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David E. Ervin
Portland State University

Steven T. Buccola
Oregon State University

Hui Yang

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Research Choice and Finance in University Bioscience

Steven Buccola,* David Ervin,† and Hui Yang‡

Academic bioscience's rising importance for downstream technology and growing private sector relationships have evoked substantial policy attention. We contribute to the scrutiny by asking how university bioscientists design and finance their research, with particular attention to the mutuality of research portfolio choice and funding success. The analysis requires consideration of other major influences on academic science, including scientific norms, human capital, and institutional environment. Drawing on a national survey of university bioscientists, we find that public financial support encourages more basic investigation and private support encourages more applied investigation. Yet downstream research is only moderately more excludable than upstream. Once research basicness and other program factors are accounted for, neither the next public nor the next private dollar brings significantly more excludable laboratory discoveries. Public money is attracted to applied and excludable research, and private and public funding crowd each other out at the margin. Professional norms have substantial impacts on the research pursued and financing obtained. 1

JEL Classification: O31, O32, O33, O34, O38

1. Introduction

Much of the economics of science is concerned with factors underlying the direction and productivity of laboratory work. The factors are highly varied, including alternative elaborations of the scientist's incentive structure, human capital and training, specialty field and scientific opportunities, laboratory infrastructure and assistance, professional network and culture, and institutional reputation and support. Policy implications include research institution design (Holmstrom 1989), administrative structure (Landry and Amara 1998), reporting protocols (Levitt and Snyder 1997), strength and structure of intellectual property rights (Thursby and Thursby 2003; Dillon 2005), and size and allocation of public funding (Cockburn and Henderson 1998; David, Hall, and Toole 1999; Diamond 1999).

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* 213 Ballard Hall, Oregon State University, Corvallis, OR 97331, USA; E-mail sbuccola@oregonstate.edu; corresponding author.

† Portland State University, 241M Cramer Hall, Portland, OR 97207, USA; E-mail dervin@pdx.edu.

‡ Bank of America, 315 Montgomery St., San Francisco, CA 94104-1866, USA; E-mail hui.yang@bankofamerica.com.

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The importance of such work lies in the broad social controversy over whether, and if so how, publics ought to intervene in the traditionally autonomous character of scientific communities; for example, by encouraging greater exposure to market forces. Dasgupta and David (1994) argue that economic forces normally conducive to dynamic efficiency are unavailable in the relations between university-based open science and commercial research and development (R&D). Perhaps as a result, popular opinion about scientific work reflects widely divergent opinions ranging from an awe of science's obvious technological power to a suspicion that it has betrayed the social good by selling itself to commercial interests (Sheldon 2003).

A major obstacle in evaluating these concerns, and in guiding public policy, is the partly ineffable nature of scientific knowledge. Scientific inputs and outputs are difficult for third parties to monitor or measure, so scientists have substantial control over how and whether their results are disseminated. And science often is pursued—at least in academia—for nonmonetary rewards that are difficult to elucidate, quantify, or observe (Dasgupta and Maskin 1987; Rosenberg and Nelson 1994; Stephan 1996). Price-mediated supply and demand models are, in particular, largely inappropriate to upstream scientific inquiry. Following Merton (1973), analysis instead has focused on how scientists' choices are influenced by their norms, reward structures, and institutional environments. Much empirical work is confined to subsets of factors for which data are available and which illuminate selected topics (Breschi, Lissoni, and Montobbio 2005; Walsh, Cho, and Cohen 2005; Azoulay, Ding, and Stuart 2007). Cohen, Nelson, and Walsh (2002) trace impacts of public research on industry R&D success. Agrawal and Henderson (2002) and Geuna et al. (2004) examine faculty-industry program and funding relationships in a single university. Others concentrate on generic differences in the way upstream and downstream research is best managed (Aghion, Dewatripont, and Stein 2005).

We contribute to this literature by developing and estimating a bench-level model of how a subset of university bioscientists design, finance, and communicate their research. The model enables us to address in a new way some of the fundamental questions in public science policy: Does private support steer university research toward more applied or privately appropriable inventions and thus away from publicly accessible knowledge? In this Bayh-Dole era, is basic research still substantially less excludable than applied research? Does private funding facilitate public funding or vice-versa? How do investigators' professional norms affect what they study? These topics cannot adequately be addressed without considering other major influences on academic science, including human capital, institutional environment, and in-kind contract terms (Xie and Shauman 1998).

We draw on literature in both the time-series and cross-sectional dimensions. The time-series tradition has focused on aggregate scientific effort and outcome, embodied in research input-output relations and factor demands (Jaffe 1989; Griliches 1990; Jaffe, Trajtenberg, and Henderson 1993) or scientific labor supplies (Levin and Stephan 1991; Ehrenberg 1992; Leslie and Oaxaca 1993). The cross-sectional tradition instead has concentrated on research programs themselves, allowing a detailed look at scientists' objectives, funding sources, and institutional environments. Studies of university-industry relationships by Blumenthal et al. (1986, 1996), Curry and Kenney (1990), Campbell and Bendavid (2003), Breschi, Lissoni, and Montobbio (2005), and Walsh, Cho, and Cohen (2005) fall in this genre. So do Mansfield's (1995, 1998) surveys of research firms' university relationships; Hall, Link, and Scott's (2003) analysis of commercial research projects; and Zucker, Darby, and Brewer's (1998) and Toole and Czarnitzki's (2005) focus on the influence of leading academic scientists. Huffman and Evenson

(1993) have characterized the culture and institutional environment of university agricultural research in particular.

We assume markets are indeed present in academic bioresearch in an implicit sense. Funding agents provide support to university bioscientists in exchange for research with certain goals. Scientists pursue research plans in exchange for monetary and in-kind support and for the journal publications that enhance their professional careers.[1] Scientists' laboratory plans depend on the financial support they attract and on the scientists' human capital, professional norms, research discipline, and university environment.

Our 2003–2004 survey of university bioscientists conducting agriculturally related work gives insight into relationships as yet unexamined in the literature. For example, less patentable or excludable research tends to be more basic, and more basic research less excludable, suggesting policies that strengthen intellectual property rights promote applied research at the expense of basic research. However, the relationship between basicness and nonexcludability is, controlling for other factors, rather weak. Furthermore, public funding encourages a research that is more basic but, likely on account of Bayh-Dole influences, more excludable as well. Private funding promotes work that is more applied *and* more excludable. The volume of public and private support to an individual scientist militate each other.

2. Research Program Choice

University scientists are motivated by a variety of interests, among them prestige, scientific curiosity, money for themselves and their laboratories, and professional or ethical norms (Merton 1973). Achieving one depends partly on the others. Curiosity is indulged directly through the type of research conducted. Prestige depends on the type of research, on publication success, and on grant performance, the last depending in turn on research type, publishing record and grantsmanship effort, and university infrastructure.

