AN ABSTRACT OF THE DISSERTATION OF

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The objectives and characteristics of university biotechnology research, including its applicability to such industries as agriculture and food processing, arise from formal and informal linkages among university scientists, public and private-nonprofit funding sources, and industry. In the present study I develop, specify, and estimate a model of the supply and demand of university agricultural biotechnology research. The model reveals, among other things, how funding levels and sources both affect and are affected by the basicness and nonexcludability of university research. A national survey of 1,067 bioscientists employed at 80 randomly selected U.S. research universities forms much of the data for testing the hypotheses.

Results suggest a positive relationship between the amount of research basicness and nonexcludability supplied. Higher non-labor budgets boost the research basicness the scientist offers, holding its nonexcludability fixed, but

reduce the nonexcludability the scientist offers, holding its basicness fixed. More graduate students and technicians in the bioscientist's laboratory tend to contribute to more applied research, while more postdoctoral fellows tend to contribute to more basic research. Labor inputs in general tend to contribute to more public or nonexcludable research. A scientist's productivity, such as her publication and patent output, and her views about the proper role of science, significantly affect her research choices.

Funding agents are less willing to finance basic than applied research, in contrast to scientists' preference for more basic research. Federal agencies, especially the National Institutes of Health, lead university agricultural biotechnology research toward more nonexcludable objectives than do other sources. Not surprisingly, industry funding, more than any other, steers academic scientists toward the applied end of the research spectrum and to more privately excludable research. Compared with other federal agencies, USDA funding encourages more applied and more excludable research.

To advance the more basic end of university agricultural biotechnology research, government might direct funding toward more basically-oriented disciplines such as cell & molecular biology or biochemistry, or toward such relatively basic research fields as plant/animal protection or production. Channeling government support through the National Institutes of Health and National Science Foundation would lead to more nonexcludable research findings.

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

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Hui Yang, Author

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The Supply and Demand of University Agricultural Biotechnology Research

Chapter 1: Introduction

U.S. agriculture has been one of the most productive sectors in the U.S. economy, with an average productivity growth rate of nearly 2% per year since 1947 (Shoemaker 2001). While part of this growth is due to greater fertilizer and pesticide application, better agronomic practices, and agricultural capitalization, a large part can also be attributed to improved plant varieties (Thirtle 1985; Fuglie et al. 1996). The public and private sector each has an important role to play in plant breeding. Private-sector investments generally focus on crops that hold greatest potential for net return. The public sector has taken the lead in the use of traditional breeding techniques to develop new plant varieties and animal breeds. Advances in biological research and extensive adoption of biotechnology in agricultural have accelerated this growth rate and altered institutional arrangements, such as the roles of the public and private sectors in plant breeding. "Since the advent of hybrid corn in the mid-20th century, the role of the private sector in plant breeding has steadily increased, while that of the public sector has declined" (USDA 2001). The private sector now releases more new crop varieties than do the Land Grant universities and USDA's Agricultural Research Service. Partly as a result of genetic modification technology, private-sector investment in agricultural and food R&D have nearly tripled in real terms, from about $1.2 billion in 1960 to $3.4 billion in 1995 (Fuglie et al. 1996).

Given the increasing private-sector demand for agricultural biotechnology research and the stagnation in federal and state agricultural funding, a growing number of scientists in public and private universities are involved in close working relationships with the private sector. Expanding university-industry collaboration represents many promises as well as poses many questions. The relationships offer potential benefits to both parties, such as providing academic scientists with additional research funding and opportunities to bring technologies to the marketplace, as well as providing private firms with access to scientific intelligence and cutting-edge science. Concerns, however, have surfaced about the influence of university-industry relationships on the traditional role of the public research system in providing basic science and applied research with a public-good component.

The issues associated with agricultural biotechnology are complex and varied, and differences in the public reception of new technologies are apparent when one compares agricultural biotechnology with pharmaceutical biotechnology (NABC Report 2003). Economic understanding of university-industry relationships and of public policies affecting agricultural biotechnology is less well developed than it is for information technology or other sectors. The fundamental issue is whether biotechnology and the university-industry relationships arising from it will lead academic bioscientists to focus more heavily on commercial products than on discoveries freely available to other scientists and the public, such as those regarding basic cellular mechanisms. Such upstream academic research has a long-run effect on the direction and pace of biotechnology innovation (Xia and Buccola 2005). Research is needed that will assist government, industry, and universities in designing and implementing policies to foster research and innovation in agricultural biotechnology that contributes directly to the public good.

In the absence of an understanding of both the demand and supply side of university bioscience research, one cannot well assess these public policy issues. The goal of the present dissertation is to examine: (i) how funding levels and sources, and other key factors, affect a university scientist's research agenda, and (ii) how the scientist's research agenda and other factors in turn affect her funding levels and sources. A conceptual model, casting the university scientist as a supplier and a funding agent as demander of a research contract, is developed and estimated in order to better understand these issues. A web-based national survey of 1,067 bioscientists employed at 80 randomly selected U.S. research universities forms much of the data for testing the hypotheses from the conceptual model. I ask questions about scientists' research objectives, funding levels and sources, research activities, research outputs, human capital, and other resources. Results shed light on the relationships between university bioscience research designs and funding influences, and offer implications for a wide variety of university, industry, and public policies.

Chapter 2: Literature Review

University-industry relationships (UIRs) have emerged as key forces in the development and commercialization of agricultural biotechnology. There are a number of indications that UIRs have strengthened over the past few decades, and many scientists in public and private institutions are involved in close working relationships with biotechnology firms. For example, the share of overall university R&D funding supported by industry, while still small, has steadily increased from 2.6% in 1970, to 3.9% in 1980, 6.9 % in 1990 (Geiger 1992), the number of industry-university R&D centers has increased by more than 60 percent during the 1980s (Cohen et al. 1998), and a recent survey of U.S. science faculty revealed that many of them desire even more partnership relationships with industry (Morgan 1998).

The overall pattern of biotechnology research, with its applicability to such industries as agriculture and food processing, has emerged out of a series of formal and informal linkages between industry and universities. While most biotechnology companies pursue applications in pharmaceuticals and diagnostics, a large number are also involved in agricultural biotechnology.

Historically, Land Grant universities, which traditionally are committed to "generate new knowledge and apply that new knowledge to the problems of society," have developed relationships with the private sector, including working closely with producers and commodity groups and with seed, fertilizer, and food-processing companies. These relationships constitute a small portion of the scientists' research agenda. In their efforts to become full participants in the new bioscience research, the Land Grant universities are experiencing dramatic changes. The new types of UIRs, particularly in agricultural biotechnology, are "generally more varied, wider in scope, more aggressive and experimental, and more publicly visible than the relationships of the past" (Lacy 2000).

The recent growth in private support for academic research has resulted in a rich literature on the forces, formation, or trends in university-industry collaboration, on the prevalence of UIRs, on industry/university motivations in establishing this collaboration, and on the debate about the potential benefits and risks of such alliances.

However, the issues surrounding UIRs in agricultural biotechnology are not clearly defined, nor have they been deeply enough studied to inform the public and guide government policy. New research is needed to clarify the relationships, to understand the motivations driving those relationships, to analyze their effects on academic scientists' research agenda and on the university's roles in delivering public goods, and to infer their implications for social welfare and public policy. The present study attempts to fill these information gaps in the study of UIRs in agricultural biotechnology.

2.1 Literature on Science, Technology, and Economic Growth

Some papers have concentrated on the relationships between science and technology and between science and economic growth. They distinguish between science and technology in the innovation process. They often argue that the production of knowledge involves several market failures, but that coexistence of science and technology can eliminate many of these failings. Science tends toward full disclosure and creates positive externalities, but is burdened with agency problems, i.e. moral hazard, free riding, and consequently low effort. Technology is highly motivating, but prevents many positive spillovers and strategically can hold up others' research. A game-theoretic model makes it possible to demonstrate the above result and to characterize key features of an optimal research policy (Carraro et. al 2001). Stephan (1996) explains the relationship between science and economic growth in terms of payoff and lag structure. He emphasizes the public nature of knowledge and the characteristics of the reward structure that encourage the production and sharing of knowledge.

Argyres and Liebeskind (1998) claim that, more than in any other area of science, biotechnological discoveries are likely to originate from scientists (as opposed to trial-and-error technologists). Yet universities' commitment to open access has led them to grant rather narrow licensing rights on their discoveries. The patentability of many university discoveries has also raised the opportunity cost of operating the university as an intellectual commons.

Zucker et al. (1998, 2002) study the interaction between scientific and technological progress through in-depth case studies and econometric analysis of the science underlying biotechnology.

2.2 Literature on Formation of and Trends in University-Industry Relationships

2.2.1 Changing University Industry Relationships

Relationships between university and industry - primarily through the provision of consulting services - have existed through much of the twentieth century (Swan 1988). Public institutions governing university agricultural R&D have changed dramatically during the past two decades. Several policy actions, including the 1980 U.S. Supreme Court decision in *Diamond v. Charkrabarty*, the Bayh-Dole Act in 1980, and the Stephen-Wyndler Technology Innovation Act in 1986, speed the transfer of technology from public to private sector via public-private relationships. At least in theory, those actions gave universities and their scientists a financial motive to cooperate with industrial partners (Campbell and Blumenthal 2000).

Partly as a result of those changes, UIRs have grown substantially over the past two decades. By 1990, 1,056 university-industry R&D centers existed, and approximately 60% were established in the 1980s. Patent activity has also increased. The number of patents granted to U.S. universities increased from 300 in 1980 to 3,661 in 1999 (AUTM 2000). According to a study of biotechnology companies (Blumenthal et al. 1986), university research generated 4.2 times more patent applications than did other firm research per dollar invested. Industry support accounted for nearly $2 billion in sponsored research at universities in 1998, compared to $13.5 billion accounted for by the federal government. The most recent data suggest that the share of academic research supported by industry has risen from 2.6% in 1970 to approximately 7.7% in 2000 (NSF 2000). An overwhelming majority of faculty members (94%) and industry technology managers (91%) think they are likely to expand or at least maintain the present level of collaboration with one another (Lee 2000). We can expect university-industry collaboration in the U.S. to continue in the future.

Huffman and Just (2000) point out that public agricultural scientists are increasingly encouraged to obtain funding from private corporations and producers, including cooperatives. The private-sector share of state agricultural experiment station funding increased from 7.5% in 1960 to 9.2% in 1980 and to 14.3% in 1996. University-industry relationships, particularly in agricultural biotechnology, are "more varied, wider in scope, more aggressive and experimental, and more publicly visible than in the past" (Lacy 2000), due to partners' rather wide-ranging goals and characteristics, and diversity in institutional design.

2.2.2 *Industry and University Motivation*

Santoro and Alok (1999) review the importance of university-industry relationships and contend that a good fit exists between industry's needs and current university missions. The descriptive research on changing UIRs falls broadly into examinations of either industry or university motivations for engaging in UIRs (Cohen et al. 1997; Holt and Bullock 1999; Nelsen 1991).

The literature has identified two broad industry motivations for engaging in a university/industry relationship. The first is access to complementary research activity and research results. Cohen et al. (1997) provide a selective review of this literature, emphasizing the studies that have documented that university research enhances firms' sales, R&D productivity, and patenting activity. Rather than provide a substitute for it, UIRs stimulate and enhance the power of R&D conducted in industry (Hall 2000). The second industry motivation is access to key university personnel and unique biological material (Leyden and Lind 1992).

Link (1995) documents that one reason for the growth of Research Triangle Park in North Carolina was the desire of industrial research firms to locate near the triangle universities. Industry seeks a university research partner more for access to ideas, knowledge, and talented researchers, that is, for human capital, than for special marketable inventions (Blumenthal et al. 1996).

University motivations for collaborating with industry seem to be financially based. Public-private collaborations are means of raising new funds for university research, graduate education, and postdoctoral fellowships, given the stagnation in federal and state agricultural funding (Lacy 2000). Licensing revenue provides income to support whatever activities the university chooses, for example, enhance its fundamental research capacity through new equipment. Annual university licensing revenue grew from $160 million in 1991 to $862 million in 1999. Still, licensing revenue is a very small percentage of total university support; it was only 2.7% in 1998. Moreover, some data suggest that only a slim number of university patents are licensed, and even fewer generate significant revenue.

2.2.3 Influence of UIRs on University Research and Private Firms

New directions in agricultural research highlight potential conflicts of interest between the public and private sector. The federal government has played a major role in transforming U.S. agriculture from a resource-based to a science-based industry. Over the past three decades, the private sector has becoming more important in both funding and conducting agricultural research (Fuglie et al. 1996). These changes in the relative importance of funding sources for agricultural research may well lead to greater economic influences on public agricultural research, particularly on plant breeding (Hansen 1990).

Since universities and the private sector differ with respect to research goals, values, and the way they pursue them (Nelson 1999), there are fears that UIRs will slow scientific progress in a number of ways. Involving the nation's most talented academic investigators in commercially relevant work might distract them from the pursuit of fundamental questions whose answers could set the stage for the next biological revolution (Campbell and Blumenthal 2000). Under material transfer and other types of agreements, university scientists often promise to withhold discoveries from publication for a specified period, providing their sponsoring firm with exclusive early access to the new results. Research topics may originate from sponsoring-firm pressure, implicit or explicit, rather than from the scientist's own judgment. Research that lacks commercial application, especially environmental public goods that suffer from missing market incentives, can be neglected.

Just and Huffman (1992) examine the response of public agricultural research, and in particular the Land Grant system, to the increasing UIRs and public pressure. They argue that inappropriate use of research priorities lead to high research transaction costs, such as the cost of adjustment and risk associated with funding uncertainty, and reduced perspective and creativity. The increased share of private research suggests that public research will become more rather than less oriented toward public goods.

Although not as frequently analyzed, industry collaborators also have concerns about UIRs. Research may not be delivered in timely fashion. Companies must invest time and effort in their university collaborators to assure the project moves toward projected goals. Some company officials believe university scientists do not have insights that will lead to commercial products, and that the research will be too costly and challenging to achieve. An imbalance does appear between the high level of patenting of basic research and the relatively limited development of those discoveries into marketable products.

With the ongoing concerns about UIRs' influence of on the academic research agenda, and debate about the benefits and risks of UIRs, numerous empirical studies have been conducted, although of a limited nature.

2.3 Empirical Literature on Public-Private Collaborations

Despite major changes in university-industry relationships, little empirical evidence is available either on the forces shaping these relationships or on their socioeconomic implications. Most extant studies are broadly descriptive or concentrate on principal issues and hypotheses (Alfranca and Huffman 2001; Fowler 1982; Harman et al. 2002; Holt and Bullock 1999; Rappert 1997; Santoro and Chakrabarti 1999).

2.3.1 Descriptive Studies on Principal Issues in UIRs

About 90% of biotechnology firms now say they are engaged in "collaborations with academia" (Royal Society of Canada, 2000). Public spending in plant breeding has been declining since the mid-1990s. Private-sector investment in plant breeding is rising at 7% per year (Heisey et al. 2001). Fuglie et al. argue that publicly funded agricultural research leads to an annual rate of return of at least 35% higher than the returns on conventional investments in the private sector. They find that the public sector remains responsible for most basic or pre-technology research and that public resources have shifted toward public goods such as food safety.

Huffman (2001) looks at public- and private-sector linkages and their importance in creating value in agricultural research and development. He points out that discoveries from basic research are primarily global public goods, while those embodied in products or processes are patentable and are private or impure public goods.

Using a panel of developed countries, Alfranca and Huffman examine aggregate private agricultural R&D. They show that stronger contract enforcement and stronger patent rights lead to larger private agricultural R&D investment, other things equal. The findings suggest that the public sector may be investing too heavily in applied discoveries which compete directly with private R&D, and too little in discoveries from basic/general and pre-technology sciences.

In their paper on the role of CRADAs in fostering public-private partnerships in agricultural research, Klotz and Day-Rubenstein say that public-sector researchers, particularly in the federal government, increasingly emphasize public-good aspects in their biotechnology research as a way of balancing the increasing role of the private sector in agricultural biotechnology. Offutt (1991) has argued that biotechnology research planning often neglects the full range of stakeholder interests, such as food and environmental safety. In biotechnology research, a knowledge gap has recently emerged between private life science companies and public research institutions.

2.3.2 Empirical Studies on Special Issues in UIRs

A number of papers on technology transfer processes have recently appeared. Nelson discusses university-industry technology transfer, from single-patent licensing agreements through more complicated research and development collaborations. In the biotechnology industry, the university is the primary source of new product ideas. He argues that the expected income from licensing is small (only 1% to 2% of universities' total research budgets). Hence, the university's mission to transfer technology for the public good, bringing practical industrial problems into the university and as well as licensing revenues, is the reason the university wants alliances with industry. Parker et al. (2001) outline alternative campus arrangements for conducting and diffusing innovation. Special attention is given to the Office of Technology Transfer, especially its new role in helping university scientists gain access to patented databases.

Zucker and Darby focus on the use of basic science knowledge in commercial firms and on the impact of that knowledge on firm performance. They identify 327 "star" bio-scientists, based upon genetic-sequence discoveries reported in GenBank. Co-publishing between academic and firm scientists is used as a detector of joint research and university-industry technology transfer. Their result confirms the strong effects of academic science on firm success.

Several empirical analyses recently have appeared on research parks or centers established around universities, and on geographical location of private firms. Link (1996) studies the technology flows between universities and industry that result because of linkages between university faculty and industrial organizations located in a science park. Proximity of the science park to the university affects various aspects of the university's academic mission. For example, a science park located on or close to university campus confers greater employment opportunities for doctoral graduates and induces a more applied university research curriculum. Zucker et al. (1998) argue that the growth and diffusion of intellectual human capital was the main determinant of where and when the U.S. biotechnology industry developed. Some basic research results are implicit knowledge naturally excludable in the sense that they cannot be written down in publications or patent documents. Some direct scientist involvement in the applied technological process is essential and thus involves physical proximity. Their results indicate that the presence of star scientists is significant in university-industry relationships, even controlling for the quality of the university. As a result, centers organized with industrial funds at major universities now total over 1,000 (Lee), providing participating firms with privileged access to university resources and a role in shaping research agendas.

2.3.3 Survey-Based Empirical Studies on UIRs

In the process of examining projects financed by the federal Advanced Technology Program (ATP) – which tended to finance technology development in its generic and early stages – between 1991 and 1997, Hall and colleagues say that "no systematic data exists regarding universities as research partners at either the firm level or the project level." The focus of this ATP-funded survey-based study is on universities as research partners. Ordered probit models were estimated to explain inter-project difference. Projects involving universities as partners are less likely to develop and commercialize technology sooner that expected than are those without university partners; and large projects or those with large lead participants are less likely to expect to commercialize their technology sooner than expected than are projects with non-profit or medium-sized lead participants (Hall et al.). Biotechnology project leaders reported less unproductive research expenditures but more unproductive research time than did leaders in the other technology areas (electronics, chemicals, energy, and materials). Hall et al. provide no evidence of causality because they have no conceptual model from which to work. Furthermore, they ask no questions about project breadth or difficulty. Hence they can only speculate on reasons for most of the responses provided.

Blumenthal and co-researchers have led a series of surveys and case studies that in this area. To collect information about the prevalence, magnitude, commercial benefits, and potential risk of UIRS, they conducted a 1984 survey of 106 biotech companies, a 1985 survey of university faculty, and 1994 and 1995 follow-up surveys of biotech firms and universities.

Results suggest that nearly one-half of surveyed biotechnology companies fund research in universities. In some higher educational institutions, industry may support as much as one-quarter of all biotech research. Most research relationships tend to be short-term and involve small amounts of funding, suggesting that industries support applied research or development rather than basic or fundamental research. Over 60% of firms providing support for life-science research had received patents, products, or sales revenues as a result of those relationships. Per dollar invested, university research has produced more than four times as many patent applications as has commercial research. The data also reveal that government is now, and seems likely to remain, the principal source of support for university research in biotechnology.

Separate surveys (1985, 1995) of university administrators, faculty, and students were conducted by Blumenthal and colleagues to explore more fully the implications of UIRs for academia. The statistical significance and direction of reported associations were tested by multivariate linear and logistic regressions adjusted for professional age, sex, academic rank, clinical or nonclinical department, and total research budget from all sources. Findings indicate that researchers with industrial support published at higher rates, patented more frequently, participated in more administrative and professional activities, and earned more than did colleagues without such support. But no statistically significant differences were found in teaching time. The data suggest that faculty who receive more than two-thirds of their research support from industrial sources have lower academic productivity than do those with less support from industry. Biotechnology faculty with industry links are four times as likely as are other biotech faculty to report that trade secrets have resulted from their university research and that the likelihood of commercial application influences their choice of research topics.

In both the university faculty surveys, UIRs are positively related to scholarly productivity. But as Blumenthal et al. point out, the positive relationship between faculty productivity and UIR involvement does not necessarily indicate that UIRs have a positive effect on scholarly productivity. It may be that industry successfully seeks out faculty whose work seems likely to have commercial application. Or companies selectively support talented and energetic faculty who were already highly productive before they received industry funds.

Blumenthal et al. (1997) separately investigated how UIRs in various life-science fields vary in extent and consequence. Their data suggest genetics firms are significantly more likely than non-genetics firms to support university-based training. Genetics faculty with UIRs are significantly more likely than non-genetics faculty with UIRs to report patents, licenses, trade secrets, and start-up companies. Typical durations of UIRs involving genetics firms were longer than those involving non-genetics firms.

Campbell et al. (2000) say the most recent, nationally representative data on the prevalence and magnitude of UIRs stem from surveys of industries and faculty members conducted by Blumenthal et al. in 1994-1995. From those surveys, the authors conclude that biotechnology UIRs are generally beneficial to the major U.S. research universities.

Curry and Kenney surveyed 185 biotechnology faculty members in Land Grant colleges of agriculture in 1987. Comparisons were made to Blumenthal's earlier survey of biotechnology faculty in nonagricultural research universities (Blumenthal 1986). The study provides insights into the state of biotechnology research in Land Grant universities. Their survey instrument was nearly identical to that used by Blumenthal et al. Agricultural college faculty with industry support reported more publications than did those without industry support. However, those with higher industry funding have lower university productivity than do those with lower industry funding. Agricultural biotechnologists report higher industry involvement and more optimism about it than do their nonagricultural university counterparts. Industry funding levels are a significant factor in the activities and attitudes of agricultural college biotechnology faculty. Contrary to expectation, only a small number of the biotechnology faculty in colleges of agriculture had strong industry connections. It is widely believed that agricultural scientists have a stronger tradition of applied research and a closer involvement with the end-users of their research than do nonagricultural bioscientists (Busch and Lacy, 1983). However, Curry and Kenney's (1990) statistical evidence indicates the difference between Land Grant and non-Land-Grant biotechnologists is not great in this regard.

A related study by Lee examines the sustainability of university-industry collaboration by focusing on actual "give-and-take" outcomes between university faculty members and industrial firms. Based on separate surveys of faculty members and industry technology managers in 1997, he reports that the most significant firm benefit is increased access to new university research. For faculty, the foremost reason for collaborating with industry is to support basic research, such as graduate students and equipment support and insights into research problems, while the least important reason is commercial opportunity. In the context of biotechnology research, Blumenthal et al. (1986) feared that biotechnology faculty with industry support may be unduly influenced by the consideration that "the results would have commercial application," which may occur "at the expense of more fundamental research." This concern cannot be verified in Lee's survey.

Other analysts have sought to identify and measure the links between academic research and industry innovation. Mansfield, for example, finds that 11% of new products and 9% of new processes introduced by surveyed firms could not have been developed in the absence of the academic research carried out during the 15 years preceding the commercialization. The mean lag between a relevant academic research finding and the product's or process's commercial introduction was about 7 years. Based on a follow-up survey, however, there seems to have been a serial decline in the average lag between academic research and the first related commercial introduction. If the social benefits from the commercialization of an academic finding are indeed being obtained more quickly than they were a decade ago, it is becoming increasingly important to promote closer working relationships between firms and academic researchers. Arguing against this, several analysts have claimed that the decreased average time lag implies that universities are conducting more applied and short-term work. In that case, the declining lag would not necessarily mean that fundamental knowledge is being translated more quickly into commercial products and processes. Using data from 66 firms in seven major manufacturing industries and from about 200 academic researchers, Mansfield asks whether the NAS/NRC quality ratings of the university's faculty, scale of the university's R&D activities in the relevant area, and the university's geographical proximity to the firms, are useful in explaining university differences in number of citations. Results suggest all three factors are important.

Most of the literature summarized above concentrates on industry funding's impact on university bioscientists' research activities. In fact, federal and other funding agents have been and still are key financial supporters of U.S. academic research. A more general study of how university scientists and funding agents (including industry) decide upon the nature of agricultural biotechnology research will help provide a more complete view of these issues for policy makers, academic scientists, and the public. Few economic studies have raised this general question. It will be important in the present study, therefore, to identify how funding levels and sources affect the basicness of university bioscientific research, the public-good aspects of those findings, and the types of plant or animal characteristics that are likely to be forthcoming from it. The conceptual model in the next chapter sheds light on how to determine causality in such relationships and hence forms the basis of the remainder to this dissertation.

Chapter 3: Conceptual Framework

To explain the potential factors that affect an academic scientist's research program formulation, a conceptual model is developed to cast the university scientist as a supplier and the funding agent (government, industry, or other agent) as a demander of research products. The scientist and funding agent each has its preferred research objectives and funding levels, and hence might behave differently from one another. Competitive equilibrium is achieved by assuming competition among scientists and among funding agents.

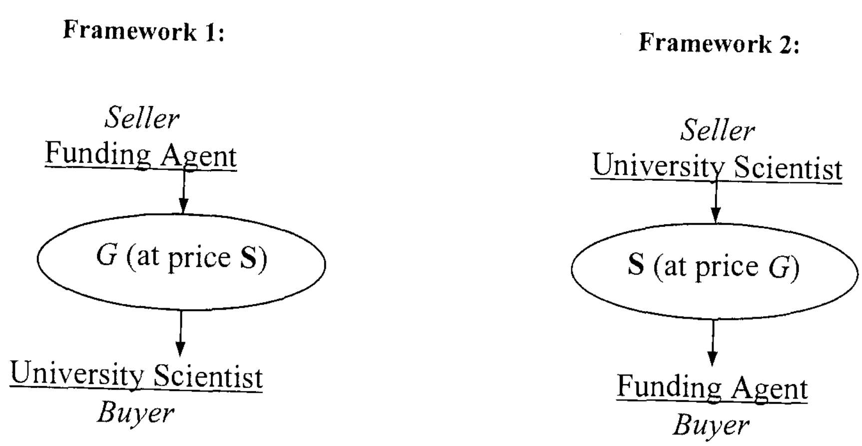
3.1 Demand and Supply Relationships in Research Contract Markets

Consider a research contract market, where the university scientist is willing to conduct research with a set of characteristics **S** in order to obtain research funding *G*. A funding agent provides research funding *G* to a university scientist in exchange for the research characteristics **S** the funding agent wants. By switching their relative market positions, the relationship between the university scientist and funding agent can be captured in two ways.

On the one hand, one may think of research funding *G* as the product of interest, and research characteristics **S** as the price the scientist must pay for this funding. More specifically, in order to obtain funding *G* she needs for her research, the university scientist is willing to provide research with characteristics **S**, that is to pay price **S**. Simultaneously, the funding agent seeks to sell product *G* at price **S**. Under such a market configuration, the scientist is a demander seeking to buy research funding G at price $\mathbf{S}$, and the funding agent is a supplier seeking to sell funding G at price $\mathbf{S}$.

On the other hand, one may instead consider the research contract terms, such as research characteristics $\mathbf{S}$, as the product of interest. Under such an assumption and as opposed to the framework in the above paragraph, the funding agent may be regarded as the demander instead of supplier, and the university scientist the supplier. The funding agent seeks to buy research with characteristics $\mathbf{S}$ at price G, and the scientist is willing to sell research characteristics $\mathbf{S}$ at price G. The two alternative frameworks are illustrated in figure 3-1.

Figure 3-1: Two Alternative Research Market Frameworks



The following discussion is based on Framework 2, in which the scientist is the seller and the funding agent the buyer of research products. However, none of the issues discussed below are affected if we consider them in terms of the supply and demand for research funding.

3.2 Structural Model

3.2.1 Scientist's Utility Maximization Problem

In developing her research program, we suppose a university life scientist pursues a number of research projects financed by various funding agents, each with its own characteristics **S**. In a given time period, let

S the vector characterizing the scientist's research program;

F the vector describing the scientist's research support, including her total research budget G, sub-vector **A** characterizing her funding sources, and sub-vector **M** characterizing the nonmonetary inputs these funding sources provide;

Pub the vector indicating quantity and quality of the scientist's professional publications;

$\mathbf{X}^s$ the vector of fixed variables affecting the scientist's preferences for alternative research characteristics **S**; and

$\mathbf{X}^d$ the vector of fixed variables affecting the funding agent's preferences for alternative research characteristics **S**.

The scientist reasonably would make choices among alternative research objectives **S** in such a way as to maximize her utility U, taking into consideration the influences the objectives will have on the support vector **F** to which she will have access. Note that a scientist's research support **F** can be measured in more that one dimension, for example, by total monetary funds G, by nonmonetary inputs **M**, or by vector **A** indicating the funding sources. To simplify the discussion below, I will employ total research funding G to represent the entire support vector **F**. Further discussion about this support vector will be provided in the next chapter.

