Do Scientists Pay to Be Scientists?*

By

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ABSTRACT

This paper explores the relationship between wages and the scientific orientation of R&D organizations. Firms who adopt a science-oriented research approach (i.e., "Science") allow their researchers to pursue and publish an individual research agenda.. The adoption of Science may be associated with a "taste" for Science on the part of researchers (a Preference effect) and/or as a "ticket of admission" to gain earlier access to scientific discoveries with commercial application (a Productivity effect). These two effects differ in their impact on wages. Whereas the Preference effect contributes to a negative compensating differential, the Productivity effect may result in rent-sharing. However, since Science may be adopted by firms employing higher-quality researchers, cross-sectional evaluations of wages and Science may be biased by unobserved heterogeneity. To overcome this bias, this paper introduces a novel empirical approach. Specifically, prior to accepting a given job, many scientists receive *multiple job offers,* allowing for the calculation of the wage-Science relationship, controlling for differences in salary levels offered to individual researchers. Using a dataset composed of multiple job offers to postdoctoral biologists, the results suggest a negative relationship between wages and Science. These findings are robust to restricting the sample to non-academic job offers, but the findings depend critically on the inclusion of researcher fixed effects. Conditional on perceived ability, scientists do indeed *pay* to be scientists.

Journal of Economic Literature Classification: Nonwage Labor Costs and Benefits (J32); Professional Labor Markets and Occupations (J44); Industry Studies, Drugs (L65); Innovation and Invention (O31); Management of R&D (O32). *Keywords:* Economics of science, R&D employment, R&D management, multiple job offers, pharmaceuticals, drug discovery, biology, hedonic wage equation, compensating differentials, rent-sharing.

I. Introduction

Since the seminal work of Nelson (1959) and Arrow (1962), economists and management scholars have attempted to understand the incentives for abstract knowledge production. To the extent that abstract knowledge serves as a non-rivalrous input into technological innovation, its production plays a critical role in the process of economic growth (Romer, 1990). Because knowledge production is costly to monitor and subject to expropriation, the level of production may be inefficiently low in the absence of alternative institutions.

On the one hand, several institutions supporting the production of knowledge (from trade secrecy to prizes to patents) have been identified and investigated, both theoretically and empirically (Wright, 1983; Levin et al, 1987). However, the economic consequences of the institution most closely associated with the production of abstract knowledge – Science – have only recently begun to be explored (David and Dasgupta, 1994). Science differs from alternative knowledge production systems insofar as researchers are offered substantial discretion in choosing research projects and the reward structure is premised on establishing intellectual priority (i.e., being first to make a discovery) through journal publication.

This paper considers two explanations for the use of a Science-oriented approach. First, researchers may have preferences for interacting with discipline-specific scientific communities and for receiving recognition for their discoveries. Simply put, scientists may have a "taste" for Science (Merton, 1973; David and Dasgupta, 1994). Whether such preferences are intrinsic or reflect long-term career motivations, a scientific "ethic" is critical for the effectiveness of Science as an economic institution. A second motivation for participation in Science, particularly for private firms, may be the productivity benefits in terms of technological innovation. Firms who adopt Science may gain earlier and more detailed access to new discoveries and so may be purchasing a "ticket of admission" which pays itself off in terms of higher R&D productivity and a higher rate of technological innovation (Cohen and Levinthal, 1990; Rosenberg, 1990).

At one level, there is no inherent conflict between these two perspectives on the drivers of the adoption of a scientific orientation. Scientists may value participation in Science (referred to as the Preference effect), and, at the same time, firms may participate to capture spillovers (referred to as the Productivity effect). However, these perspectives do offer competing economic implications, most notably for the employment relationship: whereas the Preference effect contributes to a negative compensating differential between Science and wages, the Productivity effect raises the possibility of rent-sharing between firms and researchers (and so a positive association between wages and Science). As well, the relationship between wages and Science might reflect a skill bias: under the "winner-take-all" nature of the scientific reward system, the expected benefits to Science will be higher for higher-ability researchers. As a result, firms who employ scientists of higher ability will tend to adopt Science as well.

After reviewing the "new" economics of science in Section II, Section III develops this argument by presenting a simple economic model incorporating the Preference effect, the Productivity effect, and a distribution of talent (or perceived ability) among scientists. The model incorporates the potential for rent-sharing among firms and scientists. A key result stands out: the relationship between wages and Science depends on the relative salience of the Preference and Productivity effects, and prior empirical investigations may have confounded the Preference effect, the Productivity effect, and the impact of unobserved heterogeneity among scientists.

This theoretical framework motivates the development and implementation of a novel empirical methodology (Section IV) that controls for the presence of unobserved heterogeneity. Specifically, prior to accepting a specific offer, many professionals receive *multiple job offers*. Each offer is composed of a wage offer and job characteristics (observed to the employee). Since a formal job offers confer a legal responsibility on the firm, offers will not be made unless the firm is willing to employ the worker, and firms will not make offers with a zero probability of acceptance. Using a sample of individuals seeking their first full-time employment, we are able to calculate wage-Science combinations *for randomly selected workers at a point in time.* By surveying candidates about detailed characteristics of their multiple job offers (e.g., "Does this job give you permission to publish in the scientific literature?"), it is possible to estimate the relationship between wages and Science, after taking individual heterogeneity into account through the inclusion of person-specific fixed effects. As such, the results reported here likely overcome the bias associated with earlier work in both labor economics and management which examines cross-sections of employees or focuses attention on job-switching behavior.[1]

This survey-based methodology is applied to a sample of biologists who are (just) completing a job search. PhD biologists (e.g., those completing their first postdoctoral fellowship at a top-tier medical center or university) participate in a (moderately formal) job market in which they attempt to garner long-term employment. While we can control for differences among jobs which do not relate to their scientific orientation (such as the impact on their career, or whether the job is in a start-up firm), the analysis is conditioned on a set of research-oriented job offers, all of which use the candidate's specialized biology background. However, the jobs differ in terms of the degree to which the candidate can participate in Science, either through the publication process or through the ability to choose (or continue to work on) an individual research agenda. Critically, the job market for biologists is synchronized enough so that, prior to accepting a job offer, some candidates do indeed receive multiple offers.

While the sample size is small, the data point to several important findings. Most importantly, there seems to be a tradeoff between offered wages and the scientific orientation of firms. Offers which contain science-oriented provisions, ranging from permission (or incentives) to publish in the scientific literature, to the flexibility to choose or continue research projects, are associated with lower monetary compensation and starting wages. These results are robust to several different types of controls (including job type) as well as restricting the sample to those job offers from the non-academic sector. In addition, the data suggest that accepted and rejected job offers are comparable to one another (consistent with an equilibrium theory of hedonic wage determination), and job candidates receiving multiple offers are not appreciably different from candidates receiviong only one offer. However, the findings depend critically on controlling for individual heterogeneity; simple cross-sectional comparisons result in a significant upward bias and an underestimate of the size of the compensating differential for Science.

Overall, the contribution of this paper arises from (a) developing a simple model of the relationship between wages, productivity, and participation in Science based on insights from the "new" economics of Science, (b) estimating the relationship between wages and Science using a novel empirical methodology, and therefore (c) providing an assessment of the relative salience

[1] Rather than reviewing the labor economic literature here, I defer discussion of this literature until Section IV.

of researcher preferences and firm incentives, controlling for differences among individual researchers. As an economic institution, Science helps overcome the inability to provide incentives for the production and diffusion of abstract knowledge: simply put, we rely on scientists to behave in a way which values knowledge production and diffusion for its own sake.

II. The "New" Economics of Science

Science is a distinctive institution in several ways: as a knowledge production system, as an input into technological innovation, and as a reward system. The first distinguishing aspect of Science is that it produces two extremely specialized types of knowledge: potentially testable theories and empirical tests of these theories (Kuhn, 1963). While the contribution to the theory-testing dynamic is the primary criterion by which scientists evaluate the value of new knowledge, Science serves a second function as a knowledge stock upon which firms draw for technological innovation. The knowledge and techniques produced by Science often have commercial applications which are unrelated to the initial theory-testing motivation which spurred their development (Rosenberg, 1974). In other words, Science is an important source of knowledge spillovers. This uneasy relationship between Science as a knowledge production process and as an input into technological innovation is mediated by the third characteristic feature of Science: the priority-based reward system. To receive credit for the intellectual priority of their scientific discoveries, scientists publicize their findings as quickly as possible and retain no formal intellectual property over their ideas (Merton, 1957; Dasgupta and David, 1994).