Decision Elements

To express these relationships more schematically, consider a scientist with utility

$$U = U(\mathbf{C}, \mathbf{G};\ \mathbf{X}, \mathbf{N}), \tag{1}$$

where $\mathbf{C}$ is the vector of research program characteristics; $\mathbf{G}$ is its research budgets distinguished by funding source; $\mathbf{N}$ is the scientist's professional norms; and $\mathbf{X}$ is other variables such as the scientist's human capital and her university's culture and infrastructure. Equation 1 allows, through $\mathbf{N}$, an explicit representation of the scientist's utility preferences about the substance and conduct of academic research. We assume she chooses research program characteristics $\mathbf{C}$ that maximize Equation 1, with first-order conditions

$$C_i = C_i\left(\mathbf{C}_{j \neq i}, \mathbf{G};\ \mathbf{X}, \mathbf{N}_{C_i}\right), \quad \forall i, j, \tag{2}$$

where i, j index the elements of $\mathbf{C}$, and $\mathbf{N}_{C_i}$ are the scientist's professional norms relevant to the ith research characteristic.

[1] Ward and Dranove (1995) offer a related discussion of journals and funding agencies as consumers of academic work.

In a long-run setting, the scientist does not take financing opportunities **G** in Equation 1 as given. Rather, they depend on research program choices **C**, on human capital and other exogenous factors **X**, and on unobservable efforts the scientist and her university devote to winning grants from particular sources. Denoting such efforts $\mathbf{E}_{G_m}$, we may specify the grant-effort success functions as $G_m = G_m(G_{n \neq m}, \mathbf{C}\ ;\ \mathbf{X}, \mathbf{E}_{G_m})$, where m, n index funding sources. Grant-writing effort is related to the utility importance the scientist and university attach to grants. Letting $\mathbf{N}_{G_m}$ be the subset of professional norms associated with preferences for grant support from the mth agency, we can rewrite the scientist's grant successes in estimable form

$$G_m = G_m(G_{n \neq m}, \mathbf{C};\ \mathbf{X}, \mathbf{N}_{G_m}) \quad \forall m, n, \tag{3}$$

where $\mathbf{N}_{G_m}$ is an observable proxy for $\mathbf{E}_{G_m}$. Equation 3 expresses potential jointness among research funding successes, often called crowd-in or crowd-out effects. The scientist's long-run optimization problem consists of solving the first-order conditions in Equation 2 simultaneously with the funding-success relations in Equation 3.

Measures of professional or business norms, sometimes called propensities, have been employed extensively in models of scientific behavior (e.g., Merton 1973; Jaffe 1986; Harter 1994; Hall, Jaffe, and Trajtenberg 2001; Thursby and Thursby 2002; Campbell and Bendavid 2003; Stern 2004; Walsh, Cho, and Cohen 2005). Only broad proxies to such preferences are normally possible with aggregate time series, while more direct observations can be obtained with individual scientist data. In any event, allowing directly for professional norms seems particularly important in scientist-level studies, because variations in utility parameters and thus unobservable effort would not otherwise be taken into account (Green 2003). Equations 2 and 3 make that explicit.

Two characteristics of scientific research are especially important from a policy standpoint: how basic the research is and how privately appropriable are its findings. Basic research is an investment in future applied discoveries, while applied work leads to more immediate economic gain. Socially optimal combinations of basic and applied effort therefore turn on such issues as the rate of time discount, spillovers between science and technology, and government's proper place on the basic-applied continuum (Dasgupta and David 1994). Optimal mixes of private- and public-good knowledge instead turn on questions of access and incentive. The more publicly appropriable the research findings, the more quickly they may be disseminated but the weaker the incentive to produce them. As scientific knowledge is largely nonrival (Romer 1990), we concentrate on its excludability: the legal and economic feasibility of preventing others from exploiting it without the scientist's and university's permission.

A principal issue in the science policy debate is the appropriate role of the private sector in university research funding. Many argue industry and other private finance unduly influence the university research agenda, skewing it toward more applied and excludable inventions, unfairly extracting rents from tax-financed research, and undermining the culture of free scientific inquiry (e.g., Bok 2003). Proponents say private finance facilitates the economic exploitation of academic innovations and supplements scarce government funds for academic research (e.g., Dillon 2005). Empirical work on this question has been substantial. Blumenthal et al. (1986, 1996), for example, find industry support boosts publishing and patenting rates but encourages greater research secrecy. Curry and Kenney (1990) conclude that industry funding is associated with relatively low academic output. Campbell and Bendavid (2003) show that industry contracts tend to delay the reporting of laboratory results. Breschi, Lissoni, and

Montobbio (2005) find that while laboratory productivity is strengthened by industry contacts, basic research boosts, rather than competes with, applied research.

More generally, both the literature and our own conversations with university bioscientists suggest, *ceteris paribus*, that (i) basic investigation tends to involve less excludable findings than does applied investigation; (ii) better-published and more commercially oriented academic scientists attract more funds than others do; and (iii) government research sponsorship attracts industry sponsorship. Impacts of research funding source on laboratory objectives are more controversial. All such hypotheses might be sensitive to research topic area, finance contract terms, and synergies between basic molecular results and downstream drug and plant discoveries.

3. Survey Data and Econometric Model

National Survey

Our national survey targeted academic investigators conducting basic or applied research at the molecular or cellular level with implications for agricultural, forestry, or aquaculture biotechnologies. The survey was conducted October 2003 through March 2004, followed by database development in 2005–2006. A five-step process was used in constructing the sample frame.

(a) Universities listed under the 2000 Carnegie Classification's "Research Universities—Extensive" category were divided into Land Grant (LGU), public non–Land-Grant (non-LGU), and private. Twenty universities initially were randomly sampled from each stratum.

(b) Departments identified by website as potentially involved in agriculturally related biotechnology were organized into subject categories, 36 among LGUs and 28 among non-LGUs. These categories were then reviewed independently by six bioscientists, each selecting the 15 most likely to contain the highest concentrations of our target population. Using only the categories four or more scientists agreed upon, 9 were identified in the non-LGU strata and 11 in the LGU stratum. Final department categories among the LGUs were agronomy, animal science, aquaculture, biotechnology, botany, cell and molecular biology, crop sciences, forestry, horticulture, pathology, and physiology. Among the non-LGUs, they consisted of biochemistry, biotechnology, biology, botany, cell and molecular biology, fisheries, forestry, genetics, and microbiology. Non-LGU departments included a large number of medical schools, whose work in pathology, pharmacology, neurology, microbiology, and immunology frequently has agricultural implications. Hence, our sample frame extends well beyond departments with specifically agricultural orientations.

(c) Chairs of the selected departments were asked to identify their faculty satisfying the target population definition. Chair response rate was 75.7% among LGUs, 71.0% among public non-LGUs, and 73.5% among private universities.

