AN ABSTRACT OF THE DISSERTATION OF

Sharmistha Nag for the degree of Doctor of Philosophy in Agricultural and Resource Economics, presented on December 10, 2009.

Title: Essays in Applied Economics

Abstract approved:

Steven T. Buccola Jeffrey J. Reimer

My dissertation concerns two separate issues. The first issue is examined in Essay One, and the second issue is examined in Essays Two and Three.

The first essay develops an economic model of the determination of the rental rate of leased farmland in the United States. Particular attention is placed on the exchange rates, a variable that can strongly affect both the foreign demand for U.S. agricultural products and the prices of inputs used in U.S. agricultural production. The essay explores whether the U.S. exchange rate could have an influence on cash rental rates for farmland in five U.S. corn-belt states. An econometric model shows that farmland cash rents have a strongly positive correlation with the U.S. dollar, in terms of its real value relative to

major agricultural trading partners. The correlation appears to be most strongly caused by the fact that the dollar is inversely related with the price of key inputs. A strong dollar may therefore be associated with higher net returns, in which case farmers are willing to accept higher cash rents.

The second essay examines research portfolio choice in academic bioscience. Using survey data from 1067 academic bioscientists in 80 major U.S. universities, this essay explores whether and to what extent funding agencies influence university bioscientists' research portfolio choices. I consider a bioscientist who selects a category of research topics based upon its basicness and on the size or scale of the research object. Research object scale classifications are sub-cellular or cellular, organ or organism, and ecosystem. In addition to the sources and sizes of financial grants, I consider other factors that could influence academic research choice, such as the scientist's ethical or professional norms, university type or infrastructure, and in-kind laboratory support. I hypothesize that the source and size of financial support strongly influence scientists' research choices. However, I find that funding source does not have a substantial impact on the basicness and object scale of university biotechnology research. University type – and in-kind research support such as genomic databases, soft ware, and equipment – have relatively larger influences on these laboratory research portfolios.

The third essay examines fund-raising and productivity in academic bioscience. Academic scientists have two important goals: attracting research money and publishing research results. These two goals appear to be related to one another. The premise of this third essay is that university bioscience research productivity simultaneously determines and is determined by the sizes and sources of grant funds. I use extensive survey data on individual laboratory university bioscientists to test this hypothesis, employing scientists' professional norms and experience, and the type of university at which they work, as exogenous factors. I find, under rather strong *ceteris paribus* conditions, that scientists' publication rates greatly affect their funding successes and that funding success affects publication rates. Federal funding is more publication-rate affected than is state or private funding. Controlling for other factors – including the scientist's total budget – laboratory labor usage affects laboratory output, implying that scientists misallocate resources between labor and non-labor inputs. In particular, they recruit too few research personnel and direct too many of their laboratory resources toward such non-labor factors as laboratory equipment, cell lines, and reagents.

Essays in Applied Economics

by
Sharmistha Nag

A DISSERTATION

submitted to

Oregon State University

In partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Presented December 10, 2009
Commencement June, 2010

Doctor of Philosophy dissertation of Sharmistha Nag presented on December 10, 2009.

APPROVED:

Co-Major Professor, representing Agricultural and Resource Economics

Co-Major Professor, representing Agricultural and Resource Economics

Head of the Department of Agricultural and Resource Economics

Dean of the Graduate School

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

Sharmistha Nag, Author

ACKNOWLEDGEMENTS

I express my deepest gratitude for my co-major professors, Dr Steve Buccola and Dr Jeffrey Reimer for their continuous support, encouragement, and insightful guidance during the course of my doctoral studies at this University. I consider myself immensely fortunate and privileged to be able to work with them.

I would like to thank my committee member Dr Randall Rosenberger for his valuable advice on this dissertation. I am grateful to Dr Anita Azarenko and graduate students in the Department of Horticulture – Peter Boches, S. Vidyasagar, and Michael Russell – for assisting me with one of my dissertation essays. I thank Dr Dwaine Plaza for serving as the Graduate Council Representative of my committee.

I would also like to thank Dr Santosh Mishra for helping me with SAS programming skills.

Finally, I deeply thank my parents for their unconditional love and support, without which I would not have been able to succeed in this endeavor.

TABLE OF CONTENTS

Page

Chapter 2: Essay 1: Farmland Cash Rents and the Dollar

TABLE OF CONTENTS (Continued)

Chapter 3: Essay 2: Research Portfolio Choice in Academic Bioscience

TABLE OF CONTENTS (Continued)

Chapter 4: Essay 3: Fund-Raising and Productivity in Academic Bioscience

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF TABLES

LIST OF TABLES (Continued)

LIST OF APPENDIX TABLES

LIST OF APPENDIX TABLES (continued)

LIST OF APPENDIX TABLES (Continued)

Chapter I: Introduction

I examine two different issues in my dissertation. The first issue is addressed in essay 1 and the second issue in essays 2 and 3.

In essay 1, I analyze whether the U.S. exchange rate could have an influence on cash rental rates for farmland in five cornbelt states. In the case of U.S. midwestern agriculture, the dollar is a determinant of foreign demand for key export commodities such as corn and soybeans. Foreign demand for U.S. products increases as the dollar weakens relative to the currencies of foreign importers. This may increase the net returns from farming, and thus farmers' demand for additional cash-rented acres. It follows that cash rental rates for farmland may have an inverse relation with the dollar.