Assuming a static-time, deterministic process, the optimization problem then is to choose **S** to

$$\underset{\mathbf{S}}{\text{Max}} \quad U = U[\,\mathbf{S},\ G,\ Pub\,(\,\mathbf{S}, G, \mathbf{X}^s),\ \mathbf{X}^s\,] \tag{3.1}$$

$$\text{s.t.} \qquad G = G\,(\,\mathbf{S},\ \mathbf{X}^d\,) \tag{3.2}$$

in which equation (3.2) is the funding agent's demand function. We assume in equation (3.1) and (3.2) that the university scientist's utility is a direct function of her total research funding G, research objectives **S**, publication quality and quantity Pub, and other fixed factors $\mathbf{X}^s$. In addition to funding G and research characteristics **S**, the scientist gains direct utility from the professional prestige earned from her publications. The scientist's publication quality and quantity vector Pub in turn is a function of the scientist's total grant funding, research objectives, and exogenous variables $\mathbf{X}^s$. More specifically, publication quality and quantity is determined by how well the laboratory is funded and by the research the scientist is planning to conduct. More basic research may lead, for example, to more publication opportunities, while more applied research may instead lead to more patenting opportunities. Exogenous variables such as the scientist's professional experience may affect her publication output as well.

In this way, the scientist's choices among alternative research objectives, and her total grant funding, each affects her utility both directly and indirectly. The scientist's or her university's fixed factors $\mathbf{X}^s$, such as her views about the proper social role of science, and the type of university to which she belongs, directly affect her utility also, hence affecting the kinds of research she is willing to conduct and the funding agent with whom she is willing to work.

In particular, observe by way of (3.2) that total funding $G(\mathbf{S}, \mathbf{X}^d)$ is, in contrast to a scientist's choice variable in equation (3.1), determined by the agent which funds her research program. The amount of research funding the agent is willing to provide depends upon the research characteristics **S** the scientist is willing to supply and upon all the fixed factors $\mathbf{X}^d$ affecting funding agent's preferences for alternative research objectives. Research publication quality and quantity, *Pub*, is in fact endogenously determined in the same fashion as total funding *G* is. However, to streamline the research supply and funding demand relationship, I incorporate *Pub* as one of the exogenous variables $\mathbf{X}^s$ in this study. Rewriting (3.1) then gives

$$\underset{\mathrm{S}}{\mathrm{Max}} \quad U = U(\mathbf{S}, G, \mathbf{X}^s) \tag{3.3}$$

Solving optimization problem (3.3) by choosing **S** and, therefore, the corresponding grant funding *G*, gives the structural form

$$\text{Supply:} \qquad \mathbf{S}^s = \mathbf{S}^s(G, \mathbf{X}^s) \tag{3.4}$$

$$\text{Demand:} \qquad \mathbf{S}^d = \mathbf{S}^d(G, \mathbf{X}^d) \tag{3.5}$$

Market Clearing: $$\mathbf{S}^s = \mathbf{S}^d \tag{3.6}$$

where $\mathbf{S}^s$ is the set of research objectives the scientist seeks ("supplied") and $\mathbf{S}^d$ the set of objectives the funding agent seeks ("demanded"). Note that equation (3.5), with **S** on the left-hand side, is the same as constraint (3.2), namely the demand function in which **S** is located on the right-hand side. This research demand function represents the funding agent's behavior and is derived from the funding agent's own optimization problem, which I do not specify here.

The research supply function, in contrast, is derived through optimization process (3.1) and (3.2). In particular, a research supply function is found by holding exogenous supply factors $\mathbf{X}^s$ fixed and parametrically varying the price G the funding agent offers. Such parametric changes in G in turn may be imagined as originating from random variations in $\mathbf{X}^d$, since offer prices vary with the funding agent's fixed factors contained in $\mathbf{X}^d$. For each given G^0 and $\mathbf{X}^d$, a new optimal $\mathbf{S}^*$ is derived through maximization process (3.1) and (3.2). Resulting $(G, \mathbf{S})$ mappings constitute the supply function corresponding to the given $\mathbf{X}^s$. As in a normal market model, that is, we derive the supply function for a given set of supply factors $\mathbf{X}^s$ by varying exogenous demand factors $\mathbf{X}^d$.

The relationship between characteristics **S** of the scientist's research and the factors potentially influencing them can be characterized in structural form (3.4) – (3.5) from both the demand and supply side. Equation (3.4) says that the research projects the scientist is willing to pursue are influenced by the funding provided (the price the funding agent is willing to pay), along with exogenous scientist-side variables $\mathbf{X}^s$. Equation (3.5) says that the research program the funding agent is willing to support is a function of the amount of funding G that the scientist demands (the price the scientist is willing to accept), along with other fixed funding agent variables $\mathbf{X}^d$.

Writing structural model (3.4) and (3.5) with the $\mathbf{S}$ vector on the left-hand side refers to the case in which we are most interested, namely in how the scientist's research program is formulated or determined. Under a circumstance in which we want instead to see what influence a scientist's research has on funding volume, we could rewrite equations (3.4) and (3.5) with G on the left-hand sides, namely

Supply: $$G^s = G^s(\mathbf{S}, \mathbf{X}^s) \tag{3.7}$$

Demand: $$G^d = G^d(\mathbf{S}, \mathbf{X}^d) \tag{3.8}$$

Market Clearing: $$G^s = G^d \tag{3.9}$$

where G^s is the price the scientist is willing to accept and G^d the price the funding agent is willing to pay for research with characteristics $\mathbf{S}$. The funding agent has a demand schedule showing the maximum price G it would pay for each given characteristic set $\mathbf{S}$. The scientist, on the other hand, has a supply schedule showing the minimum price or funding G she will accept for each given research characteristic set $\mathbf{S}$. Equations (3.7) – (3.8) thus reveal how, on both the demand and supply side, research characteristics $\mathbf{S}$ affect funding G, given the fixed factors that potentially influence them, and thus are a reversal of equations (3.4) and (3.5).

Equation (3.7) says the minimum research funding the scientist requires (the supply price the scientist is willing to accept) is influenced by the characteristics of the research project the funding agent demands and by the scientist's fixed variables $\mathbf{X}^s$, such as her academic rank and research field, and the culture of the university to which she belongs. Equation (3.8) says the maximum research funding the funding agent is willing to provide (the demand price the funding agent is willing to pay) is influenced by the characteristics of the research the scientist supplies and by the funding agent's fixed variables $\mathbf{X}^d$, such as its institutional objectives, its total available budget, and the prices of its own inputs and outputs.

3.2.2 Hedonic Relationships

Equations (3.7) and (3.8) may be viewed as a set of hedonic relationships, giving the implicit price of each research characteristic offered by the scientist and funding agent respectively. Let us define the research characteristics vector as $\mathbf{S} = (S_1, S_2, ..., S_I)$, and the corresponding research characteristics prices as $\mathbf{w} = (w_1, w_2, ..., w_I)$, where $i = 1, 2, ..., I$. Then the partial effect of S_i on *G*, namely $w_i = \partial G / \partial S_i$, shows how, holding other factors fixed, one additional unit of research characteristic S_i influences the research funding demanded or supplied. That is, it is an implicit measure of the price of research characteristic S_i. Equation (3.7) gives the implicit price of S_i as viewed by the scientist, namely the implicit supply price

$$w_i^s = \partial G^s / \partial S_i . \tag{3.10}$$

Equation (3.8) gives the implicit price of S_i as viewed by the funding agent, namely the implicit demand price

$$w_i^d = \partial G^d / \partial S_i . \tag{3.11}$$

In general, the above structural model summarized by equations (3.4) – (3.9) captures the relationships between research characteristics **S** and research funding G. It tells us how the scientist's research choices affect her research funding, or conversely how funding affects the scientist's research choices. Such mutual causality between funding amount and research objectives are among the main issues of policy interest in this dissertation.

Equations (3.4) – (3.9) allow us to distinguish between the scientist's and funding agent's behavior. Scientist behavior, embodied in the supply-side relationship, is of interest to both policy makers and funding agents since both seek to influence scientific activity. Funding agent behavior is, in turn, of interest to both policy makers and scientists since both seek to know how funding agents allocate money among alternative research projects. In particular, by better understanding the demand-side relationships, university scientists may become more efficient in seeking funding for their own research. Policy makers may more efficiently allocate government funds among alternative research goals, and influence private funding agents in a way maximizing social welfare.

If the demand for research is perfectly inelastic, so that G is constant in equations (3.5) and (3.8), we have only the supply-of-research functions (3.4) and

(3.7). If supply is perfectly inelastic, so that G is constant in equations (3.4) and (3.7), we have only demand-for-research functions (3.5) and (3.8). Supply would be perfectly inelastic if G and $\mathbf{S}$ in utility function (3.1) do not interact with one another. For example, consider the additive utility function $U(G, \mathbf{S}, \mathbf{X}^s) = U_1(G, \mathbf{X}^s) + U_2(\mathbf{S}, \mathbf{X}^s)$. The scientist's utility maximization problem (3.1) then can be rewritten as

$$\underset{\mathbf{S}}{Max} \quad U = U_1(G, \ \mathbf{X}^s) + U_2(\mathbf{S}, \ \mathbf{X}^s) \tag{3.12}$$

From the first-order condition, we set $\partial U / \partial \mathbf{S} = 0$. Thus,

$$\frac{\partial U_1(G, \mathbf{X}^s)}{\partial \mathbf{S}} + \frac{\partial U_2(\mathbf{S}, \mathbf{X}^s)}{\partial \mathbf{S}} = 0 \tag{3.13}$$

The first term on the left side of equation (3.13) is zero since U_1 is not a function of $\mathbf{S}$, and the second term involves only $\mathbf{S}$ and $\mathbf{X}^s$. Thus, the optimized $\mathbf{S}^*$ derived from (3.13) is $\mathbf{S}^s = \mathbf{S}(\mathbf{X}^s)$, in which G is eliminated. Equivalently, no real supply functions can be estimated, and one can only estimate demand functions (3.5) and (3.8).

3.3 Equilibrium Conditions

At given levels of supply-side exogenous factors $\mathbf{X}^s$, variables $\mathbf{S}^s$ and G^s in (3.4) and (3.7) characterize a representative scientist's behavior. At given levels of demand-side factors $\mathbf{X}^d$, variables $\mathbf{S}^d$ and G^d in equations (3.5) and (3.8) characterize a representative funding agent's behavior. As in a normal competitive market, in which no one can influence market price ***G***, that is in which seller and buyer take price as given, equilibrium is achieved by assuming competition among scientists and funding agents. Each scientist offers a bundle of research characteristics **S** that maximizes her utility given the budget G that funding agents offer and given other supply factors, for example her own human capital, collectively denoted by $\mathbf{X}^s$. Each funding agent similarly seeks a bundle of research characteristics **S** that maximizes its objective function, given the research budget G that scientists seek plus other demand factors, for example the input and output prices it faces.

At the aggregate level, a price G will be discovered such that what scientists are willing to supply equals what funding agents demand, that is, $\mathbf{S}^s = \mathbf{S}^d$ and $G^s = G^d$. Implicitly, scientists and funding agents simultaneously reach an agreement on the "prices" of research characteristics **S**, since $\mathbf{w}^s = \mathbf{w}^d$, where $\mathbf{w} = (w_1, w_2, ..., w_I)$ and $w_i = \partial G / \partial S_i$. Substituting (3.7) and (3.8) into (3.9) and solving for **S** gives the equilibrium or reduced-form condition

$$\mathbf{S}^* = \mathbf{S}\,(\,\mathbf{X}^s, \mathbf{X}^d) \tag{3.14}$$

Similarly, substituting (3.4) and (3.5) into (3.6) and solving for G gives the equivalent reduced form

$$G^* = G\,(\,\mathbf{X}^s, \mathbf{X}^d) \tag{3.15}$$

At the equilibrium research budget, the research characteristics supplied and demanded, as identified in equations (3.4) – (3.9), are mutually compatible;

that is the supply of research characteristics aggregated over scientists equals the demand for those research characteristics aggregated over funding agents. These equilibria are generally sensitive to the scientists' and funding agents' fixed factors $\mathbf{X}^s$ and $\mathbf{X}^d$, discussed in more detail in Chapter 4.

Chapter 4: Econometric Model

As indicated in Chapter 1, the purpose of this dissertation is to examine how a bioscientist and funding agent jointly formulate a university bioresearch program. The upstream research the university scientist pursues influences the downstream knowledge and products that flow into society and therefore the provision of public as well as private goods from agricultural biotechnology research. I pursue this goal primarily by examining the key factors influencing the nature of the scientist's research, with attention to the effects of the funding agent's identity on research orientation. For example, is government-funded more likely than private-funded research to be directed toward the basic end of the research spectrum? Do university-industry relationships shift the scientist's research toward outcomes whose use can be restricted or excluded, namely toward private goods?

In order to study this problem, we need to develop measures of (a) the scientist's research characteristics, and (b) the principal factors influencing those characteristics and thus the public availability of her research findings.

4.1 Measures of Research Characteristics (Endogenous Variables S)

Accurately capturing the nature of a scientist's research is not straightforward. She works largely with intangible ideas, which are only implicitly embedded in her observable activities.

We will express bioscience research characteristics along two dimensions. A scientist will select a vector of research objectives (**S**) according to (1) the relative basicness or appliedness of her research, and (2) the relative publicness or privateness of her research, that is, the extent to which the research benefits are nonexcludabe *versus* excludable or privately appropriable.

Initially, I tried to examine the scientist's research in two other dimensions as well, namely (i) the crop, plant, or animal category upon which the scientist focuses, and (ii) the research field she pursues. However, such a model resulted in a system of equations involving both discrete and continuous dependent variables. Econometrically, it appears to be infeasible to estimate such a structural model simultaneously, and no empirical study can be found in which it has been attempted. In addition, our primary interest is the basicness and publicness of research, since these two characteristics have been of greatest interest to both policy makers and the public. Although a large volume of literature is available on this topic (Blumenthal 1986; Fuglie et al. 1996; Hicks and Hamilton 1999), little quantitative research has been conducted on the factors influencing a scientist's research objectives and design. I therefore concentrate on research basicness and publicness in this study. Rather than treat research field and organism as endogenous, I include them as explanatory variables only.

U.S. university research traditionally has focused on the basic end of the research spectrum, although Land Grant universities, with a mission of research, education, and benefits to the public, have always had an applied research orientation. With university scientists seeking more funding from the private sector to supplement their support from federal or state government agencies, university-industry relationships have grown. Furthermore, an increasing number of patents have been issued to university researchers from privately funded agricultural biotechnology research. Observers have questioned whether this trend has affected the traditionally basic nature and public characteristics of a university scientist's research orientation (Foray and Kazancigil 1999; Slaughter and Leslie 1997).

Directly measuring or distinguishing between "basic" and "applied," or between "public" and "private," either in the scientist's research field or in the plant or animal she studies, is not straightforward. Scientists who specialize in the same research field, say plant production, may operate at one end or the other of the basic-applied research spectrum. For instance, one may work on gene expression in a particular kind of plant, an issue leaning toward the basic end of the research spectrum. Another may work on sources of abiotic stress in the same kind of plant, a problem closer to the applied end of the spectrum. Similarly, the private sector has continuously increased its role in developing and releasing new plant varieties, and the public role has gradually declined. Today, in fact, almost none of the major crops such as corn, soybeans, and cotton are public releases. Research on minor plants may in some cases be more "public" than in other cases, in the sense that the researcher cannot gain much profit from working on them because of the plant's small commercial scale. However, recent breakthroughs in molecular biology have encouraged increased private-sector investment in minor crops such as fruits and vegetables, especially in adding genetically engineered traits.

Two descriptions of the scientist's research, its basicness and its publicness, are proposed in the following.

4.1.1 Research Basicness

Identifying the boundary between the basic and applied aspects of R&D is often difficult and subjective (Audit of UK Soil Research Final Report 2003). The boundaries between them are not clear-cut and it is frequently difficult to assign a given investigation to any single category. However, typical instances may sometimes easily be recognized. A number of prominent organizations, including the National Science Foundation (NSF), Organization for Economic Co-operation and Development (OECD), and Department of Defense (DoD), have offered definitions of "basic" and "applied" research. The NSF is considered to be a major definitive voice in the classification of R&D into basic and applied research[1], and the Frascati Manual[2] (OECD 2002) has for many years provided the most reliable

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[1] A. Basic research: with the U.S. Federal government, university, and non-profit sectors, basic research is defined as research directed toward increase in knowledge or understanding of the fundamental aspects of phenomena and of observable facts without specific application toward processes or product in mind. For the industry sector, basic research projects are defined as original investigations for the advancement of scientific knowledge which do not have specific commercial objectives, although they may be in fields of present or potential interested to the reporting company. B. Applied research: within the Federal, university, and nonprofit sectors, applied research is defined as research directed toward gaining knowledge or understanding necessary for determining the means by which a recognized and specific need may be met. The applied research definition for the industry sector is modified to include research projects which represent investigations directed to discovery of new scientific knowledge and which have specific commercial objectives with respect to their products or processes. C. Development: development is the systematic use of the knowledge or understanding gained from research directed toward the production of useful materials, devices, systems or methods, including the design and development of prototypes and processes. It excludes quality control, routing testing, and production.

[2] Frascati Manual: *Basic (or fundamental) research* is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view; *Applied research* is also original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific practical aim or objective; and *Experimental development* is systematic work drawing on existing knowledge gained from research and/or practical experience that is directed to

and consistent international breakdown of R&D expenditures in basic and applied research. The sources are tacitly consistent with one another, although they do not define basic vs. applied research in exactly the same way.

Broadly speaking, they say that basic research typically refers to experimental or theoretical discoveries (for example, genomics) that add to fundamental science and engineering knowledge, with no specific applications to products or processes. Applied research refers to findings (for example, a transgenic plant) that draw from basic or other applied research to create new knowledge that can be used more immediately to develop new or improved products and processes.

Two sets of basicness measures are developed, as follows, for the present study.

(1) The percentage of a scientist's research program allocated, respectively, to basic and applied research:

% Basic: percentage of research program allocated to basic research;

% Applied: percentage of research program allocated to applied research.

(2) The "degree of basicness" of the scientist's research program:

Basicness: a scale indicating the bioscientist's judgment of the basicness of her research program, ranging from unity for "purely basic" to six for "purely applied."

producing new materials, products or devices; to installing new processes, systems or services; or to improving substantially those already produced or installed.

4.1.2 Research Excludability (Public vs. Private)

Publicness refers to nonrivalness and nonexcludability. A good, service, or resource is nonrival if its consumption by one person does not affect its availability to other people. Knowledge provides a good illustration of nonrivalness. A good, service, or resource is nonexcludable if it is technologically impossible or extremely costly to exclude some consumers from its benefits. Private goods are all excludable, but public goods may or may not be. "The patent system, for example, is a mechanism for excluding individuals (although imperfectly) from the use of knowledge developed by others" (Mas-Colell et al. 1995, p. 360). Note, in fact, that any knowledge is only partially excludable. In particular, patenting is not a perfect excludability tool because the patent document can be read, providing the reader with insights into methods for improving upon the patented finding. Virtually all agricultural research findings are nonrival, because the use of a piece of knowledge for one purpose does not preclude its use by others once it is published. In agricultural biotechnology research, publicness is therefore equivalent to nonexcludability. I will employ the word "nonexcludable" as equivalent to "public."

Whether privately motivated or financed research tends to decrease or increase the public character of a university's research outputs depends upon whether public and private characteristics are complements or substitutes with one another. For example, a transgenic crop that is rendered exclusive, that is, made available only to those who purchase the technology, may reduce downstream pesticide residues, a benefit that is largely nonrival and nonexcludable in society.

More basic research tends to be more public in nature because it generally has numerous applications, many of which are themselves nonrival and nonexcludable. On the other hand, some basic research projects target crops with major commercial value, as when the research is directed toward plasmid vectors or promoters considered most useful in the bioengineering of those major crops. That is, even basic research can be more or less excludable, so the correlation between basic and public is not necessarily perfect. However, basic research tends to be associated with more uncertainties, many of which may lead to a variety of applications. The fact that research is basic, therefore, adds some difficulty in excluding someone else's use of it. We would like, therefore, to examine whether a given basic innovation is conducive in equal degree to private and public characteristics or whether it is more oriented to public or to private research characteristics.

The excludability of a good or service is a function of technical, economic, and sociopolitical factors. A scientist's preferences, for example her interest in patenting her innovations, affect the characteristics of her research's downstream outputs, as well as the dissemination and excludability of the research findings themselves. Nevertheless, dissemination preferences and actions are different from the research characteristics and findings in their own right. The former are, in fact, limited by the latter, since dissemination actions are constrained by the excludability of the research itself. For example, once a scientist has decided to study the basic mechanisms of gene expression (and to the extent she continues to study it), she forgoes much chance of excluding her findings by patenting. On the other hand, if she is trying to develop a new plant variety (which fundamentally is excludable, even if the market is such that one could never license it for a profit, or if, despite its potential profitability, society chooses not to exclude it anyway), her exclusion preferences and actions may have some influence over whether it ultimately is patented or protected. None of these distinctions are possible if we merge into one measure both the underlying excludability of the finding and the scientist's preferences or efforts toward excluding it.

Capturing the technical, legal, and economic aspects of a research finding itself, as well as the scientist's own influences on the degree of public access to her discovery, are important for bringing out the policy implications of this study. But what is clear here is that we can understand the answers to such questions only in terms of the underlying excludability of the research findings themselves. That is, to the extent the findings are nonexcludable, the scientist has no choice but to maintain them in the public sector. To the extent they are excludable, she may have some choice (in conjunction with others) about whether to exclude them or not. Thus, understanding her choices about whether to exclude can be understood only in reference to the constraints she faces, namely the technical and legal excludability of the findings in question.

It is, therefore, desirable to separate the two sets of determinants, that is the characteristics of the research itself and the scientist's own efforts or intentions for the use of her work. A measure of the excludability of the scientist's research, focusing on the nature of the research itself, namely the nature of research considered *ex ante* rather than the scientist's intentions or actions for its dissemination, is developed here. Two types of measures of the underlying excludability of a scientist's research findings are possible:

(1) The percentage of the scientist's research program allocated between inherently nonexcludable and excludable research.

% Public: percentage of the scientist's research program allocated to nonexcludable research; and

% Private: percentage of the scientist's research program allocated to excludable research.

(2) Degree of excludability of the scientist's research program.

Publicness: a scale indicating the bioscientist's judgment of the excludability of her research program, ranging from unity for "completely nonexcludable" to six for "completely excludable" research.

By combining the scientist's view of the basicness and publicness of her research with her statements about her research discipline, field, topic, and organism, we can obtain a fairly complete view of her research program.

4.2 Measure of Research Funding (G)

In Chapter 3, we noted that total research funding G in equation (3.1), representing the demand the scientist is facing, generally is endogenously determined with research characteristics. More generally, as we defined in Chapter 3, we may refer to funding vector $\mathbf{F} = (G;\ \mathbf{M};\ \mathbf{A})$, where G is total budget; $\mathbf{M}$ is the vector of nonmonetary support obtained from the funding agent;

and **A** is the funding share vector, that is the proportion of G derived from federal and state government, foundations, industry, and so forth. I elaborate on **A** and **M** in the following.

In some circumstances, scientists obtain nonmonetary inputs, such as biomaterials, genomic databases, software, reagents, and equipment or instrumentation, from the funding agent as part of the research contract. Theoretically, nonmonetary inputs should be included in equation (3.1) in the same way that G is, since they are another form in which the funding agent compensates the scientist for her work. However, quantifying the dollar value of nonmonetary inputs is difficult. In general, a nonmonetary contribution, for instance, a unique genomic database, may be essential for the conduct of a given line of research, so its value to the scientist may be very large. On the other hand, a gene sequence, for instance, which is useful for one scientist may have no value to another. In general, then, valuing nonmonetary contributions is difficult.

Instead, therefore, of attempting to evaluate the monetary value of these inputs and combining them with total budget G, we will represent them as a set **M** of dummy variables indicating whether the scientist has obtained the respective input from her funding agents. Treating **M** as endogenous in the same way as dollar amount G would result in too many endogenous variables. **M** therefore is treated as exogenous. It is included in both demand and supply functions for the same reason that monetary contribution G is.

Because a scientist may draw grant money from a variety of funding sources, a separate grant amount theoretically is endogenously determined for each such funding source. Alternatively, funding share vector **A** should be regarded as endogenously determined along with G in the scientist's choice problem. However, endogenizing **A** would greatly complicate estimation further by requiring a set of funding share equations along with basicness, publicness, and budget equation. Moreover, we do not have enough funding agent information to econometrically identify such share equations. Instead, therefore, of treating **A** as endogenous, we may include it as part of the exogenous variable sets $\mathbf{X}^s$ and $\mathbf{X}^d$, or restrict it either to $\mathbf{X}^s$ or $\mathbf{X}^d$ so that it becomes part of the set identifying variables.

Apart from the above considerations, the ideal empirical model would be specified as:

Scientist (*Supply*)

$$B^s = f_1\,(P^s,\ G,\ \mathbf{X}_B{}^s) \tag{4.1}$$

$$P^s = f_2\,(B^s, G, \mathbf{X}_P{}^s) \tag{4.2}$$

Funding Agent (*Demand*)

$$G = f_3\,(B^s, P^s, \mathbf{X}_G) \tag{4.3}$$

$$B^d = f_4\,(P^d,\ G,\ \mathbf{X}_B{}^d) \tag{4.4}$$

$$P^d = f_5\,(B^d, G\,,\ \mathbf{X}_P{}^d) \tag{4.5}$$

where B and P refer to *%Basic* and *%Public*, and $\mathbf{X}^B$, $\mathbf{X}^P$, $\mathbf{X}^G$ are vectors of exogenous variables in the basicness, publicness, and budget equation respectively. However, we do not have enough identifying variables, especially for funding agents, to estimate such a model. Hence, we are forced on the funding agent side to drop all but the budget function. An operational empirical structure of the demand-supply relationship outlined in equations (3.4) and (3.5) can thus be written as

Scientist *(Supply)*

$$B = f_1\ (P, G, \mathbf{X}_B) \tag{4.6}$$

$$P = f_2\ (B, G, \mathbf{X}_P) \tag{4.7}$$

Funding Agent *(Demand)*

$$G = f_3\ (B, P, \mathbf{X}_G) \tag{4.8}$$

For a given budget G^0, the scientist solves equation (4.6) and (4.7) simultaneously from her optimization problem (3.3), providing new values of (B^{00}, P^{00}). The optimal (B^{00}, P^{00}) values then are substituted back into the funding agent's equation (4.8) and a new money offer, G^{00}, derived from the funding agent's own objective function, is generated. Facing G^{00}, the scientist solves equation (4.6) and (4.7) again to obtain new values for B and P. Iteration continues in this way until the system stabilizes in the sense that, for given G^*, the amounts of basic and public research the scientist supplies are the same as those the funding agent demands, and at these supplies, the budget forthcoming equals that which induced the supplies and demands. That is, $B^s = B^d$ and $P^s = P^d$, and $G^s = G^d$ in equilibrium.

For simplicity in the following, I refer to (4.6) as the Basicness equation, (4.7) as the Publicness equation, and (4.8) as the Budget equation. Note that the Basicness and Publicness equations represent scientist-side, and the Budget equation represents funding-agent-side, preferences or behaviors.

The equilibrium condition of system (3.14) and (3.15) in Chapter 3 can, from equation (4.6) – (4.8), be rewritten in the estimable reduced form

$$B = g_1(\mathbf{X}_B, \mathbf{X}_P, \mathbf{X}_G) = g_1(\mathbf{X}) \tag{4.9}$$

$$P = g_2(\mathbf{X}_B, \mathbf{X}_P, \mathbf{X}_G) = g_2(\mathbf{X}) \tag{4.10}$$

$$G = g_3(\mathbf{X}_B, \mathbf{X}_P, \mathbf{X}_G) = g_3(\mathbf{X}) \tag{4.11}$$

where $\mathbf{X} = (\mathbf{X}_B, \mathbf{X}_P, \mathbf{X}_G)$. In equilibrium, endogenous variables *B*, *P*, and *G* are determined by all fixed factors $\mathbf{X}_B$, $\mathbf{X}_P$, $\mathbf{X}_G$ in this system.

4.3 Measures of Demand and Supply Factors ($\mathbf{X}_B, \mathbf{X}_P, \mathbf{X}_G$)

To examine the determinants of a scientist's research program, and identify the demand-supply relationships between university scientist and funding agent, it is essential to identify measures of the key factors influencing scientist and funding agent behavior.

4.3.1 Distinguishing Between Demand and Supply Factors

Recall the demand-supply relationships described in Chapter 2. We assume the university scientist is a supplier and the funding agent a demander in a research contract market. The scientist wishes to sell her research plans with characteristics **S** at "price" or total revenue *G*, and the funding agent seeks to buy research characteristics **S** at price *G*. An important issue is the identity of the conditioning variables to be included among supply factors $\mathbf{X}^s = (\mathbf{X}_B, \mathbf{X}_p)$ and demand factors $\mathbf{X}^d = \mathbf{X}_G$. Without such a distinction, we cannot identify demand and supply functions separately, as is evident from equations (3.4) and (3.5) in Chapter 2 and (4.6) – (4.8) above.

In general, factors other than **S** and *G* affecting the scientist's utility function, such as her professional ideology and human capital, or her university's characteristics, would belong to supply factors $\mathbf{X}^s$. Similarly, any factors other than **S** and *G* affecting the funding agent's behavior alone belong to demand factors $\mathbf{X}^d$. The latter might include the funding agent's mission, the prices of its inputs and outputs, and its total capitalization. Such factors need not describe the funding agent's utility or resources alone. They may also characterize the agent's expectations of the quality of the research it is considering supporting. For instance, the scientist's human capital variables and university reputation influence the efficiency with which she conducts her work and hence the opportunity cost of her time. The key here is that research quality may not be observable to the funding agent, and the agent may use observed characteristics of the scientist or university as forecasters of that quality.