(d) Of these, 595 faculty were randomly sampled from those identified by LGU department chairs. All 280 public non-LGU faculty and all 250 private university faculty were maintained in the sample.

(e) Because of the relatively low target population densities in non-LGU universities, an additional 10 institutions were each drawn randomly from the public non-LGU and private university strata.[2] From this second sampling stage, we added 220 faculty to the public non-LGU stratum and 96 to the private university stratum, bringing the total sample to 1441 scientists.

The survey was constructed following the tailored design method (Dillman 2000) in collaboration with the Social and Economic Research Center at Washington State University. Cognitive pre-tests, a focus group of nonsample bioscientists, and sample pre-tests were used to refine the instrument structure and content. A letter was sent to potential respondents directing them to our online survey instrument, together with a $5 cash payment to indicate the seriousness of the request. Response rate was 63.8%.[3]

The survey instrument asked scientists to indicate, on a 1–6 Likert scale, the degree of basicness of their research program and the nonexcludability of a typical research finding. It then asked for the percentages of the scientist's program allocated to basic and applied research, and the percentages devoted to excludable and nonexcludable outcomes. ''Basic'' was defined as referring to how fundamental are the expected discoveries, and ''applied'' to how oriented they are toward product development. Excludability refers instead to the expected legal and economic feasibility of excluding anyone from using the results. See the Appendix for the survey definitions and examples of these concepts provided to survey respondents.[4] Analysis in the present paper is drawn from the percentage of program responses. ''Program'' is defined to include all the scientist's projects, whether or not separately identifiable in funding source or time allocation.

Other data requested were (i) annualized budgets by funding source; (ii) intensities of view on a range of motivating norms in professional life; (iii) laboratory assistance, divided into postdoctoral fellows, graduate students, and technicians; (iv) academic rank and professional experience; (v) in-kind contributions: materials (cell lines and reagents), capital (laboratory equipment, genomic databases, and software), services (student training and staff support), or other support; (vi) mean annual journal article output[5]; (vii) university assistance with funding and technology transfer; and (viii) the scientist's biological discipline (biochemistry, genetics, cell/molecular biology, physiology/pathology, ecology, or other), and field (plant and animal characteristics and protection, human health and nutrition, natural resources and environment, or microbes).

Table 1 displays the relevant survey variables and Table 2 their sample statistics. The mean respondent devotes 67% of his program to basic and 85% to nonexcludable research. But the high associated standard deviations (31% and 21%), respectively, suggest research basicness

[2] Response rate from this second group of department chairs was 65.7% among public non-LGUs and 54.3% among private non-LGUs.

[3] Sample size for the analysis that follows was 672 (after removing the 247 of the 919 survey responses that contained missing values). Response bias was checked with an email survey of the 433 non-respondents. The 58 responses to the query suggested nonrespondents conduct somewhat more basic research, publish more, and have a higher percentage of industry funding than do respondents.

[4] Some aspects of a given project may be more applied or excludable than other aspects of the same project. For example, Gittelman and Kogut (2003) and Murray and Stern (2007) consider instances in which a project generates both publications and patents. Such instances are consistent with both our Likert and percent-of-program characterizations of respondents' work.

[5] Ward and Dranove (1995) similarly use unweighted journal article counts as measures of the importance of specified drugs. Dranove and Meltzer (1994) find unweighted counts are highly correlated with other drug-importance measures.

Table 1. Definitions of Variables

Variable	Definition
Research program characteristics	
Basic%	Percentage of research program allocated to basic research
NExcl%	Percentage of research program allocated to nonexcludable research
Research funding categories	
G_{Public}	Annual research funding from federal and state sources
$G_{Private}$	Annual research funding from industry (firm and trade association) and foundation sources
Scientist's norms	
	Extent of scientist's agreement, on a Likert scale, that the following norms are important in her choice of research goals and money sources. Unasterisked norms were measured on a 7-point scale in which 1 indicates "not important" and 7 "very important." Asterisked norms are on a 6-point scale in which 1 indicates "disagree" and 6 "agree."
N_{Theory}	Contributes to scientific theory
$N_{Curiosity}$	Appeals to scientific curiosity
$N_{ProbPatent}$	Provides opportunities to patent and license
$N_{Nexcl\ Benef}$	Provides opportunities to produce nonexcludable benefits*
$N_{Panel\ Agenda}$	Scientist panels should determine research agenda*
$N_{Public\ Funding}$	Involves availability of public funding
$N_{Industry\ Agenda}$	Industry should influence research agenda*
$N_{Private\ Funding}$	Involves availability of private or corporate funding
Scientist's rank and output	
Prof, *Assoc*, and *Assis*	Zero/one variables respectively indicating whether the scientist is a professor, associate professor, or assistant professor
Publ Rate	Annual number of articles published between January 2000 and December 2004
Characteristics of Scientist's University	
LG, *PNLG*, *Private*	Zero/one variables indicating whether scientist's university is a LGU, public non-LGU, or private university, respectively.

and nonexcludability are distributed broadly.[6] Emphasis on research with agricultural implications does little, therefore, to limit the sample to applied or patentable work.

A scientist's mean annual public (federal and state) support was \$229,000, and mean private (industry and foundation) support was \$51,000. On average, 42% of federal support was from the National Institutes of Health (NIH), 23% from the National Science Foundation (NSF), and 24% from the U.S. Department of Agriculture. The high NIH shares confirm findings from patent analysis that pharmaceutical and agricultural research have become deeply intertwined (Pray, Oehmke, and Naseem 2005; Xia and Buccola 2005). State funding constituted 19% of federal and state money. Forty-one percent of private support was from biotechnology firms and trade associations, 36% from private foundations, and the remainder

[6] These percent-of-program responses were consistent with the scientists' Likert-scale responses. On a 6-point scale in which 1 indicated their research program was "purely basic" and 6 "purely applied," the mean response was 2.67 and standard deviation 1.35. On a 6-point scale in which 1 indicated the program was "completely nonexcludable" and 6 "completely excludable," the mean was 1.92 and standard deviation 1.06. That is, programs tend to the basic and nonexcludable ends of the spectra, although a substantial number are applied and excludable.