In this essay, I show that a weaker dollar does not automatically translate into higher net returns for farmers, however, since their costs may go up. A weak dollar may raise the price of imported inputs such as nitrogen and potash fertilizers. A depreciating dollar may therefore reduce the net returns from renting additional acres, and reduce the demand for cash-rented farmland, and hence cash rents. To the extent that this purchasing power argument is important, it means that cash rental rates for farmland may have a positive relationship with the dollar. Based on the two above arguments, the relationship between the dollar and cash rental rates is an empirical issue.

When one plots deflated cash rents for U.S. cornbelt states since 1975, they often trend monotonically for a number of years in one direction before changing course and trending monotonically in the other direction. Since the 1970s there have been clearly demarcated periods in which the U.S. dollar was monotonically increasing and then monotonically decreasing. This study asks whether these patterns have any relation, and if so, whether there is any meaningful relationship.

To get at this issue more systematically, I develop econometric models to quantify the relationship between cash rents and exchange rates over time, along with other potentially important factors.

In essays 2 and 3, I examine how resource allocation affects university research and development. Relationships between universities and research funding sources have emerged to play a significant role in the development of agricultural biotechnology. Universities attract industry investments to raise their research productivity (Jaffe 1989), and a major force behind firms' increased investments in academic R&D is to obtain direct access to university labs, students, and staff (Thorn 1996). US academic institutions performed $48 billion of R&D in 2006 (National Science Board, Chapter 5). Evidence indicates monetary support from all sources for university research increased between 1972 and 2000 but industrial funding declined in 2001 and 2003 and rebounded between 2004 and 2006.

Cutting-edge research tools, databases, and financial support from prominent funding agencies are widening the breadth of bioscience research. Some bioscience research areas are drawing more grants than others. In essay 2, I ask: to what extent does the size and source of financial support from research funding agencies influence or constrain a scientist's research choice decisions about the object-scale, distinguished according to whether it is a cell or sub-cellular entity, an organism or organ, or an ecosystem, and basic vs. applied content of their laboratory work? My hypotheses point to the possibility that, and to the ways in which, money sources matter in scientists' research choices. I control for factors found important in other studies - scientific norms, university infrastructure, and in-kind support.

Academic science traditionally has specialized in relatively basic, public-good, research. One of its primary goals, however, is fund-raising because funding expands research opportunities. Another major goal is the publication of the scientist's research results. Publication leads to professional advancement and allows other researchers to evaluate and use one's laboratory results for their own further work. Financial reward and publications influence one another. On the one hand, a scientist with a good publication record likely will be awarded more grant money. On the other hand, financial support may motivate and enable scientists to pursue high-quality research and publish their discoveries. The premise of essay 3 is that bioscientist output, measured in terms of publications, is strongly affected by the source and size of financial support, and that the latter are influenced by publication output rates. In the process of examining these questions, we are interested as well in how other important factors – research topic choice, in-kind support, ethical norms, human capital, and university characteristics – affect scientists' output and funding.

Chapter II: Farmland Cash Rents and the Dollar

Essay I

Sharmistha Nag

1. Introduction

This essay provides an analysis of whether the U.S. exchange rate could have an influence on cash rental rates for farmland in five cornbelt states. The exchange rate is of interest because it is well known to affect many outcomes in agriculture (Schuh, 1974; Batten and Belongia, 1986; Pick, 1990). In the case of U.S. midwestern agriculture, the dollar is a determinant of foreign demand for key export commodities such as corn and soybeans. Foreign demand for U.S. products increases as the dollar weakens relative to the currencies of foreign importers. This may increase the net returns from farming, and thus farmers' demand for additional cash-rented acres. It follows that cash rental rates for farmland may have an inverse relation with the dollar.

In this essay I show that a weaker dollar does not automatically translate into higher net returns for farmers, however, since their costs may go up. In the short run the dollar tends to have a negative correlation with the price of oil (Krugman, 1983). This is important because oil and related energy-based resources, such as natural gas, tend to underpin many of the inputs used in agriculture. In addition, a weak dollar may raise the price of imported inputs such as nitrogen and potash fertilizers. A depreciating dollar may therefore reduce the net returns from renting additional acres, and reduce the demand for cash-rented farmland, and hence cash rents. To the extent that this purchasing power argument is important, it means that cash rental rates for farmland may have a positive relationship with the dollar. Based on the two above arguments, the relationship between the dollar and cash rental rates is an empirical issue.

Cash rental agreements are an increasingly common way of leasing farmland in the U.S. cornbelt. In Iowa, for example, 77% of leased farmland is done through a cash lease. Indeed, more farmland in Iowa is cash rented (46%) than owner-operated (40%) (Iowa State University Extension, 2008). The situation in other cornbelt states is similar (Ryan et al., 2001).