Each of these features helps to identify Science as an economic institution that is distinct from a commercially-motivated knowledge production system. For example, while most economic analysis of knowledge production emphasizes the importance of institutions such as intellectual property, trade secrecy or entry barriers in ensuring the incentives for innovation (Nelson, 1959; Arrow, 1962; Levin et al, 1987; Kremer, 1998), the scientific incentive system specifically rejects non-disclosure, tight control over intellectual property, or monopolization in the use of novel scientific knowledge (Dasgupta and David, 1994).[2] I therefore define

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[2] One might also distinguish Science by its locus in universities, its association with general human capital

participation in Science to be distinguishable from commercially motivated knowledge production, involve the formulation and testing of theories (which may but need not result in commercial spillovers), and result in public disclosure in academic journals.[3]

Perhaps surprisingly, formal analysis of the priority-based reward system in economics and management is recent.[4] Two recent research streams have begun to address the distinct economic and strategic issues associated with Science, particularly the adoption of Science by profit-oriented firms. In the first stream, David and Dasgupta (1987; 1994) and David (1998) evaluate how the assumption that scientists (as a group) are attempting to maximize the flow of new knowledge influences the economic efficiency of the priority-based reward system. Dasgupta and David argue that, relative to a system in which knowledge production is rewarded purely by monetary rents, the priority-based reward system is relatively efficient. On the one hand, the priority-based system discourages shirking, since lower effort is associated with lower probability of reward. On the other hand, the system encourages knowledge diffusion, since scientists expend effort publicizing their results in order to achieve as much credit as possible. Given that scientists are attempting to maximize the rate of production and diffusion of scientific knowledge (i.e., scientists have a taste for Science), this priority-based system is an effective mechanism for achieving these goals.[5] Though this argument implicitly relies on a taste for Science by researchers, Dasgupta and David neither delineate the testable empirical implications of this theory nor compare it to alternative theories of the economic impact of Science.

In contrast to Dasgupta and David, who evaluate the efficiency properties of Science from the perspective of researchers having a taste for Science, Rosenberg (1990), Cohen and

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investments and training, and its long-term responsiveness to overall societal needs. For present purposes, I focus on the salient elements distinguishing Science from more traditional economic models of the research process.

[3] Obviously, this is a stylized conceptualization of Science as a knowledge production system (Latour and Wollgar, 1986). While acknowledging that Science is more subtle and dynamic than proposed here, this simple characterization allows for the development of the key hypotheses directly related to the underlying phenomena.

[4] Of course, economists have studied scientists' behavior to evaluate other aspects of behavior (e.g., Freeman's seminal studies of scientific labor markets (1976) or Levin and Stephan's careful test of Becker's life-cycle human capital model (1991)). See Stephan (1996) for an extremely informative synthesis of this work.

[5] It is useful to note that a "taste" for Science is likely concentrated among individuals in research-oriented careers, perhaps reflecting their education, career incentives or the selection of individuals in this profession. In this sense, this study examines a more specific job attribute than traditional on-the-job amenities such as safety or pension benefits (see Hamermesh (1984) or Viscusi (1993) for reviews). As well, David and Dasgupta (and David (1998)) also highlight important inefficiencies associated with Science, most notably the possibility of overinvestment and overnarrowness in research due to racing effects.

Levinthal (1989, 1990), and Arora and Gambardella (1994) examine how profit-maximizing firms might exploit Science for their own purposes. Specifically, given that Science tends to produce knowledge spillovers, relying on Science may provide access to new discoveries, improve the productivity of technological search, and employ codified forms of knowledge which allow for cumulative progress (Fleming and Sorenson, 2003; Foray, 2003). Thus, private firms who would like to exploit novel scientific knowledge must purchase a "ticket of admission" which pays itself off in terms of higher R&D productivity and a higher rate of technological innovation (Rosenberg, 1990).[6]

These two perspectives from the "new" economics of science are not mutually exclusive. Scientists may possess a taste for participating in Science (the Preference hypothesis), and some firms may find it worthwhile to participate in Science to capture knowledge spillovers (the Productivity hypothesis).[7] However, these effects have separate empirical implications, most notably for the employment relationship. While the Preference effect contributes to a negative compensating differential), the Productivity effect can contribute to a positive association between Science and wages (as long as there is "rent-sharing" between firms and researchers).

Though not mutually exclusive, prior empirical work that has focused on the relationship between Science and firm *performance* has confounded the Preference and Productivity effects (e.g., in the context of the life sciences industries, see Gambardella, 1995; Powell, 1996; Zucker and Darby, 1996; 1998, and Cockburn, Henderson, and Stern, 1999). However, similar to this paper, recent studies highlight the tension within public/private scientific networks between scientific advance, commercial gains, and career concerns (Owen-Smith and Powell, 2001; Gittelman and Kogut, 2003; Murray, 2003; Lim, 2003; Murray and Stern, 2003).[8]

It is important to note that estimating the economic impact of Science is confounded by the selection of more able scientists into science-oriented firms. Correlation between Science

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[6] More precisely, if a commercial "prize" is available to the first firm that translates a scientific advance into a novel technology, then firms have incentives to gain early access to absorb novel discoveries; according to many observers, participation in Science by at least some employees may be an efficient way to achieve this goal (Hicks, 1995).

[7] A fully specified model might place limits on the share of activity attributable to the profit-maximizers, insofar as this group may tend to exhibit free-riding in the absence of intrinsic preferences. Theoretical conditions for the existence of a priority-based equilibrium is an interesting area for future work but beyond the scope of this paper.

[8] Indeed, these studies reflect a broader body of research on the development of local technical communities, also

and researcher ability arises from the internal logic of the priority-based reward system. First, higher-quality researchers may be willing to trade off more income to earn the higher expected "prestige" rewards associated with their ability. Second, firms who employ higher-quality scientists may find participating in Science more attractive; with their better reputations, these researchers will gain better access to the external scientific community, (Zucker and Darby, 1996).[9] Consequently, without detailed controls for scientist ability, empirical assessments of the impact of Science on performance may be biased upwards since Science may be associated with the higher performance associated with higher-ability researcher distributions.[10]

III. A Simple Economic Model of Science and Wages

We now build on this qualitative discussion and develop a simple model incorporating the Preference effect, the Productivity effect, a distribution of talent among scientists, and rent-sharing between firms and scientists. By deriving the equilibrium relationship between Science and wages, we identify the empirical implications of the Preference and Productivity effects.

The model is composed of two stages. In the first stage, firm j chooses whether to adopt a scientific orientation for its R&D department (SCI = 1, else SCI = 0).[11] In the second stage, firms hire a single researcher with ability γ_i (observable to market participants but unobserved by the econometrician). As noted earlier, the population of researchers is subject to a skewed distribution of talent and so this variance is directly incorporated into the model. For firm j, the quality of worker i (the most attractive scientist who applies for a job at firm j) is drawn from a

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referred to as communities of practice (Feldman, 1994; Rosenkopf and Tushman, 1998; Almeida and Kogut, 1999).

[9] Zucker and Darby (1996) and Zucker, Darby and Brewer (1998) present evidence that biotechnology firms are more successful if they employ or interact (through copublication) with "star" researchers. While this evidence highlights the importance of the human capital distribution, they do not explicitly distinguish the underlying economic forces leading to such a bias or the impact of these structural characteristics on economic observables.

[10] Of course, other forces may also determine the adoption of Science. For example, firms may differ in their idiosyncratic return to Science as a result of their therapeutic specialization (Cockburn, Henderson and Stern, 1999).

[11] As discussed in Section II, participation in Science involves doing research which involves the formulation and testing of theories and results in public disclosure of findings through the academic publication process; however, science-oriented firms, in achieving the goals of Science, will also tend to (a) allow researchers discretion in choosing new research projects or continuing old ones and (b) tend to base promotion decisions on a researcher's external scientific reputation. The model does not distinguish between these characteristics. As well, the model assumes that each firm chooses a firm-wide scientific orientation (rather than tailoring the scientific orientation to each employee), an assumption consistent with prior qualitative and quantitative evidence (Gambardella, 1994; Zucker and Darby, 1996; Henderson, Cockburn, and Stern, 1999).

firm-specific distribution, $g_j(\gamma)$, bounded below at zero and with mean $\overline{\gamma}_j$.[12] Each scientist's utility depends on the offered wage and the preference for a science-oriented job environment:[13]

$$U_i = \alpha_0 + \alpha_S \gamma_i SCI_j + w_j \tag{1}$$

Scientists of higher ability place higher value on a science-oriented research environment; as discussed earlier, this interaction is strongly implied by the internal logic of the priority-based reward system and the ever-increasing rewards from "prestige."[14] Firms, on the other hand, earn profits according to the ability of hired scientists, the wages paid to these employees (w_j), and their scientific orientation:

$$\pi_{i,j} = \gamma_i(\beta_0 + \beta_S\, SCI_j) - w_{i,j} - \delta\, SCI_j \tag{2}$$

While firms pay a fixed fee to adopt a scientific orientation,[15] the benefits that the firm receives from adopting a scientific orientation depend on the quality of the scientist. Like our assumption about the interaction in (1), the interaction in (2) is motivated by the nature of the priority-based reward system: higher-quality scientists will have better access to the external scientific community and will be able to monitor external developments more skillfully than less-talented colleagues. In other words, the benefits from Science are skill-biased.

Firms who adopt Science earn a quasi-rent, which is increasing in γ_i. However, if the firm faces a search cost for new scientists and scientists can (credibly) threaten to receive additional job offers from other science-oriented firms, then scientists may extract some of this quasi-rent in wage bargaining.[16] To account for this possibility, I follow recent work on rent-

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[12] Alternatively, one could assume that the firm employs N researchers of known quality with mean ability $\overline{\gamma}_j$.