Table 2. Sample Statistics

Variable	Units	Mean	Standard Deviation
Research program characteristics			
Basic%	% of program	67.40	30.78
NExcl%	% of program	85.15	20.67
Research funding categories			
G_{Public}	$000/year	229.33	343.43
$G_{Private}$	$000/year	50.59	121.48
Scientist's norms			
N_{Theory}	1 not, 7 very	6.06	1.44
$N_{Curiosity}$	1 not, 7 very	6.43	0.93
$N_{Prob\ patenting}$	1 not, 7 very	2.00	1.47
$N_{Nexcl\ Benefit}$	1 disagree, 6 agree	4.97	1.06
$N_{Panel\ Agenda}$	1 disagree, 6 agree	4.49	1.26
$N_{Public\ Funding}$	1 not, 7 very	5.56	1.71
$N_{Industry\ Agenda}$	1 disagree, 6 agree	2.94	1.03
$N_{Private\ Funding}$	1 not, 7 very	3.17	2.10
Scientist's rank and output			
Professor	0 or 1	0.49	0.50
Associate Professor	0 or 1	0.25	0.43
Assistant Professor	0 or 1	0.26	0.44
Publication Rate	annual pubs since 01/2000	3.75	3.15
Characteristics of scientist's university			
LG	0 or 1	0.47	0.50
PNLG	0 or 1	0.35	0.48
Private	0 or 1	0.18	0.36

from other private sources.[7] However, as the standard deviations indicate, scientists' budgets varied widely. About one-third of respondents had total annual support of $100,000 or less, 37% had between $100,000 and $250,000, and 10% had over $500,000.

Scientists tended to value theoretical contributions and scientific curiosity highly (means 6.0 and 6.4, respectively, on a 7-point scale). They cared rather less about patenting (mean 2.0 on a 7-point scale) and typically believed publicly supported scientists should focus on knowledge with nonexcludable benefits (mean 5.0 on a 6-point scale). Their tendency was to regard public funding as important to science (5.6 on a 7-point scale) and private funding less so (3.2 on a 7-point scale). Most leaned toward thinking science panels should determine university research agendas (4.5 on a 6-point scale); fewer thought industry should have a significant hand in them (2.9 on 6-point scale). However, dispersions around these means—particularly in industry's proper role in the research agenda—are moderately high, with standard deviations ranging from 0.9 to 2.1. The average scientist had published 3.75 journal articles per year since January 2000; but as one would expect, publication rates varied widely and were strongly right-skewed.[8] Forty-nine percent held professor rank. In short, substantial

[7] Industry, including firms and trade associations, provides just under 10% of assistance to the mean scientist in our sample, compared with the 6% it contributes to all (biological and nonbiological) U.S. university research funds (National Science Foundation 2004).

[8] Twenty-four percent of respondents receive research materials as part of their grant, contract, or gift; 40% receive capital items; and nearly 50% receive in-kind services, chiefly student training and internships.

sample variety is apparent in scientists' research designs and objectives, budgets, productivities, and professional norms.

Econometric Model

Our interest is in the interdependencies between academic bioresearch programs and the public and private support provided to them. Scientists supply research and demand funding; funders demand research and supply funding. Nevertheless, although science characteristics (Equation 2) and funding (Equation 3) are derived from the scientist's utility function, Equation 2 is econometrically identified as a set of supplies and Equation 3 as a set of demands only to the extent that control factors $\mathbf{X}$, $\mathbf{N}_{C_i}$, and $\mathbf{N}_{G_m}$ depict scientists' rather than funders' costs and preferences. Much of the information obtainable in cross-sectional surveys about scientists' institutional and human capital—such as rank, publication record, discipline, and university characteristics—is relevant to and can be observed by the funder as well as by the scientist and econometrician. As observed by the scientist, they represent perceptions of research cost; as observed by the funder, they represent perceptions of research quality. Such common variables thus serve to give Equations 2 and 3 both a supply and demand force. Furthermore, many—like scientist rank—are relevant to decisions about both science characteristics and science funding decisions.

However, because our data on scientist norms, $\mathbf{N}_{C_i}$, are specific to particular research dimensions *i*, *j* and funding sources *m*, *n*, and change little within the one- to five-year time horizons of most science projects and grants, they are especially suitable for identification purposes. Indicators of scientists' ethical views about, for example, public research funding, serve as proxies for federal and state grant effort and thus identify the relationship between research basicness and public funding as a public-funding-success equation, provided that comparably unique effort proxies are included in the remaining equations. Because norms about private funding, research excludability, and basicness have no direct bearing on those about public funding, their exclusion from the basicness equation provides the random variation tracing out fundings' impacts on basicness.

With these considerations in mind, we specify the following set of simultaneous equations:

Research Characteristics

$$Basic\% = g_1\left(NExcl\%, G_{public}, G_{Private}; \mathbf{X}, \mathbf{N}_{Basic}, \varepsilon_b\right), \tag{4}$$

$$NExcl\% = g_2(Basic\%, G_{Public}, G_{Private}; \mathbf{X}, \mathbf{N}_{NExcl}, \varepsilon_n), \tag{5}$$

Grant Funding

$$G_{Public} = g_3\left(G_{Private}, Basic\%, NExcl\%; \mathbf{X}, \mathbf{N}_{Public}, \varepsilon_{pu}\right), \tag{6}$$

$$G_{Private} = g_4\left(G_{Public}, Basic\%, NExcl\%; \mathbf{X}, \mathbf{N}_{Private}, \varepsilon_{pr}\right), \tag{7}$$

in which $\mathbf{C} = Basic\%, NExcl\%$, $\mathbf{G} = G_{Public}, G_{Private}$ (see Table 1) are endogenous; $\mathbf{X}$ is the vector of exogenous human and institutional capital variables observed by both scientist and funder; $\mathbf{N}_{C_i} = (\mathbf{N}_{Basic}, \mathbf{N}_{NExcl})$ and $\mathbf{N}_{C_i} = \mathbf{N}_{Public}, \mathbf{N}_{Private}, \mathbf{N}_{Private}$ are the excluded instruments indicating, respectively, the scientist's professional norms regarding basic and nonexcludable research and public and private funding; and ε_{ba}, ε_{ne}, ε_{pu}, and ε_{pr} are zero-mean error terms independent of **X** and **N**.

We use the scientist's academic rank (full, associate, or assistant professor) and university type (LGU, public non-LGU, and private) to model the commonly observable human and institutional capital variables **X**. University type and academic rank were, respectively, nonsignificant in the nonexcludability and funding equations and were excluded from those equations. Biological discipline, biological field, laboratory staff configuration, and in-kind contract provisions also are natural candidates for capital factors but had rather weak impacts in Equations 4–7 and were, in the interest of parsimony, eliminated from both the regressions and instruments.[9] The surveyed norm indicators relevant to Equations 4–7 are defined in Table 1: theory and curiosity norms bearing on the program's basicness, patenting and nonexcludability norms on its excludability, panel-style agenda control and public-financing norms affecting efforts to secure public funding, and industry agenda control and corporate-financing norms affecting efforts to secure private funding. Because the scientist's publication record presumably offers funders important information about a proposed project's quality, we also include it as an explanatory factor in public and private funding success in Equations 6 and 7.