When one plots deflated cash rents for U.S. cornbelt states since 1975, they often trend monotonically for a number of years in one direction before changing course and trending monotonically in the other direction. The U.S. dollar exhibits similar patterns with respect to its value against other major currencies over time. Since the 1970s there have been clearly demarcated periods in which the U.S. dollar was monotonically increasing and then monotonically decreasing. This study asks whether these patterns have any relation, and if so, whether there is any meaningful relationship.

Looking at plots of data, I find a rough positive correlation between the real exchange rate (strength of the dollar) and real cash rents. According to the simple theory outlined above, this suggests that a weaker dollar may be reducing the purchasing power of farm operators.

To get at this issue more systematically, I develop econometric models to quantify the relationship between cash rents and exchange rates over time, along with other potentially important factors. Although I do not imagine that the exchange rate *per se* is taken into consideration during cash rent negotiations, models developed below account for the fact that it may underlie some of the key determinants of cash rents. Like other studies of farmland cash rents, the regression analysis controls for inflation and the large changes in government commodity support programs that have occurred over time. Similar to other studies, I find that government support for farmers has a positive and statistically significant effect on cash rents (Roberts, Kirwan, and Hopkins, 2003; Lence and Mishra, 2003; Patton et al., 2008). Relative to these studies, however, this analysis is concerned with long-term cyclical variations in cash rental rates. It is more aggregated and less focused on site specific determinants of cash rents.

Across a variety of specifications I find that there is a positive relationship between the real strength of the dollar and real cash rents. To foreshadow my proposed idea, when I look at the prices of inputs that are heavily imported, such as nitrogen and potash, they are not necessarily cheaper when the dollar is stronger (USDA, 2009b). However, as mentioned above, a year in which the dollar is strong also tends to be a year in which oil prices are low. This would matter because roughly eight out of every 10 dollars spent in agriculture is in some way tied to oil (Roberson, 2008). Schnitkey and Gupta (2007) find that variation in crude oil prices account for roughly two-thirds of changes in the cost of Illinois corn and soybean production over time. Similarly, USDA balance sheet data show that energy-based inputs account for approximately 60% of operating costs for U.S. bulk crop producers (USDA, 2009a).

To be clear, I make no claim regarding cause and effect between the dollar and oil prices. This relationship is poorly understood and unlikely to be resolved anytime soon (Krugman, 1983). My point here is merely that in the near term there seems to be an inverse correlation, and although a weak dollar raises commodity prices, it may have a stronger, more immediate effect on the costs of production. This possibility is consistent with some of the estimated coefficients on interaction terms that we include in some of the regressions. The association between exchange rates and cash rents varies according to the relative importance of imported inputs in production. In particular, cash rents have a closer positive relationship with the dollar in time periods and states in which there was greater dependence on imported inputs.

The literature on cash rents to which I can compare the results is fairly small; there is a much larger literature, for example, on farmland values (e.g., Just and Miranowski, 1993; Weersink et al., 1999; Tsoodle, Golden, and Featherstone, 2006). Some of the studies in this literature are similar to the present study in that they take a relatively “macro” approach and focus on long-term cycles and trends (Featherstone and Baker, 1987; Irwin and Colling, 1990; Clark, Fulton, and Scott, 1993; Schmitz, 1995; Erickson, Mishra, and Moss, 2003). Although it is likely that the dollar has some effect on farmland values, none of the studies in this literature appear to have explored this possibility. Some studies such as Chavas and Shumway (1982) and Moss (1997) find that inflation plays a role in the demand for land. It may be that inflation in these studies picks up some of the effects of exchange rates, e.g., if a strong dollar works against “cost push” inflation. There are additional channels by which exchange rates might affect farmland values, such as through foreign investors’ demand functions for U.S. farmland as an asset.

Relative to studying cash rents, understanding the relationship between the dollar and the value of farmland would be more difficult because land is a long-lived asset, and thus is affected by asset bubbles, transaction costs, and the potential for conversion to urban or industrial land use. We focus instead on cash rental rates in part to avoid some of these problems. Cash rents can be renegotiated on an annual basis and are arguably more representative of profitability in a given year relative to farmland values. In cornbelt agriculture, the opportunity cost of not renting land to one farmer is likely to be the value of leasing it out to another local farmer who wants to pick up additional acres.

This study is also related to a literature in labor economics that quantifies the impact of changes in the dollar on wages and employment in U.S. manufacturing industries. Revenga (1992), for example, finds that the appreciation and subsequent depreciation of the dollar during the 1977-1987 period had significant impacts on average labor wages. Campa and Goldberg (2001) look at the 1972-1994 period and also find that labor wages were affected by the strength of the dollar. They find that the effects varied with the importance of exports in an industry, and the importance of imported input use in an industry. Although I study cash rents instead of labor wages, I use these findings – which rely on inclusion of certain interaction terms – to inform some of the specifications.

In addition to these literatures, this study contributes to the extensive literature on exchange rates and agriculture. Schuh (1974) was one of the first studies to argue that exchange rates have an impact on outcomes in agriculture. Since then the literature has addressed many topics, including exchange rate pass-through, pricing-to-market, and the effects of exchange rate uncertainty (e.g., Carter and Pick, 1989; Pick, 1990; Cho, Sheldon, and McCorriston, 2002; Kandilov, 2008). My contribution is to show that exchange rates may have a meaningful relationship with cash rental rates. It is argued that exchange rates may matter as much on the *input cost* side as on the foreign demand side. To my knowledge this point has not been considered in the literature.