Characteristics of Research Contract and Scientist

The planned characteristics of a university research project, and the "price" G of that collection of characteristics, constitute the terms of the research contract and consequently are endogenous. In order to characterize the scientist's research, however, we must distinguish between:

(i) the characteristics of the research "sold" to the funding agent, that is of the research contract itself;

(ii) the characteristics of the research buyer (funding agent), which influence this demand for research characteristics; and

(iii) the characteristics of the research seller (scientist), which influence her supply of the same research characteristics.

The difficulty here is that the research a scientist conducts reflects the characteristics of the scientist herself. That is, (i) and (iii) appear, in some way, to be the same thing. Similarly, we can reasonably assume that the characteristics of the research which the funding agent is willing to support directly reflects the characteristics of the funding agent itself. For example, if the scientist is a geneticist, the research contract agreed upon likely will involve genetics research. "Genetics" is both a characteristic of the scientist and of the research program. We can go further to say that genetics is a characteristic of the funding agent, because something must have been true about the agent that induced it to purchase a research project for which genetics was a principal theme. Distinguishing between the characteristics of the research contract and of the research buyer or seller depends upon how well we divide research program, field, or topic into categories that are both understandable and exhaustive of all the important features of that research. In the genetics example, it requires that the research categories adequately include the information that the project will involve genetic research in a substantial way.

Initially, I sought to represent a research program at three levels: discipline, research field, and research topic. In this, discipline was considered to be the major scientific work area, research field the major specialization within the discipline, and research topic the specific activities in the laboratory, being a subset of both discipline and field. In this dissertation, I am inclined to regard both discipline and field as characteristics of either the scientist or the funding agent rather than of the research itself, influencing, respectively, the cost of providing or using the measured research characteristics, namely basicness and publicness.

4.3.2 Factors on Both the Demand and Supply Side

A scientist's discipline is a relatively fixed condition, changing only slowly if at all, once she begins her career. We define the scientist's discipline as

Discipline: $Discipline^i = 1$ if the scientist's discipline is i, $Discipline^i = 0$ otherwise, $i = 1, \ldots, 6$. The six discipline categories are (1) biochemistry, chemistry, and biophysics, (2) cell, molecular, and developmental biology, (3) ecology, systematics, and environmental life sciences, (4) genetics, (5) physiology, anatomy, and pathology, and (6) other agricultural and life sciences.

A scientist's field is more likely to change than is her discipline and might therefore be regarded as endogenous. Empirically, however, it is impractical to estimate simultaneous equations involving both continuous dependent variables and multiple discrete choices. Empirical studies in the social sciences have estimated system equations involving only continuous and binary discrete choices, or continuous and an ordered probit model. To simplify the analysis and concentrate on the primary nature of the scientist's research, I treat research field as another exogenous variable along with **Discipline**, indicating the scientist's and funding agent's characteristics. Research field categories are based on the USDA's Classification of Agricultural and Forestry Research, employed in its Current Research Information System (CRIS, version VI, 1998). We have added several categories to the CRIS list in order to incorporate more basic-oriented researchers (see Chapter 7, *Data Sources and Descriptions*, for details). Define the scientist's field as

Field: $Field^i = 1$ if the scientist's field is i, $Field^i = 0$ otherwise, $i = 1, \ldots, 6$. The six field categories are (1) natural resource and environment (including non-foods), (2) human health and nutrition (including foods), (3) microbes and other, (4) plant protection and production, (5) animal protection and production, and (6) plant/animal production and protection.

The scientist's discipline and field can be a partial indicator of her research area and signal an emphasis or style of research that would not be formally specified in the research contract. On the other hand, discipline and field can also indicate a type of human capital and hence affect the funding agent's expectation of how basic the research will be, again in a way not revealed in the contract.

Organism variables representing the bioscientist's crop, plant, or animal categories also are included as explanatory variables in both scientist and funding agent equations. A direct way of characterizing a scientist's agricultural biotechnology research is by examining the organisms she studies. To represent crop, plant, or animal category, we look to the primary organism with which the scientist works. Some work is with organisms such as *arabidopsis* that are intended as models of molecular processes or genetic structure. Other work is with organisms such as wheat that have immediate economic value. Scientists who work with model organisms intend eventually to apply their results to products with commercial value. We therefore employ three research organism categories: major commodity (among plants: corn, wheat, soybeans, rice, cotton, potatoes, and hay; among animals: beef, swine, dairy, and poultry), minor commodity (all those with commercial value but not listed as major), and model organism. Let the following dummy variables indicate the bioscientist's crop, plant, or animal category,

$organism^{major} = 1$ if major commodity, $organism^{major} = 0$ otherwise.

$organism^{minor} = 1$ if minor commodity, $organism^{minor} = 0$ otherwise.

$organism^{model} = 1$ if model organism, $organism^{model} = 0$ otherwise.

Details on categorizations of **Discipline**, **Field**, and **Organism** will be discussed at greater length later in Chapter 6, *Data Sources and Descriptions*.

The nonmonetary contributions vector **M** discussed above is represented by dummy variables $M^{material}$, $M^{capital}$, $M^{service}$, and M^{other}, defined respectively as indicating whether the funding agent has provided materials (biomaterials or reagents), capital (databases, equipment, or software), services (student internships or staff support), and other nonmonetary inputs. More than one of these categories may be provided.

A scientist's human capital may serve as both a demand-side and supply-side factor in the determination of a university research program. It influences, on the one hand, what the scientist seeks to do and, on the other hand, what the funding agent thinks she can do. The scientist's recent outputs provide one proxy of her human capital. On the supply-of-research side, her recent research quality and quantity may influence the nature or orientation of her current research. On the demand-for-research side, her publication quantity and the number of patents she holds might affect the funding agent's expectation of how productive or applied her research would be, and how excludable would be its findings. Let

Pub be the total number of the scientist's refereed publications since January 2000.

Patent be the total number of the scientist's patents issued since January 2000.

Another proxy for a scientist's human capital is academic rank, which may be associated with her ability or willingness to conduct relatively more basic or more applied research. One hypothesis is that senior scientists wish to or are more capable of conducting more applied research. Younger professionals, in contrast, are more prone to conduct more basic research since they are newly trained and more tenure- or promotion- motivated. Three dummy variables, *Prof*, *Assoc*, and *Assist*, are used to indicate a scientist's academic rank, namely full, associate, and assistant professor, respectively. They are included in both the demand and supply equations.

The type of university at which the scientist works likely influences her preferences for conducting more basic or excludable research, as well as the funding agent's expectation of the scientist's or university's ability to deliver on research with these characteristics. Bioscientists at Land Grant universities may choose more applied research programs than do those at non-Land-Grant universities, given the nature of the Land Grant university mission. Three dummy variables, *LG*, *PNLG*, and *Private*, indicating Land Grant, public non-Land-Grant, and private universities respectively, are included in both the scientist and funding agent equations.

Besides these factors common to both supply and demand equations, others belong exclusively to either supply or demand, that is serve as identifying variables in equations (4.6) – (4.8). I discuss these next.

4.3.3 Identifying Variables in the Supply of Research Characteristics

The scientist is assumed here to make a simultaneous decision about how basic and excludable her research will be. That decision is influenced not only by her research field, human capital, and university culture, but by her professional objectives and by her opinions about the proper role of scientific inquiry. Such attitudes, therefore, are natural candidates for identifying the supply-of-research equations. We can take the further step of employing separate attitude variables for distinguishing between the separate supply functions, one set for research basicness and the other for research excludability.

To identify the Basicness equation, I include the following attitude or ideology variables:

$Ideology^{theory}$ scale indicating the importance of "contribution to scientific theory" in the scientist's choice of research program, varying from unity for "not important" to seven for "very important."

$Ideology^{probpub}$ scale indicating the importance of "the probability of publishing in professional journals" in the scientist's choice of research program, varying from unity for "not important" to seven for "very important."

$Ideology^{curi}$ scale indicating the importance of "scientific curiosity" in the scientist's choice of research program, varying from unity for "not important" to seven for "very important."

To identify the Publicness equation, I include the following attitude or ideology variables:

$Ideology^{patent}$ scale indicating the importance of "the potential to patent and license the research findings" in the scientist's choice of research program, varying from unity for "not important" to seven for "very important."

$Ideology^{public}$ scale representing agreement or disagreement with the statement that "public scientists should focus on producing knowledge or technologies with public (nonexcludable) benefits," varying from unity for "strongly agree" to five for "strongly disagree."

With these measures, we can examine from equations (4.6) – (4.7) whether scientists' professional objectives and opinions are consistent with their research choices. One hypothesis, for example, is that those who highly value scientific theory contributions tend to concentrate on more basic research than do those who highly value the marketability of research findings.

University-level data include university characteristics such as university size, the broad disposition of its R&D expenditures, university intellectual property (IP) policies, and average faculty or research program quality. University size can be reflected in the number of faculty members, the graduate student enrollment, or total R&D expenditures.

A university's funding allocations, for example its total federally funded vs. privately funded R&D expenditures, may influence its scientists' average positions on the basicness and excludability spectra. On average, federally funded research tends to be more basic than is non-federally funded research, while industry-supported research tends to be more excludable than is non-industry funded research (Fuglie et al., 1996). To proxy these effects, the university's total federally financed research expenditures, *FedRD*, and total privately financed research expenditures, *IndRD*, are included as identifying variables in the Basicness and Publicness equation, respectively. Hence, for example, universities attracting relatively more federal funding likely have, or adopt, a culture more oriented toward basic research, including promotion and salary incentives that favor research of this sort.

The university's intellectual property policies, such as its helpfulness or hindrance in securing patents or negotiating license royalty rates, affect the ease with which the scientist works with the private sector, and therefore further influence the excludability of the scientist's research program. Universities providing greater IP assistance likely encourage scientists to seek funding from the private sector and to conduct research more oriented toward excludable results. For this reason, annual FTE (including both licensing as well as other FTE) in the university technology transfer office, *UnivFTE*, in included in Publicness equation (4.7).

The size of the scientist's laboratory may affect her research orientation as well: larger labs may be more conducive to more basic or more applied research. The scientist's laboratory size, measured by the annual number of FTEs employed in it (*FTEtotal*), is therefore used as a supply-side factor, included in both the Basicness and Publicness equation. We may further decompose total laboratory FTE into post-docs, graduate students, and technicians (*Postdoc*, *Grad*, *Tech*) in order to examine whether the allocation of laboratory labor inputs affects the nature of the research supplied. Post-doctoral fellows, for example, may be relatively well-trained in basic research, enabling the professor to orient her program in a more basic direction.

Including FTE variables together with *G* provides a test of allocative efficiency in a scientist's research activities, namely whether post-docs and graduate students are efficiently allocated in basic and public research (Xia and Buccola 2005). To illustrate, suppose

$$B = B(G, PD, \mathbf{X}^{B})$$

$$G = G(B, PD, \mathbf{X}^{G})$$

where B indicates a scientist's research basicness; G is total budget; and PD and NPD are postdoctoral and non-postdoctoral inputs in a scientist's laboratory. The marginal effect of PD on basicness is $\frac{\partial B}{\partial PD} \mid_{G^0}$. A scientist's total research budget G can be divided into postdoctoral (PD) and non-postdoctoral inputs (NPD) inputs, so that $G = W_{PD}\, PD + W_{NPD}\, NPD$, where W_{PD} and W_{NPD} are inputs prices. The total change in G can be expressed as $\partial G = W_{PD}\, \partial PD + W_{NPD}\, \partial NPD$. If we hold G fixed, so that $\partial G = 0$, we have $W_{PD}\, \partial PD = -W_{NPD}\, \partial NPD$. That is, the increase in PD inputs measured in dollar value must be the same as the decrease in NPD inputs measured in dollar value, provided G is fixed. We can therefore decompose marginal effect $\frac{\partial B}{\partial PD} \mid_{G^0}$ as

$$\left.\frac{\partial B}{W_{PD}\, \partial PD}\right|_{G^0} = \left.\frac{\partial B}{W_{PD}\, \partial PD}\right|_{NPD^0} - \left.\frac{\partial B}{W_{NPD}\, \partial NPD}\right|_{PD^0}.$$

Multiplying both sides by W_{PD}, we get

$$\left.\frac{\partial B}{\partial PD}\right|_{G^0} = \left.\frac{\partial B}{\partial PD}\right|_{NPD^0} - \frac{W_{PD}}{W_{NPD}} \left.\frac{\partial B}{\partial NPD}\right|_{PD^0}.$$

Postdoctoral and other inputs are allocatively efficient in basic research if

$$\frac{\left.\frac{\partial B}{\partial PD}\right|_{NPD^0}}{\left.\frac{\partial B}{\partial NPD}\right|_{PD^0}} = \frac{W_{PD}}{W_{NPD}}.$$

That is when

$$\left.\frac{\partial B}{\partial PD}\right|_{G^0} = 0.$$

If budget G is minimized at given research characteristics, basicness is unaffected by reallocation of inputs between *PD* and *NPD*, and the marginal effect, namely the coefficient estimate of *PD* in Basicness equation (4.6), is zero. If the coefficient estimate instead is negative (positive), too many (too few) post-doctoral fellows are employed in basic research. Similar arguments may be used to test for allocative efficiency in the use of graduate students.

4.3.4 Identifying Variables in the Demand for Research Characteristics

As discussed earlier, any variables representing a funding agent's characteristics or preferences belong to research demand function (4.8). These include an indicator of whether the agent is a private firm, and if it is, the geographic location of the firm, its size, and any restrictions it imposes on the scientist's research program. With this in mind, let

Firm dummy variable indicating whether the scientist obtains funding from private firms.

Loc geographic location of the biotechnology firm, where *Loc* = 1 if it is located near the scientist's university, *Loc* = 0 otherwise.

$\%firm^L$ proportion of funding from large firms (over 10,000 employees).

$\%firm^M$ proportion of funding from medium-sized firms (between 500 and 10,000 employees).

$\%firm^S$ proportion of funding from small firms (less than 500 employees).

To some extent, a university's reputation acts as a forecaster of the quality of the scientist's research program, especially in terms of the mean quality of university facilities and graduate students. The key here is that prospective research quality is only imperfectly observable to the funding agent, and it may use the university's observed characteristics, such as its ranking, as forecasters of that quality. The research funding to which the scientist has access will therefore partially be affected by the regard in which her university is held, all else constant. The presence of a university-ranking effect on the scientist's research supply is not as obvious as it is on the funding agent's research demand, since the scientist's awareness of her research capabilities presumably is greater than the agent's awareness. Thus, the scientist's provision of research characteristics likely is relatively weakly associated with her university ranking. University ranking is, therefore, included in the research demand equation (4.8) only. Two measures of a university's ranking, one for any agricultural program if it may have (*AgRank*), and the other for its general biological program (*BioRank*), are included.

As mentioned above, vector **A,** representing the proportionate shares of the scientist's funding derived from each funding agent category, may be included as exogenous variables in both the scientist-side and funding-agent-side equations. Or we may restrict **A** to serve as identifying variables for only one of these two equation sets. In the present model, I argue that share vector **A** is more properly a funding-agent-side rather than a scientist-side factor. Generally, I define **A** as the vector indicating the proportion of research budget G derived from each funding agent category, namely federal, state, firm, trade/commodity associations, and foundations.

The reasoning that portfolio variables **A** belong primarily, if not completely, to the Budget equation is that each funding agent is hypothesized to have a given willingness to contribute money for research of a given basicness and excludability. This willingness is determined by the size of that agent's research budget, its research-funding mission as dictated by its board of directors or Congressional intent, and its mission statement. Such intent is on the research demand side of the ledger and independent of a particular scientist's wishes. Vector **A** therefore can be thought of as the set of proportions of the scientist's total grant G derived from the respective class of funding agents. As the proportion of funding from a given agent class rises, research characteristics vector **S** increasingly represents, *ceteris paribus*, the preferences of that agent class. Because I do not represent such preferences explicitly in demand function (3.5), **A** acts much like a set of continuous dummy or proxy variables, in the present case gradually shifting $\mathbf{S}^d$ toward or away from the unobserved ideological or policy preferences of the respective funding agent class.

Placing portfolio variables **A** instead on the research supply, that is the funding demand, side would permit us to observe the representative scientist's demand for funding from each source, that is, her supply of basicness and excludability to that source. A scientist may have ethical predilections for particular funding sources, or find one easier to deal with or to provide more or better nonmonetary inputs (accounted for explicitly in vector **M**) than another does. For example, a scientist might wish to pursue a more basic research program if funded by NSF rather than by a private firm because it is easier and thus less costly to conduct basic research in conjunction with NSF than with the firm. However, considerations of research cost are more properly modeled as funding supply factors and thus in the Budget equation *G* rather than the scientist equations. Considering **A** as a research supply-side factor would as well reflect those features of a contract not reflected in other supply variables like **M**. Because such factors already are explicitly included in supply, **A** is not as likely important in the supply as in the demand functions. Our survey data contain a large number of variables describing the scientist and her university, which collectively compose the supply-side variables. In contrast, we have little specific information on the agents providing funding, which together would compose the demand-side variables.

Funding source thus affects research basicness and publicness, but indirectly rather than directly and through demand rather than supply. Data limitations require treating it exogenously. We define vector **A** as the proportion of research budget G derived from:

A^{NIH}	National Institutes of Health (NIH);
A^{NSF}	National Science Foundation (NSF);
A^{USDA}	U.S. Department of Agriculture (USDA);
A^{OthFed}	other federal agencies, except NIH, NSF, and USDA;
A^{State}	state governments (including Agricultural Experimental Stations);
A^{Ind}	industry (both private firms and trade/commodity associations);
A^{Found}	private foundations and non-profit organizations; and
$A^{OthFund}$	funding sources other than those above.

The descriptive statistics of variables discussed above and correlation tabulations of some key variables are summarized in Appendix A and Appendix B, respectively. In sum, a reasonable and econometrically estimable model of equations (3.4) – (3.5) is:

<u>Scientist Side (Supply)</u>

$$\begin{aligned} B \quad = f_1 (\; & P, G \;; \\ & Ideology^{theory},\ Ideology^{probpub},\ Ideology^{curi},\ FedRD,\ LG,\ PNLG, \\ & Prof,\ Assoc,\ Assis,\ Grad,\ Postdoc,\ Tech,\ OthFTE, \\ & Pub,\ Patent,\ \mathbf{Field},\ \mathbf{Discipline},\ \mathbf{M}) \end{aligned} \tag{4.12}$$

$$P = f_2 \,(\; B,\; G\,; \; Ideology^{patent},\; Ideology^{public},\; IndRD,\; UnivFTE,\; LG,\; PNLG,\; Prof,\; Assoc,\; Assis,\; Grad,\; Postdoc,\; Tech,\; OthFTE,\; Pub,\; Patent,\; \mathbf{Field},\; \mathbf{Discipline},\; \mathbf{M}) \tag{4.13}$$

Funding Agent Side (Demand)

$$G = f_3 \,(\; B,\; P;\; \mathbf{A},\; \mathbf{A}\times B,\; \mathbf{A}\times P,\; firm,\; \%firm^{l},\; \%firm^{m},\; Loc,\; AgRank,\; BioRank,\; Prof,\; Assoc,\; Assis,\; Pub,\; Patent,\; \mathbf{Field},\; \mathbf{Discipline},\; \mathbf{M}) \tag{4.14}$$

where **Discipline** = $Discipline^{j}$, $j = 1, \ldots, 6$, **Field** = $Field^{k}$, $k = 1, \ldots, 6$, and **M** = M^{l}, $l = 1, \ldots, 6$, are as defined earlier in this chapter.

Consequently, an econometrically estimable model of reduced form (3.14) – (3.15) is:

$$B = g_1 \,(\; Ideology^{theory},\; Ideology^{probpub},\; Ideology^{curi},\; FedRD,\; Ideology^{patent},\; Ideology^{public},\; IndRD,\; UnivFTE,\; \mathbf{A},\; firm,\; \%firm^{l},\; \%firm^{m},\; Loc,\; AgRank,\; BioRank,\; Prof,\; Assoc,\; Assis,\; Pub,\; Patent,\; LG,\; PNLG,\; Grad,\; Postdoc,\; Tech,\; OthFTE,\; \mathbf{Field},\; \mathbf{Discipline},\; \mathbf{M},) \tag{4.15}$$

$$
\begin{aligned}
P \quad = g_2 (\ & \mathit{Ideology}^{theory},\ \mathit{Ideology}^{pub},\ \mathit{Ideology}^{curi},\ \mathit{FedRD}, \\
& \mathit{Ideology}^{patent},\ \mathit{Ideology}^{public},\ \mathit{IndRD},\ \mathit{UnivFTE}, \\
& \mathbf{A},\ \mathit{firm},\ \%\mathit{firm}^{l},\ \%\mathit{firm}^{m},\ \mathit{Loc},\ \mathit{AgRank},\ \mathit{BioRank}, \\
& \mathit{Prof},\ \mathit{Assoc},\ \mathit{Assis},\ \mathit{Pub},\ \mathit{Patent},\ \mathit{LG},\ \mathit{PNLG}, \\
& \mathit{Grad},\ \mathit{Postdoc},\ \mathit{Tech},\ \mathit{OthFTE},\ \mathbf{Field},\ \mathbf{Discipline},\ \mathbf{M})
\end{aligned} \tag{4.16}
$$

$$
\begin{aligned}
G \quad = g_3 (\ & \mathit{Ideology}^{theory},\ \mathit{Ideology}^{probpub},\ \mathit{Ideology}^{curi},\ \mathit{FedRD}, \\
& \mathit{Ideology}^{patent},\ \mathit{Ideology}^{public},\ \mathit{IndRD},\ \mathit{UnivFTE}, \\
& \mathbf{A},\ \mathit{firm},\ \%\mathit{firm}^{l},\ \%\mathit{firm}^{m},\ \mathit{Loc},\ \mathit{AgRank},\ \mathit{BioRank}, \\
& \mathit{Prof},\ \mathit{Assoc},\ \mathit{Assis},\ \mathit{Pub},\ \mathit{Patent},\ \mathit{LG},\ \mathit{PNLG}, \\
& \mathit{Grad},\ \mathit{Postdoc},\ \mathit{Tech},\ \mathit{OthFTE},\ \mathbf{Field},\ \mathbf{Discipline},\ \mathbf{M})
\end{aligned} \tag{4.17}
$$

4.4 Estimation Issues

I used a simple linear specification for the dependent and independent variables in this study. In order to implement the demand-supply relationships, equations (4.12) – (4.14), several estimation issues need to be addressed.

4.4.1 Survey Data Analysis Issues

Since a complete survey frame listing all our targeted scientists was not available, we utilized a complex sample design involving stratification, multi-stage sampling, and unequal sampling rates (see Chapter 5). A number of factors, such as non-response rates and sampling procedures, may introduce biases into the coefficients and an underestimation of standard errors.

A common supposition in statistical inference is that each individual in the population should have an equal chance of being selected. In a stratified sampling procedure, all units in the sample do not have the same chance of selection. Because our sampling procedure results in an over-sampling from non-Land-Grant (NLG) universities, a weighted correction device is needed to make statistically valid inferences from our present sample to the study population. However, deriving the appropriate weights requires knowing the size of the targeted population in each stratum, namely in LG and NLG universities. Unfortunately, such information is not available. For that reason, I stratified regressions by university type. In tests of cross-strata coefficient equality in (4.12) – (4.14), I found no significant differences between LG and NLG universities. Pooling the two groups therefore provides unbiased estimators.

Additional potential bias may result from department-level clustering. Department clustering produces correlated observations, violating the assumption of independent random sampling. An undesirable consequence of ignoring the clustering is that the variances of estimates are underestimated. Multi-level modeling is an example of a technique appropriate for cluster samples (Goldstein 1995). However, multi-level modeling further complicates the model variance-covariance structure and requires additional department-level information. It is common practice to treat data from cluster samples as if they were randomly sampled and to report standard errors based on that assumption.

Because the population size is unknown and cluster-level information is lacking, I conducted the analysis without adjusting error structures for the stratification and clustering in the sampling procedure. The sampling procedure should make little difference to regression coefficient estimates if the model is well defined, although it does affect the second-order statistics (variance estimates) that allow analysts to estimate standard errors of the first-order statistics (Lohr 1999, p. 364). Researchers employing multistage sampling in large national surveys frequently report standard error algorithms based on the assumption of simple random samples. However, ignoring complex sample design and using simple random sampling methods runs the risk of biased variance estimates (Landis et al. 1982; Kish 1992; Korn and Graubard 1995).

4.4.2 Simultaneous Equations and Contemporaneous Correlations

Each endogenous variable in each of (4.12) – (4.14) also appears on the right-hand sides of the other equations in the same block. Hence, two-stage least squares (2SLS) estimation will lead to unbiased or consistent estimates. In addition, as Basicness and Publicness equations (4.12) – (4.13) represent a university scientist's research choices, one would expect contemporaneous correlation between the error terms in these two equations. Finally, by examining the scientist's supply equations simultaneously with funding agent demand (4.14), one would expect to observe contemporaneous correlation between the error terms of the Basicness and Budget equation and between the Publicness and Budget equation. In the presence of contemporaneous correlation, equation-by-equation estimation will be consistent but not necessarily efficient. In summary, simultaneous equation estimation such as two-stage or three-stage least squares (3SLS) is necessary to account for simultaneity and contemporaneous correlation.

In reduced-form estimation, the equilibrium condition consists of the three equations (4.15) – (4.17). Since no endogeneity exists in a reduced form, single-equation OLS provides a consistent estimator of these equations. Nevertheless, assuming contemporaneous correlation, estimation by seemingly unrelated regressions (SUR) will improve efficiency. The greater the correlations among the error terms, the greater the efficiency gains will be.

Comparisons of regression results between 2SLS and 3SLS, and between OLS and SUR, are addressed in Chapter 7.

4.4.3 Interaction Terms

In light of its mission, each funding agent has its own preferences over research basicness and excludability. As discussed in section 4.2, we ideally would like to specify a set of research demand equations (4.4) – (4.5). From partial effects $\partial B^d / \partial A^i$ and $\partial P^d / \partial A^i$, $i = 1, ..., I$, we could then determine each agent's research demand for basicness and publicness. The limited sample variation on funding agents' characteristics, however, does not allow us to identify such demand-side equations. How might we obtain more information on a given funding agent's preferences over research characteristics? One possibility is to use interaction terms of the form $B^d \times \mathbf{A}$ and $P^d \times \mathbf{A}$ in Budget equation (4.8). To do this, we would rewrite (4.8) as

$$G \quad = f_3 (B,\ P,\ \mathbf{A},\ B \times \mathbf{A},\ P \times \mathbf{A},\ \mathbf{X}^G) \qquad (4.18)$$

In order to see the effect of these interaction terms, let us display elements of **A** more specifically:

$$
\begin{aligned}
G = {} & \chi_0 + \chi_1 B + \chi_2 P \\
& + \alpha_{NIH} A^{NIH} + \alpha_{USDA} A^{USDA} + \alpha_{Ind} A^{Ind} + \ldots \\
& + \beta_{NIH} (B \times A^{NIH}) + \beta_{USDA} (B \times A^{USDA}) + \beta_{Ind} (B \times A^{Ind}) + \ldots \\
& + \delta_{NIH} (P \times A^{NIH}) + \delta_{USDA} (P \times A^{USDA}) + \delta_{Ind} (P \times A^{Ind}) + \ldots
\end{aligned}
\tag{4.19}
$$

where χ, α, β, δ are the regression coefficients. The marginal effect of B, P, and the A^i (for example A^{NIH}) on G are

$$\frac{\partial G}{\partial B} = \chi_1 + \beta_{NIH} A^{NIH} + \beta_{USDA} A^{USDA} + \beta_{Ind} A^{Ind} + \ldots \tag{4.20}$$

$$\frac{\partial G}{\partial P} = \chi_2 + \delta_{NIH} A^{NIH} + \delta_{USDA} A^{USDA} + \delta_{Ind} A^{Ind} + \ldots \tag{4.21}$$

$$\frac{\partial G}{\partial A^{NIH}} = \alpha_{NIH} + \beta_{NIH} B + \delta_{NIH} P \tag{4.22}$$

Because the A^is essentially are shift terms, parameters β_i and δ_i in (4.20) – (4.21) reveal the respective funding agent's marginal preference over basicness and publicness, expressed relative to the agent class withheld from A^i to avoid perfect linear dependence. For example, as the proportion of the scientist's program allocated to basic research rises by one percentage point, the amount of money NIH is willing to provide the scientist will vary by β_{NIH}. Parameter δ_{NIH} in (4.21) reveals NIH's preference over publicly appropriable research in a similar way. If funding agents do not differ in these marginal proclivities, then

$\beta_i = \delta_i = 0$ and the total effect of basicness and publicness on funding level is, respectively, χ_1 and χ_2 in equation (4.20) and (4.21).