Two issues stand out in the choice of estimator for Equations 4–7: endogenous variable truncation and missing common effects. The truncation issue is that some respondents reported no public support and others no private support, so that error terms in linear fits of Equations 6 and 7 probably are not exactly normally distributed. The common effects problem is that one ought to account not only for endogenous variables' mutual impacts on one another, but for the influences on each that are unaccounted for in the model. Although two-stage logit procedures might be constructed on an equation-by-equation basis to model any individual error truncation, it is impractical in a four-equation system to proceed to a third stage incorporating systemwide effects.[10] Particularly with scientist-level cross section data, in which the number of missing variables and, hence, magnitude of the common-effects problem likely is substantial, we judged it more important to focus on the system than on the truncation issue. We therefore jointly estimated Equations 4–7 in linear form with three stage least squares (SAS Institute 2005).

4. Results

First-stage estimates, in which endogenous variables *Basic%*, *NExcl%*, G_{Public}, and $G_{Private}$ were each regressed against instruments (**X**, **N**), had respective R^2s 0.45, 0.25, 0.23, and 0.18, not inconsiderable for cross-sectional data, but indicating a comparative difficulty in modeling private funding success. *F*-statistics of the joint significance of the excluded instruments in these

[9] University technology-transfer effort, total university federal- and state-financed research budgets, and university biological and agricultural program rankings also were typically nonsignificant factors and dropped from the analysis.

[10] Packaged programs capable of estimating simultaneous systems with multiple truncated endogenous variables are presently unavailable. Lee (1995) and Dionne and Triki (2004) employ minimum-distance-estimator (MDE) methods to fit simultaneous equations in which at least one endogenous variable is censored. However, neither model admits more than two simultaneous equations.

Table 3. System Estimates: Determinants of Life-Science Research Characteristics and Funding Sources[a]

	Basicness ($Basic\%$)		Non-Excludability ($NExcl\%$)		Public Funding (G_{Public})		Private Funding ($G_{Private}$)	
Variable	*Parameter*	*t*	*Parameter*	*t*	*Parameter*	*t*	*Parameter*	*t*
Intercept	−6.68	−0.48	75.60	5.47	638.79	3.11	227.51	3.46
Research program characteristics								
$Basic\%$			*0.16*	*3.29*	*−2.10*	*−1.82*	*−0.90*	*−2.40*
$NExcl\%$	*0.27*	*2.11*			*−3.06*	*−1.65*	*−0.99*	*−1.48*
Research funding								
G_{Public}	*0.03*	*2.99*	*−0.01*	*−0.93*			*−0.31*	*−5.18*
$G_{Private}$	*−0.16*	*−5.85*	*0.03*	*1.31*	*−2.21*	*−4.46*		
Scientist's norms								
N_{Theory}	6.60	7.35						
$N_{Curiosity}$	4.12	3.42						
$N_{Prob\ Patenting}$			−5.72	−11.56				
$N_{NExcl\ Benef}$			1.65	2.55				
$N_{Panel\ Agenda}$					7.70	1.59		
$N_{Public\ Funding}$					2.72	0.44		
$N_{Industry\ Agenda}$							3.67	1.53
$N_{Private\ Funding}$							3.19	2.05
Scientist's rank and productivity								
Prof	−4.31	−1.57	4.99	2.61				
Assoc (base group: Assist. Prof)	−2.01	−0.75	5.63	2.83				
Publ. Rate					23.14	8.97	8.32	7.65
University characteristics								
LG	−18.00	−4.66			−263.27	−4.67	−96.37	−4.49
PNLG (base group: Private Univ)	−6.18	−1.61			−179.64	−3.57	−61.73	−3.06

[a] Coefficients of endogenous variables are shown in italics ($N = 672$).

regressions were 17.23, 6.33, 2.60, and 4.67, respectively, compared to the tabled values $F(9, 733) = 2.41$, $F(8, 679) = 2.51$, $F(8, 679) = 2.51$, and $F(7, 679) = 2.64$, at 1% significance.

The third-stage 3SLS estimates, shown in Table 3, were robust to specification changes, including disaggregation of the two grant-funding equations into three, aggregation into one, and use of Likert-scale rather than percentage-of-scientist-time measures of basicness and nonexcludability in Equations 4 and 5. An interesting source of additional robustness testing is that, despite filling out our survey, 30% of respondents said their research is not conducted at the molecular level or has no implications for agriculture, forestry, or aquaculture. Coefficients obtained by removing this 30% subset and re-estimating differed insignificantly in Wald tests from those drawn from the full sample, suggesting the results apply to a comparatively broad range of bioscientific work.

Research Basicness and Excludability

An important first insight from Table 3 is that, although a scientist's supply of basic research boosts her supply of nonexcludable research and vice versa, the impacts are only moderate and are far from symmetric. A one-percentage-point rise in the nonexcludable portion of the research program boosts the basic portion by 0.27 percentage points ($t = 2.11$), while a one-point rise in basicness boosts nonexcludability by only 0.16 points ($t = 3.29$). Nonexcludability's impact on basicness likely was enhanced—and the latter's influence on the former reduced—by the 1980 Bayh-Dole Act and related court rulings, which in permitting federally funded scientists to patent living organisms allowed a wider range of basic molecular research to become excludable. But asymmetry between basicness and nonexcludability is more than an artifact of intellectual property scope. The Patent Office's "new, non-obvious, and useful" hurdle remains, even after 1980, easier to surmount in more applied settings for the simple reason that the potential number of applied innovations remains greater than that of basic ones.

Consistent with Blumenthal et al. (1986), but contrary to suggestions in Thursby and Thursby (2003), research basicness appears to be affected by the sources and magnitudes of grant funds. Boosting federal and state monetary support by $1000 induces a 0.03 percentage-point increase in the basic portion of the scientist's research portfolio ($t = 3.0$). Boosting industry and foundation support by $1000 acts in the opposite direction, increasing the program's applied portion by 0.16 percentage points ($t = -5.8$). That is, the marginal public (private) dollar encourages more basic (applied) research even when the excludability of the findings and the scientist's professional norms and university culture are held constant. The canonical perception that the presence of government money in the university laboratory encourages basic research while the presence of industry money encourages applied research is verified under strong *ceteris paribus* conditions.

It is revealing to examine these money-source effects in proportional terms. At sample means, a 10% increase in public funding lifts program basicness by 1.0%, and a 10% increase in private funding reduces basicness by 1.2%. Expressed as elasticities, in other words, public funding's impacts on a research program's basic-versus-applied content are greater relative to private funding's impacts than they would be had they been expressed in marginal terms, since the large total size of public funds means a given dollar increase represents a comparatively small proportional rise. Funding elasticities of program basicness in the range of 0.10 to 0.12 are substantial considering that scientists often can switch the organisms, disease types, or other topics on which they focus while continuing to work at a given level of basicness and excludability. Higher elasticities, in other words, likely would have been encountered had more specific program metrics, such as laboratory organism, been studied instead.