[13] To highlight the relationship between the wages from research jobs and scientific orientation, I adopt Rosen's (1974, 1986) hedonic characteristics approach and further assume that (a) each scientist supplies one unit of labor inelastically, (b) there is a competitive (no search cost) labor market for jobs where SCI=0, (c) all firms observe the same information about each scientist, (d) firms cannot verify the characteristics of competing job offers (until they are accepted), and (e) except for differences in talent, all scientists share the same utility function. As such, the model abstracts away from some of the more subtle issues which arise in the context of hedonic wage determination when workers' preferences for nonpecuniary characteristics are heterogeneous (Hwang, et al, 1992), or the nonpecuniary characteristic has continuous support, all jobs require substantial search, and firms differ in the cost of providing the nonpecuniary benefit (Hwang, et al, 1998).

[14] As well, this interaction could represent a "reduced-form" income effect (Weiss, 1976; Sattinger, 1977).

[15] One could imagine δ as the per-scientist cost of sending scientists to conferences, financing a staff to approve scientific articles, or the budget for discretionary research activities (e.g., specialized materials or equipment).

[16] More precisely, each scientist's bargaining position depends on her (exogenous) outside option in a non-science-oriented jobs, the *average* expected cost of searching for another science-oriented offer and the expected cost to the

sharing and incorporate a "rent-splitting" parameter, $\phi \in (0,1)$, which determines the allocation of the quasi-rent between scientist and firm (Abowd and Lemieux, 1993; van Reenen, 1996). As a result, the second stage wage equilibrium is given by:

$$w_{i,j}^{*} = \gamma_i \beta_0 + \gamma_i (\phi \beta_S - \alpha_S) SCI_j \qquad (3)$$

Equation (3) describes the empirical relationship between wages and scientific orientation, conditional on the quality of scientists. As long as the compensating differential parameter, α_S, is larger (smaller) than that part of the quasi-rent extracted by the scientist, then wages will be decreasing (increasing) in the firm's scientific orientation. As well, it is important to note that, by the very logic of the Preference and Productivity effects, the labor market for researchers will straddle both academic and non-academic employment opportunities, and so offers from both sectors will ultimately identify the relationship between Science and offered wages. Of course, in our empirical work, it will be important to distinguish between science-oriented job characteristics per se and the more diffuse set of attributes associated with university employment. As well, the adoption of Science will be concentrated in those firms who expect to recruit high quality scientists (i.e., $SCI_j = 1 \; iff \; \bar{\gamma}_j > \frac{\delta}{(1-\phi)\beta_S + \alpha_S} = \gamma^*$); both the Preference and Productivity theories contribute to a positive impact of Science on measures of firm performance. Finally, it is useful to highlight that the model has been tailored to highlight the different economic consequences of the Preference and Productivity effects. It is of course possible that the Preference effect does not capture an intrinsic utility parameter but instead reflects career concerns on the part of researchers. Career concerns are particularly salient since scientific publications are a publicly observable signal of researcher quality. It is important to emphasize that whether the Preference effect is driven by an intrinsic concerns or career concerns, both are alternatives to the Productivity hypothesis – so far the dominant explanation offered in the economics of technological change for the adoption of Science by private firms.

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firm of finding another job candidate of similar quality. The presence of these competing sources of bargaining power can yield a rent-sharing equilibrium (Mortensen, 1990; Abowd and Lemieux, 1993; Hwang, et al, 1998).

IV. An Empirical Model of Science and Wages

The wage equation is a function of the Productivity and the Preference parameters, α_S and β_S; consistent estimation of (3) therefore provides insight into the precise motivation for and welfare implications of the adoption of Science. Both parameters, α_S and β_S exert competing effects on w^*. As such, examining the labor market for scientists seems like a fruitful place to begin distinguishing the relative importance of these two effects.[17] However, a central issue for empirical work is that the potential for bias from heterogeneity in worker ability is likely to be important in the current context. Not only is the adoption of Science predicted to covary with researcher ability according to the underlying theory, but the distribution of scientific ability is well-known to be skewed (Stephan, 1996). This paper addresses this problem by introducing a novel empirical methodology exploiting the fact that in job markets for "novice" professionals (i.e., no prior career-oriented job experience), many candidates receive *multiple job offers* prior to accepting a single job offer. By observing more than one combination of wages and job characteristics for each of these "novice" job candidates, we are able to construct different points on the wage-characteristics curve *for a randomly selected worker at a point in time.*[18] By exploiting the specific institutions of professional labor markets, this methodology likely leads to a substantial reduction in the bias associated with unobserved heterogeneity.

Consider an empirical wage equation that does not account for ability heterogeneity:

$$w_{i,j} = \theta_0 + \theta_S \, SCI_j + \varepsilon_{i,j} \qquad (6)$$

If ability, γ_i, is uncorrelated with the adoption of SCI, then $E(\hat{\theta}_S) = \overline{\gamma}(\phi \, \beta_S - \alpha_S)$, or the relative salience of the preference versus productivity effect, evaluated at the mean ability level. However, if SCI is associated with higher-quality researchers, then there will be an upward bias on the estimate of the marginal impact of Science on wages. This bias combines two sources of bias identified in earlier applications. On the one hand, higher-ability individuals will tend to "consume" higher levels of positively valued hedonic characteristics. While earlier work has

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[17] I am not aware of any earlier empirical studies in the economics of science which have attempted to disentangle these parameters, or the relative importance of the talent effect in biasing cross-sectional results.

[18] For this condition to hold, it is of course important that individuals who receive multiple offers are not systematically different than those who receive only one offer. This is ultimately an empirical question; in Section VI, we provide evidence suggesting that the offers received by these two groups are in fact comparable.

attributed such covariation to wealth effects (Weiss, 1976; Sattinger, 1977; Rosen, 1986) or the impact of heterogeneous preferences (Hwang et al, 1992), the current application motivates this bias from the nature of a prestige-based reward system. On the other hand, the potential for "skill bias" from new technologies and the associated bias for productivity studies is well-established (Berman, Bound, and Griliches, 1994; Autor, Katz, and Krueger, 1998; Entorf and Kramarz, 1998). Though Science is not a "technology," it is an organizational practice more likely to be adopted when higher-quality workers are employed.

This paper proposes a novel field-based methodology – based on the concept of "multiple job offers" -- to overcome this bias.[19] This methodology is based on the process by which professional labor markets operate, which likely reduces the above-mentioned biases. For most graduate or postdoctoral scientific researchers, a job search involves sending out resumes to a large number of universities and firms, receiving a smaller number of interviews with those firms, and then receiving one or more job offers before accepting a final offer of employment.[20] I exploit two facts about this process. First, since all graduates must engage in some job search, graduating professionals are a particularly attractive sample from the perspective of selectivity. Second, and more importantly, prior to accepting a specific offer, many professionals receive *multiple job offers*. Each offer is composed of a wage offer and job characteristics (including scientific orientation) which are observed to the employee.[21] By surveying candidates about their multiple job offers, it is therefore possible to estimate the relationship between wages and scientific orientation, controlling for a "fixed effect" for each individual in the sample. In other

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[19] Prior research has addressed this bias through the use of ability-associated controls and the exploitation of panel data. While the use of control variables is useful when workers are easily distinguished by observables such as educational attainment (see, e.g., Hamermesh, 1984; Rosen, 1986; Kostiuk, 1990; Viscusi, 1993), this approach will be of limited value if most demographics are unlikely to distinguish individuals (e.g., when there is no variation in educational attainment among PhD recipients). As well, it is possible to exploit panel data by including a fixed effect for each individual and examining the impact of "job switches" (Brown, 1980; Duncan and Holmlund, 1983; Murphy and Topel, 1987; Abowd, Kramarz, and Margolis, 1999; Entorf and Kramarz, 1998). However, as discussed by Gibbons and Katz (1992), job switching is (generally) endogenous and reflects a population of individuals who are badly "matched" for their current positions, leading to a separate bias.

[20] As mentioned earlier, the very logic of the argument suggests that the labor market will straddle both academic and non-academic employment opportunities. However, we are careful to distinguish between the impact of Science and a more general impact of university employment.

[21] Since a formal job offer confers a legal responsibility on the firm, such offers will not be made unless the firm is willing to employ the worker under the proposed package. As well, in equilibrium, firms will not make offers which have a zero probability of acceptance.

words, the multiple job offers methodology allows us to observe different points on the wage-Science curve *conditional on the quality of the researcher* ($w_{i,j} = \theta_i + \theta_S\, SCI_j + \varepsilon_{i,j}$). The use of an individual fixed effect allows us to fully take into account heterogeneity among individuals in terms of their overall ability or their attractiveness to employers. Without such a precise control, it would be impossible to distinguish whether science-oriented jobs are associated with a discount (or premium) from an unobserved correlation between researcher quality and the firm's scientific orientation.