In initial model tests, I found the sample variances of funding portfolio variables A^i to be large, dominating the A^i 's interactions with *B* and *P*. To avoid multicollinearity we may retain only one of these three vector sets, namely, **A**, $B \times \mathbf{A}$, or $P \times \mathbf{A}$, in Budget equation (4.18), giving three alternatives of equation (4.19):

$$\begin{aligned} G &= \chi_0 + \chi_1 B + \chi_2 P \\ &\quad + \alpha_{NIH} A^{NIH} + \alpha_{USDA} A^{USDA} + \alpha_{Ind} A^{Ind} + \ldots \end{aligned} \tag{4.23}$$

$$\begin{aligned} G &= \chi_0 + \chi_1 B + \chi_2 P \\ &\quad + \beta_{NIH} B \times A^{NIH} + \beta_{USDA} B \times A^{USDA} + \beta_{Ind} B \times A^{Ind} + \ldots \end{aligned} \tag{4.24}$$

$$\begin{aligned} G &= \chi_0 + \chi_1 B + \chi_2 P \\ &\quad + \delta_{NIH} P \times A^{NIH} + \delta_{USDA} P \times A^{USDA} + \delta_{Ind} P \times A^{Ind} + \ldots \end{aligned} \tag{4.25}$$

Partial effects of A^{NIH} on *G* in (4.23) – (4.25) become, respectively,

$$\frac{\partial G}{\partial A^{NIH}} = \alpha_{NIH} \tag{4.26}$$

$$\frac{\partial G}{\partial A^{NIH}} = \beta_{NIH} B \tag{4.27}$$

$$\frac{\partial G}{\partial A^{NIH}} = \delta_{NIH} P \tag{4.28}$$

Equation (4.22) is a more flexible representation than any of (4.26) – (4.28) of the marginal effect of funding portfolio on total funding supplied. As the percentage of the budget provided by NIH increases, its marginal effect on G is determined in (4.22) by fixed level α_{NIH} along with factors varying with research basicness and publicness, that is $\beta_{NIH}B$ and $\delta_{NIH}P$ respectively.

Because of the absence of interaction terms in (4.26), the marginal effect of research portfolio A^{NIH} on total funding G is fixed at α_{NIH}. Note that the marginal effects in (4.27) and (4.28) equal that in (4.22) only when evaluated at the mean of B and P. Although equations (4.27) and (4.28) are not as flexible as (4.22), they reveal more information than does (4.26), which lacks interaction terms. By (4.27) and (4.28), we can test whether funding agents differ in their preferences for research basicness or publicness.

Hence, we estimate two separate versions of the empirical model, one with interactions $B \times \mathbf{A}$ and the other with interactions $P \times \mathbf{A}$. Adding interaction terms where one is not needed does not affect the model much unless only few data points are available. On the other hand, if an interaction actually is present and is not estimated, the two regression lines must be parallel and may badly miss some data points. The statistical significance of the interaction terms in the Budget equation (see Chapter 7) confirm our hypothesis that the money a funding agent is willing to provide is influenced by a research program's basicness and publicness.

Note that we may always measure the equilibrium effect of funding agent type on basicness and publicness by estimating reduced forms (4.15) – (4.16).

4.5 Technology in the Scientist's Laboratory

An important issue is whether inputs in a scientist's laboratory are joint or non-joint with respect to the relevant division of outputs or research characteristics. This question bears on the internal operations or technology of the laboratory. Hall (1973) says that a multiple output technology is joint if "there is no way to portray it in terms of separate production functions, and nonjoint if it can be so portrayed." Observation that more than one output is produced in the same laboratory is not sufficient to exclude nonjoint technology.

Following Hall (1973) and Denny and Pinto (1978), input nonjointness would imply that research characteristics such as public appropriability are produced essentially in separate parts of the laboratory, so that inputs used on less appropriable projects can be kept separately from those used on more appropriable projects. To state this more clearly, I define Q^{public} and $Q^{private}$ as research outputs with public and private characteristics, respectively; $\mathbf{X}^{public}$ and $\mathbf{X}^{private}$ as vectors of inputs allocated to Q^{public} and $Q^{private}$ respectively. Then the technology in a scientist's laboratory is nonjoint if we can write

$$Q^{public} = f(\mathbf{X}^{public})$$

$$Q^{private} = g(\mathbf{X}^{private})$$

That is, there are no inputs spill-ins or spill-outs across the two types of projects. In other words, more than one output is produced in the same laboratory.

In the case of input jointness, on the other hand, we can only write

$$h\,(Q^{public},\ Q^{private},\ \mathbf{X}) = 0$$

where **X** is the vector of inputs, unallocable between Q^{public} and $Q^{private}$. Inputs **X** here disappear into a single laboratory operation, so that two streams of characteristics Q^{public} and $Q^{private}$ come out of it. From conversations with bioscientists, we find that it is not easy for them to allocate laboratory inputs separately to several streams of characteristics. The joint contribution of inputs to many research characteristics would seem to be a standard situation in a scientist's laboratory. We therefore made no effort to collect the scientist's research inputs by research characteristic, such as private research inputs and public research inputs.

The other issue is to decide whether the analysis of research characteristics and their determinants should be based upon project-level or program-level information, that is whether the inputs in a scientist's laboratory are joint or nonjoint with respect to her several projects. "A research project is defined as an activity at a single location that addresses a clearly definable problem, a sizable part of a larger problem, or a number of closely related elements of a logical and manageable problem. Normally, a research project will not exceed five scientist years of effort" (CRIS Manual). By research program, we mean the portfolio of all of the scientist's on-going research projects. Usually, a research program is relatively stable and represents the scientist's long-run research orientation, remaining unchanged over a period of several years.

Our initial thinking was that project-by-project data would be necessary for an analysis of the determinants of a scientist's research objectives. The rationale was that project-level information would be essential for obtaining adequate sample variation on the proportions of the scientist's time allocated to alternative objectives, organisms, fields, and publicness and basicness characteristics. However, project-level information may be obtained only to the extent a scientist's research technology is project-nonjoint, that is that she operate a laboratory in which projects are essentially separable from one another. More likely, bioscience laboratory technology is project-joint: the scientist's several "projects" feed into a joint research program. Furthermore, if her projects really are joint, attempts to obtain data on each of them separately would confuse and frustrate the respondent. We therefore asked each scientist to provide responses only for her overall research program, defined as the portfolio of all her current research projects. Respondents who maintain more than one research program that are only weakly related to one another are invited to provide responses for their "most important" one.

Chapter 5: Sample Selection and Survey Design

Recall that our goal is to examine the determinants of a scientist's agenda in agricultural biotechnology research, with special attention to biotech firms' impacts on this agenda. A web-based national survey of academic bioscientists' agricultural biotechnology research forms much of the data for testing our empirical models. Before preceding with such a survey, it was necessary to develop a representative sample of the targeted population.

5.1 Targeted Population

First, we need to clarify the targeted population itself. Its exact nature is not straightforward. We intend to make direct inferences about the entire population of university biological scientists working on agricultural biotechnology. The identification of such a population is based upon how we define "agriculture" and "biotechnology" in this context. In the current study, we interpret both "agriculture" and "biotechnology" in a broad way. By biotechnology, we encompass more than gene splicing, the traditional definition of biotechnology, and include instead all modern molecular biology research, including both applied and theoretical investigation. We also seek a broad definition of "agriculture." By agriculture, we refer not only to research on plants, crops, and animals, but also to research on natural resource and environmental issues.

Most biologists who work on applied problems in agriculture falls into this category, especially those at Land Grant universities working in colleges of agriculture. Those who work on basic molecular research are less likely to deal directly with agricultural issues, and even if their research does have implications for agriculture, they may not realize this themselves. Thus the question is one of degree of proximity to agricultural applications. Presumably, all basic molecular work is of potential use in agricultural biotechnology. So, to obtain a complete sample, we would need to sample from the population of all bioscientists, that is, include both basic and applied biotechnological researchers working directly or indirectly with agriculture. We therefore define our targeted population as "all academic scientists who conduct basic or applied research at the molecular or cellular level with implications for biotechnologies in agriculture, forestry, or aquaculture."

Recall that, among the entire population of university biological scientists, we are particularly interested in those who have significant dealings with agricultural biotechnology firms. On the other hand, it would be useful to have information on the behavior of both biological scientists "involved" with agricultural biotechnology firms and those "not involved" in order to deduce the effects of such industry relationships. It would be preferable, then, if we could identify such information ex post and conduct stratified sampling from the two groups of interest. However, no existing professional list or directory permits such a priori delineation. Thus, instead of attempting to obtain out-of-sample information about the sub-sample of bioscientists who have relationships with agricultural biotechnology firms, we will estimate such a sub-sample ourselves in the course of our investigation.

5.2 Sampling Issues

Once we have decided upon our targeted survey population, we need to decide how to identify the sample of university scientists which fits or represents that criterion. Only about 10% of R&D expenditures in applied biotechnology are on agricultural problems; the rest have primarily pharmaceutical applications and are hence out of our purview (NSF). Sampling from all molecular bioscientists would therefore produce too many zeros in our regression sample and be an inefficient way of achieving our goals. We want, that is, to sample from the full population of molecular bioscientists, except for those who do *not* focus to some degree on agricultural or molecular-level research.

With these problems in mind, consider the following possible sources of bioscientist directories.

One alternative is simply to sample from broad lists of bioscientists, such as Peterson's Guides to Graduate Programs or any scientific society directory. The search costs would be low, but we probably would receive responses from many scientists with inactive research programs, little connection to agriculture, or only oblique connection to cellular or molecular research. And our response rate likely would be quite low.

Another possibility would be lists of university bioscientists who have been awarded an agricultural biotechnology patent or who have authored a paper that has been cited in an agricultural biotechnology patent. We know that everyone on such a list would be connected in some way to agricultural applications, and many to biotech firms as well. Most scientists identified in that approach would be ones we wish to survey. However, many others we wish to survey as well, and who yet have no patent-related achievement, would be prescreened by such a list. That is, patent-related achievements would constitute a "necessary" but not a "sufficient" list.

Directories from major government funding agencies, such as USDA, NIH, and NSF, would also be potential sources of sampling information. Each government list has its own advantages and disadvantages. Yet none would provide a sample representative of our targeted population. The USDA lists are rich in bioscientists working on agricultural problems, or at least on basic molecular topics which the scientist and USDA see as potentially relating to agriculture. On the other hand, they presumably exclude those who may be working on agriculturally related issues but who have not recently received USDA grants. Solving this problem by adding scientists funded by other government funding agencies, such as NIH and NSF, will however add many scientists who fall out of our category. Even though the biological work in which some are engaged may have potential applications to agriculture, we would need additional information to cull the scientists who have no apparent relationships to agricultural problems, namely those who do basic research alone or in conjunction with pharmaceutical applications only.

Several surveys have already been conducted on the relationship between university bioscientists and biotechnology firms, and their survey approaches can provide us with guidance (Blumenthal et. al. 1986, 1996; Curry and Kenney 1990; Lee 2000; Campbell et. al. 2002). Blumenthal and Campbell first identified the universities attracting the most federal research money, then identified in those universities the departments most likely to contain faculty conducting research involving new biotechnology.[1] Finally, they obtained the faculty names and addresses in such departments through Peterson's Guides to Graduate Programs. Their study, however, focuses only on top universities and on any bioscientist working in general biotechnology. Their lists, therefore, necessarily include a great proportion of strictly pharmaceutical bioscientists, in which we are not interested. Furthermore, no agricultural colleges were included in the Blumenthal-Campbell study. Curry and Kenney instead surveyed researchers in colleges of agriculture at Land Grant universities, identifying the biotechnology faculty from USDA directories of university professionals in all fields receiving federal agricultural research funding. However, the sample so obtained is not representative of all biological scientists working on agricultural-biotechnology, because agricultural colleges at Land Grant universities operate in a different institutional context than do most biological departments in non-Land-Grant universities.

In summary, no directories of university scientists working specifically in agricultural biotechnology are currently available, and other researchers' lists do not fit our population criteria. We therefore developed a three-stage sampling procedure, first focusing on universities, then on departments, then on scientists, in order to construct an unbiased national database of bioscientists conducting research related to agricultural biotechnology.

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[1] These fields include monoclonal antibodies or hybridomass, recombinant DNA, gene splicing, genetic engineering, fermentation, enzymology, gene sequencing, gene synthesis, large-scale purification, cell/tissue culture, and peptide synthesis.

5.3 Sampling Procedure

Lists of university scientists working in agriculturally related biotechnology were developed from internet searches, written requests of department heads, and telephone contacts with department heads at a stratified random sample of colleges and universities across the nation.

5.3.1 Sample Universities

Biological scientists conducting agricultural biotechnology research are spread broadly across U.S. universities. Besides scientists who obviously work on agricultural topics in Land Grant universities, we wish to include those pursuing basic molecular biology and who do not think of themselves as "agricultural" but whose work has agricultural implications. I hypothesize that greater cross-scientist and cross-university variability will be found in the non-Land-Grant sector; that is, the Land Grant sector will provide us with greater uniformity of situations and responses, given the close cultural affinity that Land Grant universities have with one another (Curry and Kenney 1990). Hence, we want to sample from both Land Grant and non-Land-Grant universities and include both basic and applied researchers in our sample. Sampling across universities will allow us to examine the impact of university type and size on scientists' research objectives.

We first restricted our university population to "Doctoral/Research Universities – Extensive" from the 2000 Carnegie Classification of universities (http:// www.carnegiefoundation.org / Classification/index.htm). See Appendix C: Carnegie Classification: Doctoral/Research Universities – Extensive. These institutions typically offer a wide range of baccalaureate programs, offer graduate education through the doctorate, and award 50 or more doctoral degrees per year across at least fifteen disciplines. The number of universities in this category is 151, among which 48 are Land Grant (including Cornell University), 55 are public non-Land-Grant, and 48 are private non-Land-Grant universities (excluding Cornell University). NSF's *Science and Engineering Indicators* (1996) reports that 96% of all university research conducted in the U.S. is concentrated in about 200 public and private higher education institutions. The Carnegie list therefore includes most research-extensive universities in the United States.

The density of biotechnology scientists in public universities specializing in plants and animals is much greater than that in private universities. And, within public universities, the density in Land Grant universities is greater than that in public non-Land-Grant universities. If only a small number of bioscientists at public non-Land-Grant and private universities are involved in biotechnology research with implications for agriculture, a sampling rate in these two cells equal to or greater than that in Land Grant universities would be justified. We therefore drew twenty universities in each of the three following categories: Land Grant, public non-Land-Grant, and private. After sampling departments and identifying bioscientists by department chairs, a total of 1,371 bioscientists was identified, 841 at Land Grant, 280 at public non-Land-Grant, and 250 at private universities. As expected, the number of observations in non-Land-Grant institutions is not balanced with that in the Land-Grant stratum, raising the possibility that we may not be able to obtain enough sample variation in these two strata for our analysis.

Thus, ten additional universities were drawn from public non-Land-Grant and private universities, providing 220 additional names at public non-Land-Grant and 96 at private institutions. A total of 80 universities is therefore included in our sample, 20 from Land Grant, 30 from public non-Land-Grant, and 30 from private universities. See Appendix C for the stratified random sample of 80 universities employed in this study, together with their Carnegie classifications.

5.3.2 Sample Departments

After randomly sampling 80 universities from the Carnegie Classification, we next went to each university's website and recorded the names of all biologically-related departments at that university. Only academic university departments were included; programs, institutes, and research centers were excluded. At universities without a departmental structure, the corresponding schools or programs were chosen instead. Potential departments are defined as those associated with agriculture or biology, excluding those that were human-focused only. Thus, medical school departments were included, except those obviously related only to human medicine, such as departments of nursing, human anatomy, and surgery. A master list of all possible departments that might contain our targeted population was compiled in this manner. Because faculty conducting research related to agricultural biotechnology are spread widely across departments, we asked a panel of six bioscientists to then revise downward the departments we would employ for assembling our sample.

In order to streamline this process, departments in both Land Grant and non-Land-Grant universities were grouped into main and sub-categories to provide a reduced list of generic department names. For example, animal biology, structural biology, organism biology, evolutionary biology, and biological science were grouped under the main category of Biology, while plant biology, plant sciences, and plant growth facilities were grouped under Botany. A list of such generic department names (36 for Land Grant, 28 for non-Land-Grant) was generated based upon this approach (see Appendix D). Next, we showed the Appendix D list to a panel of six bioscientists and asked them to "mark the fifteen names that in your best judgment we ought most to target, given the scientist population in which we are interested." Our decision rule was to select the generic department names upon which at least four panel scientists agreed. Eleven genetic department names at Land Grant and nine at non-Land-Grant universities (See Appendix E) resulted from these bioscientists' selections. The final list of departments consisted of all departments grouped under the respective generic department names selected. A total of 336 departments from our sample of 80 universities was identified in this way, 136 departments from Land Grant, and 97 and 103 departments from public non-Land-Grant and private universities, respectively.

5.3.3 Sample Bioscientists

We obtained a potential list of faculty members in each selected department by drawing their names and email addresses from university websites. All faculty at the rank of assistant professor or higher in each selected department and program are included in this potential list. Post-doctoral researchers, emeriti, and technicians were excluded. We sent the potential list in each department to the department chair, explaining the nature of our targeted population and asking the chair to designate or write in those faculty names meeting our screening criteria.[1] If the chair did not respond, one email reminder and up to two phone-call reminders were placed.

A total department-head response rate of 64.47% was achieved at this step, 75.7% from Land Grant, 62.03% from public non-Land-Grant, and 52.78% from private universities. Of the 239 (71.13%) department heads responding (from the 336 departments contacted), 63 indicated none of their faculty fit our criteria, and eight refused to provide such information, either for no reason or because they were otherwise occupied. Lee (2000) used a similar method to identify faculty scientists and engineers who collaborate with industry on research. Of those he contacted, 185 (74.6%) of chairs responded, only eight explicitly declining to cooperate. In our case, nonresponding departments did not differ significantly in university rank or department size from responding departments.

A list of 1689 faculty scientists believed to be involved in agricultural biotechnology research was developed from those department head responses, among which 841 are at Land Grant, 500 at public non-Land-Grant, and 346 at private universities. From this list, we randomly sampled 595 scientists from the Land Grant university stratum but included all scientists in the public non-Land-Grant and private strata. A total sample of 1441 scientists believed to be involved in agricultural biotechnology research was identified in this way.

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[1] (a) Hold a faculty appointment and have a research program (By research program, we mean the portfolio of his/her research projects); (b) act as principal investigator or co-principal investigator for at least one project in his/her research program; and (c) conduct basic or applied research at the molecular or cellular level with implications for biotechnologies in agriculture, forestry, or aquaculture.

The purpose of the above procedures was to obtain an unbiased national random sample of academic scientists conducting molecular-level research having what the scientist regards as potential implications for plant or animal products. This national database will, we believe, capture the depth and variety of university-industry relationships in agricultural biotechnology.

5.4 Survey Design and Survey Response Rate

As mentioned earlier, a survey of academic bioscientists, concentrating on their research objectives, resources, research contract terms, budgets, and research outputs, will enable construction of the first university laboratory-level economic database on plant and animal biotechnology. The survey will form much of the data for testing (3.4) – (3.5) and therefore will provide the means for examining the impact on university bioscience agendas of a wide variety of university, industry, and public policies.

5.4.1 Web-Based Survey Design and Procedure

The design of the survey instrument was informed by case study questions and findings, interviews with knowledgeable biological researchers, discussions with colleagues, and a review of the literature. A focus group discussion with eight researchers and a pretest of 60 respondents helped put final shape to the survey instrument.

A final internet-based survey of 171 questions was administered to 1441 university scientists across the nation from October 31, 2003 through March 19, 2004. The questions asked about the scientist's research funding sources and allocations, discipline and research field, academic activities, research output, human capital and ideology, and industry impact upon academic research in agricultural biotechnology. The survey approach was to send each of the 1441 scientists on the survey list a postal letter explaining our research objectives and survey outline and including a $5 incentive payment. Up to three email reminders and one final postal letter were sent as reminders to non-respondents. Both the initial postal invitation and subsequent reminders included the website address at which the internet survey instrument could be accessed, along with a personal access number necessary for gaining entry to the survey pages.

The survey instrument itself contains two further screening questions asking whether the scientist holds a regular faculty appointment at her college or university, and whether she is a principal investigator for at least one project in her research program. Once respondents had successfully logged on to the survey, the two screening questions determined their intended eligibility for the remainder of the survey questions. Following the two screening questions, we further ask whether the scientist pursues biotechnological research at the cellular or molecular level and which would have agricultural implications.

Based upon the department chair's judgment, all scientists in our sample are supposed to conduct basic or applied research at the molecular or cellular level with implications for biotechnology in agriculture, forestry, or aquaculture. However, around thirty percent of our respondents (18.2% at Land Grant, and 40.8% and 49% at public and private non-Land-Grant universities) answered "no" when we asked whether they did so. We will call the scientists who answered *yes* to this question the "ag-biotech" respondents, and those who answered *no* the "non-ag-biotech" respondents. When testing for equality of means and variances (two-sample t-tests) in a number of key variables, and for equality of coefficients in stratified regressions of equations (4.15) – (4.17) (Wald and F-tests), I did not find any significant differences between these two groups. For our purposes, that is, the non-ag-biotech group appears to be part of the same population as the ag-biotech group. We could on two grounds, therefore, be justified in pooling the answers from both types of respondents. First, the commonality of distributions of key variables suggests the department chairs were right that the non-ag-biotech scientists' work is at the cellular or molecular level with implications for agricultural biotechnology, and that the later group was wrong in denying it. As discussed above, those who work in basic molecular research, especially, at non-Land-Grant universities, are less likely to deal directly with agricultural issues, and even if their work is related to or has implications for agriculture, they may not realize it. The comparatively high rate of respondents at non-Land-Grant institutions considering themselves as non-ag-biotech researchers supports this argument. Second, even if the work of these scientists is not at the molecular or cellular level or related to agriculture, combining their responses with the ag-biotech group in our final dataset makes no empirical difference because "non-ag-biotech" and "ag-biotech" scientists evidently behave in the same way within the frame of our questionnaire.

5.4.2 *Final Survey Response Rate*

Ninety-seven respondents were ineligible for our analysis, excluded either by our screening questions or on some other ground such as retirement, sabbatical leave, or departure from the university. Of the eligible respondents, 859 (63.8%) submitted a complete or partially complete survey response by website or postal mail. Characteristics of survey respondents are summarized in Table 5-1. Survey nonrespondents totaled 485, of whom 49 explicitly refused to complete the form, their typical reasons including time unavailability or a policy of never responding to surveys of this sort. The response rate distribution was 68.4% at Land Grant and 60.8%, and 59.6% at public and private non-Land-Grant universities. As university type became progressively remote from agriculture, that is when moving from Land Grant to public non-Land-Grant to private, the response rate fell. Assuming scientists in all three types of institutions are equally willing to spend time filling out surveys about their research, the decline in response rate suggests that non-response is partly related to a scientist's judgment that her work is unrelated to agriculture and thus not relevant to our survey. Therefore also, we cannot interpret "non-response" in the same way as it is interpreted in most studies.

We conducted a follow-up email survey of 433 nonrespondents to collect data on their research activities and relationship with industry. Nonrespondents did not differ significantly from respondents in academic rank, number of publications, and percentage of research funding obtained from industry.

Table 5-1: Survey Sample Characteristics

Characteristic	Number	Proportion
University stratum		
Land Grant	407	0.47
Public non-Land-Grant	304	0.35
Private	148	0.17
Year in Profession		
0-5	31	0.04
6-10	137	0.17
11-20	277	0.35
21-30	220	0.28
31-40	97	0.12
>40	27	0.03
Academic Rank		
Professor	384	0.48
Associate Professor	195	0.24
Assistant Professor	208	0.26
Other	10	0.01
Annual Research Budget		
0-100K	268	0.34
100,001-250K	291	0.36
250,001-500K	158	0.20
500,001-1M	66	0.08
>1M	15	0.02
Publications		
0-5	222	0.28
6-10	250	0.32
11-20	222	0.28
21-30	73	0.09
>30	24	0.03
Total	859	

Notes: Because of question nonresponse, numbers of faculty may not add to 859 for certain characteristics.

5.4.3 Sample or Data Limitations

Our sample procedure and data are subject to limitations. First, although the universities surveyed are representative of major institutions in the United States, our sample is drawn from departments more likely to contain faculty who conduct research related to agricultural biotechnology than are other departments in the same universities. Our sample is not, therefore, representative of all academic bioscientists in every department of the sampled universities. For example, sampled departments may be more involved in applied research than are non-sampled departments. Second, despite our high response rate (63.9%), the fact that approximately 35% of those contacted did not respond to the survey may introduce non-response bias into the data. We have no way of determining the full extent or direction of any such bias, although the limited information available does not suggest a significant problem.

Chapter 6: Data Sources and Description

The national survey of bioscientists in U.S. universities provides most of the individual-level, and part of the university-level, data necessary for this study. We further collected secondary data at the university level from sources such as the Association of University Technology Managers (AUTM) and National Science Foundation (NSF). We cleaned all our survey responses, question by question. We placed all the responses to each question together, examined outliers or extreme values, and adjusted accordingly. A given respondent's answers to related questions were checked for consistency, and adjustments made so that the corresponding responses would be consistent with one another. Categories used for open-ended questions, such as on discipline, field, and organism, are discussed in detail in the present chapter. Other data cleaning issues were relatively straightforward and will not be discussed here at length.

6.1 Survey Data

6.1.1 Publicness and Basicness

To measure how basic or public a scientist's research is, two kinds of measures were developed in this survey. One of our survey questions asks the scientist to indicate the basicness/publicness of her research on a one-to-six Likert scale. We then asked the scientist to provide the percentages of her research program devoted to basic and applied research and the percentages devoted to public and private research (see Appendix F: Survey Questionnaire, Q8).

These two sets of questions are complementary to each other in the following way. The former set places the scientist's responses on a Likert scale, which is comparable to those of other scientists. At the same time, it assumes the scientist's individual research projects are conducted jointly with one another, that is, no single project can be distinguished within the program in any meaningful way. The latter set seeks instead for the percentage of the scientist's inputs or outputs that may be regarded as basic vs. applied or excludable vs. nonexcludable. This assumes the research program is instead nonjoint in inputs, that is, consists of a sum of individual projects, each with its allocable input set. In asking both, therefore, we give the scientist maximum leeway in thinking out her program.

Based on our case study responses and Washington State University focus group, it seems bioscientists have little difficulty in understanding what "basic" research means, while there is considerable variety in their understanding of "public." As discussed in Chapter 4, "public" generally means both "nonrival" and "nonexcludable." And since we focus primarily on the "nonexcludable" side of scientists' research, the terms "excludability" and "nonexcludability" were used in the survey instead. A definition of excludability (private) and nonexcludability (public) are provided in the survey to guide the scientist in answering this question. In our definition, we distinguish between the underlying technical excludability of the research itself and the scientist's proclivity for excluding (e.g. patenting) it.

6.1.2 Organism Categories

We asked the scientist to indicate the organism on which she is working (Appendix F: Survey Questionnaire, Q5). Note that we ask the respondent to indicate only those organisms with economic or commercial value. In other words, we exclude organisms that have no agricultural or commercial value but that are suitable for fundamental research, namely *model* organisms. The presumption is that if the scientist does not answer this question, she must be working on a model organism. The fact that about 56 percent of the respondents did not indicate any organism suggests about half the respondents do work primarily on a model organism. After consulting our scientific advisors, we are assured that the approximately 50% ratio of non-model to model organisms is plausible in the United States. We thus assume all respondents who did not answer the organism question to be working on model organisms. Thus, also, any organism the scientist did not list as a model organism is, we assume, one she studies for directly economic or commercial purposes.

The criteria we employed to categorize organisms are based principally on their value of production and agricultural significance, and common consensus about what is major or non-major among U.S. crops and animals. The National Agricultural Statistics Service (NASS/USDA) publishes U.S., state, and county agricultural statistics for many commodities and data series, including rankings based on value of production (http://www.usda.gov/nass/pubs/histdata.htm).

The organism categories I employ are: (a) model organisms; (b) commercially major plant commodities, including maize, wheat, soybeans, rice, cotton, potatoes, and hay (if the plant is not used as a model organism); (c) commercially minor plants, including all plants not categorized as model organisms or as commercially major plants, e.g., dry beans (if not used as a model organism); (d) commercially major animals, including beef, pigs, dairy, and chickens (if the animal is not used as a model organism); (e) commercially minor animals, including all animals not categorized as model organisms or as commercially major animals, e.g., bees (if not used as a model organism); (f) forestry commodities, e.g., pines (if not used as model organisms); (g) aquacultural commodities, e.g., salmon (if not used as a model organism); (h) pathogens; (i) organisms related to human health; and (j) other organisms not fitting into any of the above categories.

If any indicated organism is not a crop or animal but related exclusively to one, for example if a particular pathogen were specific to a particular crop, we categorized it under the respective plant or animal.

In an earlier (and discarded) version of this question, we were to provide respondents with a list of major and minor crops and animals and ask them to choose from among the list. However, pretest responses and focus group discussions suggested scientists tend think of their own crops as "major." We concluded that, instead of defining major and non-major crops and animals in the survey question, it would be easier to allow respondents to write the names of the organisms on which they primarily work, then classify their answers after the responses have been received.

6.1.3 Discipline, Field, and Topic

As discussed in Chapter 4, we seek to represent the scientist's research program at three different levels: discipline, research field, and research topic. It is reasonable to treat both discipline and field as exogenous factors, to be included either in both the supply and demand equations (4.12) – (4.14) or as an identifying factor in either supply or demand.

During our survey instrument design phase, our initial intention was to provide an exhaustive list of discipline, research field, and research topic possibilities and to let the scientist check one. Given that our target population is broad and widely distributed across departments, it is not easy to produce such a list of categories that would prevent a significant number of respondents from choosing "other." Furthermore, when providing a preliminary list to pilot bioscientists respondents, and from focus group feedbacks, we were persuaded that a simple list of alternatives in each of those categories would confine the scientist's possibilities too greatly. In the end, we decided upon an open-ended form in which respondents offered their own way of characterizing their discipline, field, and topic. Because "discipline", "research field", and "topic area" are potentially vague and might imply alternative levels of specificity, we provided examples (Appendix F: Survey Questionnaire, Q4).

Once the surveys were returned, our further task was to select a classification system for categorizing "discipline" and "field" responses into groups usable for descriptive and econometric analysis. The highly variable responses to "topic" rendered it difficult to group them into useful categories and they were used instead to assist in discipline and field categorizations. Alternative ways of categorizing life science disciplines and fields are summarized below.