The remainder of the essay is organized as follows. In the following section I develop a simple model that shows two channels by which the exchange rate could influence cash rental rates in farmland, while controlling for other variables that theoretically could be of greater importance. The subsequent section introduces the data and presents some basic descriptive statistics. I then consider evidence from Granger causality tests before wrapping up with discussion and conclusions in the final section.

2. Econometric model

An aggregate model is developed allowing for three channels by which exchange rates might affect cash rents. My approach draws heavily from Campa and Goldberg (2001) and other formal economic models that link the dollar to wages in manufacturing industries (Branson and Love, 1988; Revenga, 1992; Burgess and Knetter, 1998; Goldberg and Tracy, 2000). In the application of such approaches, I examine the market for rented land used to produce a composite agricultural product that is sold at home and abroad. The effect of exchange rates on cash rents differs in certain ways from their effect on labor demand in manufacturing – the topic of the aforementioned studies. First, the supply of land probably is likely more inelastic than the supply of manufacturing labor. Cash rents may therefore be more sensitive to exchange rates, since the quantity of farmland is relatively fixed. Second, farming is closer to the textbook model of perfect competition than is manufacturing. Many industries within the latter sector may have positive price-cost margins, for example. This is important because, all else the same, industries with low price-cost margins have more responsive input demand than do imperfectly competitive industries (Campa and Goldberg, 2001). Again, the implication is that cash rents are more sensitive to exchange rates. A further difference is that land may be a bigger expense in crop agriculture than labor tends to be in manufacturing. This is an additional reason why I think that the value of the dollar is especially important for cash rents.

I model a representative producer operating in a perfectly competitive environment with constant returns to scale production. At the aggregate level, land is inelastically supplied. Farmland in the cornbelt is an asset with few or no alternative values in use; for a landlord, the opportunity cost of not renting it to one farmer is to rent it to another farmer (there may be other potential uses, but during the growing season, none as great as this one). The duration of formal tenant agreements is one year, and these are renewable and renegotiable annually. Land is a homogeneous quality input and used to produce a homogeneous output. This seems reasonable in cornbelt states, where most rented cropland is used to produce a fairly even mix of corn and soybeans. These are fairly homogeneous in end use, and both heavily exported.

Production for domestic versus foreign markets is denoted q and q^*, respectively. Inputs are broken in three categories: land acreage (L), imported inputs (Z^*), and total fixed costs (*TFC*). The representative producer maximizes profit given by:

$$\text{(1)} \qquad \underset{q,L,Z^*}{\text{Max}}\,\pi = p(q)q + ep^*(q^*)q^* - wL - es^*Z^* - TFC\,,$$

where p and p^* denote prices received in domestic and foreign markets, respectively; e is the exchange rate, *w* is the rental rate of land, and s^* is the rental rate on imported inputs, respectively. *TFC* refers to things like equipment and machinery, but does not ultimately play a role in this analysis. I assume that the representative producer has enough personally owned land to cover *TFC*. This does not seem unreasonable given that 93% of farmers farm a mix of owned and rented land (Ryan et al., 2001). Producer willingness to plant for alternative levels of land rent is given the marginal revenue product curve. The cash rent market serves farmers who wish to expand their land base.[1]

Maximization of (1) is subject to production given by a Cobb-Douglas form:[2]

$$\text{(2)} \qquad Q = L^{\beta}(Z^*)^{\alpha}\,,\; Q = q + q^*\,,$$

where $\beta + \alpha = 1$, and output *Q* is segregated into foreign markets (q^*) and domestic markets (q). The production function *Q* is homogeneous of degree 1, and π is homogeneous of degree 1 in prices and convex in prices.

The segregation of output into foreign markets (q^*) versus domestic markets (q) depends on the price elasticity of demand in the domestic market, denoted $\eta < 0$, and by the price elasticity of demand in the foreign market, denoted $\eta^* < 0$. It is also determined by the exchange rate (*e*). This is reflected in the structure of the demand functions in (1):

$$p(q) = a(e)q^{1/\eta}, \; ep^*(q^*) = a^*(e)(q^*)^{1/\eta^*}. \tag{3}$$

The terms a and a^* are demand shifters that are a function of exchange rates. Exchange rate movements influence demand by potentially shifting the relative price of home versus foreign products, and therefore affecting the residual demand faced by the domestic representative producer (Campa and Goldberg, 2001).

---

[1] Cash rents are not modeled as Ricardian rent, in part because the available evidence suggests there is not a strong correspondence between the two (Du, Hennessy, and Edwards, 2007), and since studies suggest that farm family labor is a relatively fixed input (Helmberger and Chavas, 1996).

[2] This approach works with a production function more general than the Cobb-Douglas, such as CES. However, this would make no real difference in terms of the equations that we ultimately estimate (Campa and Goldberg, 2001).