In contrast, neither public nor private funding have, in the aggregate, a statistically significant effect on research excludability. The nonsignificance of any public funding impact appears to undermine the notion of a Bayh-Dole phenomenon, namely that public agencies encourage the university scientists they fund to propose projects with patenting, variety certification, or other exclusionary goals. Yet if public money did significantly discourage excludable research in pre–Bayh-Dole days, present nonsignificance of the average public-money effect does represent an important change. Furthermore, applied federal research agencies, such as the NIH, presumably encourage more excludable investigation than does, for example, the NSF.[11] The nonsignificance of private-source impacts on research excludability is understandable in several respects. First, private sources in this study include not-for-profit

[11] In other research, we document significant differences among federal and state agencies in the excludability impact of an additional dollar of scientist support.

foundations as well as for-profit firms. Second, even industry sponsors tell us they do not necessarily condition their support on promises of an exclusive license to the academic's findings. Some sponsorships are to pay for product-testing services, which universities are uniquely positioned to offer. Others are intended to buy broad access to the professor's tacit knowledge, network, and students rather than to property rights to a specific invention.

As Aghion, Dewatripont, and Stein (2005) suppose, freedom is one of the principal attractions of academic life. Up to promotion and salary considerations, professors study what they like and thus give weight to their personal utilities. Evidence in the sociological literature (see, for example, Thursby and Thursby 2002; Walsh, Cho, and Cohen 2005; and Stuart and Ding 2006) for the importance of professional norms in academic research is confirmed in Table 3. The more our respondents say they value theoretical contributions ($t = 7.3$) and scientific curiosity ($t = 3.4$) in their program choice, the more they opt to pursue basic research themselves, controlling for financial, human capital, and university culture considerations. The lower their declared regard for patenting ($t = -11.6$) and the greater it is for producing nonexcludable social benefits ($t = 2.5$), the more they opt for nonexcludable discoveries in their own laboratories. The effects are moderately large. At sample means, a 10% increment in the Likert indicator of an investigator's valuation of scientific curiosity boosts research basicness by 4%.[12]

Advancing professorial rank leads to successively more applied but more nonexcludable research. All else constant, professors devote 4.3 percentage points more of their work to applied research ($t = -1.6$), and 5.0 points more to nonexcludable work ($t = 2.6$) than do assistant professors. A career trend toward applied research likely reflects deteriorating comparative advantage at basic investigation. That likely is a vintage effect, induced through the passage of time. The greater orientation toward nonexcludability might instead reflect utility preferences not captured in the norm variables. If so, it would more likely be a generational than a vintage phenomenon, reflecting how older scientists had been trained in their craft in their early years. Stuart and Ding (2006) provide corroborating evidence of a generational trend toward commercially oriented academic science.

In strong evidence of the impact of university culture on individual scientist behavior, faculty at LGUs operate substantially more applied programs than do those at private universities, even after funding source, measured norms, and rank are controlled for. LGU bioscientists allocate 18 percentage points ($t = -4.7$) more of their program to applied research than do private university bioscientists, holding funding volumes, excludability, norms, and rank constant. This is consistent with the technological orientation of the Land-Grant system, and to Stuart and Ding's (2006) evidence of university-culture influences in science. University type had, however, nonsignificant effects on research excludability. Universities' total federally and industry-financed grant budgets, proxying for their preferences over research orientation, also were statistically nonsignificant, suggesting budget sizes alone are weak measures of university culture.

Grant Success

While the laboratory's *use* of public money encourages basic research, Table 3 shows that programs with more applied and excludable orientations are moderately more successful in

[12] Likert scales are neither continuous nor expressed on a ratio-scale metric, so elasticities based on them have only limited validity. We report an elasticity here with that caveat in mind.

attracting public money than are basic and nonexcludable programs. A one-percentage-point rise in a bioscience program's applied component brings $2,100 more annual public funding ($t = -1.8$; elasticity -0.6), and a one-percentage-point rise in its excludable component brings $3,060 more public funding ($t = -1.6$; elasticity -1.1). In its proclivity to fund, therefore, the typical federal and state agency does reveal a preference for applied and excludable, and potentially commercializable, research, even if—as Thursby and Thursby (2003) discuss—there are no plans to sell exclusive licenses to the finding. Unsurprisingly, the more applied and excludable the research, the greater is the industry and foundation money attracted as well. A one-percentage-point boost in a program's applied component brings $900 more private funding ($t = -2.4$; elasticity -1.2). The effect of boosting the excludability of one's research is similar, although with lower statistical significance ($t = -1.5$). In sum, complementarities between industry finance and academic research are found more at the applied and excludable than at the basic and nonexcludable ends of the academic research spectrum.

An issue of great importance to science policy and the endogenous growth literature is the extent of complementarity or substitutability between industry and government research. Much evidence suggests government-sponsored R&D encourages or "crowds-in" industry-sponsored R&D (e.g., Levy and Terleckyj 1983; Leyden and Link 1991; Robson 1993; Ward and Dranove 1995; Diamond 1999), while other evidence suggests a nonsignificant (Lichtenberg 1984) or negative (Lichtenberg 1988) influence. Because basic investigation enhances downstream discovery, crowding-in would be expected primarily when the government sponsorship is for basic research, the private sponsorship is for applied research, and the two expenditure streams are aggregated together (David, Mowery, and Steinmueller 1992; Cockburn and Henderson 1998; Azoulay, Ding, and Stuart 2007). Crowd-in therefore would especially be observed in data that, unlike our own, combine upstream and downstream expenditures (David, Hall, and Toole 2000). Thus also, the depiction in Table 3 (columns 3 and 4) of how public and private spending affect one another provides an acid test of the crowding-in hypothesis, inasmuch as research basicness and excludability are—along with scientist and university characteristics—held fixed.

The present results clearly suggest that public and private money crowd one another out. Raising the scientist's industry and foundation support by $1000 reduces his government support by $2,210 ($t = -4.5$). And raising his industry and foundation support by $1000 reduces his government support by $310 ($t = -5.2$). That is, more than the entire private finance, and 31% of the public finance, leaks out. These leakages are to be understood in a net sense; that is, once financing's impact on basicness and excludability, and the latters' reverse impacts on financing, are taken into account. We need also recall that Equations 4–7 reflect the scientist's demand as well as agency's supply of research money. Any funding leakages identified in it must therefore at least partly be self-induced: controlling for their professional-norm-related effort allocations, the crowding-out in Table 3 implies that scientists who cultivate public funding sources tend to neglect private sources, and vice versa. Studies concluding that public and private monies crowd each other in instead of out generally have not been conducted in such a controlled context.