6.1.3.1 Potential Lists for Categorizing Life Science Disciplines and Fields

a. Research Fields, Courses, and Discipline Classifications (RFCD) in the Australian Bureau of Statistics

A list of disciplines and research fields in the biological sciences and in the agricultural, veterinary, and environmental sciences is provided by the Australian Bureau of Statistics (*Australian Standard Research Classification 1998*). The Australian Standard Research Classification (ASRC) is the collective name for a set of three related classifications developed for use in the measurement and analysis of research and experimental development (R&D) undertaken in Australia, both in the public and private sectors. One of the component classifications, Research Fields, Courses, and Disciplines (RFCD) (http://www.abs.gov.au/ausstats), includes recognized academic disciplines and related major sub-fields taught at universities or tertiary institutions, major fields of research investigated by national research institutions and organizations, and emerging areas of study.

b. National Center for Education Statistics (NCES) Classification

A list of disciplines is also provided by the National Center for Education Statistics Classification of Instructional Programs (http://nces.ed.gov/pubs2002/cip2000). The National Center for Education

Statistics (NCES) is the primary federal entity for collecting and analyzing data related to education in the U.S. and other nations. Education statistics are used by Congress, federal agencies, state and local officials, educational organizations, and the general public.

c. NSF Surveys and Reports

NSF employs several classifications of discipline and field in its various surveys. One such survey is the Survey of Doctorate Recipients (SDR), biennially conducted since 1973. The other is the Survey of Earned Doctorates (SED), an annual census of research doctorates awarded in the United States. NSF also finds the results important for internal planning, since most NSF grants go to individuals with doctoral degrees. NSF's discipline categories are standardly employed in biological programs but lack information for agricultural programs.

d. USDA/CRIS System

The Current Research Information System (CRIS) is the U.S. Department of Agriculture (USDA)'s documentation and reporting system for ongoing and recently completed research projects in agriculture, food and nutrition, and forestry. All research sponsored or conducted by the USDA is required to be documented in CRIS. Over 95% of all publicly supported agricultural and forestry research is documented in CRIS, and the system contains both management and scientific data. Its agricultural and forestry research classification (http://cris.csrees.usda.gov/star/manual.html) is rich in details on agricultural fields, although it lacks details on biological disciplines.

6.1.3.2 General Procedure for Categorizing Discipline and Field

After consulting scientists and other sources, we decided to employ the NSF and USDA/CRIS systems as our baseline for categorizing discipline and research field, respectively. Standard categories such as those in NSF and USDA/CRIS have the advantage of being familiar and credible to U.S. academic scientists in the U.S. and offer many biological and agricultural details. Hence, they enable us to express our findings in language that is standard in the profession, and help us link our analysis to commonly accepted terms in the literature.

Two bioscientists assisted us in sorting respondents' discipline and field responses to the NSF and USDA/CRIS categories. We first separately provided the response lists to each of the two scientists, and asked each to conduct the sorting independently of the other. We then asked them to work jointly in resolving the discrepancies between their designations.

a. Research Discipline Classification

As indicated above, the NSF's Degree Field List (Biological and Agricultural Sciences Categories, (http://www.nsf.gov/sbe/srs/nsf03310/htmstart.htm), used in the Survey of Doctorate Recipients (SDR) and Survey of Earned Doctorates (SED), was employed to serve as our reference for the discipline categorization. Although NSF refers to this as a "field" list, it is closer to the notion of discipline specificity in the present study.

For the discipline dimension, we would rather not draw any lines between "agriculture," "biology," and "health" as such, but rather focus on the underlying academic discipline in which the scientist has been trained. Hence, we cross over the boundaries of the "agricultural" and "biological" sections of the NFS list in drawing together a reduced list. Other categories outside "Agricultural and Biological Sciences," such as "Health and Physical Related Sciences," were used as well. We later listed these categories under "Other Agricultural and Biological Sciences." In cases where the respondent listed two or more disciplines, we further referred to the respondent's field and topic responses for clues about which of the two is more important. If no clues were available, the first discipline listed was used.

SDR categories are more general than those in the SED (see Appendix G: NSF Degree Field List: *Biological and Agricultural Sciences*). We used the finer SED categories in the survey rather than the broader SDR ones, as they can easily be aggregated for subsequent analysis. Based on the SED codes and the broader SDR codes, we further aggregated agricultural and life scientists into the following six discipline categories: (1) biochemistry, chemistry, and biophysics, (2) cell, molecular, and developmental biology, (3) ecology, systematics, and environmental life sciences, (4) genetics, (5) physiology, anatomy, and pathology, and (6) other agricultural and life sciences.

b. Research Field Classification

The Current Research Information System's (CRIS) agricultural and forestry research classification (http://cris.csrees.usda.gov/star/manual.html) was employed to group the scientists' research field responses (see Appendix H: USDA/CRIS Classification).

As stated earlier, discipline and field are intended to be independent of one another; that is, the field selected for a given respondent should be independent of the discipline selected for that respondent, so that discipline and field form a matrix of two independent columns. In some of the survey responses, we obtained some overlap between discipline and field because some NSF discipline categories overlap partly with several CRIS field categories. Respondents range from basic to very applied researchers, and we cannot expect any single system of discipline-field breakdowns to be optimal for every respondent. Thus, we must select a system that is best only on average. When we encounter a respondent for whom it is not optimal, we may observe that discipline and field overlap to some extent.

In several instances, the specificity of a scientist's discipline and field responses were the same. That is, the scientist wrote a discipline-level response to the field question. For instance, a scientist may have listed biochemistry as her "discipline" and endocrinology or immunology as her "field." Both biochemistry and endocrinology are discipline-level specificities. In such cases, either Plant Production or Animal Production was employed as her field. The reason for this choice is that the CRIS list, which contains our field designations, places more basic types of research under either Plant Production or Animal Production than under other categories. For example, the sub-field "Basic Plant Biology" is listed under "Plant Production." Generally speaking, the problem we face here is that, as a USDA unit, the CRIS list has a somewhat applied focus, while many of our respondents conduct research closer to the basic end of the research spectrum. Whenever we encounter such a basic-research-oriented respondent, we surmount this problem by assigning her to the Plant Protection or Animal Production field.

On the field side, one would also like to distinguish between plants and animals, as that distinction is important and of interest to policy makers. That is, plants and animals represent two alternate (and possibly opposing) interest groups, and one would like to reflect in the field categories the scientist's choices between the two groups.

Consistent with the rules discussed above for discipline assignment, we proceeded as follows in cases where a respondent listed a field, for example abiotic stress, which was not easily placed in a CRIS category. We asked our two scientific consultants to use the respondent's "topic" response for clues about which CRIS category to select. If no clues were available for field, we created several new field categories. For example, if the respondent did not indicate whether her work dealt with plants or animals, but did indicate under Field that she works in the Protection area in the CRIS sense of the word, we designated her Field as Plant/Animal Protection. Similarly, if her field related to Production but animal or plant was left unspecified, we designated the field as Plant/Animal Production. In all, four non-CRIS field categories were employed: i) Plant/Animal Production, ii) Plant/Animal Protection, iii) Microbial, and iv) other research field. Final research field categories are (1) plant protection, plant production, (2) animals protection, animal production, (3) plant/animal protection, plant/animal production, (4) natural resources/environment and non-foods, (5) human health and nutrition, or foods, and (6) microbes and other.

6.1.4 Scientist's Ideology Variables

We also asked a number of questions regarding the effect of university technology transfer policies on the scientist's research activities. We did not include questions on scientists' views about national science policy, because such questions as the effect of the Bayh-Dole Act have been studied widely in the literature. Instead, we asked about the helpfulness or hindrance of the scientist's own university's policies in her pursuit of industry research support and patents. For example, questions were asked about the university's indirect cost rates, license royalty rates, and staff assistance in securing patents (Appendix F: Survey Questionnaire, Q23, Q24).

Finally, we asked a set of questions about the scientist's values or ethical orientation, such as the importance to her of contributing to scientific theory, or the importance of publishing her results. Answers to these questions may serve as a decision intermediary between the scientist's resources and her choice of research program (Appendix F: Survey Questionnaire, Q43, Q44). I employ these value variables, defined in Chapter 4 by such expressions as $Ideology^{theory}$, $Ideology^{curi}$, and $Ideology^{public}$, as identifying factors in the scientist-side equations of my simultaneous models (4.12) – (4.13).

6.1.5 Research Funding Variables

We asked each scientist to estimate the current annual budget of her research program, excluding overhead and indirect costs. Questionable responses were checked by examining the respondent's answers to other questions, and adjusted if corrections were needed. Extreme response values, such as an annual budget of $50 million, were coded as missing values. In certain cases, zero budgets were treated as missing also.

We asked for the approximate proportion of the scientist's annual research budget that is derived from each alternative funding source, namely federal government agencies (NSF, NIH, USDA, and other federal), state government, foundations/non-profit organizations, trade or commodity associations, individual firms, and other sources.

6.2 Secondary Data

In addition to the data collected from individual respondents in our survey, we drew upon data at the university level, such as university size, program rankings, and technology transfer policies.

6.2.1 AUTM Data

A number of sources are available on university-level technology transfer policies and resources. The Annual Licensing Survey compiled by the Association of University Technology Managers (AUTM) is the most comprehensive of its kind. The AUTM Licensing Survey population for fiscal year 2002 consisted of

225 U.S. universities and colleges. The survey provides summaries of research funding and expenditures; numbers of invention disclosures, patents, patent applications, and licenses, and income from startup companies.

Our dataset represents a total number of 66 universities, and the 2002 AUTM data does not include information for 11 of those universities.[1] We therefore contacted the 11 institutions directly. Five universities responded. For the remaining six and for any missing values in the ATUM data, the relevant NSF data were used instead.[2]

AUTM data often are inconsistent in level of specificity. For example, some AUTM data refer to an entire university system and other data to individual campuses or to a main campus. We sampled, for instance, the Ohio State University Main Campus, while the AUTM data applied to the whole OSU System. AUTM's University of California data are aggregated over the entire UC system and data for individual campuses are not available. On the other hand, AUTM data for the University of North Carolina - Chapel Hill are listed as an entity separate from the UNC system. We made university-by-university decisions on whether it would be appropriate to ascribe university-wide AUTM data to a specific campus or vice versa. In many universities, there is little research activity outside the main campus, so the error in ascribing system-wide to main-campus activity would be small. We used the NSF data for SUNY - Binghamton and

[1] The nine universities are Boston College, George Washington University, Georgia State University, Lehigh University, Marquette University, Purdue University, University of California-Davis, University of California-Los Angeles, and University of California-Santa Barbara, Western Michigan University, and Yale University,

[2] For example, two variables, total federal research expenditure *FedRD* and total industrial research expenditure *IndRD*, are missing in AUTM data for Texas Tech University and Georgetown University. NSF data were used instead.

SUNY - Buffalo instead of AUTM data for the SUNY Research Foundation, which includes 29 campuses. The following secondary-data-level variables, *FedRD*, *IndRD*, and *UnivFTEtotal*, are used as explanatory variables in our model.

6.2.2 University Ranking Data

Four principal sources are available on universities' agricultural and biological program rankings.

a. U.S. News

In its print edition of *America's Best Graduate Schools*, *U.S. News* provides rankings of top graduate programs in various fields by surveying all programs in a discipline that meet generally recognized criteria for a professional program. Although it is claimed that the *U.S. News* ranking is highly associated with other major graduate program rankings such as the NRC's, it ranks only a limited number of professional fields such as business, education, engineering, law, and medicine. For agricultural and biological program rankings, it is not very helpful.

b. Major Federal Government Agencies

NSF's Science Resource Statistics (SRS) provides annual data on academic research and development expenditure in U.S. universities and colleges (http://www.nsf.gov/sbe/srs/nsf03316/sectb.htm#rd2). The data set includes total R&D expenditure, R&D expenditure by source of fund (federal government, state and local government, industry, institutional funds, and other), and R&D expenditure in the life sciences and its sub-fields (agricultural sciences, biological sciences, medical sciences, and other). However, dollar inputs do not necessarily represent program quality. We instead use university-level federally financed R&D expenditure and industry financed R&D expenditure as bases for examining funding's scale effect on a scientist's research program.

c. The *Gourman Report*

The *Gourman Report* rates graduate and professional degree programs in U.S. and international universities. It assigns a precise numerical score in assessing the strengths and shortcomings of the top programs in 105 disciplines. It reflects thorough evaluations of graduate programs' effectiveness and is the most widely used system of rating graduate programs. Among the major factors influencing a program's or school's rating are the caliber of its faculty and facilities and the breadth of its curriculum. The *Gourman Report* also studies the hundreds of other critical considerations that affect the quality of education. It constantly reexamines programs, and has updated its ratings in 1983, 1985, 1987, 1989, 1993, 1996, and 1997. Ratings in the *Gourman Report* reflect the constant changes that take place at institutions of higher education. Increases or decreases in funding, shifts in curriculum, and modifications in research facilities all affect the quality of a program or school. The data are available only in hard copy. Both agricultural and biological sciences are included in the *Gourman* guide, but ratings are given only to programs in the top-quality group in each field, that is the top 40 to 50 programs in each discipline.

The 1997 *Gourman* ranking of agricultural graduate programs assigns a rank only to the top 32, all of which, except Texas Tech University, are in Land

Grant universities. Of those 32 universities, 17 (including Texas Tech) are included in our survey data. To the four unranked Land Grant universities[1] in our dataset I assigned the number 35, implying they are equally rated. Because the 1997 *Gourman* ranking of biological graduate programs lists only the top 33, only 15 of which are included among the 66 universities in our survey sample, a more complete ranking of biological programs is necessary for our analysis.

d. National Research Council (NRC)

The National Research Council (NRC) of the National Academy of Science conducted two studies (in 1982 and 1993) to assess the status and quality of many fields of science, engineering, and arts and humanities in the United States. The data are available online (http://www.nap.edu/readingroom/books/researchdoc/index.html). The NRC's *Research-Doctorate Programs in the United States: Continuity and Change* examines 3,634 programs in 41 fields at 274 institutions.

NRC assigns a quality rank to approximately 200 programs in each discipline. The quality of a given university's total life-science program can be measured by averaging the NRC's "Relative Rankings of Research-Doctorate Programs" in the biological fields, including biochemistry and molecular biology, cell and developmental biology, ecology, molecular and general genetics, pharmacology, and physiology. I assigned the number 200 to every university the NRC does not rank, indicating they are equally rated.

[1] The four universities are New Mexico State University Main Campus, University of Delaware, University of New Hampshire, and Virginia Polytechnic Institute and State University.

Chapter 7: Estimation Results

7.1 Initial Estimation and Testing

As discussed in Chapter 4, in order to further examine each funding agent's preference over research basicness and excludability, I introduced into the Budget equation interaction terms between these characteristics and funding portfolio variables A^i, which are the only nonlinear terms in this model. Initial testing revealed that incorporating the interaction terms introduced strong multicollinearity because the funding portfolio sample variances are large, dominating the interaction terms. Consequently, only one of the three interactions can be included in any estimation.

Recall that we seek to represent a scientist's research program at three levels: Discipline, Field, and Organism. All three were included in initial testing. However, research field and organism categories overlap with one another to some extent. Including all of them therefore introduced multicollinearity and added little explanatory power. The fact that most organism variables were nonsignificant implies they do not significantly affect either the scientist's preferences or the funding agent's money supply. Hence, I do not include organism variables in the results reported in this chapter. The final econometrically estimable form of (4.6) – (4.7) can be rewritten as:

Scientist Side

$$
\begin{aligned}
B \; = \; & \alpha_0 + \alpha_1 \; P + \alpha_2 \; G \\
& + \alpha_3 \; Ideology^{theory} + \alpha_4 \; Ideology^{probpub} + \alpha_5 \; Ideology^{curi} + \alpha_6 \; FedRD \\
& + \alpha_7 \; Prof + \alpha_8 \; Assoc + \alpha_9 \; OthRank + \alpha_{10} \; LG + \alpha_{11} \; PNLG \\
& + \alpha_{12} \; Grad + \alpha_{13} \; Postdoc + \alpha_{14} \; Tech + \alpha_{15} \; OthFTE \\
& + \alpha_{16} \; Pub + \alpha_{17} \; Patent \\
& + \alpha_{18}{}^{j} \; Discipline^{j} + \alpha_{19}{}^{k} \; Field^{k} + \alpha_{20}{}^{l} \; M^{l}
\end{aligned}
\tag{7.1}
$$

$$
\begin{aligned}
P \; = \; & \beta_0 + \beta_1 \; B + \beta_2 \; G \\
& + \beta_3 \; Ideology^{patent} + \beta_4 \; Ideology^{public} + \beta_5 \; UnivFTE + \beta_6 \; IndRD \\
& + \beta_7 \; Prof + \beta_8 \; Assoc + \beta_9 \; OthRank + \beta_{10} \; LG + \beta_{11} \; PNLG \\
& + \beta_{12} \; Grad + \beta_{13} \; Postdoc + \beta_{14} \; Tech + \beta_{15} \; OthFTE \\
& + \beta_{16} \; Pub + \beta_{17} \; Patent \\
& + \beta_{18}{}^{j} \; Discipline^{j} + \beta_{19}{}^{k} \; Field^{k} + \beta_{20}{}^{l} \; M^{l}
\end{aligned}
\tag{7.2}
$$

Funding Agent Side

$$
\begin{aligned}
G \; = \; & \chi_0 + \chi_1 \; B + \chi_2 \; P + \chi_3{}^{i} \; A^{i} \times B \\
& + \chi_5 \; Firm + \chi_6 \; \%Firm^{L} + \chi_7 \; \%Firm^{M} + \chi_8 \; Loc \\
& + \chi_9 \; Prof + \chi_{10} \; Assoc + \chi_{11} \; OthRank + \chi_{12} \; Pub + \chi_{13} \; Patent \\
& + \chi_{14} \; LG + \chi_{15} \; PNLG + \chi_{16} \; AgRank + \chi_{17} \; BioRank \\
& + \chi_{18}{}^{j} \; Discipline^{j} + \chi_{19}{}^{k} \; Field^{k} + \chi_{20}{}^{l} \; M^{l}
\end{aligned}
\tag{7.3}
$$

or

$$
\begin{aligned}
G \quad &= \chi_0 + \chi_1\ B + \chi_2\ P + \chi_4{}^{i}\ A^{i} \times P \\
&+ \chi_5\ Firm + \chi_6\ \%Firm^{L} + \chi_7\ \%Firm^{M} + \chi_8\ Loc \\
&+ \chi_9\ Prof + \chi_{10}\ Assoc + \chi_{11}\ OthRank + \chi_{12}\ Pub + \chi_{13}\ Patent \qquad (7.4) \\
&+ \chi_{14}\ LG + \chi_{15}\ PNLG + \chi_{16}\ AgRank + \chi_{17}\ BioRank \\
&+ \chi_{18}{}^{j}\ Discipline^{j} + \chi_{19}{}^{k}\ Field^{k} + \chi_{20}{}^{l}\ M^{l} \\
&i = 1,\ldots,I;\ j = 1,\ldots,J;\ k = 1,\ldots,K;\ l = 1,\ldots,L
\end{aligned}
$$

in which (7.3) differ from (7.4) only in $A^{i} \times B$ and $A^{i} \times P$.

The simultaneous model consists of three equations: (7.1) and (7.2), respectively explaining the scientist's choices over basicness and publicness, and (7.3) or (7.4), explaining the funding agent's money supply. The model is estimated using the cross-sectional data on 666 bioscientists described in the previous chapter. Equations (7.1) – (7.4) were fitted alternately with two-stage least squares (2SLS), three-stage least squares (3SLS), and a heteroskedastic 2SLS (H2SLS) model to correct for heteroskedasticity. The 2SLS was employed to correct for endogeneity and the 3SLS to check for unobserved factors affecting both the scientist's research supply and funding agent's demand. Regression results are reported in tables 7-1 – 7-2 and 7-4 – 7-5.

Unsurprisingly, a Wu-Hausman test of endogeneity could not be rejected in any of the three equations. 2SLS therefore is appropriate and provides us consistent estimates. Heteroskedasticity was detected in both the Basicness and Publicness equations, but not in the Budget equation. Uncorrected estimates in the Budget equation are efficient since no heteroskedasticity was detected. A key

2SLS assumption is that disturbances are identically and independently distributed. In the presence of heteroskedasticity, 2SLS is still consistent but no longer efficient. However, regressing the estimated error terms against the explanatory variables did not provide an appropriate model of the heteroskedasticity. A heteroskedastic two-stage least squares (H2SLS) model has been proposed to account for heteroskedasticity of unknown form in estimating a system of equations (Greene 2000, p.685). H2SLS is a single-equation estimator, using weighted observations with White's consistent estimator of the error correlation matrix, which is more efficient than the 2SLS estimator. 2SLS and H2SL provide rather similar good-of-fitness measures in our case, with R^2s of 0.46, 0.19, and 0.25 in the Basicness, Publicness, and Budget equation under 2SLS, and 0.47, 0.18, and 0.23 respectively under H2SLS.

A Lagrange Multiplier (LM) test of contemporaneous error correlation was conducted to capture unobserved factors affecting all three equations. No contemporaneous correlations were detected between the scientist-side equations and the funding agent equation. Contemporaneous correlation does exist between the scientist's modeled choices, that is between error terms of the Basicness and Publicness equations. Single equation estimation of the Budget equation provides consistent and efficient estimates since no contemporaneous correlation was detected. As shown in tables 7-1 – 7-2 and 7-4 – 7-5, 2SLS and 3SLS produce rather similar coefficient estimates, and 3SLS improves estimation efficiency only a little. No strong contemporaneous correlation appears to exist among the three equations: the cross-model correlation is around 0.18.

Coefficient and standard error estimates of the statistically significant variables in the 2SLS, H2SLS, and 3SLS models, also are rather close to one another. A number of factors should be taken into account in choosing an estimation method. Although system methods are asymptotically most efficient in the absence of specification error, they are more sensitive to specification error than are single-equation methods. In practice, models are never perfectly specified and 2SLS may produce better parameter estimates when specification is incorrect. 3SLS estimates also are affected by sampling variation in the error covariance matrix. Since we elected not to correct coefficient standard error estimates for possible non-randomness in our sampling procedure, we should use system estimation methods like 3SLS with caution. A Hausman specification test of the 3SLS and 2SLS estimates resulted in a negative Wald statistic, -31.2. The short rank of the matrix in the Wald statistic is an algebraic result. The failure of the Wald matrix to be positive definite, however, is often a finite sample problem that is not part of the model structure. In such a case, forcing a solution by using a generalized inverse may be misleading. Hausman suggests, in this instance, simply taking the result as zero and, by implication, not rejecting the null hypothesis. Both 2SLS and 3SLS are then consistent, but 3SLS is more efficient than 2SLS.

In the following, I discuss the Basicness, Publicness, and Budget equation results based on 3SLS estimation. The base group for the **Discipline** and research **Field** dummy variables are Cell & Molecular Biology and Human Nutrition and Food, respectively. I use assistant professor as the base group for academic rank, and private university as the base group for university type (*LG* and *PNLG*). In the Budget equation, all funding portfolio variables A^i add to one hundred percent. The percentage of a scientist's funding from USDA, A^{USDA}, was therefore left out of the estimation to avoid perfect multicollinearity. All other funding portfolio variables A^i are then compared with base group A^{USDA}. Similarly, the percentages of funding from large and medium-sized firms, $\%firm^L$ and $\%firm^M$, are expressed relative to that from small firms, $\%firm^S$, which is left out of the equation.

7.2 Research Supply and Funding Demand – Structural Model Results

7.2.1 University Scientist Side: Research Supply and Funding Demand

Equations (7.1) and (7.2) provide insights into the supply side of the research contract market, that is into university scientists' preferences over basicness and publicness at given total research budgets *G* and other factors $\mathbf{X}_B$.

7.2.1.1 Basic and Nonexcludable Research

From (7.1) and (7.2), the scientist's research choices *B* and *P* are affected simultaneously by one another as well as by budget *G* and the exogenous variables. That is, holding these other factors constant, the scientist's willingness to conduct basic research is influenced by her willingness to conduct excludable research, and *vice versa*.

Table 7-1: University Bioscientist's Supply of Research Basicness: Parameter Estimates

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Intercept	-43.189***	-3.38	-50.807**	-4.14	-59.455**	-4.85
G	0.017	0.96	0.012	0.69	0.035**	2.35
P	0.638***	5.23	0.662**	5.73	0.871**	8.04
Ideology ^{theory}	5.703***	5.94	6.530**	7.12	6.109**	7.28
Ideology ^{probpub}	1.561***	2.42	1.589**	2.56	1.240**	2.41
Ideology ^{Curi}	4.362**	3.35	4.408**	3.47	2.793**	2.53
FedRD	1.20E-05*	1.69	7.50E-06	1.1	5.86E-06	0.98
Professor	-2.044	-0.84	-2.258	-0.96	0.634	0.27
Associate Prof	-2.139	-0.87	-2.980	-1.25	-1.080	-0.44
Other Rank	0.176	0.02	-0.028	0	159.504**	2.7
LG	-10.592**	-3.27	-9.587**	-3.1	-8.962**	-3.02
PNLG	-0.592	-0.21	0.003	0	0.571	0.22
Grads	-1.287*	-1.92	-1.000	-1.57	-1.013*	-1.87
Post-Docs	0.831	0.56	1.732	1.25	0.216	0.18
Technicians	-3.828**	-2.9	-3.106**	-2.54	-4.181**	-3.81
Other FTE	-0.660	-0.98	-0.851	-1.31	-1.630**	-2.66
Publications	-0.316**	-2.44	-0.382	-3	-0.414**	-3.37

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Patents	-1.430**	-2.37	-1.839**	-3.18	-1.550**	-2.88
$Discipline^{Biochemistry}$	-3.991*	-1.67	-2.954	-1.25	-4.023*	-1.73
$Discipline^{Ecology}$	-17.949**	-3.87	-14.933**	-3.28	-21.191**	-4.15
$Discipline^{Genetics}$	-8.545**	-3.26	-7.498**	-2.89	-10.583**	-4.02
$Discipline^{Physi\&Path}$	-12.103**	-3.67	-11.144**	-3.51	-14.702**	-4.67
$Discipline^{Other}$	-22.546**	-6.55	-22.806**	-6.75	-25.352**	-7.7
$M^{Material}$	-3.751**	-1.65	-3.206	-1.44	-5.292**	-2.34
$M^{Capital}$	0.143	0.07	0.830	0.38	3.090	1.42
$M^{Service}$	0.503	0.25	0.530	0.26	0.337	0.17
M^{Other}	-9.197	-1.35	-8.885	-1.32	-8.534	-1.33
$Field^{Micro/Other}$	7.175**	2.05	6.407*	1.87	9.121**	2.73
$Field^{Res/Env}$	-7.820	-1.4	-11.221**	-2.09	-8.998*	-1.7
$Field^{Plant}$	5.403	1.33	5.714	1.45	9.455**	2.42
$Field^{Animal}$	8.439**	2.51	7.110**	2.14	8.778**	2.75
$Field^{Plant/Animal}$	10.880**	2.79	9.068**	2.38	12.471**	3.29
R^2	0.46		0.47			

Notes: 1. ***, **, and * indicate parameter significant at 99%, 95% and 90% confidence level, respectively.

2. The base group for **Discipline** is Cell & Molecular biology, for **Field** is Human Nutrition and Food, and for academic rank is Assistant Professor.

Table 7-2: University Bioscientist's Supply of Research Publicness/Excludability: Parameter Estimates

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Intercept	82.555**	13.35	82.179**	14.84	76.618**	14.69
G	-0.024**	-2.23	-0.025*	-1.8	-0.029**	-2.52
B	0.216**	4.35	0.221**	5.15	0.278**	6.96
Ideology ^{Patent}	-5.100**	-9.29	-5.044**	-7.82	-4.060**	-7.03
Ideology ^{Public}	-2.858**	-4.01	-2.324**	-3.22	-1.722**	-2.91
Univ. FTE	-0.015	-0.7	-0.013	-0.68	-0.024	-1.51
IndRD	5.25E-06	0.17	1.80E-05	0.72	3.20E-05	1.61
Prof	4.520**	2.47	3.180*	1.77	3.639**	2.12
Associate Prof	4.983**	2.5	3.981**	2.19	4.586**	2.6
Other Rank	12.978	1.2	11.367**	2.52	12.628**	3.05
LG	-2.168	-0.83	-2.033	-0.81	-2.302	-0.95
PNLG	-3.973	-1.61	-3.162	-1.28	-3.709	-1.61
Grads	0.329	0.76	0.298	0.58	0.466	1.12
Post-Docs	0.492	0.53	0.588	0.49	0.029	0.03
Technicians	2.075**	2.28	2.014*	1.91	1.722*	1.94
Other FTEs	0.859*	1.69	0.907*	1.78	1.151**	2.42
Publications	0.261**	2.39	0.239**	2.55	0.325**	3.76

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Patents	-0.057	-0.1	0.032	0.06	0.314	0.98
$Discipline^{Biochemistry}$	2.403	1	2.380	1.21	1.868	0.33
$Discipline^{Ecology}$	5.603	1.53	4.346	1.42	0.976	-0.28
$Discipline^{Genetics}$	-1.353	-0.58	-0.522	-0.24	-0.605	2.49
$Discipline^{Physi\&Path}$	6.613^{**}	2.71	6.942^{**}	2.88	5.542^{**}	2.32
$Discipline^{Other}$	6.272^{**}	2.15	6.497^{**}	2.61	5.561^{**}	1.22
$M^{Material}$	2.812	1.56	1.888	1.14	1.880	-2.71
$M^{Capital}$	-3.546^{**}	-2.11	-3.530^{**}	-2.15	-4.338^{**}	1.39
$M^{Service}$	1.261	0.78	1.560	0.99	2.007	0.89
M^{Other}	0.605	0.12	2.100	0.52	3.525	-0.67
$Field^{Micro/Other}$	0.832	0.28	0.396	0.14	-1.758	2.56
$Field^{Res/Env}$	4.689	1.3	6.340^{*}	1.77	8.636^{**}	-0.89
$Field^{Plant}$	-1.075	-0.38	-1.436	-0.52	-2.289	0.02
$Field^{Animal}$	0.623	0.24	0.659	0.25	0.041	-0.62
$Field^{Plant/Animal}$	-2.353	-0.66	-1.856	-0.55	-1.979	
R^2	0.19		0.18			

Note: 1. ***, **, and * indicate parameter significant at 95% and 90% confidence level, respectively.
2. The base group for **Discipline** is Cell & Molecular biology, for **Field** is Human Nutrition and Food, and for academic rank is Assistant Professor.

