB500
		NBREG	NBREG	NBREG	NBREG
	1	2	3	4	5
	uspapp	**uspapp**	**uspapp**	**uspapp**	**uspapp**
ESTAB100	-0.435*	-0.356			
	[0.206]	[0.203]			
ESTAB500	-0.038	0.082			
	[0.166]	[0.165]			
IMP_SAL		0.153*	0.087	-0.425*	0.247**
		[0.073]	[0.161]	[0.168]	[0.075]
IMP_BEN		-0.057	0.287	0.265	-0.07
		[0.073]	[0.170]	[0.161]	[0.073]
IMP_SEC		-0.260**	-0.716**	-0.273	-0.236**
		[0.066]	[0.147]	[0.171]	[0.065]
IMP_CHAL		0.488**	0.255	-0.007	0.445**
		[0.079]	[0.185]	[0.210]	[0.076]
IMP_IND		0.142*	-0.385	0.343	0.140*
		[0.064]	[0.203]	[0.176]	[0.065]
IMP_ADV		-0.058	0.319	-0.387*	-0.073
		[0.063]	[0.168]	[0.155]	[0.063]
IMP_RESP		-0.137*	0.042	0.102	-0.145*
		[0.067]	[0.182]	[0.176]	[0.064]
IMP_SOC		-0.005	0.372*	0.006	-0.013
		[0.054]	[0.163]	[0.134]	[0.055]
HRSWORKED			0.040**	0.030*	0.014*
			[0.011]	[0.014]	[0.006]
IND_NAICS(27)		incl.	incl.	incl.	incl.
HD_FIELD (15)		incl.	incl.	incl.	incl.
WAPRI: applied	0.320*	0.251	0.436	0.745	0.12
	[0.163]	[0.157]	[0.336]	[0.442]	[0.152]
WAPRI: development	0.057	0.046	1.435**	0.717	-0.147
	[0.167]	[0.162]	[0.377]	[0.421]	[0.157]
WAPRI: design	-0.332	-0.335	0.822	0.606	-0.494**
	[0.188]	[0.182]	[0.424]	[0.488]	[0.177]
WAPRI: computers	-1.218**	-1.224**	-0.175	-0.359	-1.485**
	[0.188]	[0.182]	[0.376]	[0.517]	[0.177]
WA_NONRD	-0.054	-0.048	-0.07	-0.047	-0.059*
	[0.028]	[0.028]	[0.064]	[0.071]	[0.028]
DEGREE: masters	0.556**	0.510**	-0.247	1.058**	0.413**
	[0.108]	[0.106]	[0.313]	[0.288]	[0.105]
DEGREE: phd	1.661**	1.577**	1.100**	2.026**	1.513**
	[0.097]	[0.097]	[0.276]	[0.305]	[0.093]
HDTENURE	-0.023	-0.025	-0.005	0.002	-0.031*
	[0.017]	[0.016]	[0.042]	[0.035]	[0.016]
HDTENURE_SQ	0	0	0.001	0	0.001
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
JOBTENURE	0.028	0.03	0.192	-0.1	0.045**
	[0.016]	[0.016]	[0.134]	[0.057]	[0.015]
JOBTENURE_SQ	0	0	-0.025	0.003	-0.001*
	[0.001]	[0.000]	[0.015]	[0.002]	[0.000]
JOBDEGREE	0.244**	0.221**	0.128	0.05	0.222**
	[0.065]	[0.064]	[0.151]	[0.169]	[0.061]
LN_SUPDIR	0.250**	0.263**	0.108	0.218	0.259**
	[0.046]	[0.046]	[0.124]	[0.161]	[0.046]
EMPLCHANGE			0.540*	-0.795**	-0.054
			[0.224]	[0.251]	[0.106]
GOVT_DOD	-0.216	-0.221	0.167	0.051	-0.338*
	[0.139]	[0.136]	[0.388]	[0.288]	[0.144]
GOVT_NASA	-0.418	-0.450*	1.156	-1.206**	-0.405
	[0.225]	[0.229]	[0.877]	[0.468]	[0.231]
MALE	0.712**	0.705**	0.809**	0.624*	0.664**
	[0.095]	[0.094]	[0.274]	[0.313]	[0.091]
USCITIZEN	0.046	0.068	-0.078	-0.456	0.17
	[0.110]	[0.109]	[0.221]	[0.268]	[0.103]
RACE (4)	incl.	incl.	incl.	incl.	incl.
Constant	-4.905**	-6.049**	-29.398	-21.384**	-6.533**
	[0.472]	[0.629]	[.]	[1.886]	[0.592]
Observations	7900	7900	572	1066	7971