Maximization of (1) subject to (2) and (3) gives rise to the following first order conditions:

(4) $aq^{1/\eta}\left(1+\eta^{-1}\right)=a^{*}(q^{*})^{1/\eta^{*}}\left(1+\eta^{*-1}\right)$, or more simply $p\left(1+\eta^{-1}\right)=ep^{*}\left(1+\eta^{*-1}\right)$,

(5) $\left[p\left(1+\eta^{-1}\right)(1-\chi)+ep^{*}\left(1+\eta^{*-1}\right)\chi\right]\beta L^{\beta-1}(Z^{*})^{\alpha}=w$,

(6) $\left[p\left(1+\eta^{-1}\right)(1-\chi)+ep^{*}\left(1+\eta^{*-1}\right)\chi\right]\alpha L^{\beta}(Z^{*})^{\alpha-1}=es^{*}$.

To get equation (4) I make use of the fact that $q^{*}=Q-q$ and that $\partial q^{*}/\partial q=-1$. Equation (4) implies that marginal revenue in the domestic market, $p\left(1+\eta^{-1}\right)$, is equated to marginal revenue in foreign markets, $p\left(1+\eta^{*-1}\right)$.[3]

---

[3] To derive equations (5) and (6) I make use of the fact that $q=Q(1-\chi)$, and that $q^{*}=\chi Q$. So I get that: $\partial q/\partial Q=1-\chi$ and that $\partial q^{*}/\partial Q=\chi$.

Equations (5) and (6) imply that marginal revenue product is equal to a factor's rental rate. To derive equations (5) and (6) I make use of the fact that $q = Q\left(1-\chi\right)$, and that $q^{*} = \chi Q$. I then have that: $\partial q / \partial Q = 1-\chi$ and that $\partial q^{*} / \partial Q = \chi$. The part in brackets $\left[p\left(1+\eta^{-1}\right)\left(1-\chi\right)+ep^{*}\left(1+\eta^{*-1}\right)\chi \right]$ is simply marginal revenue, with χ being the share of foreign sales in overall sales. Note that I can re-state (5) as $p\left(1+\frac{1}{\eta}\right)\beta L^{\beta-1}(Z^{*})^{\alpha} = w$, using the result from (4). This tells us that the product of marginal revenue product, $p\left(1+\eta^{-1}\right)$ and marginal physical product, $\beta L^{\beta-1}(Z^{*})^{\alpha}$, is equal to land's rental rate (*w*). The derivation and interpretation of (6) is analogous to that of (5).

The solution to the first-order conditions yields optimal land demand by the representative farmer. I start with Euler's theorem for the homogeneous production function:

$$(7) \qquad Q = L\frac{\partial Q}{\partial L} + Z^{*}\frac{\partial Q}{\partial Z^{*}} = \frac{wL}{p\left(1+\eta^{-1}\right)} + \frac{es^{*}Z^{*}}{p\left(1+\eta^{-1}\right)}.$$

The right expression holds because at the optimum, marginal physical product equals the ratio of an input's price to marginal revenue (Helmberger and Chavas, 1996). Optimal land demand can be found as:

$$(8) \qquad L = \frac{Q}{w}\left(p\left(1+\frac{1}{\eta}\right)\left(1-\chi\right)+ep^{*}\left(1+\frac{1}{\eta^{*}}\right)\chi - es^{*}\alpha\left(\frac{\partial Q}{\partial Z^{*}}\right)^{-1} \right),$$

making use of the fact that: $\frac{Z^*}{Q} = \alpha\left(\frac{\partial Q}{\partial Z^*}\right)^{-1}$. Equation (8) shows that optimal land demand depends on domestic and foreign demand, and on the substitutability between productive factors measured alongside their costs.

I can now derive the elasticity of land demand with respect to exchange rates. First note that *p* and p^* are functions of *e*, and let $\frac{\partial p}{\partial e}\frac{e}{p} = \eta^{pe}$ and $\frac{\partial p^*}{\partial e}\frac{e}{p^*} = \eta^{p^*e}$. I can then show that a 1% increase in *e* leads to the following percent change in *L*:

$$(9)\quad \frac{\partial L}{\partial e}\frac{e}{L} = \frac{1}{\beta}\left[p\left(1+\frac{1}{\eta}\right)\eta^{pe}\left(1-\chi\right) + ep^*\left(1+\frac{1}{\eta^*}\right)\chi\left(1+\eta^{p^*e}\right) - \alpha es^*\left(\frac{\partial Q}{\partial Z^*}\right)^{-1}\right].$$

Following Campa and Goldberg (2001), I can further simplify (9) to make it suitable for empirical analysis. I assume that: η^{pe} is proportional to import penetration of domestic markets (M), η^{p^*e} is proportional to M^*, the law of one price holds ($p = ep^*$), $\chi M = 0$ holds, $\chi M^* = 0$ holds, and foreign real input cost equals 1: $s^* / p^* = 1$.[4]

---

[4] The implications of these assumptions are discussed in Campa and Goldberg (2001). They have little bearing on our final estimating equations.