Scientist norms in the public and private funding relationships in Table 3 have, like those in the basicness and nonexcludability relationships, the expected signs. Scientists draw more money from private sources to the degree they believe industry ought to have a substantial say in the university science agenda ($t = 1.5$) and that they consider private-funding prospects when making research plans ($t = 2.0$). They draw more money from government sources to the degree they believe (primarily public) scientific panels should determine the academic research agenda ($t = 1.6$).

Publication rate is a very strong predictor of grantsmanship. One more scientific article per year in the scientist's previous four-year resume brings $23,140 more in annual government grants ($t = 9.0$) and $8320 more in annual private grants ($t = 7.6$). Scientists at private universities raise significantly more money, from both public and private sources, than do those in public universities; and scientists at public non-LGUs raise more than do those at public LGUs. Since rank, publication record, and research basicness and excludability are accounted for in these effects, private universities appear to employ more successful researchers, demand fewer nonresearch activities from them, and provide a more entrepreneurial culture than do public universities. Institutions' national biological and agricultural program rankings did not significantly explain grant success.

5. Conclusions

We have inquired into the laboratories of academic bioscientists whose work has agricultural implications, focusing on the interactions between research portfolios and research funding. We find, under rather stringent *ceteris paribus* conditions, that federal and state support does encourage more basic research. This is consistent with a government that complements the private sector by supporting work that industry and foundations will not. That is, a pro basic-research policy seems a rational use of public money, since the study of basic molecular mechanisms—themselves public goods—fosters subsequent plant and drug development by reducing search costs. At the same time, industry and foundation support lead significantly to more applied investigation. A dollar of private money has, indeed, five times the leverage in moving research toward the applied direction as has a dollar of public money in moving it toward the basic direction.

Taken as an average across individual funding agencies, neither government nor private finance appears significantly to lead university research toward a patentable or otherwise excludable direction. On the other hand, bioscientists doing more applied work have more success than those doing basic work—and those promising more excludable discoveries greater success than those promising less excludable—in securing government funding. Indeed, academic scientists seeking the potential for intellectual property rights appear at least as well off looking for government as for industry and foundation money. This implied government pressure to foster more excludable discoveries is potentially troublesome. Although some university patenting is intended to prevent rather than facilitate private appropriation, university ownership of federally financed genes and platform technologies has contributed to tie-ups of laboratory intellectual property (Atkinson et al. 2003; National Academy of Sciences 2005). Creative institutions are needed to ameliorate these information blockages and, more generally, to promote public intellectual property use for nonmarket as well as commercial objectives.

An especially important factor in the scientist's ability to attract federal and state grants is her publication record. Government grant support responds, for example, three times more strongly than does industry and foundation support to another journal article in the scientist's resume. More broadly, scientists' professional norms play a major part in influencing research orientations, and successfully representing such norms in an econometric model is quite feasible. Indeed, parameter estimates arguably are biased in their absence, as variations in utility preferences, correlated with research program characterizations, otherwise would be present in error terms. Sizes of professional-norm parameters suggest that norms rival funding sources and university culture in influencing the types of research conducted and the sources of funding obtained. Dasgupta and David's (1994) emphasis on scientists' professional values appears to be well justified.

Appendix: Research Basicness and Nonexcludability

In our on-campus interviews, we found scientists to have a rather clear and consistent notion of research basicness, and a general but somewhat less distinct notion of the economists' meaning of research excludability. In the survey document, therefore, both terms were defined, but with greater attention to excludability. Care was taken that respondents recognize the difference between the two concepts, and in particular that a range of excludability can be encountered in either basic or applied research.

The survey document described basicness as follows:

By "purely basic," we mean experimental or theoretical discoveries that add to fundamental science and engineering knowledge (for example, fundamental genomics).

By "purely applied," we mean research that draws from basic or other applied research to create new products (for example, a transgenic plant).

The document described excludability as follows:

By "completely nonexcludable," we mean it is infeasible to exclude anyone from using the findings from your research. Examples from basic research include results that are not patentable and which you publish instead in a professional journal or other public outlet. Examples from applied research include processes which are patentable, but whose benefits are not legally or economically restrictable to paying parties (as in a salt-tolerance gene in a minor crop in a developing country).

By completely excludable, we mean it is fully feasible to exclude anyone from using the findings of your research. Examples from basic research include results which are patentable and for which users must obtain a license from the patent-holder. Examples from applied research include processes that are patentable and whose benefits are restrictable to paying parties (as in a gene for insect resistance in a major crop licensed for use in a developed country).

References

Aghion, P., M. Dewatripont, and J. C. Stein. 2005. Academic freedom, private-sector focus, and the process of innovation. Working Paper, Harvard University.

Agrawal, A., and R. Henderson. 2002. Putting patents in context: Exploring knowledge transfers from MIT. *Management Science* 48:44–60.

Atkinson, R. C., R. N. Beachy, G. Conway, et al. 2003. Public sector collaboration for agricultural IP management. *Science* 301:174–5.

Azoulay, P., W. Ding, T. Stuart. 2007. The determinants of faculty patenting behavior: Demographics or opportunities? *Journal of Economic Behavior and Organization* 63:573–6.

Breschi, S., F. Lissoni, and F. Montobbio. 2005. The scientific productivity of academic inventors. CESPRI Working Paper No. 168.

Blumenthal, D., E. G. Campbell, N. Causino, and K. S. Louis. 1996. Participation of life-science faculty in research relationships with industry. *New England Journal of Medicine* 335:1734–39.

Blumenthal, D., M. Gluck, K. S. Louis, M. Stoto, and D. Wise. 1986. University-industry research relationships in biotechnology: Implications for the university. *Science* 232:136–66.

Bok, D. 2003. *Universities in the marketplace: The commercialization of higher education*. Princeton, NJ: Princeton University Press.

Campbell, E., and E. Bendavid. 2003. Data-sharing and data-withholding in genetics and the life-sciences: Results of a national survey of technology transfer officers. *Journal of Health Care Law and Policy* 6:241–55.

Cockburn, I. M., and R. M. Henderson. 1998. Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *The Journal of Industrial Economics* 46:157–82.

Cohen, W. M., R. R. Nelson, and J. P. Walsh. 2002. Links and impacts: The influence of public research on industrial R&D. *Management Science* 48:1–23.

Curry, J., and M. Kenney. 1990. Land-grant university-industry relationships in biotechnology: A comparison with the non-land-grant research universities. *Rural Sociology* 55:44–57.

Dasgupta, P., and P. A. David. 1994. Toward a new economics of science. *Research Policy* 23:487–521. 2

Dasgupta, P., and E. Maskin. 1987. The simple economics of research portfolios. *Economic Journal* 97:581–95.

David, P. A., B. H. Hall, and A. A. Toole. 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy* 29:497–529.

David, P. A., D. Mowery, and W. Steinmueller. 1992. Analyzing the economic payoffs from basic research. *Economics of Innovation and New Technology* 2:73–90.