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

Table 25: Performance Regressions (Ph.D.-Sample)

	Limited Sample							
	NBREG 1	NBREG 2	NBREG 3	NBREG 4	NBREG 5	NBREG 6	NBREG 7	NBREG 8
	uspapp	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**	**uspapp**
ESTAB100	-0.862**	-0.787**	-0.845**	-0.782**	-0.807**	-0.747**	-0.781**	-0.738**
	[0.227]	[0.217]	[0.225]	[0.219]	[0.229]	[0.222]	[0.224]	[0.220]
ESTAB500	-0.616**	-0.501**	-0.604**	-0.499**	-0.563**	-0.469*	-0.535**	-0.457*
	[0.194]	[0.189]	[0.190]	[0.190]	[0.196]	[0.193]	[0.188]	[0.190]
IMP_SAL		0.168*		0.167*		0.168*		0.164*
		[0.078]		[0.078]		[0.078]		[0.078]
IMP_BEN		0.031		0.024		0.028		0.025
		[0.076]		[0.077]		[0.077]		[0.077]
IMP_SEC		-0.213**		-0.199**		-0.200*		-0.183*
		[0.077]		[0.077]		[0.078]		[0.077]
IMP_CHAL		0.289**		0.280**		0.281**		0.277**
		[0.086]		[0.086]		[0.087]		[0.087]
IMP_IND		0.317**		0.322**		0.324**		0.327**
		[0.067]		[0.069]		[0.068]		[0.069]
IMP_ADV		-0.013		-0.006		-0.003		0.003
		[0.069]		[0.069]		[0.068]		[0.068]
IMP_RESP		-0.099		-0.092		-0.114		-0.112
		[0.072]		[0.072]		[0.072]		[0.073]
IMP_SOC		-0.137*		-0.138*		-0.142*		-0.138*
		[0.060]		[0.061]		[0.061]		[0.061]
HRSWORKED					0.013*	0.013*	0.01	0.009
					[0.005]	[0.005]	[0.005]	[0.005]
ABILITY			0.134*	0.125*			0.128*	0.118*
			[0.056]	[0.054]			[0.055]	[0.053]
HRS X ABILITY							0.014*	0.013*
							[0.007]	[0.006]
IND_NAICS	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
HD_FIELD	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
WAPRI: applied	0.048	-0.041	0.042	-0.049	0.026	-0.057	0.014	-0.07
	[0.175]	[0.169]	[0.172]	[0.168]	[0.178]	[0.171]	[0.175]	[0.169]
WAPRI: development	-0.243	-0.273	-0.216	-0.257	-0.259	-0.284	-0.244	-0.278
	[0.184]	[0.179]	[0.181]	[0.179]	[0.186]	[0.181]	[0.184]	[0.180]
WAPRI: design	-0.409	-0.472*	-0.398	-0.463*	-0.406	-0.465*	-0.401	-0.462*
	[0.232]	[0.225]	[0.230]	[0.224]	[0.236]	[0.227]	[0.233]	[0.226]
WAPRI: computers	-1.403**	-1.459**	-1.382**	-1.444**	-1.392**	-1.443**	-1.388**	-1.443**
	[0.225]	[0.218]	[0.223]	[0.216]	[0.229]	[0.220]	[0.227]	[0.219]
WA_NONRD	0.032	0.016	0.025	0.01	0.019	0.004	0.015	0.002
	[0.034]	[0.034]	[0.034]	[0.034]	[0.035]	[0.035]	[0.034]	[0.034]
HDTENURE	-0.01	-0.013	-0.01	-0.013	-0.01	-0.014	-0.009	-0.013
	[0.020]	[0.018]	[0.020]	[0.018]	[0.020]	[0.018]	[0.020]	[0.018]
HDTENURE_SQ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
JOBTENURE	-0.002	0.002	-0.003	0.002	-0.002	0.003	-0.004	0.001
	[0.019]	[0.018]	[0.019]	[0.018]	[0.019]	[0.018]	[0.019]	[0.018]
JOBTENURE_SQ	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