This lets us simplify (9) to become:

$$(10) \qquad \frac{\partial L}{\partial e}\frac{e}{L}=\frac{p}{\beta}\left[\left(1+\frac{1}{\eta}\right)kM+\left(1+\frac{1}{\eta^{*}}\right)\chi-\alpha\left(\frac{\partial Q}{\partial Z^{*}}\right)^{-1}\right].$$

These results can be expressed in terms of elasticities and shares to facilitate econometric estimation. This can be done by log-linearizing an equation at a point (see Campa and Goldberg, 2001). Using equation (8) and (10) and log-linearizing, optimal land demand in the absence of adjustment costs can be expressed as:

$$(11) \qquad L=c_{0}+\left(c_{1,0}+c_{1,1}\chi+c_{2,2}M+c_{2,3}\alpha\right)e+c_{3}w+c_{5}s*,$$

where all variables other than χ, M, and α are defined in logarithms. The supply of farmland for lease is given by the simple equation:

$$(12) \qquad L=a_{0}+a_{1}w,$$

wherein supply of land (L) is a function of cash rent (w). If demand (11) is equated to supply (12), I can solve for cash rents, where the coefficients (ω) are some combination of the coefficients in (11) and (12):

$$(13) \qquad w=\omega_{0}+\left(\omega_{1}+\omega_{2}\chi+\omega_{3}M+\omega_{4}\alpha\right)e+\omega_{4}s^{*}.$$

Equation (13) is a reduced-form equation that takes the same general form as (11). Due to the process of log-linearization it is an approximation (Campa and Goldberg, 2001). This is one reason why equation (13) differs from the form of estimating equation used in other cash rent studies (e.g., Roberts, Kirwan, and Hopkins, 2003; Lence and Mishra, 2003). Another reason is that it is estimated at the state level, so does not have site-specific determinants of cash rents, such as average soil quality by county. It also does not have an explicit representation of output prices on the right-hand side. By contrast, output prices are (implicitly) embodied within χ (the share of sales to export markets) and M (import penetration of domestic markets). These differences arise from the desire to emphasize the multiple ways by which exchange rates may affect cash rents.

3. Data Sources

Data come mainly from personnel and websites of the USDA Economic Research Service (ERS), National Agricultural Statistics Service (NASS), and Bureau of Labor Statistics (BLS), which are discussed in the present section.

Cash Rents data is collected from NASS. They are collected through the annual June Agriculture Survey. Enumerators contact all agricultural producers operating land within the boundary of a randomly chosen land segment, and record the per acre cash rent paid. State estimates are based upon the total amount of cropland in each state as given by the most recent Census of Agriculture. We adjust USDA cash rents for inflation using a BLS producer price index.

Exchange Rates are calculated by the USDA as part of its Agricultural Exchange Rate Data Set. The index measures the strength of the U.S. dollar, in real terms, relative to key importers of U.S. agricultural commodities. It is calculated by first multiplying the U.S. dollar exchange rate by the ratio of CPIs in the U.S. and a foreign country. This real rate is then divided by its 2000 exchange rate to form an index. Next, its share of commodity trade is multiplied by each country's real exchange rate. The final step involves summing all of the weighted rates across countries to get the composite commodity's indexed exchange rate. The results reported in the paper are based on the USDA's composite "agricultural trade" exchange rate index. Alternatives include a USDA index created just for corn, and another just for soybeans. I find that results based upon these three alternatives are essentially identical. I report results for the composite agricultural trade index because its mean lies between that of the other two (shown in Table 1). Furthermore, as a more general index, it seems most representative of the exchange rate faced by a broad set of producers.

Real government payments per acre are calculated starting with the value of total direct government payments, by state and year, as calculated by the ERS. I then adjust for inflation using a BLS producer price index.

The cost share of imported inputs is calculated using ERS state-level agricultural balance sheets over time. Fuel and oil are viewed as the inputs on the balance sheets that are primarily imported, and calculate their share of total operating costs.

Interest rates are from the website of U.S. Federal Reserve. I start with the nominal Federal funds effective rate, in percent. I then subtract the percentage change in the Consumer Price Index to determine a real interest rate. I also tried estimating the regressions using the Prime interest rate. However, it makes essentially no difference to the results.

Export shares are computed by dividing the value of a state's agricultural exports by the total value of production. The values are based upon ERS estimates.

I compute import penetration by dividing the total imports of competing major grains by their supply, where the supply is calculated as U.S. production plus imports. The values are based upon ERS estimates.

Descriptive Statistics

I focus on five U.S. cornbelt states over the 1975-2005 period: Illinois, Indiana, Iowa, Missouri, and Ohio. There is no single exchange rate associated with the U.S. dollar, of course. I use the ERS "agricultural trade" exchange rate index, which measures the strength of the U.S. dollar, in real terms, relative to key importers of major U.S. agricultural commodities. I report some descriptive statistics regarding this series in Table 1. Looking near the top of this table, the "agricultural trade" exchange rate index has a mean of 89.9 deflated units of foreign currency per dollar. This appears to straddle ERS exchange rate indexes for corn and soybeans, which have means of 92.5 and 86.4, respectively (Table 1). Descriptive statistics regarding deflated cash rents by state are also reported in Table 1. The mean values range from $57 per acre in Missouri to $102.7 per acre in Illinois.