Taking the derivative of both sides of equation (7.1) with respect to P gives the marginal effect of research excludability on research basicness, which from table 7-1 is

$$\frac{\partial B}{\partial P} = \alpha_1 = 0.87. \tag{7.5}$$

Equation (7.5) says that, as the portion of the scientist's program devoted to public research rises by one percentage point, the portion she wishes to devote to basic research rises by 0.87 percentage point, provided budget G and all other factors are fixed. Multiplying this marginal effect by the ratio of sample-mean publicness and basicness, we obtain the elasticity form:

$$E_{B,P}\Big|_{G^0} = \frac{\partial B}{\partial P}\frac{\overline{P}}{\overline{\overline{B}}} = \alpha_1 \frac{\overline{P}}{\overline{\overline{B}}} = (0.87)(85/67) = 1.10 \tag{7.6}$$

where overbars indicate sample means. Increasing by one percent the proportion of the scientist's program devoted to nonexcludable research raises by 1.1% the proportion of her research devoted to basic biosciences holding budget G and $\mathbf{X}^{Basic}$ fixed,

The marginal effect of research basicness on research publicness, and its corresponding elasticity, can be derived in the same fashion using equation (7.2) and estimates from table 7-2. That is,

$$\frac{\partial P}{\partial B} = \beta_1 = 0.28 \tag{7.7}$$

$$E_{P,\,B}\mid_{G^0} = \frac{\partial P}{\partial B}\frac{\overline{B}}{\overline{P}} = \beta_1\frac{\overline{B}}{\overline{P}} = (0.28)(67/85) = 0.22 \tag{7.8}$$

Elasticity (7.8) shows that, holding research budget G and $\mathbf{X}^{Public}$ fixed, a 1% increase in the basicness of the representative scientist's research leads to a 0.22% increase in the nonexcludability she seeks.

A pair-wise positive relationship between the supply of basic and nonexcludable research can be seen here. More basic research usually contains greater uncertainty in the ultimate findings than does applied research, and itself may lead to a wide range of applications. It therefore is infeasible or difficult to exclude others' use of basic findings. In other words, it would seem that more basic research tends to be more nonexcludable than does applied research. By the same reasoning, applied researchers usually have specific applications in mind, so that it is easier to seek patents or other intellectual property on their results in order to exclude other parties' free use of them.

Observe that marginal effects α_1 and β_1 in (7.5) and (7.7), and elasticities (7.6) and (7.8) evaluated at sample means of B and P, indicate that the leverage of basicness on nonexcludability is smaller than that of nonexcludability on basicness. That is, although basicness and publicness are correlated with one another, the two equations are identified separately so that each has a distinct *ceteris paribus* impact on the other.

7.2.1.2 Funding Level and Research Choices

In this section, I examine the marginal effects of research budget G on basicness and nonexcludability in order to analyze funding impacts on a scientist's research choices.

The marginal budget effect on research basicness and publicness can be expressed by the following partial derivatives, using table 7-1 and 7-2:

$$\frac{\partial B}{\partial G} = \alpha_2 = 0.035 \tag{7.9}$$

$$\frac{\partial P}{\partial G} = \beta_2 = - 0.029 \tag{7.10}$$

Equation (7.9) tells us that, holding fixed the percentage of a scientist's program devoted to nonexcludable research, a scientist is willing to provide 0.035 percentage point more basic research for every \$1,000 increase in budget G. Equation (7.10) says that, holding fixed the percentage of a scientist's program devoted to basic research, she seeks to reduce the proportion of her program devoted to publicly accessible research by 0.029 percentage point for every \$1,000 increase in budget.

The elasticity forms of (7.9) and (7.10) can be calculated by multiplying the marginal effects by the mean ratio of budget G to the relevant mean research characteristic B or P:

$$E_{B,G}\Big|_{P^0} = \frac{\partial B}{\partial G}\frac{\bar{G}}{\bar{\bar{B}}} = \alpha_2 \frac{\bar{G}}{\bar{\bar{B}}} = (0.035)(273/67) = 0.14 \tag{7.11}$$

$$E_{P,G}\Big|_{B^0} = \frac{\partial P}{\partial G}\frac{\bar{G}}{\bar{\bar{P}}} = \beta_2 \frac{\bar{G}}{\bar{\bar{P}}} = (0.029)(273/85) = -\ 0.09 \tag{7.12}$$

Equation (7.11) says that, provided P and other factors are constant, the portion of research the scientist wishes to be basic increases by 0.14% for each 1% increase in research budget G. Larger budgets encourage more basic research, holding research excludability constant. One justification for this is that university scientists generally wish to conduct more basic research because it is more likely to contribute broadly to the scientific field and in turn enhance the scientist's professional prestige. If basic research, typically considered a relatively long-run process, requires more equipment, training, and labor, than does more applied research, rising budgets would permit the scientist to shift incrementally in the direction of basic investigation.

Equation (7.12) says that, provided B and other factors are constant, the portion of research the scientist wishes to be nonexcludable decreases by 0.09% for each 1% increase in research budget G. Higher research budget encourages more *excludable* research, that is discourages nonexcludable research, holding basicness constant. When additional funding becomes available, scientists naturally would consider applications or extensions of their current research. Patentable outputs are not necessarily targeted at the beginning of one's work, but often are formed as an extension of initially targeted basic research. That is, more money provides more flexibility, encouraging the scientists to conduct a greater variety of work. Research with higher payoffs usually are accompanied also with higher risk, in turn requiring greater inputs. Expressed the other way, greater inputs raise an expectation of higher output, so scientists pay more attention to finding applied uses of their innovations.

Recall that, earlier in this chapter, we found that basicness and nonexcludability are positively, although not perfectly, related to one another. In the present section, we find also that factors such as budget not only increase a scientist's preference for a basic research program but may also raise her preference for output excludability. That is, controlling for all but the budget factor brings out a negative correlation between the supply of basicness and nonexcludability. The *ceteris paribus* nature of the structural model outlined in Chapter 4 is such that we hold excludability constant in examining the research budget impact on basicness, and hold basicness constant in examining the budget impact on nonexcludability. However, as endogenous variables, basicness and publicness do not in fact stay constant in (4.6) – (4.8) when budget varies, as each is simultaneously determined by the other as funding agents' budget offerings change. Thus, conclusions about partial effects alone can be misleading and are incomplete. We need a clearer understanding of whether these relationships change after allowing for their simultaneous interaction.

In order to allow both basicness and publicness to vary when research budget does, we may derive the net effect on basicness of a change in budget, taking into account the budget change's impact on excludability supplied and the consequent effect of excludability on basicness supplied. Allowing publicness to vary gives

$$\left.\frac{dB}{dG}\right|_{P\ vary} = \left.\frac{\partial B}{\partial G}\right|_{P^0} + \left.\frac{\partial B}{\partial P}\right|_{G^0} \left.\frac{\partial P}{\partial G}\right|_{B^0} \tag{7.13}$$

This net effect consists of two parts: the first is the direct or partial effect of budget G on basicness, holding publicness fixed as in equation (7.9); the second is the indirect effect, consisting of the budget's impact on publicness times the impact of publicness on basicness. Combined effect (7.13) allows research publicness to vary with the budget. Substituting table 7-1 – 7-2 parameter estimates into (7.13), we get

$$\left.\frac{dB}{dG}\right|_{P\ vary} = \alpha_2 + \alpha_1\beta_2 = 0.035 + (0.87)(-0.029) = 0.0098 \tag{7.14}$$

The elasticity form is obtained by multiplying both sides of (7.14) by the sample-mean ratio of research budget to basicness:

$$\begin{aligned} \left.E_{B,G}\right|_{P\ vary} &= \left.\frac{dB}{dG}\right|_{P\ vary} \frac{\bar{G}}{\bar{B}} \\ &= (\alpha_2 + \alpha_1\beta_2)\frac{\bar{G}}{\bar{B}} = 0.0098(273/67) = 0.04 \end{aligned} \tag{7.15}$$

The net marginal effect in (7.14) says that as total laboratory budget rises by $1,000, the proportion of her program the scientist wishes to devote to basic research increases by 0.01 percentage point. In elasticity terms, each 1% budget increase drives up the laboratory share of basic research by 0.04%. This elasticity is rather small.

Similarly, we derive the elasticity form of the net effect of budget on publicness as:

$$E_{P,G}\Big|_{B\,vary} = \frac{d\,P}{d\,G}\Big|_{P\,vary}\frac{\bar{G}}{\bar{P}} = (\beta_2 + \beta_1\alpha_2)\frac{\bar{G}}{\bar{P}} = (-0.0192)(273/85) = -0.06 \qquad (7.16)$$

Equation (7.16) shows that a 1% increase in budget reduces the proportion of publicly accessible research the scientist is willing to provide by 0.06%.

Our structural model makes clear that the funding agent's and scientist's behavior are determined simultaneously. The net effects in (7.14) – (7.16) above also show that, given a particular research budget, simultaneity also is present within the scientist's own optimization problem. The proportion of program she wishes to devote to basic research is influenced by the proportion of her program devoted to excludable research; and the amount of excludable research desired in turn is influenced by the proportion that is basic.

The partial and net effects of research funding G on the basicness and publicness of the scientist's research program are summarized in Table 7-3.

Table 7-3: Funding Effects on Basicness and Publicness

	Partial Effect		Net Effect	
	Slope	Elasticity	Slope	Elasticity
Basicness	0.035	0.14	0.010	0.04
Publicness	-0.029	-0.09	-0.019	-0.06

First, observe from both the partial and net effect that, when basicness and publicness are both allowed to vary, budget consistently has a positive effect on basicness but negative effect on nonexcludability. In neither case does the sign of the net effect differ from that of the partial or direct effect. As shown in equation (7.14) and (7.16), the signs of the partial and net effects can differ from each other only if the second or indirect term is large enough. For example in (7.16), positive effect β_1 of basicness on publicness, or positive effect α_2 of budget size on basicness must be sufficiently large. In elasticity form, a 1% budget increase reduces the proportion of the scientist's program devoted to nonexcludable research by 0.09%, holding research basicness constant, while it reduces the proportion by 0.06% if one also takes into account the corresponding change in basicness.

The above effects suggest a scientist's budget has little influence on the characteristics of her research. Expressed as elasticities, the effects range in the neighborhood of -0.09 to 0.14. One explanation is that, because we include the laboratory's labor inputs, namely graduates, post-docs, and technicians, as exogenous variables, the marginal effect of budget G on the scientist's research choices reflect only the laboratory's non-labor effect. That is, the effect of the scientist's dollar-valued inputs G on B and P presumably is diminished by holding labor inputs fixed. Therefore, we cannot conclude from above that total research funding is only a minor factor in a university scientist's research choices. Nevertheless, other factors such as the scientist's ideology and human capital may be more influential in determining her research design choices.

Other factors in tables 7-1 – 7-2 provide insights into determinants of the scientist's supply of agricultural biotechnology research.

7.2.1.3 Laboratory FTE Allocations and Research Choices

The marginal effects of the labor-FTE variables, namely *Grad*, *Postdoc*, and *Tech*, are informative as they not only measure the effects of labor allocation choices, but also illustrate whether universities efficiently allocate graduate students and post-doctoral fellows in agricultural biotechnology research.

Research basicness responses to the proportion of the representative scientist's laboratory labor inputs allocated to graduate students, post-docs, and technicians are reflected in parameter estimates α_{12}, α_{13}, and α_{14} in equation (7.1). As one more FTE of post-doctoral time is expended in the scientist's laboratory, the proportion of the program devoted to basic research rises by 0.22 percentage point, although the effect in table 7-1 is nonsignificant. Nevertheless, as one more FTE of graduate student or technician time is expended, the proportion of the program devoted to basic research falls by 1.01 and 4.18 percentage points, respectively, and these effects are statistically significant. As discussed in Chapter 4, we can use the coefficient estimates of these FTE variables to test for allocative efficiency in the use of graduate students, post-docs, or technicians. The significant negative coefficients of *Grad* and *Tech* in table 7-1 indicate that university scientists have allocated too many graduate students and technicians for a given level of basic research. In contrast, the nonsignificance of the coefficient of *Postdoc* would seem to imply that postdoctoral fellows are efficiently allocated in university basic research.

These marginal effects can be expressed in elasticity form as

$$E_{B,\,Grad} = \frac{\partial B}{\partial\, Grad}\frac{Grad}{B} = \alpha_{12}\frac{Grad}{B} = (-1.01)(2.4/67) = -\,0.036 \tag{7.17}$$

$$E_{B,\,Postdoc} = \frac{\partial B}{\partial\, Postdoc}\frac{Postdoc}{B} = \alpha_{13}\frac{Postdoc}{B} = (0.22)(1.4/67) = 0.005 \tag{7.18}$$

$$E_{B,\,Tech} = \frac{\partial B}{\partial\, Tech}\frac{Tech}{B} = \alpha_{14}\frac{Tech}{B} = (-4.18)(1.2/67) = -\,0.075 \tag{7.19}$$

A one-percent increase in postdoctoral time raises the proportion of the scientist's program devoted to basic research by a nonsignificant 0.005%. Yet a *ceteris paribus* 1% increase in graduate student and technician time reduces the proportion of research basicness offered by a statistically significant 0.04 % and 0.08%, respectively.

Marginal effects of laboratory inputs on publicness, and the corresponding elasticities, are calculated through the same procedure. The elasticities are:

$$E_{P,\,Grad} = \frac{\partial P}{\partial\, Grad}\frac{Grad}{\%\,P} = \beta_{12}\frac{Grad}{\%\,P} = (0.466)(2.4/85) = 0.013 \tag{7.20}$$

$$E_{P,\,Postdoc} = \frac{\partial P}{\partial\, Postdoc}\frac{Postdoc}{P} = \beta_{13}\frac{Postdoc}{P} = (0.029)(1.4/85) = 4.8\text{E-}04 \tag{7.21}$$

$$E_{P,\,Tech} = \frac{\partial P}{\partial\, Tech}\frac{Tech}{P} = \beta_{14}\frac{Tech}{P} = (1.722)(1.2/85) = 0.024 \tag{7.22}$$

Grad, *Postdoc*, and *Tech* are all positively related to research publicness. A 1% rise in graduate student, post-doc, and technician time in the biotechnology laboratory raises the proportion of the scientist's program devoted to nonexcludable research by 0.013%, 0.0005%, and 0.024% respectively. However, only the technician labor effect is statistically significant. It suggests that, for a given degree of research nonexcludability, too few technicians are employed in university scientists' laboratories.

7.2.1.4 Scientist Ideology and Research Choices

The coefficient estimates of the Likert-scale attitude or ideology variables, which serve as identifying factors in the Basicness and Publicness equations, suggest that ideology has a strong and significant impact on research design. In other words, they play an important role in distinguishing between the supply of basicness and publicness. Beyond that, these parameter estimates shed light on whether university scientists' behaviors are consistent with their socio-ethical views. Parameter estimates of α_3 to α_5 and β_3 to β_5 in table 7-1 – 7-2 indicate that a bioscientist's criteria for framing her research program have significant effects on her research choices. Recall that the ideology variables are positive integers on a one-to-seven Likert scale and it is meaningless to consider them as varying by a given percentage. Therefore, the corresponding elasticities are the marginal effects multiplied by the reciprocals of the research characteristics. From tables 7-1, we have

$$E_{B,\,Ideology^{theory}} = \frac{\partial B}{\partial\, Ideology^{theory}}\frac{1}{B} = \alpha_3\frac{1}{B} = 6.1/67 = 0.09 \qquad (7.23)$$

$$E_{B,\,Ideology^{probpub}} = \frac{\partial B}{\partial\, Ideology^{probpub}}\frac{1}{B} = \alpha_4\frac{1}{B} = 1.24/67 = 0.019 \qquad (7.24)$$

$$E_{B,\,Ideology^{curi}} = \frac{\partial B}{\partial\, Ideology^{curi}} \frac{1}{B} = \alpha_5 \frac{1}{B} = 2.79/67 = 0.042 \tag{7.25}$$

In the Basicness equation, for example, as "making a contribution to scientific theory" and "scientific curiosity" rises in the scientist's importance by one Likert point, the proportion of her program devoted to basic research rises by 6.11 and 2.79 percentage points, respectively. Expressed by elasticities, the proportion of her program devoted to basic research increases by 0.09% and 0.04%, respectively. As the importance of "potential to publish" in professional journals rises by one Likert point, the proportion of her program devoted to basic research goes up by 1.24 percentage points.

The more importantly the scientist views the "potential to patent or license her research findings," the more excludable is the research she wishes to conduct. Based on parameter estimates β_3 and β_4 in table 7.2, the proportion of her program allocated to nonexcludable research falls by 4.06 percentage points for every one-Likert-point rise in such importance. Alternatively, the more important the scientist considers "focusing on producing knowledge or technologies with public benefit," the more nonexcludable is the research she is willing to supply. In particular, the proportion of her research program devoted to nonexcludable research rises by 1.72 percentage points for every Likert-point increase in this attitude.

7.2.1.5 Scientist Experience and Output and Research Choices

The nonsignificance of coefficients α_7 and α_8 in table 7-1's Basicness equation appear to say that academic rank has little effect on a scientist's willingness to conduct basic research. In the Publicness equation, table 7-2, holding basicness, research budget, and other factors constant, coefficient estimates β_7 and β_8 indicate that full and associate professors offer, respectively, 3.64 and 4.59 percentage points more nonexcludable research than do assistant professors. In elasticity form, full and associate professors, respectively, are willing to offer 0.04% and 0.05% more nonexcludable research than are younger professors. Note that the elasticities, evaluated at the sample mean of *B* and *P*, indicate a rather small academic-rank effect on research nonexcludability, although they are statistically significant.

The scientist's research outputs, *Pub* and *Patent*, represent her productivity or human capital and, to that extent, her ability or interest in pursuing basic or excludable research. Impacts of *Pub* and *Patent* on her propensity to conduct basic research are captured in coefficients α_{16} and α_{17} in table 7-1. Publication and patenting rates are both negatively related to the supply of basic research. One more publication in the bioscientist's last four years of activity decrease the proportion of the program she wishes to devote to basic research by 0.41 percentage point. One more patent decreases the proportion of her program devoted to basic research by 1.55 percentage points. It is generally reasonable that scientists holding more patents are more willing to provide applied and thus more patentable research. Nevertheless, the finding that more publications induce more applied research as well is contradictory to our expectations that intent and skill in publishing would be positively related to an interest in basic research. Possibly, applied research is comparatively easier to publish than is basic research. However, recall that the publication numbers used in present study are not quality-weighted, so that we likely underrepresent the productivity of scientists whose publications are of higher quality.

The significant coefficient estimate β_{16} in the Publicness equation, table 7-2, suggests that scientists who publish more provide more nonexcludable research. A 1% rise in publication output brings forth a 0.05% increase in the proportion of the research program that is nonexcludable. The nonsignificant coefficient estimates β_{17} might, in the absence of the high standard errors, suggests that scientists who patent more provide more excludable research. These results are straightforward and consistent with common findings in literature.

7.2.1.6 University Characteristics and Research Choices

Elasticities of explanatory factors represented by dummy variables may be computed by multiplying the dummy variable coefficient by the dependent variable's inverse. Thus, for example, the proportionate effect on research basicness of moving from the base university group (i.e., private universities) to a Land Grant university is

$$E_{B,LG} = \alpha_{10} \frac{1}{B} = (-8.96)/67 = -0.13 \qquad (7.26)$$

Holding all else fixed, a Land Grant scientist spends 0.13 % more of her time on applied research than do those in private universities. This finding is consistent with the traditional mission of Land Grant universities, which is to focus on applications and practical usefulness. The coefficients of *LG* and *PNLG*, β_{10} and β_{11}, of Publicness equation table 7-2 are both nonsignificant, with negative sign. They might, in the absence of the high standard errors, say that scientists at Land Grant and public non-Land-Grant universities devote 2.3 and 3.7 percentage points more of their effort to excludable research than do those in private universities. The signs of β_{10} and β_{11} are consistent with those of α_{10} and α_{11} in the sense that they are consistent with α_1 and β_1 in table 7.1 –7.2, which indicate that more applied research tends to be more excludable and *vice versa*.

The impact of the university's federal R&D expenditures on the mean scientist's research basicness and of university's industry-sourced R&D expenditure on the mean scientist's research excludability are both positive, but statistically nonsignificant.

7.2.1.7 Other Impacts on Research Choices

As to the Discipline variables, cell and molecular biologists, along with biochemists and chemists, are more basic researchers than are other bioscientists. Ecologists and other agricultural and life scientists conduct the most applied research, *ceteris paribus*. Scientists in genetics and physiology & pathology stand between these two extremes. In the Publicness equation, physiologists and pathologists, along with other agricultural and life scientists, conduct more nonexcludable research than do cell and molecular biologists.

Coefficients $\alpha_{19}{}^{k}$ reflect the impact of a scientist's research field on basicness. Scientists in natural resources and environmental sciences conduct more applied research than do those in other fields. Scientists in plant/animal protection or production devote a higher proportion of their program to basic research than do those in other fields. Animal biologists and microbiologists are more basically-oriented than are bioscientists working in human nutrition or food science. Plant biologists lie in the middle of this spectrum. However, little significant evidence of Field effects is detected in the Publicness equation.

We observe from coefficients $\alpha_{20}{}^{l}$ and $\beta_{20}{}^{l}$ in tables 7-1 – 7-2 that scientists who obtain material support such as plant/animal tissues or reagents from funding agents tend to conduct more applied research than do those without such support. Those who obtain nonmonetary inputs in the form of research equipment and service tend to conduct more basic research than do those without such inputs, although these effects are nonsignificant. The latter finding is consistent with the perception that basic research is more capital intensive, while applied research is more labor intensive. We note also that those who obtain capital inputs such as genomics, software, or equipment tend to conduct more excludable research than do those without such support.

7.2.2 Funding Agent Side: Funding Supply and Research Demand

As discussed above in this chapter, two versions of Budget equation (4.14) were estimated simultaneously with the Basicness and Publicness equations, namely equation (7.3) with interaction terms between B and funding source vector $\mathbf{A}$, and equation (7.4) with interaction terms between P and $\mathbf{A}$. Parameter estimates of (7.3) and (7.4) are reported in table 7-4 and 7-5, respectively. For cross-sectional data, 2SLS and H2SLS provide reasonably close goodnesses-of-fit, with R^2s of 0.25 and 0.23 in table 7-4, and R^2s of 0.29 and 0.26 in table 7-5. The discussion below is based on the 3SLS estimates in table 7-4, except that discussion about the interaction terms between P and $\mathbf{A}$ is based on table 7-5.

7.2.2.1 <u>Funding Level and Research Characteristics</u>

At a given research budget, the scientist chooses the research basicness and publicness she is willing to supply. In exchange for a given basicness and publicness offer, the funding agent in turn chooses the financial support it wishes to supply. The change in the funding agent's money offer brought about by a one-percentage point increase in the proportion of basic research offered is, from table 7-4,

$$\frac{\partial G}{\partial B} = \chi_1 + \sum_{i=1}^{7} \chi_3^{\,i}\, \overline{A}^{i} = -\,0.191 \tag{7.27}$$

Table 7-4: Funding Agent Budget Supply: Parameter Estimates (with interaction terms $A^i \times B$)

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Intercept	759.722**	4.83	557.608**	3.35	513.748**	3.29
B	-3.995**	-2.67	-2.553**	-2.09	-1.438	-1.31
P	-4.335**	-2.48	-2.638*	-1.74	-2.567	-1.76
$A^{NIH} \times B$	0.038**	3.68	0.041**	4.19	0.034**	4.05
$A^{NSF} \times B$	0.020*	1.92	0.014*	1.92	0.007	1.14
$A^{OthFed} \times B$	0.028*	1.92	0.027**	2.28	0.031**	2.95
$A^{State} \times B$	-0.011	-0.82	-0.006	-0.67	-0.007	-0.87
$A^{Ind} \times B$	-0.065**	-2.09	-0.035	-1.09	-0.015	-0.55
$A^{Found} \times B$	0.014	1.05	0.005	0.48	-0.001	-0.08
$A^{OthFund} \times B$	0.014	1.11	0.009	1.07	0.001	0.13
Firm	-1.820	-0.03	23.264	0.44	9.737	0.2
$\% Firm^I$	1.287	1.57	0.153	0.15	0.570	0.67
$\% Firm^M$	1.490	1.62	0.721	0.74	1.049	1.32
Location	-45.434	-0.75	12.607	0.27	2.766	0.07
AgRank	1.531	0.81	2.241*	1.66	2.610**	2.28
BioRank	-0.825**	-2.03	-0.740**	-2.41	-0.628**	-2.4

Variable	2SLS Estimate	2SLS Asymptotic t	H2SLS Estimate	H2SLS Asymptotic t	3SLS Estimate	3SLS Asymptotic t
Prof	2.381	0.06	-11.574	-0.37	-23.601	-0.81
Associate Prof	-21.264	-0.51	-23.480	-0.79	-26.018	-0.91
Other Academic Rank	52.571	0.25	66.051	1.01	61.537	0.96
LG	-133.964**	-2.5	-75.899	-1.36	-85.727*	-1.64
PNLG	-115.587**	-2.6	-54.072	-1.19	-46.512	-1.07
Publications	14.944**	8.69	7.099**	3.33	7.774**	3.77
Patents	28.957**	2.86	38.972**	3.07	38.833**	3.14
$Discipline^{Biochemistry}$	-15.772	-0.33	13.949	0.35	22.550	0.59
$Discipline^{Ecology}$	-11.275	-0.15	-46.608	-0.9	-49.565	-0.99
$Discipline^{Genetics}$	-51.217	-1.09	8.705	0.26	17.600	0.55
$Discipline^{Physi\&Path}$	52.821	1.15	58.239	1.25	51.461	1.18
$Discipline^{Other}$	-112.789*	-1.91	-53.687	-1.29	-28.612	-0.72
$M^{Material}$	-8.231	-0.23	-1.375	-0.05	-19.720	-0.68
$M^{Capital}$	-28.240	-0.84	-31.058	-1.23	-22.626	-0.92
$M^{Service}$	33.318	1.04	16.728	0.61	-0.752	-0.03
M^{Other}	-105.008	-1.1	-39.369	-0.63	-28.146	-0.48
$Field^{Micro/Other}$	39.221	0.68	-51.874	-1.02	-59.481	-1.23
$Field^{Res/Env}$	73.417	1.02	-6.055	-0.1	-16.727	-0.28

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
$Field^{Plant}$	32.493	0.61	-18.255	-0.35	-32.523	-0.66
$Field^{Animal}$	41.718	0.80	-6.589	-0.11	-22.870	-0.42
$Field^{Plant/Animal}$	33.146	0.49	-20.725	-0.35	-39.621	-0.69
R^2	0.25		0.23			

Note: 1. ***, **, and * indicate parameter significant at 95% and 90% confidence level, respectively.

2. The base group for **Discipline** is Cell & Molecular biology, for **Field** is Human Nutrition and Food, for academic rank is Assistant Professor, and for funding sources is USDA.