The multiple job offers methodology rests on several important assumptions. First, the method assumes that observed job offers are comparable in terms of the "seriousness" of the offer. As much as possible, the data were gathered just prior to the time the candidate accepted an offer; according to survey respondents, these "final-round" offers reflected their beliefs about the job characteristics they would be accepting if they chose an offer. As well, we check for this effect directly by including an "accepted job" dummy variable into the hedonic wage regression, providing information about whether accepted jobs are associated with significantly higher wages as well as providing a control for the potential relationship between the Science variables and the seriousness of the offer. Second, candidates who receive multiple job offers must be drawn independently from the distribution of candidates. In particular, individuals with more offers may be drawn from a more attractive portion of the distribution (Gibbons and Katz, 1992). At one level, this is an empirical question that can be checked directly by comparing the wage offers and characteristics of multiple offer candidates and single offer candidates. In addition, discussions with survey respondents suggests that the receipt of multiple job offers is more likely associated with the degree to which a candidate synchronizes their job search over all potential employers rather than necessarily be associated with the level of ability. Third, the method assumes that scientific orientation is uncorrelated with alternative unobserved sources of variation in R&D productivity. If firms' scientific orientation is correlated with unobserved practices which are the structural sources of productivity gains, then the hedonic equation will obviously be subject to omitted variable bias. However, since the survey used to implement the procedure can be tailored to the specific labor market under study (and after detailed informal information-gathering and piloting), it is possible to specifically ask each respondent about the most visible "candidates" for such bias. For example, it is possible to ask detailed questions about the possibility of promotion or career advancement at each job (another potential reason why researchers might trade off initial wages), and so at least provide a first-order control for this competing effect. Finally, this procedure assumes that differences in information among offering firms about the quality and preference of candidates is uncorrelated with scientific orientation. If science-oriented firms can judge researcher's abilities more accurately than others, then science-oriented firms may tend to make fewer but more attractive job offers, introducing a positive bias into the hedonic estimate.

V. Data

The data used to evaluate the hedonic wage equation for biologists was collected using an author-developed survey administered to life science researchers.[22] The survey records information about the experience, preferences, and decisions of individual candidates on the job market. This section describes the sample selection procedure, and then reviews the survey and the summary statistics for the dataset.

Sample Selection

The sample population was drawn from individuals who, with some probability, were in a position to receive multiple private sector life sciences research job offers. To ensure compatibility across responses, the sample is restricted to PhD biologists (though several candidates also hold an MD). The target population was therefore current researchers who held a PhD in biology, were currently searching for a permanent research position, and expressed interest in receiving offers from non-academic employers. To access this target population, surveys were distributed to the following populations:

* current postdoctoral researchers whose funding was expiring at four American research institutions,
* participants in two AAAS-sponsored Biology Job Fairs (held in Cambridge, MA and Palo Alto, CA), and

[22] Data was gathered between June, 1998, and June, 1999 by mail and telephone interviews (and a small number of e-mail responses). Except for a small number of individual cases, the surveys were administered prior to the time the individual commenced working for the accepted employment offer. The survey appears in Stern (1999).

*	post-PhD biologists with resumes posted to

For each data source, several candidates were interviewed more extensively in order to ensure that each group was comparable with the others (conditional on researcher quality). Overall, data was collected from 107 biologists who received a total of 223 job offers. Non-research-oriented job offers (e.g., management consulting, software start-up management, lab management) were excluded as were observations composed of candidates who received only one job offer. Once these jobs are excluded, the sample includes 63 job candidates who received a total of 164 offers. It is important to emphasize that this final dataset is quite special, in that it conditions on a set of postdoctoral biologists, most from "top-tier" institutions, who received multiple job offers. However, by their demographics and average salary offers, this sample is likely comparable to the researchers considered in other studies focused on life science researchers who are at the margin between academic and non-academic employment (Cockburn and Henderson, 1998; Zucker and Darby, 1996; Owen-Smith and Powell, 2001).

The Survey Instrument

The data are drawn from the information collected on the surveys administered to the populations described above. The goal in developing the survey was to collect information about the relationship between the job market environment and different elements of the job offers received by life science researchers.[23] The survey is composed of five sections (see Stern, 1999). The first elicits resume information about the respondent's background and demographics. Part II gathers data about the length and outcome of the job search. In Part III, respondents compare job offers according a number of distinct dimensions and provide an *ordinal* ranking of their offers. In other words, if an individual received three offers, she would rank these three offers in terms of an individual dimension, such as "Quality of Internal Research Environment," with the highest quality offer receiving a "1," the next preferred offer a "2" and the lowest-quality research environment rated a "3." Part IV asks more concrete data about

[23] The final form of the survey resulted from an iterative process. In response to a pre-test of the survey, the survey was amended using feedback from both researchers with prior experience in field-based survey work and focus group discussions with biologists who served as pre-test subjects. My special thanks to Eric von Hippel for his detailed comments on an early draft of the survey. From the perspective of this paper, the main changes in the survey over time were to refine the descriptive wording of the scientific environment and to divide out individual elements of the salary package (SALARY vs. BONUS, etc…).

each individual offer, denoted hereafter as *cardinal* data (i.e., generally comparable in magnitude and intensity). In addition to questions about measurable characteristics (such as salary or permission to publish in the public scientific literature), a number of questions are asked according to five-point Likert scales (with higher levels on the scale corresponding to higher objective rankings). The final survey section asks for a ranking of the importance of different job characteristics.[24]

It is useful to distinguish between the use of the ordinal and cardinal data. Whereas ordinal information provides comparative information about monetary and non-monetary qualities of each job, the cardinal data is composed of data from each candidate where the information about one offer is independent of the information from other offers. Both types of information are subject to limitations. Ordinal data, by its very nature, cannot be used to provide a measure of the intensity of different rankings either within a given job characteristic or across characteristics. On the other hand, cardinal data is subject to various types of measurement error; for example, the use of Likert scales in regression analysis imposes strong assumptions about how different responses differ from each other. However, the empirical approach overcomes these issues in two distinct ways. First, throughout the analysis, fixed individual effects are employed to derive the principal results; by construction, this limits the measurement bias to differences across responses *within individuals*. Second, the analysis evaluates both the ordinal and cardinal data, identifying those conclusions that are robust across data types.

Variables and Summary Statistics

The dataset is composed of 164 job offers from 66 individuals who received multiple job offers; the average individual received 2.88 offers and 30% of the observed offers were the offers actually accepted by the candidate (see Table 1 for variable definitions and descriptive statistics).[25] The first set of variables is based on the cardinal data drawn from the Job Offer Record. The dependent variable is the baseline salary associated with each offer, SALARY.

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[24] This paper does not fully exploit the richness of the survey. We focus only on those aspects of the survey which help to identify the relationship between Science and wages.

[25] As mentioned earlier, we gathered demographic information but do not use it in the current analysis as it is subsumed by the use of fixed effects. Briefly, most of the sample is married (71%) male (63%), and the average age is just above 34. The average respondent applied for 15.7 jobs and received their first job offer after 4.3 months. The maximal number of job offers is equal to 6, though more than 90% of the sample is composed of individuals with between 2 and 4 offers. The key results are robust to the inclusion or exclusion of any specific individual.

The average SALARY offer is a little higher than $60,000 though the standard deviation is quite large. Of course, SALARY only captures one dimension of the monetary compensation package, and we check the robustness of our findings to the inclusion of controls associated with other dimensions of earnings in the firm (particularly expectations of long-term compensation growth), including a dummy for the presence of stock options (STOCK_DUMMY, mean = 0.36) and long-term career opportunities (PROMOTION, mean = 3.49 rated on a 1-5 Likert scale).[26]

Several different cardinal variables are used to evaluate the scientific orientation of each organization: whether researchers are allowed to continue to publish discoveries (PERMIT_PUB), how strong the incentives for publication are (INCENT_PUB, rated on a 1-5 Likert scale), and whether researchers are allowed to continue postdoctoral research projects (CONTINUE RESEARCH). Interestingly, while most research positions do permit researchers to publish (the mean is over .9), there is a substantial variance among offers in terms of the incentives to publish and just under 50% of positions allow researchers to continue their prior research agenda. Finally, the analysis includes a Likert scale measure of access to cutting-edge equipment (EQUIPMENT). Consistent with Hamermesh and Oster (2002), the adoption and use of research tools may be driven either by productivity concerns (as "tools") or by their consumption value (i.e., as "toys").

Each of our measures of the scientific orientation of the firm is imperfect, and each is also correlated with the others (see Table A1). We therefore construct a composite index equal to the principal factor of PERMIT_PUB, CONTINUE RESEARCH, and INCENT_PUB. This variable, SCIENCE INDEX, is just a linear combination of the three raw measures, where the weights are determined according to a standard principal factor analysis (see Hamilton (1992) for a more complete description). In contrast to the raw measures, SCIENCE INDEX takes on 15 distinct values across the sample, and provides more refined variation across offers within individuals.

Each job offer is also coded with one of six different JOBTYPE categories: Established Firm, Start-up Firm, Government Lab, Medical Center/Hospital, University Faculty, and

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[26] Stern (1999) also experiments with the use of BONUS, which is equal to the "signing bonus" for the job offer. BONUS is highly correlated with STOCK_DUMMY, and so we exclude BONUS from the current analysis. The qualitative findings do not change when BONUS is included instead of STOCK_DUMMY.