JOBDEGREE	-0.041	-0.023	-0.029	-0.012	-0.039	-0.023	-0.024	-0.011
	[0.068]	[0.065]	[0.068]	[0.065]	[0.068]	[0.065]	[0.068]	[0.065]
LN_SUPDIR	0.231**	0.250**	0.235**	0.254**	0.206**	0.228**	0.221**	0.240**
	[0.055]	[0.054]	[0.055]	[0.054]	[0.056]	[0.054]	[0.055]	[0.054]
EMPLCHANGE	-0.087	-0.09	-0.085	-0.086	-0.094	-0.097	-0.099	-0.097
	[0.114]	[0.110]	[0.114]	[0.110]	[0.116]	[0.111]	[0.115]	[0.111]
GOVT_DOD	-0.126	-0.122	-0.108	-0.106	-0.105	-0.106	-0.095	-0.094
	[0.183]	[0.189]	[0.185]	[0.191]	[0.186]	[0.191]	[0.186]	[0.191]
GOVT_NASA	-0.561*	-0.597*	-0.554	-0.587*	-0.564*	-0.594*	-0.572*	-0.599*
	[0.283]	[0.268]	[0.289]	[0.272]	[0.276]	[0.263]	[0.280]	[0.266]
MALE	0.467**	0.454**	0.475**	0.463**	0.457**	0.445**	0.468**	0.455**
	[0.100]	[0.098]	[0.100]	[0.098]	[0.102]	[0.099]	[0.102]	[0.099]
USCITIZEN	0.072	0.079	0.056	0.067	0.056	0.071	0.031	0.05
	[0.121]	[0.110]	[0.120]	[0.111]	[0.123]	[0.112]	[0.122]	[0.112]
RACE (4)	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	-1.464**	-3.075**	-1.976**	-3.589**	-2.056**	-3.614**	-2.400**	-3.984**
	[0.465]	[0.625]	[0.499]	[0.658]	[0.530]	[0.667]	[0.562]	[0.698]
Observations	2486	2486	2486	2486	2486	2486	2486	2486

Standard errors in brackets

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

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Biography

Henry Sauermann was born in Dresden, Germany, on March 12, 1976. Henry attended the University of Potsdam, Germany, where he graduated in 2001 with a Diplom-Volkswirt (Economics) and in 2002 with a Diplom-Kaufmann (Business Administration). He studied as an exchange student in the Economics graduate program at Duke University in 2000-2001.

Henry gained industry experience working in and consulting for technology-based ventures in Germany and France.

Henry has coauthored a book chapter with Wesley M. Cohen ("Schumpeter's prophecy and individual incentives as a driver of innovation", Cambridge University Press), has published an article on career decision making ("Vocational choice – A decision making perspective", Journal of Vocational Behavior), and has contributed two articles to the German journal "Personal" ("Anreizsysteme für Wissensarbeiter" and "Kreativität und HR Management").

As a doctoral student at Duke, Henry received a Kauffman Foundation Dissertation Fellowship in 2006, a travel grant from the National Bureau of Economic Research in 2007, and the "Best Student Paper Award" at the Sixth Roundtable for Engineering and Entrepreneurship Research in 2006. He has presented his work extensively at conferences and as an invited presenter in North America and in Europe.