Table 7-5: Funding Agent Budget Supply: Parameter Estimates (with interaction terms $A^i \times P$)

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Intercept	741.492**	4.85	524.198**	3.2	523.023**	3.37
B	-4.074**	-3	-2.087	-1.63	-1.095	-0.92
P	-3.967**	-2.22	-2.508	-1.62	-2.980**	-2.04
$A^{NIH} \times P$	0.036**	4.5	0.039**	4.71	0.031**	4.37
$A^{NSF} \times P$	0.019**	2.17	0.012*	1.86	0.005	0.99
$A^{OthFed} \times P$	0.019*	1.89	0.019**	2.27	0.020**	2.59
$A^{State} \times P$	-0.006	-0.72	-0.004	-0.71	-0.005	-1.02
$A^{Ind} \times P$	-0.025**	-1.97	-0.010	-0.89	-0.009	-0.89
$A^{Found} \times P$	0.009	0.89	0.003	0.31	-0.001	-0.13
$A^{OthFund} \times P$	0.009	0.96	0.005	0.76	-0.001	-0.21
Firm	-15.378	-0.27	-1.133	-0.02	-5.680	-0.13
% Firm^I	1.367*	1.72	0.228	0.25	0.585	0.75
% Firm^M	1.710*	1.9	1.057	1.11	1.371*	1.74
Location	-55.763	-0.97	15.940	0.36	9.228	0.27
AgRank	1.578	0.86	2.286*	1.82	2.196**	2.06
BioRank	-0.834**	-2.12	-0.768	-2.61	-0.632**	-2.45

Variable	2SLS Estimate	2SLS Asymptotic t	H2SLS Estimate	H2SLS Asymptotic t	3SLS Estimate	3SLS Asymptotic t
Prof	-5.284	-0.15	-10.776	-0.36	-12.660	-0.45
Associate Prof	-26.426	-0.66	-26.062	-0.92	-20.166	-0.74
Other Academic Rank	89.535	0.44	82.221	1.31	85.064	1.39
LG	-158.083**	-3.07	-93.900	-1.76	-95.080*	-1.89
PNLG	-116.353**	-2.7	-62.319	-1.39	-52.864	-1.23
Publications	14.527**	8.66	6.092**	2.8	6.872**	3.26
Patents	26.804**	2.73	37.941**	3.02	38.100**	3.1
$Discipline^{Biochemistry}$	-12.424	-0.27	16.034	0.42	23.445	0.64
$Discipline^{Ecology}$	-36.781	-0.5	-50.521	-0.97	-59.512	-1.19
$Discipline^{Genetics}$	-58.465	-1.28	13.351	0.4	23.111	0.72
$Discipline^{Physi\&Path}$	38.413	0.86	57.272	1.28	49.442	1.18
$Discipline^{Other}$	-98.363*	-1.72	-33.554	-0.87	-18.903	-0.51
$M^{Material}$	-21.570	-0.62	-4.596	-0.15	-23.323	-0.8
$M^{Capital}$	-26.183	-0.8	-17.911	-0.74	-13.543	-0.57
$M^{Service}$	35.056	1.13	14.171	0.53	0.294	0.01
M^{Other}	-75.980	-0.82	-15.411	-0.27	-10.106	-0.19
$Field^{Micro/Other}$	65.892	1.14	-37.698	-0.72	-38.447	-0.78
$Field^{Res/Env}$	90.729	1.28	14.526	0.23	22.070	0.37

	2SLS		H2SLS		3SLS	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
$Field^{Plant}$	62.711	1.17	-0.002	0	-12.506	-0.25
$Field^{Animal}$	61.282	1.18	3.898	0.07	-6.949	-0.13
$Field^{Plant/Animal}$	58.898	0.88	-9.844	-0.16	-23.295	-0.4
R^2	0.29		0.26			

Note: 1. ***, **, and * indicate parameter significant at 95% and 90% confidence level, respectively.

2. The base group for **Discipline** is Cell & Molecular biology, for **Field** is Human Nutrition and Food, for academic rank is Assistant Professor, and for funding sources is USDA.

As the proportion of the scientist's program that she proposes devoting to basic research raises by one percentage point, the funding agent is willing to provide \$191 less financial support. Alternatively, a one-percentage point increase in the proportion of proposed applied research would attract \$191 additional research funding. Funding supply responds negatively to the basicness of a research proposal. In elasticity terms, a 1% increase in the proportion of the scientist's program allocated to basic research induces a 0.05% decrease in the research budget the agent is willing to supply. Alternatively, a 1% increase in the proportion of her time proposed for applied research leads to a 0.05% increase in her budget.

The marginal funding effect of the proportion of the scientist's program allocated to public or nonexcludable research can be obtained by taking derivatives with respect to P on both sides of equation (7.3). Using table 7-4, we obtain $\partial G / \partial P = \chi_2 = -2.567$. At sample means, the corresponding elasticity is -1.38. The scientist's research budget negatively responds to an increase in the proportion of her program that she proposes devoting to nonexcludable research. In particular, a one-percentage point increase in proposed public research provokes the funding agent to provide \$2,567 less monetary support. Expressed as an elasticity, a 1% increase in the proportion of her program proposed for nonexcludable research reduces the monetary support the funding agent is willing to provide by 0.87%. This effect is significant at the 10% level.

Recall from Chapter 3, equations (3.7) – (3.8), that the impacts of research characteristics on the supply of research money may be viewed as a set of hedonic relationships, each giving the implicit price of the corresponding characteristic. The marginal effects illustrated just above represent the implicit prices of research basicness and publicness as viewed by funding agents. For example, holding basicness and other factors fixed, parameter estimate χ_2 = - 2.567 says the funding agent is willing to pay $2,567 for each additional program percentage point of excludable research. Similarly, holding research excludability and other factors fixed, equation (7.27) says the funding agent is willing to pay $191 for each additional program percentage point of applied research. Expressed in terms of the notation in equation (3.10) – (3.11), $w_{basic}{}^{d} = 0.19$ and $w_{public}{}^{d} = 2.57$. Equivalently, reversing the marginal effects in (7.9) and (7.10) gives us the implicit prices of research basicness and publicness as viewed by university scientists; that is,

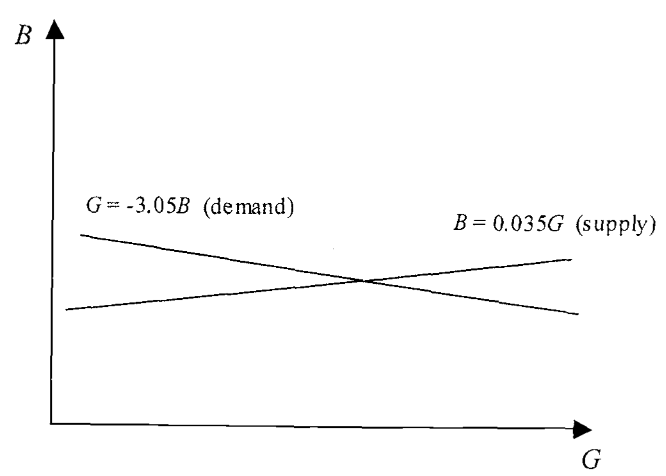
$$w_{basic}{}^{s} = \frac{1}{\partial B / \partial G} = \frac{1}{\alpha_2} = 58.82 \tag{7.28}$$

$$w_{Public}{}^{s} = \frac{1}{\partial P / \partial G} = \frac{1}{\beta_2} = 41.67 \tag{7.29}$$

Equation (7.28) says that, holding excludability and other factors fixed, the scientist asks for $58.83 to offer each additional percentage point of a basic research program. Similarly, holding research basicness and other factors fixed, the scientist asks for $41.67 to offer each additional percentage point of an excludable research program.

In sum, funding agents prefer, *ceteris paribus*, more applied and more excludable research projects. Nevertheless, from university scientists' standpoint, budget availability G has a significant and positive impact on the amount of basic research that is desirable. A picture of the supply and demand for research basicness is provided in figure 7-1, where B represents quantity and G represents "price." The supply of research basicness and publicness is rather inelastically related to budget G, with elasticities in the range of 0.06 and 0.08. That is, university scientists' broad research program designs are only weakly responsive to funding opportunities and more influenced by other factors. However, keep in mind that these small elasticities indicate pure non-labor effects, holding labor and funding agents' nonmonetary contributions constant. Funding agents' financial support is very responsive to the nonexcludability of the research proposal, with an elasticity of 0.87, but on the other hand is inelastically responsive to the basicness of the proposal, with an elasticity of 0.05.

Figure 7-1: Research Basicness – Supply and Demand



7.2.2.2 Funding Supply and Funding Sources

Marginal effects of the scientist's funding portfolio variables in the Budget equation are especially useful because they allow us, in an indirect way, to identify given funding agents' preferences for basicness and excludability in scientists' research proposals. The change in the supply of research funding brought about by a change in the proportion of funding obtained from agent i can generally be derived as

$$\frac{\partial G}{\partial A^i} = (\chi_3{}^i)(\overline{B}) \qquad \textbf{or} \qquad \frac{\partial G}{\partial A^i} = (\chi_4{}^i)(\overline{P}) \tag{7.30}$$

Drawing on results from table 7-4, and evaluating B at sample mean, we have

$$\frac{\partial G}{\partial A^{NIH}} = \chi_3{}^{NIH}\ \overline{B} = (0.034)(67) = 2.278$$

$$\frac{\partial G}{\partial A^{NSF}} = \chi_3{}^{NSF}\ \overline{B} = (0.007)(67) = 0.469$$

$$\frac{\partial G}{\partial A^{OthFed}} = \chi_3{}^{OthFed}\ \overline{B} = (0.031)(67) = 2.077$$

$$\frac{\partial G}{\partial A^{State}} = \chi_3{}^{state}\ \overline{B} = (-0.007)(67) = -\ 0.469$$

$$\frac{\partial G}{\partial A^{Ind}} = \chi_3{}^{Ind}\ \overline{B} = (-0.015)(67) = -\ 1.005$$

$$\frac{\partial G}{\partial A^{Found}} = \chi_3{}^{Found}\ \overline{B} = (-0.001)(67) = -\ 0.067$$

$$\frac{\partial G}{\partial A^{OthFund}} = \chi_3^{OthFund}\ \overline{B} = (0.001)(67) = 0.067$$

where marginal effects of A^{i} are expressed relative to A^{USDA}. That is, a one-percentage point increase in A^{i} indicates the same percentage point decrease in A^{USDA} since all the portfolio variables add to one hundred percent and we hold other portfolio variables constant. As the proportion of the scientist's budget originating from the National Science Foundation (NSF) rises by one percentage point, and other factors are held fixed, the scientist's total funding rises by \$2,278. Alternatively, a 1% increase in the NIH proportion of the scientist's budget and a consequent 1% decrease in the USDA portion bring a 0.21% increase in the aggregate funding agent's willingness to supply research support. Observe that NIH funding has the largest positive marginal influence (2.28) on budget G, followed by other federal agencies and NSF (2.08 and 0.47, respectively). Industry funding, on the contrary, has the greatest negative marginal effect (-1.04) on funding supply. USDA stands somewhat between state (including agricultural experimental station) and foundation/nonprofit support in this respect. The marginal effect of state government is 0.47, which is rather close to USDA.

These marginal effects parallel, to some extent, portfolio variables A^{i}. That is, they partially mirror the relative contributions of these funding sources to university agricultural biotechnology. However, the marginal effects do not necessarily equal the A^{i}, which correspond to the proportion of these funding agents in total funding. Table 7-6 provides a summary of the marginal effects and funding portfolio percentages. Table 7-6 show that NIH and NSF are the top two financial supporters, consistent with their marginal effects on the scientist's budget. However, industry funding ranked behind that only of NIH, NSF, and USDA, while its marginal effect on total budget was the lowest of any funding source. Other federal agencies and foundations/non-profit instead provide the lowest funds.

Table 7-6: Mean Funding Portfolio, Compared to Marginal Portfolio Effects on Total Budget

	Marginal Effect	% of Budget (A^i)
NIH	\$2,278	26.5
NSF	\$469	14.7
Other Federal	\$2,077	7.3
USDA	---	14.7
State	-\$469	14.0
Industry (firms and associations)	-\$1,005	9.3
Foundations/non-profit	-\$67	8.2
Other Funds	\$67	5.4

Notes: Marginal effects are computed relative to USDA funding.

Taking the derivative of equation (7.27) with respect to the A^i gives the second derivative $\frac{\partial G}{\partial B \partial A^i} = \chi_3^i$. This says that, as the proportion of the scientist's program devoted to basic research rises at the margin, holding publicness and other factors fixed, the marginal impact of agent i's share of funding on the scientist's total financial support rises by χ_3^i. The derivative of equation (7.32) with respect to B gives the same result, and provides information about differences among funding agents' preferences for basic and applied research. From the χ_3^i in (7.29), we observe that NIH and other federal agencies are more willing to support basic research than is NSF, USDA, or other sources. The reason is that $\chi_3^{NIH} = 0.034$ and $\chi_3^{OthFed} = 0.031$ are algebraically greater than the other χ_3^i in table 7-4. Since $\chi_3^{Ind} = -\ 0.015$, industry evidently leans more toward applied research than does any other financial source.

Second derivatives χ_4^i in equation (7.4) similarly reveal differences among funding agents' relative preferences for nonexcludable and excludable research. From table 7-5, NIH, followed by NSF and other federal agencies, are more willing at the margin to support nonexcludable research than is USDA. In contrast, industry tends to support excludable research more than does any other funding source.

7.2.2.3 Other Factors Influencing Funding Supply

Other elasticities from table 7-4 provide insights into factors influencing the supply of funding for agricultural biotechnology research.

The impact of the scientist's current research output on an agent's willingness to provide monetary support is captured by the marginal effects of Pub and Patent in funding supply equation (7.3), namely coefficients χ_{12} and χ_{13}. Table 7-4 shows that one more publication in the bioscientist's vita would elevate by \$7,774 the amount a funding agent is willing to provide. One more patent to the scientist's credit elevates the funding agent's willingness by \$38,833. Scientists who are more productive are, in other words, more competitive in attracting research support. In elasticity form, we have

$$E_{G/Pub} = \frac{\partial G}{\partial Pub}\frac{Pub}{G} = \chi_{12}\frac{Pub}{G} = (7.77)(11.28/273) = 0.32 \tag{7.31}$$

$$E_{G/Patent} = \frac{\partial G}{\partial Patent}\frac{Patent}{G} = \chi_{13}\frac{Patent}{G} = (38.833)(0.40/273) = 0.06 \tag{7.32}$$

Equation (7.31) and (7.32) say that a 1% increase in the scientist's publication and patent holdings respectively raises her total research budget by 0.32% and 0.06%. Publications have, proportionately, a larger effect on funding opportunities than do patents.

The effect of a university's agricultural and biological program rankings on its scientists' funding opportunities can be derived in elasticity form by differentiating both sides of (7.3) with respect to the program ranking variables and multiplying this derivative by the reciprocal of total research funding G. From the table 7-4 estimates, we have

$$E_{G/AgRank} = \frac{\partial G}{\partial AgRank}\frac{1}{G} = \chi_8\frac{1}{G} = 2.61/273 = 0.0096$$

$$E_{G/BioRank} = \frac{\partial G}{\partial BioRank}\frac{1}{G} = \chi_9\frac{1}{G} = (-0.628)/273 = -\ 0.0023$$

The program ranking variables are positive integers with non-unique base values, so it is meaningless to think of them as changing by a given percentage. We find that university program rankings have rather small effects on a funding agent's willingness to provide support for an individual scientist. Increasing a university's biological program ranking by one step boosts an agent's willingness to support its bioscienitsts by only 0.002%, *ceteris paribus*. Indeed, a university's agricultural program ranking has a negative impact on its scientists' financial support. As a university's agricultural program ranking rises by one step, availability of research support decreases by 0.01%. Note that agricultural biotechnology program rankings are assigned to LG universities only, so corresponding estimates are unavailable for other universities.

The size of firms providing research support is nonsignificant in the Budget equation. Had they been significant, we would conclude that large- and medium-sized firms provide more support than do small ones, the medium-sized firms providing even more support than do large ones. The contributing firm's geographic proximity to the supported scientist is negatively related to the funding supplied to her. That is, a firm located close to the scientist's university tends to provide more money than do those farther away. However, the confidence interval around this estimate is wide, since the t-statistic, 0.07, is rather small.

None of the variables representing donors' nonmonetary contributions is statistically significant in the Budget equation. Although nonmonetary research inputs such as databases, reagents, and biomaterials may be crucial to the university bioscientist's research, they may impose little additional cost on the donor that provides them. Their presence in the research contract may not, therefore, be crucial from the funding agent's point of view and hence would not affect the amount of cash it offers. Neither are the dummy variables indicating scientists' discipline and field significant in the Budget equation. Note that budget G represents the scientist's funding from all sources. In reality, one source may differ from another in its views about the importance of nonmonetary contributions and about particular disciplines or research fields. Introducing interaction terms between such variables and funding portfolio variables A^i probably would reveal more information about those issues. Unfortunately, multicollinearity problems similar to those discussed in Chapter 4 prohibit us from investigating them. The nonsignificance of nonmonetary inputs, discipline, and field dummy variables in table 7-4 may be explained partially by the fact that the Budget equation is modeled as a representative agent's preference rather than each independent agent's preference.

7.3 Research Demand and Supply: Equilibrium Conditions

In reduced form (4.10) – (4.12), each endogenous variable, which in our case consist of research basicness, research publicness, and research budget, is regressed against every exogenous variable. If the disturbances in these regressions are correlated across equations, parameters will be estimated consistently, if not efficiently, by ordinary least squares. A SUR estimator instead will provide consistent and efficient estimates. However, when all equations have the same regressors in a SUR model, the efficient estimator is single-equation ordinary least squares. In that case, generalized least squares is equivalent to equation-by-equation OLS (Greene 2000, p. 616). The reduced-form results, reported in table 7-5, are therefore estimated by single-equation OLS. No heteroskedasticity was detected in these reduced forms when the error terms were fitted against the explanatory variables. In particular, a White test of heteroskedascity in all three equations was not rejected at the 95% level.

7.3.1 Funding Source Effect

In equilibrium, the National Science Foundation encourages more basic and more public/nonexcludable research than does any other funding agent. Recall that in the structural model, table 7-4, the National Institutes of Health instead ranks first in preferences for basic research. Industry funding, more than any other, steers academic scientists' research programs toward the applied end of the research spectrum. Other federal agencies, state governments, and private industry favor excludable research more than does USDA. However, the latter two differences are not statistically significant, so state, industry, and USDA preferences for excludability appear to be approximately the same.

The National Institutes of Health, and other federal agencies besides NSF, provide higher budget support, *ceteris paribus*, than do USDA, state government, and private industry. Private industry contributes, *ceteris paribus*, the least to university agricultural biotechnology research, although its difference from USDA in this respect is not statistically significant.

Large- and medium-sized firms, in equilibrium, provide greater financial support than do small-sized firms. Biotechnology firms' geographical proximity to universities has, in equilibrium, nonsignificant impact on university scientists' research budgets.

7.3.2 Other Effects

Observe from table 7-5 that the scientist ideology measures, which serve as identifying variables in the Basicness and Publicness equations, remain significant in the reduced form. Their interpretation is similar to that in the structural model, as discussed in section 7.2.1.4. Greater use of graduate students and technicians in the laboratory leads to more applied research, and of postdocs to more basic research, although the latter effect is nonsigficant. The use of postdocs is significantly associated with the production of more excludable research.

As is evident in table 7-5, the greater the scientist's patent holdings, the more applied and excludable is the research she produces. Her publication output is positively related to the nonexcludability of her research but remains, as in the structural model results, related to its degree of application also. The scientist's publication and patent holdings have a nonsignificant effect on her budget. Professors and associate professors devote, in equilibrium, more time to nonexcludable research than do assistant professors.

Land Grant university scientists are oriented toward more applied research in equilibrium than are those in non-Land-Grant universities. University type is nonsignificant in the Budget equation at the 5% level. Ignoring standard errors, they would suggest that, holding other factors fixed, scientists at public non-land-grant universities obtain less financial support than do those at Land Grants, and those at Land Grants less than those at private universities. Other university-level variables, such as federally and industry-sourced R&D expenditures, university technology transfer office FTEs, and agricultural and biological program rankings, are statistically nonsignificant in all the reduced-form estimates.

Table 7-7: Reduced Form Results: Parameter Estimates

	Basicness		Publicness		Budget	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Intercept	2.183	0.22	89.877**	10.77	62.314	0.42
$Ideology^{theory}$	5.282**	8.32	1.434**	2.66	-30.686**	-3.18
$Ideology^{probpub}$	0.989*	1.81	-0.297	-0.64	2.651	0.32
$Ideology^{Curi}$	4.056**	4.18	-0.054	-0.06	11.211	0.75
$Ideology^{Patent}$	-2.042**	-3.44	-5.595**	-11.02	7.693	0.86
$Ideology^{Public}$	2.220**	2.83	-2.364**	-3.53	-7.104	-0.59
FedRD	1.60E-05	1.48	5.89E-06	0.63	1.56E-04	0.94
IndRD	-3.00E-05	-0.70	-8.82E-06	-0.24	-5.70E-04	-0.9
Univ. FTE	0.026	0.98	-0.011	-0.51	-0.221	-0.56
A^{NIH}	0.137**	3.46	-0.012	-0.35	1.464**	2.43
A^{NSF}	0.227**	5.63	0.067**	1.97	0.152	0.25
A^{OthFed}	-0.031	-0.64	-0.083**	-2.02	1.776**	2.42
A^{State}	-0.071	-1.63	-0.030	-0.79	-0.117	-0.17
A^{Ind}	-0.229**	-4.10	-0.052	-1.1	-0.577	-0.68
A^{Found}	0.054	1.08	0.026	0.62	0.348	0.46
$A^{OthFund}$	0.123**	2.48	0.113**	2.67	0.254	0.34

	Basicness		Publicness		Budget	
Variable	Estimate	Asymptotic t	Estimate	Asymptotic t	Estimate	Asymptotic t
Firm	-1.831	-0.56	-0.573	-0.2	-21.985	-0.44
% Firm^L	0.017	0.37	0.005	0.13	1.485**	2.12
% Firm^M	-0.008	-0.15	-0.054	-1.21	1.431*	1.81
Location	-4.994	-1.48	0.571	0.2	-8.679	-0.17
AgRank	-0.064	-0.58	-0.052	-0.56	0.752	0.45
BioRank	0.012	0.34	-0.008	-0.29	0.144	0.28
Prof	-0.513	-0.25	5.059**	2.86	1.623	0.05
Associate Prof	-1.403	-0.62	5.651**	2.96	-25.190	-0.73
Other Academic Rank	-8.885	-1.03	9.525	1.07	96.241	0.68
LG	-6.305**	-2.01	-1.027	-0.39	-32.829	-0.69
PNLG	-1.430	-0.55	-2.306	-1.03	-48.955	-1.22
Grads	-0.850**	-2.11	-0.258	-0.75	23.251**	3.82
Post-docs	0.442	0.87	-0.979**	-2.22	68.529**	8.87
Technicians	-2.497**	-4.70	0.318	0.71	59.897**	6.12
Other FTEs	-0.111	-0.23	0.171	0.41	23.763**	3.21
Publications	-0.024	-0.20	0.173*	1.67	1.948	1.06
Patents	-1.498**	-2.47	-0.463	-0.9	1.154	0.13
Discipline^{Biochem}	0.353	0.13	2.780	1.22	10.476	0.26

Variable	Basicness Estimate	Basicness Asymptotic t	Publicness Estimate	Publicness Asymptotic t	Budget Estimate	Budget Asymptotic t
$Discipline^{Ecology}$	-12.993**	-3.22	1.288	0.38	72.879	1.19
$Discipline^{Genetics}$	-7.897**	-3.11	-4.343**	-2	2.467	0.06
$Discipline^{Physi\&Path}$	-6.658**	-2.71	2.803	1.34	104.492**	2.81
$Discipline^{Other}$	-13.915**	-4.76	3.114	1.25	11.288	0.25
$M^{Material}$	-0.887	-0.44	2.469	1.43	5.976	0.2
$M^{Capital}$	-2.680	-1.44	-3.837**	-2.42	-8.019	-0.28
$M^{Service}$	2.315	1.28	1.675	1.09	4.531	0.17
M^{other}	-3.924	-0.74	-0.579	-0.13	-3.661	-0.04
$Field^{Micro/other}$	11.798**	3.57	3.892	1.38	-31.602	-0.63
$Field^{Res/Env}$	0.608	0.15	3.958	1.11	6.663	0.1
$Field^{Plant}$	11.449**	3.68	2.288	0.86	-62.557	-1.33
$Field^{Animal}$	12.820**	4.42	3.064	1.24	-0.092	0
$Field^{Plant/Animal}$	11.683**	3.12	0.024	0.01	-66.480	-1.17
R^2	0.61		0.33		0.48	

Note: 1. ***, **, and * indicate parameter significant at 95% and 90% confidence level, respectively.
2. The base group for **Discipline** is Cell & Molecular biology, for **Field** is Human Nutrition and Food, for academic rank is Assistant Professor, and for funding sources is USDA.

Chapter 8: Conclusions

To better understand the nature and provision of academic research in agricultural biotechnology, a conceptual model has been developed to explain an academic scientist's decisions in constructing a research program and funding agents' preferences for financing those programs. Research program designs are represented by their basicness and by the expected publicness or market excludability of their findings.

Results suggest that a scientist's choice of research basicness influences her choice of research publicness and *vice versa*. In particular, a positive relationship is observed between the research basicness and research publicness supplied. Basic research usually involves greater uncertainty than does applied research and may itself lead to a wide range of applications. Hence, it is difficult to exclude others' use of it.

My model also provides information about the impact of the laboratory budget, including both non-labor and labor inputs. Higher non-labor budgets boost the research basicness the scientist offers, holding its publicness fixed, but reduce the publicness the scientist offers, holding its basicness fixed. Even when we allow both basicness and publicness to vary, non-labor budgets consistently have a positive effect on research basicness but a negative effect on research excludability. Whether or not basicness and publicness are permitted to vary together, funding impacts on a scientist's research choices are rather small. We cannot conclude, however, that total budget is only a minor factor in a bioscientist's research, since labor inputs such as graduate students and postdoctoral fellows are included in the model as well. Holding non-labor budget fixed, more graduate students and technicians in the bioscientist's laboratory tend to contribute to more applied research, while more postdoctoral fellows tend to contribute to more basic research. Labor inputs in general tend to contribute to more public or nonexcludable research. Results also suggest that university postdoctoral fellows are efficiently allocated in both basic and nonexcludable research in agricultural biotechnology. In contrast, too many technicians are allocated to the production of a given amount of basic research and too few to the production of a given amount of nonexcludable research. Taking into account both non-labor and labor inputs, total budget effects on research design are moderate.

A scientist's productivity, such as her publication and patent output, significantly affect her research choices. Consistent with my expectations, patent holdings lead to more applied and more excludable research. Surprisingly, I find that scientists with greater publication output conduct less basic research. However, publication numbers employed in this study are not quality-weighted, so may underrepresent the productivity of those with high-quality publications. A scientist's views about the proper role of science do have a significant impact on her research choices.

University characteristics influence the scientist's research design to some extent. All else constant, scientists at Land Grant universities tend to conduct more applied and more excludable research than do those at private universities. At universities with higher federally originated R&D expenditures, scientists tend to conduct more basic research, holding the scientists' own budget and laboratory resources constant.

Funding agents are less willing to finance basic than applied research, in contrast to scientists' preference for more basic research. The scientist's willingness to conduct basic research responds inelastically to funding availability, while the funding agent's willingness to provide support is rather responsive to both research basicness and nonexcludability. On the other hand, a scientist's ethical views or ideologies appear partly to insulate her research choices from funding agents' influence. Federal agencies, especially the National Institutes of Health, lead university agricultural biotechnology research toward more nonexcludable objectives than do other sources. Not surprisingly, industry funding, more than any other, steers academic scientists toward the applied end of the research spectrum and to more privately excludable research. Compared with other federal agencies, USDA funding encourages more applied and more excludable research.

Indicators of the scientist's own productivity, such as her recent publication and patent output, positively influence funding agents' willingness to provide financial support. Publications have, proportionately, a larger effect on a scientist's funding opportunity than do patents. A university's biological program ranking has a positive but very limited impact on the financial support available to its bioscientists. Scientists at Land Grant universities, and to a lesser extent those at public non-Land-Grant universities, attract less money than do those at private universities. In sum, funding agents are more willing to support scientists at higher ranked universities and non-Land-Grant universities.

My model focuses on the scientist's intentions and behaviors, not on her research results such as her publication or patenting successes. Nor does it permit us to explain university or government policies themselves. Nevertheless, we may use the findings to assess alternative policy options for influencing the supply of basic science and public goods in agricultural biotechnology research. To advance the more basic end of such research, alternative policy options include: (i) concentrating federal R&D expenditures at given universities, since the university cultural climate that concentration induces boosts the basic portion of the mean scientist's research; (ii) steering government funding toward more basically oriented disciplines such as cell & molecular biology or biochemistry, or toward research fields such as plant/animal protection or production; and (iii) guiding less R&D expenditure to Land Grant universities and through USDA-funded projects. Alternative policy options to encourage more publicly appropriable (nonexcludable) research include: (i) increasing R&D investment in disciplines such as physiology and pathology; (ii) providing a greater share of public support in the form of monetary rather than nonmonetary inputs such as research equipment, databases, and software; and (iii) steering government funding toward the National Institutes of Health and the National Science Foundation.