University Postdoc (see Table A2). Though the plurality of offers are received from established firms and start-up firms, our main analysis includes jobs from the public and university sectors. According to our focus groups and interviews, public sector and medical center employment are perceived to be similar to employment by private firms (the only difference being the formal status of the organization), while academic jobs are imperfect substitutes offering job characteristics not captured in our empirical measures (e.g., collegiality, the option value of moving to the private sector, etc…). We therefore define "academic" offers to be those associated with a University Faculty or University Postdoc position, and the analysis is careful to distinguish how the results depend on the inclusion or exclusion of offers from these categories.

The second set of variables is ordinal in nature – each individual ranked their jobs in order of their preference according to each dimension. Not surprisingly, the mean of each of these variables is slightly less than 2 (recall that while the average number of job offers per respondent is 2.88, the data count each job offer as a separate observation and so individuals with a larger number of offers appear more frequently than those with only two or three offers). The principal dependent regressor that we will use in this context is MONETARY, or the ranking of offers in terms of "overall monetary compensation." The analysis focuses on evaluating the relationship between the MONETARY rank and two elements of the scientific orientation of each organization: first, the overall research quality (RESEARCH QUALITY) and whether researchers have discretion in choosing their own projects (FLEXIBILITY).[27] Based on the focus group discussions and interviews, the survey also asked respondents to rank jobs according to several control factors, such as the availability of research funding (FUNDING), the impact of the job on career (CAREER), and the degree of fit between specific training (JOBFIT). While this study takes each of these latter factors as a control variable, one could imagine separate investigations of each. For example, the JOBFIT variable might provide information about the degree of idiosyncratic bargaining power that a worker possesses with each employee, allowing more nuanced evaluation of the degree of bargaining power held by the employee. As well, by including CAREER in all regressions, the analysis explicitly distinguishes between participation in Science as a career-advancement strategy and intrinsic

[27] The survey includes another element of the scientific orientation (Publication Incentives) but the wording of this

preferences for a Science-oriented research environment.

Before turning to the empirical results, two final sampling issues arise. While there are 164 job offers for which an alternative job offer for that candidate is observed (i.e., a multiple), many surveys were only completed with either the ordinal or cardinal data but not both. As a result, the final sample in the cardinal analysis includes 121 job offers across 52 individuals; when we examine non-academic offers only, this reduces to 71 offers across 30 individuals. In the ordinal analysis, 134 job offers across 51 individuals are included, and this sample is reduced to 74 offers over 28 individuals when examining non-academic offers only. For some offers, a subset of the control variables are missing (e.g., the respondent did not report whether stock options were received); in these cases, a dummy variable for a missing value has been included.

VI. Empirical Results

This section presents the empirical evidence about the relationship between measures of monetary compensation and the scientific orientation of organizations. The analysis proceeds in three stages, beginning with the cardinal data, followed by the ordinal (ranked) data, and then addressing some potential limitations and concerns with the multiple job offers methodology. Overall, the evidence is consistent with the predictions of the Preference hypothesis.

Cardinal Data

We begin in Table 2 with a simple non-parametric comparison of the variation in salary offers by the scientific orientation of different jobs (in the spirit of Card and Sullivan 1988). For each of our three principal measures of scientific orientation (PERMIT_PUB, CONTINUE RESEARCH, and INCENT_PUB), we perform a t-test of differences in the means focusing exclusively on individuals who experienced variation in that characteristic across their offers. We first compute the average salary offer for each individual for each of two values of a given characteristic, creating a person-specific "wage-characteristic" pair.[28] We then compute the average value of each pair, yielding a "weighted" average salary for each individual (where the weights are implicitly equal to 0.5 for each value of the characteristic). To abstract away from

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question led to a relatively low response rate of usable responses.

[28] Though INCENT_PUB is a five-point Likert scale measure, we implemented the above procedure by grouping the

differences in the *level* of salary offers across individuals, we subtract each individual's "weighted" average salary from each element of their wage-characteristic pair. In other words, for each individual and characteristic value, we calculate an "average deviation" measuring how salary offers associated with a given value of a characteristic differ from the average salary offer received by that individual. The test is a simple comparison of the deviations associated with a "high" value of the scientific characteristic versus the deviations associated with a "low" value of the scientific characteristic.

The upper half of Table 2 reports the results of this test for the complete sample, including "academic" offers. Given the limited size of the sample (and the smaller number of instances in which offers vary in terms of a specific attribute within individuals), the degrees of freedom for each test is modest, ranging from 8 for the PERMIT_PUB measure to 30 for the INCENT_PUB measure. Despite this small number, equality of the deviations in salary offers by scientific attribute is rejected at the 10% significance level for each of the three scientific orientation measures. These deviations are quantitatively significant as well: for example, for PERMIT_PUB, the (weighted) average for offers where publication is allowed is more than $14,000 lower than the (weighted) average for offers where publication is restricted.

It is important to demonstrate that such differences are not simply the result of differences between academic and non-academic job offers. As such, the lower half of Table 2 repeats the test, excluding academic offers from the sample. Equality of the means is rejected at the 5% level for both PERMIT_PUB and INCENT_PUB, though the test for CONTINUE RESEARCH can only reject equality at the 20% level.. As well, the quantitative size of the average differences is still substantial, though smaller in absolute size for PERMIT_PUB and CONTINUE RESEARCH. In other words, though there are some differences depending on the sample, the core findings are similar. Whether academic offers are excluded or not, and controlling for the "average" salary received by each individual, salary offers associated with a low value of the scientific orientation measure are significantly higher than salary offers associated with a high value of the same scientific orientation measure.

Tables 3 and 4 turn to regression analyses to further assess the relationship between

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INCENT_PUB responses into two groups ({1, 2, 3} versus {4, 5}) salary offers and the scientific orientation of the firm. In particular, we are interested in (a) contrasting results depending on whether we take account of individual differences, (b) controlling for other factors that may impact the salary offer for a given job, (c) comparing the salience of different measures of the scientific orientation of each job offer and (d) comparing how the results depend on whether academic offers are included or not.

The first three columns of Table 3 examine the relationship between the (natural log of) offered SALARY and PERMIT_PUB, using both academic and non-academic offers.[29] In some sense, this is the most direct test of the relationship between Science and wages, since the permission to publish is the hallmark of Science as an institution. The first column of Table 3 reports the unconditional pairwise correlation between SALARY and PERMIT_PUB, which is both quantitatively small (.03) and statistically insignificant. In sharp contrast, once we include individual fixed effects in (3-2), the parameter estimate becomes negative and significant (-0.27), both statistically and quantitatively. This result is robust to a variety of control structures. As an illustration, (3-3) includes controls for the career prospects offered by each job (PROMOTION), the value of the compensation package (STOCK DUMMY), the "seriousness" of the job offer (ACCEPTED JOB) and dummies for each job category.[30] Together, these measures should capture the most obvious sources of omitted variable bias. The coefficient on PERMIT_PUB remains negative and significant, though the estimated coefficient is approximately 25% smaller in absolute value.

These estimates allow us to evaluate the salience of the effects identified in the economic model. First, at the point estimate provided in (3-3), $\bar{\gamma}(\phi\beta_S - \alpha_S) = -.19$. In other words, at the mean human capital level in the observed sample, the Preference effect outweighs the impact of the Productivity effect and implies nearly a 20% discount on the wage rate for Science-oriented firms. Second, the difference between the cross-sectional results and the fixed effects results provides information about the "size" of the ability bias. Taking the results at face value,

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[29] While the hedonic is in the form of ln(SALARY) throughout, the results are robust to the use of SALARY level.
[30] In most specifications, other elements of compensation and opportunities for promotion are positively associated with offered salaries. In one sense, this contrasts with the simplest model of wage determination where one expects compensating differential for these characteristics. However, such evidence *is* consistent with the presence of rent-sharing: some firms are more successful and provide higher compensation to all recruits (perhaps with some efficiency wage benefits); for present purposes, it is useful to note that the Science effects are distinguished from

the estimates rejects the pooled regression and imply that the size of the bias is more than 20%.

Figure 1 plots the distribution of the researcher fixed effects, illustrating the magnitude of the researcher ability effects more directly. According to Figure 1, the inter-quartile distribution ranges from more than 40% wage discount for the 25th percentile scientist to nearly a 40% wage premium for the scientist at the 75th percentile. These results are particularly striking when one considers that the sample *conditions* on a population of PhD holders. It is useful to emphasize that these fixed effects do not capture the *scientific* ability of researchers per se but differences in the attractiveness of different individuals on the labor market at the time in question.[31] While the small sample size and simple specification suggest that these results should be treated with caution, the large magnitude suggests the existence of differences between jobs that permit publication (or not) and between the job offers for different individuals in the sample.

The final three columns of Table 3 incorporate multiple scientific orientation measures into the analysis. In (3-4), we include PERMIT_PUB, CONTINUE RESEARCH, INCENT_PUB and EQUIPMENT simultaneously (along with other controls). Each of the first three coefficients is negative (though only CONTINUE RESEARCH is significant), and EQUIPMENT is positive and significant.[32] Rather than attempt to separately disentangle the separate impact of each of these variables,[33] the final two columns of Table 3 examine their combined effect, using SCIENCE INDEX (the first principal factor of PERMIT_PUB, CONTINUE RESEARCH, and INCENT_PUB) as the key regressor. The coefficient on SCIENCE INDEX is negative in both specifications, though it becomes insignificant when job category dummies are included. As suggested by Table 2, this reduced precision is not surprising, given the limited amount of within-researcher variation in the sample.