Diamond, A. M. 1999. Does federal funding 'crowd in' private funding of science? *Contemporary Economic Policy* 17:423–31.

Dillman, D. 2000. *Mail and internet surveys: The tailored design method.* 2nd edition. New York: John Wiley & Sons.

Dillon, S. 2005. At public universities, warnings of privatization. *New York Times*. 16 October 2005. Available at http://www.nytimes.com/2005/10/16/education/16college.html.

Dionne, G., and T. Triki. 2004. On risk management determinants: What really matters? HEC Montreal Risk Management Chair Working Paper No. 04-04.

Dranove, D., and D. Meltzer. 1994. Do important drugs reach the market sooner? *Rand Journal of Economics* 25:402–23.

Ehrenberg, R. 1992. The flow of new doctorates. *Journal of Economic Literature* 30:830–75.

Geuna, A., P. Llerena, M. Matt, and M. Savona. 2004. Collaboration between a research university and firms and other institutions. In *R&D, Innovation, and Competitiveness in the European Chemical Industry*, edited by F. Cesaroni, A. Gambardella, and W. Garcia-Fontes. Dordrecht: Kluwer Academic Publishers, pp. 145–73.

Gittelman, M., and B. Kogut. 2003. Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science* 49:366–82.

Green, W. 2003. *Econometric Analysis.* 5th edition. New York: Prentice Hall.

Griliches, Z. 1990. Patent statistics as economic indicators: A survey. *Journal of Economic Literature* 28:1661–1707.

Hall, B. H., A. N. Link, and J. T. Scott. 2003. Universities as research partners. *Review of Economics and Statistics* 85:485–91.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2001. The NBER patent citations data file: Lessons, insights, and methodological tools. NBER Working Paper No. 8498.

Harter, J. F. R. 1994. The propensity to patent with differentiated products. *Southern Economic Journal* 61:195–201.

Holmstrom, B. 1989. Agency costs and innovation. *Journal of Economic Behavior and Organization* 12:305–27.

Huffman, W. E., and R. E. Evenson. 1993. *Science for agriculture: A long-term perspective*. Ames, IA: Iowa State University Press.

Jaffe, A. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review* 76:984–1001.

Jaffe, A., M. Trajtenberg, and R. Henderson. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* 108:577–98.

Landry, R., and N. Amara. 1998. The impact of transaction costs on the institutional structuration of collaborative academic research. *Research Policy* 27:901–13.

Lee, M.-J. 1995. Semi-parametric estimation of simultaneous equations with limited dependent variables: A case study of female labor supply. *Journal of Applied Econometrics* 10:187–200.

Leslie, L., and R. Oaxaca. 1993. Scientist and engineer supply and demand. In *Higher education: Handbook of theory and research,* volume 9, edited by John C. Smart. New York: Agathon Press, pp. 154–211.

Levin, S., and P. Stephan. 1991. Research productivity over the life cycle: Evidence for academic scientists. *American Economic Review* 81:114–32.

Levitt, S. D., and C. M. Snyder. 1997. Is no news bad news? Information transmission and the role of 'early warning' in the principal-agent model. *Rand Journal of Economics* 28:641–61.

Levy, D. M., and N. E. Terleckyj. 1983. Effects of government R&D on private R&D investment and productivity: A macroeconomic analysis. *Bell Journal of Economics* 14:551–61.

Leyden, D. P., and A. N. Link. 1991. Why are governmental R&D and private R&D complements? *Applied Economics* 23:1673–81.

Lichtenberg, F. R. 1984. The relationship between federal contract R&D and company R&D. *American Economic Review* 74:73–8.

Lichtenberg, F. R. 1988. The private R&D investment response to federal design and technical competitions. *American Economic Review* 78:550–9.

Mansfield, E. 1995. Academic research underlying industrial innovations: Sources, characteristics, and financing. *Review of Economics and Statistics* 77:55–65.

Mansfield, E. 1998. Academic research and industrial innovation: An update of empirical findings. *Research Policy* 26:773–6.

Merton, R. K. 1973. *The sociology of science*. Chicago: University of Chicago Press.

Murray, F., and S. Stern. 2007. Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior and Organization* 63:688–715.

National Academy of Sciences. 2005. *Rising above the gathering storm*, Pre-publication copy, Committee on Science, Engineering, and Public Policy, Available at http://www7.nationalacademies.org/cosepup/.

National Science Foundation. 2004. *Science and engineering indicators,* volume 1, chapter 5, Washington, D.C. Available at http://www.nsf.gov/statistics/seind04/.

Pray, C., J. Oehmke, and A. Naseem. 2005. Innovation and dynamic efficiency in plant biotechnology: An introduction to the researchable issues. *AgBioForum* 8:52–63.

Robson, M. T. 1993. Federal funding and the level of private expenditure on basic research. *Southern Economic Journal* 60:6371.

Romer, P. 1990. Endogenous technological change. *Journal of Political Economy* 98:S71–S102.

Rosenberg, N., and R. R. Nelson. 1994. American universities and technological advance in industry. *Research Policy* 23:323–48.

SAS Institute. 2005. *SAS/ETS user's guide.* Version 6. Cary, NC.

Sheldon, K. 2003. *Science in the private interest: Has the lure of profits corrupted biomedical research?*. Lanham, MD: Rowman and Littlefield.

Stephan, P. E. 1996. The economics of science. *Journal of Economic Literature* 34:1199–235.

Stern, S. 2004. Do scientists pay to be scientists? *Management Science* 50:83–153. 3

Stuart, T. E., and W. W. Ding. 2006. When do scientists become entrepreneurs? *American Journal of Sociology* 112:97–144.

Thursby, J. G., and M. C. Thursby. 2002. Who is selling the ivory tower? Sources of growth in university licensing. *Management Science* 48:90–104.

Thursby, J. G., and M. C. Thursby. 2003. University licensing and the Bayh-Dole act. *Science* 301:1052.

Toole, A. A., and D. Czarnitzki. 2005. Biomedical academic entrepreneurship through the SBIR program. NBER Working Paper No. 11450.

Walsh, J. P., C. Cho, and W. M. Cohen. 2005. The view from the bench: Patents, material transfers, and biomedical research. *Science* 309:2002–3.

Ward, M. R., and D. Dranove. 1995. The vertical chain of research and development in the pharmaceutical industry. *Economic Inquiry* 33:70–87.

Xia, Y., and S. Buccola. 2005. University life science programs and agricultural biotechnology. *American Journal of Agricultural Economics* 87:229–43.

Xie, Y., and K. A. Shauman. 1998. Sex differences in research productivity: New evidence about an old puzzle. *American Sociological Review* 63:847–70.

Zucker, L. G., M. R. Darby, and M. B. Brewer. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* 88:290–306.

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