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APPENDICES

Appendix A: Descriptive Statistics of Variables (n=666)

Variable	Mean	Std Dev	Minimum	Maximum
B	67.563	31.032	0	100
P	85.772	20.126	0	100
G (/$1,000)	272.815	405.990	3	4500
$Ideology^{theory}$	6.065	1.435	1	7
$Ideology^{curi}$	6.444	0.915	1	7
$Ideology^{Patent}$	1.967	1.453	1	7
$Ideology^{Public}$	1.991	1.033	1	5
$Ideology^{Probpub}$	5.962	1.523	1	7
A^{NIH}	26.188	39.108	0	100
A^{NSF}	14.483	28.962	0	100
A^{OthFed}	14.388	24.771	0	100
A^{State}	7.065	20.169	0	100
$A^{Industry}$	9.274	21.035	0	100
A^{Found}	8.246	19.545	0	100
$A^{OtherFund}$	5.243	20.163	0	100
$M^{Material}$	0.242	0.428	0	1
$M^{Capital}$	0.405	0.491	0	1
$M^{Service}$	0.468	0.499	0	1
M^{Other}	0.023	0.148	0	1
Firm	0.203	0.402	0	1
% $Firm^{L}$	6.462	22.626	0	100
% $Firm^{M}$	5.302	19.576	0	100
Location	0.065	0.246	0	1
Prof	0.491	0.500	0	1
Assoc	0.240	0.428	0	1
Other Academic Rank	0.005	0.067	0	1
Pub	11.276	9.416	0	110
Patent	0.401	1.490	0	20
Grad	2.378	2.234	0	26
PostDoc	1.375	2.291	0	29
Tech	1.172	1.412	0	15
OtherFTE	0.967	1.689	0	18
FedRD (/$1,000)	171480.770	137799.300	6299.94	1197533.8
IndRD (/$1,000)	20311.640	24257.130	513.992	165000
UnivFTE	19.249	34.899	0	140
AgRank	8.674	10.722	0	35
NRCRank	65.402	40.718	7.17	160
LG	0.500	0.500	0	1
PNLG	0.345	0.476	0	1

Appendix A: Descriptive Statistics of Variables (n=666) (Continued)

Variable	Mean	Std Dev	Minimum	Maximum
$Discipline^{BioChem}$	0.134	0.341	0	1
$Discipline^{Genetics}$	0.167	0.373	0	1
$Discipline^{Ecology}$	0.066	0.249	0	1
$Discipline^{PhysiPath}$	0.195	0.397	0	1
$Discipline^{OthAgLife}$	0.140	0.347	0	1
$Field^{Micro/other}$	0.129	0.336	0	1
$Field^{ResEnv}$	0.090	0.287	0	1
$Field^{Plant}$	0.353	0.478	0	1
$Field^{Animal}$	0.222	0.416	0	1
$Field^{PlantAnimal}$	0.069	0.254	0	1

Appendix B: Correlation Tabulation of Key Variables

	B	P	G	Ideology^{theory}	Ideology^{curi}	Ideology^{probpub}	Ideology^{patent}	Ideology^{pub}	A^{NIH}	A^{NSF}	A^{USDA}	A^{Ind}	Pub	Patent
B	1	0.286	-0.043	0.504	0.395	0.179	-0.207	0.037	0.327	0.299	-0.177	-0.475	-0.045	-0.077
P	0.286	1	-0.069	0.136	0.101	-0.023	-0.465	-0.168	0.044	0.154	-0.069	-0.168	0.001	-0.137
G	-0.043	-0.069	1	-0.005	0.050	-0.025	0.077	0.024	0.264	-0.070	-0.124	-0.038	0.462	0.259
Ideology^{theory}	0.504	0.136	-0.005	1	0.418	0.238	-0.048	-0.013	0.184	0.144	-0.076	-0.248	0.077	0.039
Ideology^{curi}	0.395	0.101	0.050	0.418	1	0.164	-0.096	-0.045	0.167	0.109	-0.021	-0.274	0.038	0.038
Ideology^{probpub}	0.179	-0.023	-0.025	0.238	0.164	1	0.107	-0.041	0.006	0.100	0.060	-0.126	0.005	-0.012
Ideology^{patent}	-0.207	-0.465	0.077	-0.048	-0.096	0.107	1	0.113	-0.116	-0.124	0.140	0.135	0.076	0.132
Ideology^{pub}	0.037	-0.168	0.024	-0.013	-0.045	-0.041	0.113	1	0.013	0.018	-0.064	0.013	-0.001	0.162
A^{NIH}	0.327	0.044	0.264	0.184	0.167	0.006	-0.116	0.013	1	-0.248	-0.332	-0.261	0.132	0.048
A^{NSF}	0.299	0.154	-0.070	0.144	0.109	0.100	-0.124	0.018	-0.248	1	-0.172	-0.186	-0.042	-0.051
A^{USDA}	-0.177	-0.069	-0.124	-0.076	-0.021	0.060	0.140	-0.064	-0.332	-0.172	1	-0.033	-0.045	-0.045
A^{Ind}	-0.475	-0.168	-0.038	-0.248	-0.274	-0.126	0.135	0.013	-0.261	-0.186	-0.033	1	0.032	0.051
Pub	-0.045	0.001	0.462	0.077	0.038	0.005	0.076	-0.001	0.132	-0.042	-0.045	0.032	1	0.247
Patent	-0.077	-0.137	0.259	0.039	0.038	-0.012	0.132	0.162	0.048	-0.051	-0.045	0.051	0.247	1

Appendix C: Sampled Universities and Their Carnegie Classifications

Land-Grant	Public non-Land-Grant	Private
Clemson Univ.	Arizona State Univ. Main	Boston College
Colorado State Univ.	City Univ. of New York Graduate Center	California Institute of Technology
Kansas State Univ.	Georgia State Univ.	Carnegie Mellon Univ.
Louisiana State Univ.	Ohio Univ. Main Campus	Columbia Univ. in the City of New York
Michigan State Univ.	Southern Illinois Univ. at Carbondale	Duke Univ.
New Mexico State Univ. Main Campus	State Univ. of New York at Albany	George Washington Univ.
Ohio State Univ. Main Campus	State Univ. of New York at Binghamton	Georgetown Univ.
Oklahoma State Univ. Main Campus	State Univ. of New York at Buffalo	Harvard Univ.
Oregon State Univ.	Temple Univ.	Johns Hopkins Univ.
Pennsylvania State Univ.	Texas Tech Univ.	Lehigh Univ.
Purdue Univ. Main Campus	Univ. of Alabama	Marquette Univ.
Univ. of Arizona	Univ. of California-Los Angeles	Massachusetts Institute of Technology
Univ. of California-Davis	Univ. of California-Santa Barbara	New York Univ.
Univ. of Delaware	Univ. of Cincinnati Main Campus	Northeastern Univ.
Univ. of Georgia	Univ. of Colorado at Boulder	Northwestern Univ.
Univ. of Illinois at Urbana-Champaign	Univ. of Houston	Rensselaer Polytechnic Institute
Univ. of Massachusetts	Univ. of Iowa	Saint Louis Univ.
Univ. of New Hampshire	Univ. of Kansas Main Campus	Stanford Univ.
Utah State Univ.	Univ. of Michigan-Ann Arbor	Syracuse Univ.
Virginia Polytechnic Institute and State Univ.	Univ. of Mississippi	Teachers College, Columbia Univ.
	Univ. of North Carolina at Chapel Hill	Tufts Univ.
	Univ. of Oklahoma Norman Campus	Univ. of Chicago
	Univ. of Pittsburgh, Pittsburgh Campus	Univ. of Denver
	Univ. of South Florida	Univ. of Miami
	Univ. of Texas at Arlington	Univ. of Pennsylvania
	Univ. of Toledo	Univ. of Rochester
	Univ. of Utah	Univ. of Southern California
	Univ. of Washington	Vanderbilt Univ.
	Virginia Commonwealth Univ.	Washington Univ.
	Western Michigan Univ.	Yale Univ.

Appendix D: Initially Identified Generic Department Names

Land-Grant Universities

Agricultural Engineering
Agronomy *
Animal Science *
Aquaculture *
Biochemistry
Bioengineering
Biology
Biomolecular Engineering
Biotechnology *
Botany *
Cell and Molecular Biology *
Chemistry
Crop Sciences *
Dairy Science
Ecology
Entomology
Environmental Science and Engineering
Fisheries
Food and Nutritional Science and Engineering
Forestry *
Genetics
Horticulture *
Microbiology
Molecular and Cellular Biochemistry
Molecular Biophysics
Molecular Virology
Pathology (both animal and plant) *
Pharmacology (including molecular)
Physiology (including molecular and plant) *
Soil Sciences
Toxicology (including molecular)
Veterinary science and medicine
Viticulture and Enology
Wildlife Sciences

Non-Land-Grant Universities

Animal Science
Biochemical Engineering
Biochemistry *
Bioengineering
Biology *
Biomolecular Science and Engineering
Biotechnology *
Botany *
Cell and Molecular Biology *
Cellular and Molecular Biophysics
Cellular Physiology
Chemistry
Ecology
Environmental Sciences
Fisheries *
Food and Nutritional Sciences
Forestry *
Genetics *
Microbiology *
Molecular Sciences
Neuroscience
Pathology
Pharmacology (including cellular and molecular)
Physiology (including molecular)
Soil Science
Toxicology
Veterinary Medicine
Zoology

* *Indicates major categories selected*

Appendix E: Generic Department Names Finally Selected

Land-Grant Universities	**Non Land-Grant Universities**
Agronomy	Biochemistry
Animal Science	Biology
Aquaculture	Biotechnology
Biotechnology	Botany
Botany	Cell and Molecular biology
Cell and Molecular Biology	Fisheries
Crop Sciences	Forestry
Forestry	Genetics
Horticulture	Microbiology
Pathology (both animal and plant)	
Physiology (both molecular and plant)	

Appendix F: Survey Questionnaire

Academic BioScientists and University-Industry Relationships

The survey is part of a grant funded by
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October 2003

YOUR RESPONSES ARE COMPLETELY CONFIDENTIAL.

ABOUT THIS SURVEY

Academic bio-scientists face persistent challenges in adequately financing their laboratory research programs. Budget pressures exacerbate the funding challenge. An important alternative to government funding is to seek support from industry. Many academic scientists are involved in working relationships with private biotechnology firms. The relationships are a source of both promise and anxiety, and often surface in policy discussions off and on campus. Yet, we have little understanding of the forces that shape the relationships or of their influence on the output and direction of academic research.

We are writing to request your participation in a nationwide survey of university-industry cooperation in plant and animal biotechnology research. The survey includes scientists from 60 major U.S. universities, and is financed by a grant from the U.S. Department of Agriculture. Information about this project can be found on our website, http://www.agri-biotech.pdx.edu/.

The survey will enable construction of the first national laboratory-level database on plant and animal biotechnology research. It will provide the means for examining the impact on university bioscience agendas of a wide variety of university, industry, and public policy factors. For this reason, the survey is of great importance for the development of rational government and university policy choices.

Your name was selected as part of a national random sample of academic scientists who potentially are working in plant and animal biotechnology fields. Your responses will be treated strictly confidentially. Among other confidentiality measures, we will remove your name from your survey responses as soon as we receive them.

The survey should require approximately 20 to 25 minutes of your time. Kindly accept this $5 gift as an expression of our gratitude for completing the survey.

Please phone us at 503.725,3937 or email us at 'minor@pdx.edu' if you have questions or comments.

Thank you in advance for your participation in this important survey.

Agricultural Biotechnology Survey

Question 1 of 48

Do you hold a *faculty appointment* at a college or university and conduct research as a regular part of that appointment?

- ○ Yes
- ○ No

Question 2 of 48

Are you a principal investigator or co-principal investigator for *at least one* project in your research program? By research program, we mean the portfolio of your current research projects.

- ○ Yes
- ○ No

Question 3 of 48

Do you conduct basic or applied research at the *molecular or cellular level* with implications for biotechnologies in agriculture, forestry, or aquaculture?

- ○ Yes
- ○ No

Questions 4 of 48

What is your *primary discipline*?

[Examples are animal science, biochemistry, cellular biology, genetics, molecular biology, or pathology.]

What is your *primary field* of research?

[Examples are plant reproduction, wheat breeding, stress tolerance, or microbial genomics.]

What is the *primary topic* of your current research?

[Examples are MADS genes in barley, herbicide tolerance genes, or equine encephalitis.]

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Question 5 of 48

Some scientists work with organisms such as *Arabidopsis* that are intended as models of molecular processes or genetic structure. Others work with organisms such as wheat that have or will eventually have value to producers or consumers. If you work on organism(s) that have or will have such economic value, please list them in order of importance, with a maximum of three.

[ ] Highest priority
[ ] Second priority
[ ] Third priority
○ Does not apply

Question 6 of 48

Please indicate *the degree of basicness or appliedness* of your research program, using a scale in which 1 means "purely basic" and 6 means "purely applied."

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).

	Purely Basic 1	2	3	4	5	Purely Applied 6
Your Research Program	○	○	○	○	○	○

Question 7 of 48

Please indicate the percentages of your research program that fall into the following categories.

[ ] % Basic Research
[ ] % Applied Research
[ ] % Development and Testing
(Responses should total 100%)

Question 8 of 48

Please indicate the *degree of non-excludability or excludability of a typical finding* of your research program, using a scale in which 1 means "completely non-excludable" and 6 means "completely excludable."

By "completely non-excludable," we mean it is *infeasible* to exclude anyone from using the findings of your research.

- **Examples from basic research include results which 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 developing countries*).**

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 which *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).**

	Completely Non-Excludable 1	2	3	4	5	Completely Excludable 6
Typical Finding of Your Research Program	○	○	○	○	○	○

Question 9 of 48

Please indicate the percentages of discovery(s) and/or finding(s) in your research program that fall into the following categories.

[ ] % Non-excludable Discovery(s) and Finding(s)
[ ] % Excludable Discovery(s) and Finding(s)
(Responses should total 100%)

Question 10 of 48

If you make an excludable research finding, do you typically work with university officials to:

○ Patent it and seek exclusive licenses for commercial uses
○ Patent it and seek nonexclusive licenses for commercial uses
○ Release it into the public domain
○ Other (Please specify) [ ]

Question 11 of 48

What is the approximate *current annual budget* of your research program? Include all sources on which you are either the principal investigator or co-principal investigator, and only research activities funded by or through your university from whatever source. Exclude overhead/indirect costs.

$ [ ] Current Annual Budget of Your Research Program

Question 12 of 48

Do you currently receive research funding from the following source(s)?

	Receive	Do Not Receive
a. Federal Government		
i. National Institutes of Health	○	○
ii. National Science Foundation	○	○
iii. U.S. Department of Agriculture	○	○
iv. Other(s) Federal (Please specify) [ ]	○	○
b. State Government (Including Agricultural Experiment Station funding)	○	○
c. Foundations/Non-Profit Organizations	○	○
d. Trade or Commodity Associations	○	○
e. Individual Firms (Biotechnology or other)	○	○
f. Other(s) (Please specify) [ ]	○	○

*** Answer the next two questions only for those sources listed above in Question 12:**

Agricultural Biotechnology Survey

Question 13 of 48

Please indicate the approximate proportion of your current annual research budget represented by each of the following source(s).

	% of Total Research Budget
a. Federal Government Agencies	
i. National Institutes of Health	%
ii. National Science Foundation	%
iii. U.S. Department of Agriculture	%
iv. Other(s) Federal:	%
b. State Government (Including Agricultural Experiment Station funding)	%
c. Foundations/Non-Profit Organizations	%
d. Trade or Commodity Associations	%
e. Individual Firms (Biotechnology or other)	%
f. Other(s):	%
	(Responses should total 100%)

Question 14 of 48

Please indicate the *typical duration* of your current research project(s) funded by the following source(s). Rounding to the nearest whole year is fine.

	Typical Duration of Research Project(s)
a. Federal Government Agencies	
i. National Institutes of Health	Year(s)
ii. National Science Foundation	Year(s)
iii. U.S. Department of Agriculture	Year(s)
iv. Other(s) Federal:	Year(s)
b. State Government (Including Agricultural Experiment Station funding)	Year(s)
c. Foundations/Non-Profit Organizations	Year(s)
d. Trade or Commodity Associations	Year(s)
e. Individual Firms (Biotechnology or other)	Year(s)
f. Other(s):	Year(s)

Question 15 of 48

Do you currently receive the following in-kind contribution(s) from the organization(s) supporting your research program?

	Receive	Do Not Receive
a. Biomaterials (antibodies, cell lines, clones, germplasm, gene sequences, plant/animal tissues, organisms, etc.)	○	○
b. Reagents	○	○
c. Genomic or other databases	○	○
d. Equipment or instrumentation use	○	○
e. Software	○	○
f. Student internships/training	○	○
g. Staff support and technical services	○	○
h. Other(s) (Please specify)	○	○

*** Answer the next two questions only for those contributions listed above in Question 15:**

Question 16 of 48

Please indicate to what extent the in-kind contribution(s) provided to you are important for the progress of your research.

	To a Great Extent	To Some Extent	Very Little	Not at All
a. Biomaterials (antibodies, cell lines, clones, germplasm, gene sequences, plant/animal tissues, organisms, etc.)	○	○	○	○
b. Reagents	○	○	○	○
c. Genomic or other databases	○	○	○	○
d. Equipment or instrumentation use	○	○	○	○
e. Software	○	○	○	○
f. Student internships/training	○	○	○	○
g. Staff support and technical services	○	○	○	○
h. Other(s):	○	○	○	○

Question 17 of 48

Please indicate whether the in-kind contribution(s) came primarily from industry (trade/ commodity associations or individual firms) or from a non-industry source.

	Primarily From Industry	Primarily From Non-Industry
a. Biomaterials (antibodies, cell lines, clones, germplasm, gene sequences, plant/animal tissues, organisms, etc.)	○	○
b. Reagents	○	○
c. Genomic or other databases	○	○
d. Equipment or instrumentation use	○	○
e. Software	○	○
f. Student internships/training	○	○
g. Staff support and technical services	○	○
h. Other(s):	○	○

*** Answer the next two questions only if you indicated receipt of funds from trade or commodity associations or individual firms in Question 12d or 12e:**

Agricultural Biotechnology Survey

Question 18 of 48

Of the funding you received from industry (trade/commodity associations or individual firms), what percent is "unrestricted," such as gifts or funds with "no strings attached"?

[ ] % Unrestricted Funds from Industry

Question 19 of 48

Please indicate, in each of the following categories, the *approximate* proportion of funding you are receiving from individual firms.

	% of Firm Funding
a. Large Firm (over 10,000 employees)	[ ] %
b. Medium Firm (more than 500 but less than 10,000 employees)	[ ] %
c. Small Firm (less than 500 employees)	[ ] %

(Responses should total 100%)

*** Answer the next two questions only if you indicated receipt of funds from trade or commodity associations or individual firms in Question 12d or 12e OR if any in-kind contributions primarily from industry were reported in Question 17 :**

Question 20 of 48

Following is a list of potential benefits of faculty involvement with industry. Please indicate to what extent your own industry involvement provided these benefits.

	To a Great Extent	To Some Extent	Very Little	Not At All
a. Contribution to your promotion or tenure	○	○	○	○
b. Ability to publish in a professional journal	○	○	○	○
c. Ability to commercialize (e.g. patent or license) your findings	○	○	○	○
d. Ability to collaborate with your colleagues	○	○	○	○

Question 21 of 48

Please indicate whether any of the following relationships were influential in your obtaining research support from industry (trade/commodity associations or individual firms).

	Influential	Not Influential
a. Consulting with the industry	○	○
b. Employment of your graduate students at the industry	○	○
c. Your own former employment at the industry	○	○
d. Your other research relationships with the industry	○	○
e. Other personal contact(s)	○	○

Question 22 of 48

Please indicate whether the industry (trade/commodity associations or individual firms) that supports your research program tends to be located near or distant from your university.

- ○ Located near your university (within 30 miles)
- ○ Located distant from your university (greater than 30 miles)

Question 23 of 48

University policies may influence a faculty member's decision to pursue industry research support. Please indicate the degree of helpfulness or hindrance of your university's policies in your pursuit of industry research support.

	Very Helpful	Helpful	Neutral	Some Hindrance	Significant Obstacle	No Experience
a. University indirect cost rate	○	○	○	○	○	○
b. Assistance securing a patent on your findings	○	○	○	○	○	○
c. License royalty rate charged by the university	○	○	○	○	○	○
d. License royalty rate shared with me	○	○	○	○	○	○
e. Conflict of interest policy (e.g., on consulting)	○	○	○	○	○	○

*** Answer Question 24 for each policy in Question 23 above that was a significant obstacle.**

Question 24 of 48

You indicated that "*university indirect cost rate*" presented significant obstacles. Please briefly describe the nature of those obstacles.

You indicated that "*assistance securing a patent on your findings*" presented significant obstacles. Please briefly describe the nature of those obstacles.

You indicated that "*license royalty rate charged by the university*" presented significant obstacles. Please briefly describe the nature of those obstacles.

You indicated that "*license royalty rate shared with me* " presented significant obstacles. Please briefly describe the nature of those obstacles.

You indicated that "*Conflict of interest policy, e.g., on consulting* " presented significant obstacles. Please briefly describe the nature of those obstacles.

How often have the following occurred as a consequence of your industry (trade/commodity associations or individual firms) supported research?

	Always	Sometimes	Rarely	Never
a. Research could not be published without the review and consent of the industry sponsor	○	○	○	○
b. Publications delayed by more than 6 months	○	○	○	○
c. Never able to publish work	○	○	○	○
d. Association or firm is granted exclusive licensing	○	○	○	○
e. Industry funders owned or co-owned the intellectual property	○	○	○	○
f. Association or firm kept my research results or materials secret to protect the proprietary value	○	○	○	○
g. Association or firm refused to share research results or materials	○	○	○	○

Question 26 of 48

Please indicate whether you currently hold any of the following positions with industry (trade/commodity associations or individual firms) that supports your research program.

	Hold	Do Not Hold
a. Consultant for pay	○	○
b. Member of scientific advisory board	○	○
c. Member of board of directors	○	○
d. Officer or executive of company	○	○
e. Founder of company	○	○
f. Equity holder in company	○	○

Question 27 of 48

Do you have a tenure track or non-tenure track appointment?

○ Tenure Track

○ Non-Tenure Track

Question 28 of 48

What is your academic position?

○ Professor

○ Associate Professor

○ Assistant Professor

○ Other (Please specify) [ ]

Question 29 of 48

Are you a government scientist with a university appointment?

○ Yes

○ No

Question 30 of 48

In what year did you receive your highest degree?

[ ] Year in Which You Received Your Highest Degree

Question 31 of 48

On average, how do you allocate your professional work time across the following activities?

	% of Professional Work Time
a. Teaching	%
b. Research	%
c. Administration	%
d. Extension/Outreach	%
e. Consulting	%
f. Service	%

(Responses should total 100%)

Question 32 of 48

How many of each of the following types of research staff do you currently support?

	Total Number of FTEs
a. Post-doctoral fellows	
b. Graduate students	
c. Technicians	
e. Other(s)	

Question 33 of 48

How many articles have you published (as author or co-author) in refereed journals since January 2000?

Number of Journal Article(s) Published Since January 2000

Question 34 of 48

Has your research program resulted in the following activities since January 2000?

	Yes	No
a. Patent(s) applied for	○	○
b. Patent(s) issued	○	○
c. Patent(s) licensed out	○	○
d. Trade secret(s) developed (information kept secret to protect its proprietary value)	○	○
e. Product(s) under regulatory review	○	○
f. Product(s) on the market	○	○
g. Start-up company(s) formed	○	○

* Answer only if "yes" to Question 34a above.

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Question 35 of 48

How many patents have you *applied for*?

Number of Patent(s) Applied For

* Answer only if "yes" to Question 34b above.

Question 36 of 48

How many patents have you *been issued,* including any that have been co-assigned to others?

Number of Patent(s) Issued

* Answer next two questions only if "yes" to Question 34c above.

Question 37 of 48

How many patents have you *licensed out*?

Number of Patent(s) Licensed Out

Question 38 of 48

Of the patent(s) you have licensed out, please indicate the number with the following licensing arrangements.

Number with Non-Exclusive Licensing Arrangement(s)

Number with Exclusive Licensing Arrangement(s)

* Answer only if "yes" to Question 34d above.

Question 39 of 48

How many trade secrets have you developed?

Number of Trade Secret(s) Developed

* Answer only if "yes" to Question 34e above.

Question 40 of 48

How many of your products are under regulatory review?

Number of Product(s) Under Regulatory Review

* Answer only if "yes" to Question 34f above.

Agricultural Biotechnology Survey

Question 41 of 48

How many of your products are on the market?

[ ] Number of Product(s) on the Market

* Answer only if "yes" to Question 34g above.

Question 42 of 48

How many start-up companies have you been involved in forming?

[ ] Number of Start-Up Company(s)

Question 43 of 48

During the last 5 years, how important were the following criteria in your choice of research problems? Please rate each criterion by clicking one number from "*Not Important*" (1), to "*Very Important*" (7).

	Not Important 1	2	3	4	5	6	Very Important 7
Potential contribution to scientific theory	○	○	○	○	○	○	○
Potential creation of new methods, useful materials or devices	○	○	○	○	○	○	○
Potential marketability of final product	○	○	○	○	○	○	○
Availability of public (state and federal) funding	○	○	○	○	○	○	○
Availability of private (corporate) funding	○	○	○	○	○	○	○
Publication probability in professional journals	○	○	○	○	○	○	○
Industry consulting opportunities	○	○	○	○	○	○	○
Enjoy doing this kind of research	○	○	○	○	○	○	○
Public good	○	○	○	○	○	○	○
Scientific curiosity	○	○	○	○	○	○	○
Demands raised by clientele/extension	○	○	○	○	○	○	○
Client needs as assessed by you	○	○	○	○	○	○	○
Priorities of the research organization	○	○	○	○	○	○	○
The potential to patent and license the research findings	○	○	○	○	○	○	○
Ability to collaborate with colleagues	○	○	○	○	○	○	○

Agricultural Biotechnology Survey

Question 44 of 48

Please read the following statements and choose the number that most closely represents your level of agreement or disagreement with the statement.

	Strongly Agree 1	Agree 2	Neutral 3	Disagree 4	Strongly Disagree 5	Do Not Know 6
Public scientists should focus on producing knowledge or technologies with public (non-excludable) benefits.	○	○	○	○	○	○
Public scientists should focus on producing knowledge or technologies with market potential.	○	○	○	○	○	○
Public scientists should focus on producing knowledge or technologies that advance their field or discipline.	○	○	○	○	○	○
Industry should play a central role, in influencing public research scientists' agendas.	○	○	○	○	○	○
Citizen groups should play a central role in influencing public research scientists' agendas.	○	○	○	○	○	○
Scientist panels are the most appropriate vehicles for setting the research agendas of public research scientists.	○	○	○	○	○	○
The market is the most accurate arbiter of the relative social value of new technology.	○	○	○	○	○	○
Trained scientists are the most accurate arbiters of the relative social value of new technology.	○	○	○	○	○	○
Citizen groups are the most accurate arbiters of the relative social value of new technology.	○	○	○	○	○	○
Hunger is primarily a production problem that will be solved through advances in scientific expertise.	○	○	○	○	○	○
Hunger is best solved by greater reliance on market forces and the private sector.	○	○	○	○	○	○
Hunger is primarily a wealth distribution problem.	○	○	○	○	○	○

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No questionnaire of this type can adequately cover all points considered relevant by individuals with diverse interests. We welcome in the space below any additional comments that you may have on university-industry relationships related to plant and animal biotechnologies.

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Would you like a copy of the report of the survey findings mailed to you?

○ Yes
○ No

Appendix G: NSF List

Agricultural and Food Sciences

SED/DRF Code	Field Name	SDR Codes
005	Animal breeding & genetics	605
007	Animal husbandry	605
010	Animal nutrition	605
012	Dairy science	605
014	Poultry science	605
019	Animal sciences, other	605
040	Food sciences	606
042	Food distribution	606
043	Food engineering	606
044	Food sciences, other	606
020	Agronomy	607
025	Plant breeding & genetics	607
030	Plant pathology	607
032	Plant protect. & pest management	607
039	Plant sciences, other	607
050	Horticulture science	607
045	Soil sciences	608
046	Soil chemistry & microbiology	608
049	Soil sciences, other	608
099	Agricultural sciences, other	608
098	Agriculture, general	608

Biological Sciences

SED/DRF Code	Field Name	SDR Codes
100	Biochemistry	631
103	Biomedical sciences	642
105	Biophysics	631
198	Biological sciences, general	632
120	Plant pathology	633
125	Plant physiology	633
129	Botany, other	633
136	Cell biology	634
154	Molecular biology	634
139	Ecology	635
115	Plant genetics	636
170	Genetics, human & animal	636
171	Genetics	636
156	Microbiology & bacteriology	637

157	Microbiology	637
110	Bacteriology	637
163	Nutritional sciences	638
180	Pharmacology, human & animal	639
185	Physiology, human & animal	640
186	Physiology, animal & plant	640
148	Entomology	641
175	Pathology, human & animal	641
189	Zoology	641
107	Biotechnology research	642
133	Biometrics & biostatistics	642
130	Anatomy	642
140	Hydrobiology	642
142	Developmental biology	642
145	Endocrinology	642
151	Immunology	642
160	Neurosciences	642
166	Parasitology	642
169	Toxicology	642
199	Biological sciences, other	642

Environmental Life Sciences, including Forestry Sciences

SED/DRF Code	Field Name	SDR Codes
580	Environmental sciences	680
055	Fisheries sciences	680
054	Fish & wildlife	680
060	Wildlife	681
065	Forestry science	681
066	Forest biology	681
068	Forest engineering	681
070	Forest management	681
072	Wood science	681
074	Renewable natural resources	681
079	Forestry & related sciences, other	681
080	Wildlife/range management	681

(Source: Characteristics of Recent Science and Engineering Graduate 2001: List A: Education Codes)

Appendix H: USDA/CRIS Classification

__Research Problem Area__

I. **Natural Resources and Environment (101-135)**

a. Soil (100)
b. Water (110)
c. Forest and Range Resources (120)
d. Natural Resources, general (130)

II. **Plant and their system (201-216)**

a. Plant Production (200)
b. Plant Protection (210)

III. **Animal and their system (301-315)**

a. Animal Production (300)
b. Animal Protection (310)

IV. **Engineering and support system (401-405)**

V. **Food and non-food products: development, processing, quality, and delivery (501-512)**

a. Food (500)
b. Non-food (510)

VI. **Economics, markets, and policy (601-611)**

VII. **Human nutrition, food safety, and human health and well-being (701-723)**

a. Human Nutrition (700)
b. Food Safety (710)
c. Human Health (720)

VIII. **Family and community systems (801-805)**

IX. **Research support, administration, and communication (901-903)**

(Source: Manual of Classification of Agricultural and Forestry Research, revision VI)

Appendix I: Summary of Ideology Variables by University Type

	LG (n=333)		PNLG (n=230)		Private (n=103)	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Ideology^{theory}	5.880	1.504	6.196	1.393	6.369	1.213
Ideology^{curi}	6.339	0.977	6.478	0.909	6.709	0.620
Ideology^{probpub}	5.958	1.456	5.978	1.557	5.942	1.668
Ideology^{patent}	2.144	1.530	1.796	1.324	1.777	1.414
Ideology^{pub}	1.940	0.983	2.017	1.117	2.097	0.995