Relying on a sample that combines academic and non-academic offers, Table 3 provides evidence consistent with the relative salience of the Preference effect as well as ability bias.

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this pattern.

[31] Unfortunately, confidentiality concerns do not allow me to "track" these individuals over time since the time of the Survey to examine their realized publishing and patenting productivity. However, as emphasized by Gittelman and Kogut (2003), applied research productivity may be uncorrelated (or even negatively correlated) with scientific ability; if firms understand this tradeoff, the "fixed effects" may be capturing potential employer's assessment of candidates' ability to contribute to commercially oriented research activities.

[32] This finding provides some evidence in contrast to the "toys" evidence offered by Hamermesh and Oster (2002).

[33] In most cases, two of the three measures can be separately estimated with a significant coefficient (Stern, 1999).

However, as we emphasized earlier, it is important to distinguish whether these results are simply driven by differences between the academic and non-academic sectors. Table 4 therefore employs a dataset limited to the non-academic offers of those individuals who received multiple non-academic offers (resulting in a sample of 71 offers across 30 individuals). In both specifications (including PERMIT_PUB and SCIENCE INDEX as the key regressors, respectively), there is a negative and significant correlation between each scientific orientation measure and offered salary. The magnitudes of these effects continues to be significant as well; for example, a one-standard deviation shift in SCIENCE INDEX is associated with more than a 6% reduction in the predicted wage. These qualitative findings are robust to the inclusion or exclusion of controls for promotion opportunities, whether stock options are offered, and the seriousness of the job offer. As well, in contrast to the noisy results in (3-6), the coefficient on SCIENCE INDEX remains significant (and quantitatively important) at the 10% level even after job category dummies are included. In other words, whether we employ PERMIT_PUB or SCIENCE INDEX as our measure of scientific orientation and focusing only on non-academic employment offers, the labor market for life scientists reflects a wage discount for science-oriented job offers.

Ordinal Data

We now turn to the ordinal data to highlight results from this separate part of the survey. Of course, since one cannot concretely identify the intensity associated with an ordinal ranking, the use of the ordinal data is not ideal. However, this type of data can be used to support the cardinal results; in particular, we can examine whether similar patterns hold, given that nearly half of all respondents in the ordinal dataset are not included in the cardinal dataset.

Table 5 presents a series of regressions using the MONETARY rank of each job as the dependent variable.[34] Each regression includes both a full set of individual fixed effects as well as controls for JOBFIT, CAREER, and FUNDING (the results are robust to alternative controls

[34] A more informal analysis of the ordinal data is presented in Table A3, which presents pairwise cross-tabulations between the MONETARY rank and four other job dimensions. While the majority of the rankings for JOBFIT and CAREER are on or just off the diagonal of the cross-tabulation with MONETARY (indicating a positive correlation between these dimensions), rankings for RESEARCH QUALITY and FLEXIBILITY are more dispersed. In other words, Table A3 suggests a tradeoff between the MONETARY ranking and RESEARCH QUALITY or FLEXIBILITY. See Stern (1999) for more details.

structures). Beginning with the full sample of observed job offers, (5-1) and (5-3) demonstrate that MONETARY is negatively correlated with RESEARCH QUALITY and FLEXIBILITY, respectively.[35] These results continue to hold even when we include academic job offers, though the FLEXIBILITY coefficient is close to but not quite significant at the 10% level (see (5-2) and (5-4)).[36] Overall, these results provide additional supporting evidence for the salience of the Preference effect in shaping the relationship between monetary compensation and Science. Research environments that allow workers access to high-quality research colleagues and an ability to choose their own projects tend to offer less attractive monetary compensation.

Single versus Multiple Offers

As discussed in Section IV, the multiple job offers methodology relies on several implicit assumptions. Among the important of these is the assumption that those individuals who receive multiple job offers are not drawn systematically from a different part of the ability distribution than those who receive only one offer (this is required in order for us to estimate the mean value of (in the population). While we cannot provide dispositive evidence regarding this assumption, we are able to gain some insight into the seriousness of the problem by comparing the offers associated with multiple offer individuals with the characteristics of the offers of those who accept the first job they are offered (see Table 6A). Essentially, relative to the variance associated with each of the characteristics, the single-offer averages are not substantially different than the multiple-offer averages (none of the means is significantly different from each other). For example, while the mean salary offer associated with single offer candidates is 8% lower, the likelihood of being able to publish is 6% higher. Along with the informal evidence (drawn from detailed interviews with job market participants) that the likelihood of receiving a multiple offer depends on whether one synchronizes the job search so that all employment offers are made at roughly the same time, this comparison suggests that there is no obvious source of evidence for selectivity associated with the use of the multiple job offers.

Accepted Versus Rejected Offers

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[35] If we take the estimates at face value, the results suggests that as the value of RESEARCH QUALITY increases by one, the predicted value of MONETARY declines approximately .3.

[36] The results continue to hold if RESEARCH QUALITY and FLEXIBILITY are included simultaneously, though the results are noisier when we limit exclusively to non-academic offers.

A second implicit assumption of the methodology is that all of the observed offers are equally "serious." If, for example, firms with a science-oriented research approach pursued a hiring strategy in which they made a larger number of less attractive offers, then the negative correlation found in the data would be a remnant of this strategy rather than the fundamental preference and productivity forces identified earlier. Indeed, concern over the degree of seriousness of offers motivated the use of the ACCEPTED JOB dummy in most of the analysis; in all of the fixed effects regressions, this variable was quantitatively small and statistically insignificant. In other words, if one excludes the ACCEPTED JOB dummy, the residuals from the hedonic wage equation cannot be explained with the ACCEPTED JOB dummy. In Table 6B, we employ a more direct approach, comparing the characteristics associated with accepted and rejected offers. While accepted offers are associated with somewhat higher salaries (approximately 6%), they are also (weakly) associated with a scientific orientation (e.g., the mean of PERMIT_PUB and EQUIPMENT are somewhat higher while the mean of the other characteristics are essentially equal across the two groups). While these results do not rule out the absence of bias, they do argue against a strong *negative* correlation between the seriousness of the offer and Science. As such, it is unlikely that the negative correlation between offered wages and scientific orientation is simply reflecting a "low-ball" job offer strategy by more scientifically oriented firms.

VII. Discussion and Conclusion

Though the sample size is small, the results consistently point towards the possibility that scientists pay a compensating differential to participate in Science. While the theoretical relationship between Science and wages is ambiguous (depending on the Preference and Productivity effects, and the degree of rent-sharing), the empirical evidence suggests that the balance is tilted in favor of the Preference effect. Offers from Science-oriented firms are associated with lower wages and a lower ranking in terms of monetary compensation. This finding is robust to different characterizations of Science, different control structures, and whether we limit the sample exclusively to non-academic offers. However, these results do depend on controlling for differences among workers in terms of their ability, and cross-sectional analysis yields an upward bias of the estimated relationship between wages and Science.

These findings have potential implications for the estimates of the benefits from science-oriented practices in the context of prior R&D productivity studies. While prior research in the economics of technical change have focused almost exclusively on the Productivity effect, such an interpretation ignores two sources of bias: the wage-savings associated with the compensating differential and the unmeasured correlated between the adoption of scientific practices and average researcher ability. While prior researchers have acknowledged the possibility of bias (Henderson and Cockburn, 1994), the results, taken at their face value, suggest that these two effects may explain an important portion of the overall measured effect.

Indeed, there may be a conflict between the preferences of researchers to participate in Science and the incentives for firm participation. Consistent with evidence offered by Cockburn, Henderson and Stern (2003), Gittelman and Kogut (2003) and Murray (2003), science-oriented firms face important challenges in providing appropriate incentives for researchers who simultaneously engage in basic and applied research activities. Of course, these results depend on the fact that the sample is drawn from an "extreme" case, and biologists with PhDs are perhaps uniquely associated with a "taste" for Science. While the generality of these results remains an open area for future research, it should be highlighted that life sciences researchers now compose over one-third of *all* graduating PhDs in the natural sciences (NSF, 1999).

An additional perspective on these findings is that they suggest that a profession-specific ethic – participation in the public scientific community – has real effects on economic observables such as wages and perhaps productivity. In particular, a "taste" for Science is most likely not universally shared among all workers but is concentrated among workers in research-oriented careers. Moreover, scientists are by no means the only professional community in which *profession-specific* values may influence behavior. For example, if physicians claim to value the health of their patients (as they often do), do physicians *pay* to cure their patients? Specifically, do HMOs who offer higher-quality health care (in terms of fewer restrictions on costly procedures and the like) extract a discount on the salary they offer new physicians as a result of their pro-patient reputation? Similarly, lawyers often claim to value justice in the legal system. Is this reflected in lower wages for those firms who participate in pro bono activities or who are more directly involved in courtroom activity or appellate work (as opposed to corporate law)? Finally, computer programmers have increasingly foregone current income to participate in the “open software” movement, a choice which may reflect intrinsic preferences or career concerns (Lerner and Tirole, 2002). Perhaps surprisingly, following the seminal study of Friedman and Kuznets (1954), there has been almost no systematic economic analysis of the impact of professional ethics on labor markets or economic organization (though Weisbrod (1983) is an important exception).