I plot the exchange rate index along with deflated cash rents for the five states over time in Figure 1. There seems to be a roughly positive correlation. The correlation averages approximately 0.3 for the five states. The positive nature of this correlation can be understood when looking at individual time periods. Considering the 1979-1985 period, for example. During this time the U.S. real exchange rate rose 43% against major agricultural trading partners' currencies. During the same period, real cash rents rose by 16% in Illinois and by 9% in both Iowa and Indiana. There were slight declines after

1982, and in Ohio this was enough to make real 1985 cash rents slightly lower than in 1979 (76.3 versus 77.1). However, the fact that there was a rise at all is somewhat surprising given that this period is well known to have had large increases in real U.S. interest rates, and declines in agricultural output prices and export volume (ERS/NASS data).

I then consider the 1985 to 1988 period (Figure 1). During these years the real value of the dollar fell 17%. Similarly, real cash rents fell in all five states: by 27% in Illinois, 27% in Indiana, 24% in Iowa, 12% in Missouri, and 18% in Ohio. These falls occurred despite an escalation of government supports for cornbelt farmers during this period. According to ERS/NASS data, real government payments to agriculture, per acre, rose by 142% - 158% in the five states during 1985-1988 (as also seen from Table 1 for descriptive statistics).

Another example of the positive correlation is the 1996-2002 period, when the U.S. real exchange rate rose 22% against major trading partners' currencies (Figure 1). During this time, real cash rents rose by 42% in Illinois, 32% in Indiana, 41% in Iowa, 73% in Missouri, and 34% in Ohio.

4. Regression results

To estimate (13) I use U.S. state-level data collected from the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS). The data correspond to five cornbelt states over the period 1975-2005. In addition to the variables represented in equation (13), I also collect information on government payments (*G*) and interest rates (*INT*) since other studies find these to influence the demand for farmland.

Letting *i* index states and *t* index time, I denote real (deflated) cash rents as w_t^i. In applying equation (13) to the data, I first tested a hypothesis of first-order serial correlation, and find that it is not rejected by a Berenblut and Webb (1973) test at the 5% level of significance. I therefore first difference the variables in the preferred specifications. Given the time-series cross-section nature of the data, I additionally carry out a Hausman (1978) test. I reject a null hypothesis that a random effects estimator is consistent and efficient. I therefore adopt a Least Squares Dummy Variable approach. I add state-level fixed effects D_j to the regression specification, where D_j is equal to one when $j = i$, otherwise zero. In implementing the model, let Δ denote a change from period *t*–1 to *t*. The change in government payments from *t*–1 to *t* in state *i*, for example, is denoted ΔG_t^i. The most general specification that I test is:

$$(14)\quad \Delta w_t^i = \left(\omega_1 + \omega_2 \chi_t^i + \omega_3 M_t + \omega_4 \alpha_t^i\right)\Delta e_t + \omega_5 \Delta G_t^i + \omega_6 \Delta s_t^* + \omega_7 \Delta INT_t + \sum_{j=1}^{5} \beta_j D_j + \varepsilon_t^i,$$

where $\omega_1,...,\omega_7$ and $\beta_1,...,\beta_5$ are parameters to be estimated. Since e_t is measured in units of foreign currency per dollar, $\Delta e_t > 0$ signifies an appreciation in the U.S. dollar. Table 2 reports the results of estimating equation (14). Variant I does not consider the interaction effects – $\chi_t^i \Delta e_t$, $M_t \Delta e_t$, and $\alpha_t^i \Delta e_t$ - variant II does not consider the interest rate, and variant III considers all possible effects represented by equation (14) above. The R^2 ranges from 0.35 to 0.39 across three variants of this equation. The coefficients in the top row of Table 2 concern the relation between the dollar and cash rents. In all three variants the coefficient of the exchange rate (Δe_t) is positive and statistically significant at conventional levels. It ranges from 13.69 in variant I to 20.30 in variant III. This means that a strong dollar is associated with higher cash rents. Based on the simple theoretical model, this result suggests that there may be purchasing power benefits of a strengthened dollar. This result corresponds to what was seen in Figure 1, i.e., real cash rents somewhat follow real exchange rates for the majority of the time period. As discussed in the Data section, these results are based on the ERS's composite "agricultural trade" exchange rate index. Results are essentially the same if the ERS index created just for corn, or the ERS index created just for soybeans are used (see also the comparison in Table 1).

Results concerning the interaction term coefficients are reported in rows 2 - 4 of Table 2. The coefficients on the export orientation interaction term ($\chi_t^i \Delta e_t$) and the import penetration interaction term ($M_t \Delta e_t$) are not statistically different from zero. These aspects of the model, therefore, do not receive support from the data. Question arises whether this should surprise us. The trade literature identifies a number of reasons that dollar depreciations may not have a strong, immediate effect on exports. Exchange rate pass through may be limited due to the oligopolistic nature of international grain trade, and price transmission may be limited due to policy barriers (Krugman, 1987; Pick and Park, 1991). Prices may also be "sticky" due to menu or catalog pricing. Exports may therefore have a somewhat inelastic relationship with the dollar (Batten and Belongia, 1986).