This paper provides a new tool to perform these future studies.[37] Similar to the current context, accounting for human capital effects will be paramount in any professional labor market; however, the multiple job offers methodology will also apply to these markets. The average law student receives several job offers during their law school career, and, after residency, many physicians receive multiple offers from different HMOs. Relative to the number of postdoctoral biologists seeking first-time employment in the private sector, law schools and medical residencies offer potentially much larger cohort populations from which to gather job offer data.

Finally, the framework and empirical results may have more general implications for how we interpret Science as an economic institution. Specifically, there is a broad (though not unanimous) agreement that basic research of some type should be subsidized or encouraged because of its role in spurring long-term technological change and economic growth (Romer, 1990); however, the exact form of that subsidy is much more contentious (Wright, 1983). On the one hand, much public policy discussion argues that researchers – even basic researchers – should be evaluated on their ability to long-term commercial consequence of their research proposals (Committee for Economic Development, 1998). On the other hand, others contend that the peer-reviewed scientific research funding and publication system operates according to an internal logic which can be easily undermined by providing high-powered explicit incentives for applied commercial output (David and Dasgupta, 1994; Nelson and Rosenberg, 1994). This study points towards the potential for an empirical foundation for this latter perspective.

[37] For example, Miller (1999) employs the multiple job offers methodology to evaluate the value placed on diversity and mentoring programs by minority MBA candidates. Hsu (2003) assesses the value placed by technology entrepreneurs on the reputation and resources of venture capitalists when choosing among multiple VC offers. Though not profession-specific, these studies highlight how this methodology can be extended to other settings. In a somewhat similar vein, Royalty (1999) exploits the observation of multiple health insurance options by individual workers in a given firm to directly estimate the preference parameters.

Specifically, if the producers of abstract knowledge (a long-term public good) are sensitive to the integrity and prestige associated with the production of “pure” knowledge, then society may be able to produce such knowledge at lower cost than would be the case if researchers were only sensitive to the tradeoff between effort and realized income. Because letting the scientific community establish its own internal rules for prestige and recognition may reduce the cost of knowledge production, total spillovers from knowledge production into technological innovation may depend on *the degree of insulation from commercial incentives*. Exploring the role that the institutions of Science play in shaping R&D productivity therefore seems like a promising area for further study in management and economics.

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TABLE 1

DEFINITIONS AND DESCRIPTIVE STATISTICS

VARIABLE	DEFINITION	N	MEAN	STD. DEV.
JOB MARKET EXPERIENCE				
# OFFERS RECVD	Number of offers received	164	2.88	1.00
ACCEPTED JOB	Accepted this job = 1, No = 0	164	0.30	0.49
JOB OFFER CARDINAL RECORD INFORMATION				
JOB TYPE	1 = Established Firm, 2 = Startup Firm, 3 = Government, 4 = Medical School/Center, 5 = University, 6 = Postdoc	164	See Appendix	
Monetary Compensation and Career Incentive Measures				
SALARY	Annual starting salary (in US Dollars)	121	62263.95	31553.04
STOCK_DUMMY	Job offer includes stock options = 1, No = 0	72	0.36	0.48
PROMOTION	Likert Scale rating (1-5) of opportunities for internal promotion	111	3.49	1.29
Scientific Orientation Indicators				
PERMIT_PUB	Permission to publish in external journals = 1, No = 0	114	0.92	0.27
INCENT_PUB	Likert Scale rating (1-5) of incentives to publish in refereed outside journals	104	3.89	1.12
CONTINUE RESEARCH	Job allows continuation of current research project = 1, No = 0	111	0.46	0.50
SCIENCE INDEX	First principal factor of PERMIT_PUB, INCENT_PUB and CONTINUE RESEARCH; see Hamilton (1992)	99	0.00	0.57
EQUIPMENT	Likert Scale rating (1-5) of access to “cutting-edge” equipment	112	4.07	0.86
JOB OFFER ORDINAL RECORD DATA (1 =highest)				
MONETARY	Ranking of offer in terms of monetary compensation	134	1.96	0.99
RESEARCH QUALITY	Ranking of offer in terms of internal research environment	124	1.90	0.99
FLEXIBILITY	Ranking of offer in terms of flexibility to choose research projects	116	1.90	0.98
FUNDING	Ranking of offer in terms of availability of research funding	117	1.93	1.00
CAREER	Ranking of offer in terms of impact on career advancement	130	1.95	0.99
JOBFIT	Ranking of offer in terms of how well it ‘fits’ with prior research experience	116	1.91	1.01

TABLE 2

NON-PARAMETRIC COMPARISON OF DEVIATIONS OF SALARY MEANS BY SCIENCE ATTRIBUTES

	PERMIT_PUB (0 v. 1)	CONTINUE RESEARCH (0 v. 1)	INCENT_PUB ({1, 2, 3} v. {4, 5})
Overall Sample			
Average Difference	14200 (7241)	16809 (5189)	6694 (2678)
t-stat for means equality	1.961	3.239	2.500
Degrees of Freedom	8	26	30
p-value	0.086	0.003	0.018
Non-Academic Offers Only			
Average Difference	7200 (2352)	8143 (5954)	8430 (3223)
t-stat for means equality	3.061	1.368	2.615
Degrees of Freedom	8	12	18
p-value	0.016	0.197	0.0.18

Notes: Each "average difference" cell contains the difference in the average deviation in salary for a science characteristic, using the following procedure. For each science characteristic, we identified those individuals whose offers differed in terms of that characteristic. For these individuals, we then computed (a) the average salary offer for that individual by that specific characteristic and (b) the (weighted) average salary offer for each individual, where the weight associated with each value of the characteristic is equal to 0.5. Finally, to abstract away from differences in the level of salary across individuals, we subtracted (b) from (a). We then performed a t-test for the equality of the means based on these average salary deviations by scientific characteristic.

Though INCENT_PUB is a five-point Likert scale measure, we implemented the above procedure by grouping the INCENT_PUB responses into two groups ({1, 2, 3} versus {4, 5}).

TABLE 3

HEDONIC WAGE REGRESSION: OVERALL SAMPLE
DEPENDENT VARIABLE = LN(SALARY), # of Observations = 121

	PERMISSION TO PUBLISH			COMBINATION MODEL	SCIENCE INDEX MODEL	
	(3-1)	(3-2)	(3-3)	(3-4)	(3-5)	(3-6)
	Baseline (NO FE)	Baseline (w/ FE)	Full Model (w/ FE)	Full Model (w/ FE)	Full Model (w/ FE)	Full Model (w/ FE)
PERMIT_PUB	0.027 (0.186)	**-0.266 (0.114)**	**-0.191 (0.105)**	-0.089 (0.103)		
CONTINUE RESEARCH				**-0.134 (0.060)**		
INCENT_PUB				-0.036 (0.028)		
SCIENCE INDEX					**-0.114 (0.053)**	-0.078 (0.057)
EQUIPMENT				**0.063 (0.033)**	**0.057 (0.030)**	**0.053 (0.031)**
CONTROLS						
PROMOTION			**0.041 (0.025)**	**0.046 (0.021)**	**0.042 (0.021)**	0.031 (0.023)
STOCK_DUMMY			**0.196 (0.085)**	**0.234 (0.074)**	**0.260 (0.067)**	**0.190 (0.077)**
ACCEPTED JOB			-0.013 (0.040)	0.002 (0.043)	-0.0001 (0.043)	-0.002 (0.044)
JOBTYPE CONTROLS	NO	NO	YES (5; Sig.	NO	NO	YES (5)
INDIVDUAL FIXED EFFECTS	NO	YES (52; Sig.)	YES (52; Sig.)	YES (52; Sig.)	YES (52; Sig.)	YES (52; Sig.)
R-squared	0.001	0.915	0.955	0.958	0.954	0.958

Notes: Only persons with multiple job offers are included.
Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.
Sig. stands for joint significance of fixed effects or job type controls (at 10% level)

TABLE 4

HEDONIC WAGE REGRESSION: NON-ACADEMIC OFFERS
DEPENDENT VARIABLE = LN(SALARY), # of Observations = 71

	PERMISSION TO PUBLISH	FACTOR MODEL
	(4-1)	(4-2)
PERMIT_PUB	**-0.150** **(0.077)**	
SCIENCE INDEX		**-0.109** **(0.047)**
EQUIPMENT		-0.015 (0.038)
CONTROLS		
PROMOTION	**0.056** **(0.029)**	**0.054** **(0.029)**
STOCK_DUMMY	0.092 (0.066)	0.105 (0.065)
JOB ACCEPTED	-0.049 (0.047)	-0.021 (0.048)
INDIVDUAL FIXED EFFECTS	YES (30; Sig.)	YES (30; Sig.)
R-squared	0.967	0.970

Notes: Only persons with multiple job offers are included.
Regressions exclude postdoctoral positions and job offers from universities.
Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.
Sig. stands for joint significance of fixed effects (at 10% level).

TABLE 5

REGRESSION: JOB OFFER COMPARISON RANKINGS
DEPENDENT VARIABLE: MONETARY

	(5-1)	(5-2)	(5-3)	(5-4)
Sample	All Job Types	Exclude Academic Job Offers	All Job Types	Exclude Academic Job Offers
RESEARCH QUALITY	**-0.34**	**-0.32** **(0.16)**		
FLEXIBILITY			**-0.39** **(0.13)**	-0.27 (0.19)
JOBFIT	0.20 (0.12)	**0.29** **(0.16)**	**0.32** **(0.12)**	**0.35** **(0.17)**
CAREER	0.23 (0.12)	-0.04 (0.16)	**0.30** **(0.13)**	0.04 (0.18)
FUNDING	**0.34** **(0.13)**	0.26 (0.17)	0.17 (0.12)	0.18 (0.17)
INDIVIDUAL FIXED EFFECTS				
R-squared	0.48	0.41	0.48	0.38
# of Observations	134	74	134	74

Notes: Only persons with multiple job offers are included.
Regressions 5-2 and 5-4 exclude postdoctoral positions and job offers from universities.
Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.

TABLE 6A
COMPARISON OF SINGLE AND MULTIPLE JOB OFFERS

	SINGLE OFFERS	MULTIPLE OFFERS
SALARY	58074.01 (26859.57)	61958.85 (31394.96)
PERMIT_PUB	0.96 (0.19)	0.91 (0.28)
CONTINUE RESEARCH	0.28 (0.46)	0.46 (0.50)
INCENT_PUB	3.67 (1.24)	3.88 (1.13)
EQUIPMENT	3.71 (1.38)	4.06 (0.86)

Notes: Number of observations is different for every cell, depending on number of missing values. Standard errors are shown in parenthesis.

TABLE 6B
COMPARISON OF ACCEPTED AND REJECTED OFFER CHARACTERISTICS

	REJECTED OFFERS	ACCEPTED OFFERS
SALARY	60925.06 (32647.24)	64782.93 (29602.07)
PERMIT_PUB	0.91 (0.29)	0.95 (0.22)
CONTINUE RESEARCH	0.48 (0.50)	0.46 (0.50)
INCENT_PUB	3.93 (1.08)	3.93 (1.19)
EQUIPMENT	3.82 (0.91)	4.43 (0.66)

Notes: Number of observations is different for every cell, depending on number of missing values. Standard errors are shown in parenthesis.

APPENDIX A

TABLE A1. CORRELATION OF JOB OFFER RECORD DATA

	SALARY	PERMIT_PUB	CONTINUE RESEARCH	INCENT_PUB	EQUIPMENT	STOCK_DUMMY	PROMOTION
SALARY	1.0000						
PERMIT_PUB	-0.0082	1.0000					
CONTINUE RESEARCH	-0.0728	0.0499	1.0000				
INCENT_PUB	**-0.2729**	**0.3204**	**0.2933**	1.0000			
EQUIPMENT	0.1047	-0.0318	-0.0398	0.1787	1.0000		
STOCK_DUMMY	**0.4680**	-0.0757	**-0.3264**	**-0.3953**	0.0932	1.0000	
PROMOTION	**0.2173**	-0.0231	**0.2079**	0.0422	0.0532	**0.2742**	1.0000

Note: Significant (5%) coefficients are shown in bold.

TABLE A2. WAGE REGRESSION: ACADEMIC VERSUS PRIVATE-SECTOR JOBS
DEPENDENT VARIABLE = LN(SALARY), # of Observations = 121

JOBTYPE (Baseline = Established Firm)	No of Offers	**Baseline** (w/o Person FE)	**Baseline** (w/ Person FE)
Established Firm	40		
Startup Firm	26	-0.17 (0.12)	0.08 (0.08)
Government	6	-0.19 (0.23)	0.04 (0.16)
Medical Center	37	-0.17 (0.12)	**-0.19 (0.08)**
University	34	**-0.41 (0.13)**	**-0.40 (0.10)**
Postdoc	21	**-0.91 (0.13)**	**-0.40 (0.10)**
INDIVDIUAL FIXED EFFECTS		NO	YES (52; Sig.)
R-squared		0.34	0.93

Notes: Only persons with multiple job offers are included.
Standard errors are shown in parenthesis; significant coefficients (10%) are shown in bold.
Sig. stands for joint significance of fixed effects (at 10% level).

TABLE A3. CROSS TABULATIONS: JOB OFFER COMPARISON RANKINGS
(Rank = 1 is highest)

Table A3a: Money and Jobfit

MONETARY (Ranking of monetary compensation)	**JOB FIT** (Ranking of offer in terms of how well it 'fits' with prior research experience)					
	1	2	3	4	5	6
1	24	16	2	2		
2	21	19	5	1		
3	5	5	9			
4		2	1	4		
5						1
6					1	

Table A3c: Money and Research Environment

MONETARY (Ranking of monetary compensation)	**RESEARCH QUALITY** (Ranking of offer in terms of internal research environment)					
	1	2	3	4	5	6
1	19	20	5	3		
2	26	15	4	1		
3	6	6	8	1		1
4	1	2	3	1	1	
5		1				
6	1					

Table A3b: Money and Career Advancement

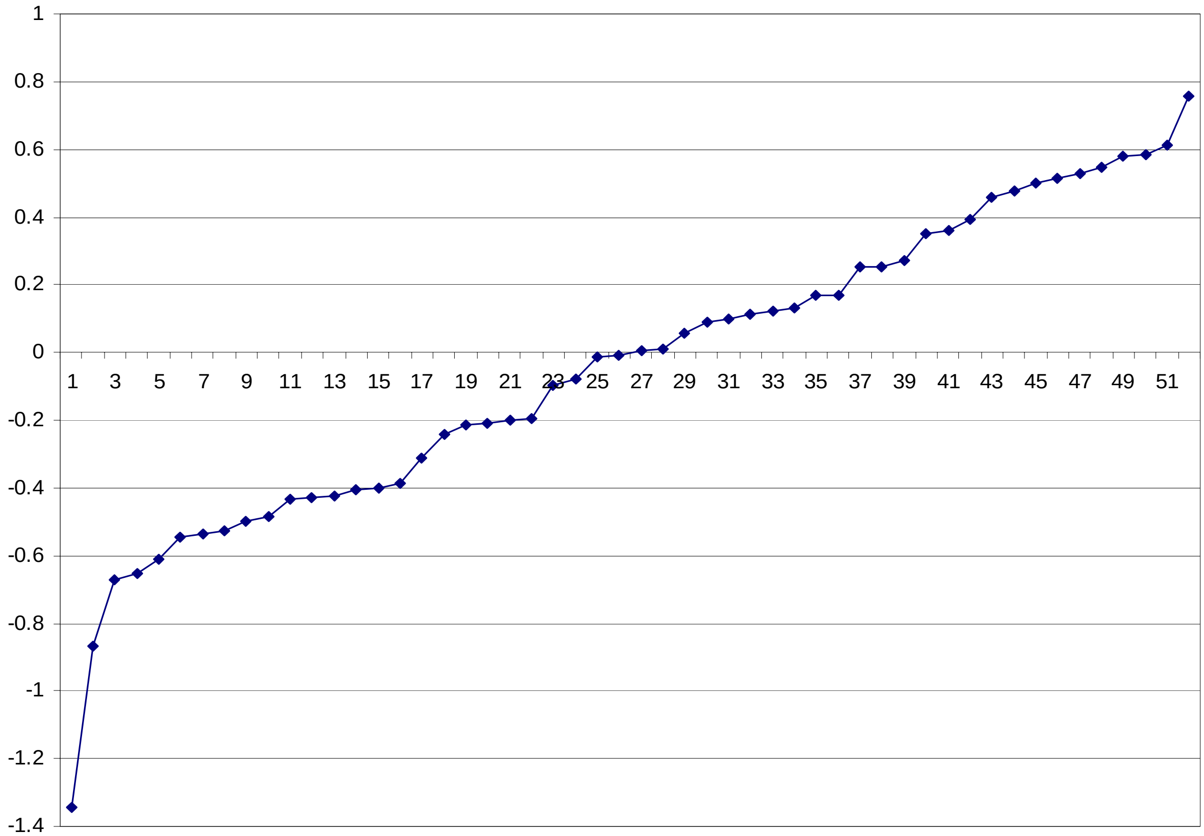
MONETARY (Ranking of monetary compensation)	**CAREER** (Ranking of impact on career advancement)					
	1	2	3	4	5	6
1	26	20	3	1		
2	20	25	3	2		
3	4	3	13	1		1
4		4	1	3		
5					1	
6				1		

Table A3d: Money and Flexibility

MONETARY (Ranking of monetary compensation)	**FLEXIBILITY** (Ranking of offer in terms of flexibility to choose research projects)					
	1	2	3	4	5	6
1	16	19	8	1		
2	25	17	2	1		
3	5	5	8	1		1
4	2	1	1	2		
5					1	
6		1				

FIGURE 1

Distribution of Individual Fixed Effects Coefficients in Regression (3-3)



By Ascending Rank of Individual Fixed Effect

Number of Individuals = 52