In separate calculations, however, I find that the share of foreign sales in overall sales (χ_t^i) does have a negative correlation with real exchange rates in four of the five states (in the case of Indiana and Ohio, for example, it is –0.46 and –0.49). Thus there is some support that a weak dollar leads to greater foreign demand for U.S. crops. However, in terms of net returns this effect may be moderated by the dollar's potential effect on input costs.

I now turn to the result concerning the cost share of imported inputs (α_t^i), which is calculated using state agricultural balance sheets over time. As described in the Data Appendix, I view fuel and oil as the inputs that are primarily imported, and calculate their share of total operating costs. In Table 2, the sign on the cost share of imported inputs term ($\alpha_t^i \Delta e_t$) is 26.63 for variant II and 25.79 for variant III. It is statistically significant at the 1% level in both cases. This means that states (and time periods) with higher dependence on imported inputs experience a *larger* increase in cash rents as the dollar appreciates. This is consistent with my expectations for this coefficient. It also reinforces the above result concerning the coefficient on Δe_t.

In thinking more about this effect, I note that the correlation between the cost share of imported inputs and the dollar is negative for all five states, ranging from –0.23 for Iowa to –0.40 for Indiana. This means that the cost share of imported inputs falls as the dollar gets stronger. This effect appears to operate through oil prices. While oil is priced in dollars, it tends to have an inverse relationship with the strength of the U.S. dollar, particularly in the near term. In the data I find this correlation to be –0.42. This is illustrated in Figure 2, which is a scatter plot of the real dollar against the crude oil acquisition cost by U.S. refiners in real dollars per barrel. The negative slope means that a strong dollar is associated with low oil prices. Taken together, these results suggest that it is possible that a strong dollar reduces costs, encouraging farmers to pay higher rents for additional, cash-rented acres.

Other aspects of the regression are in line with expectations. The sign of the coefficients on government payments is positive and statistically significant at the 1% level. This is similar to studies such as Goodwin, Mishra, and Ortalo-Magné (2003) and Lence and Mishra (2003), even though the representation of government policies is relatively blunt. While their regressions employ distinct categories of government support, I use a single, aggregate support measure. Nonetheless, I find that like these studies, government payments tend to have a positive relation with cash rents.

Variants I and III include real interest rates (ΔINT_t). The coefficient on ΔINT_t is positive in both cases, but not statistically significant in either. Although I will refrain from interpreting this result too literally, it appears that a rise in the real interest rate may tend to induce the substitution of land for other capital inputs, leading to a rise in cash rents. I also tried estimating the regressions using other types of interest rates, such as the prime interest rate. I discuss some of these alternative definitions in the Data section. However, these changes make no substantive difference in the results. To sum up, the basic results do not appear to depend on what specification is used.

The dollar’s relationship with cash rents appears to be at least as responsive as the dollar’s relationship with wages in U.S. manufacturing (Revenga, 1992; Goldberg and

Tracy, 2000; Campa and Goldberg, 2001). There are several potential reasons for this. First, the supply of land probably is likely more inelastic than the supply of manufacturing labor. Cash rents may therefore be more sensitive to exchange rates, since the quantity of farmland is relatively fixed. Second, farming is closer to the textbook model of perfect competition than is manufacturing. Many industries within the latter sector may have positive price-cost margins, for example. This is important because, all else the same, industries with low price-cost margins have more responsive input demand than do imperfectly competitive industries (Campa and Goldberg, 2001). Again, this may also explain why cash rents are more sensitive to exchange rates. A further difference is that land may be a bigger expense in crop agriculture than labor tends to be in manufacturing. This is an additional reason why cash rents may be relatively responsive to the dollar.

5. Granger causality

I can shed further light on the above results through consideration of bivariate Granger causality tests. This procedure identifies whether one time series helps forecast another (Granger, 1969). A time series variable *x* is said to Granger-cause *y* if *x* provides statistically significant information about future values of *y*. If the Granger test statistic is greater than the specified critical value, a null hypothesis that *x* does not cause *y* is rejected. The test is conducted without reference to the other explanatory variables included above.

I first test whether the dollar Granger-causes cash rents. The test statistic is 4.65 and *p*-value is 0.0039, implying that the null hypothesis is rejected. This means that the dollar Granger-causes cash rents. The converse is not true, however – as should be expected. When I swap the variables in the test, the test statistic is 0.57 and *p*-value is 0.63. The implication is that the real dollar *does* Granger-cause real cash rents, but the converse is not true. This makes sense since the value of the dollar is determined at highly aggregated levels involving many sectors of the economy. By contrast, demand for rented farmland – a tiny share of the U.S. economic system – should have no discernable influence on exchange rates. Granger causality is, of course, not a foolproof indicator of causality, since, for example, both variables could be driven by a common third process, but with a different lag. However, the results make economic sense, and corroborate the main findings of the earlier sections of the study.

6. Conclusions

Based on the results, I can make four basic points in the present essay. First, that the exchange rate is over-looked as a potential causal factor in studies of agricultural rents; indeed, it would be surprising if this macroeconomic variable did not have some effect, particularly in the case of U.S. cornbelt agriculture, which is export dependent and makes intensive use of energy-based inputs. Second, a weak dollar is not necessarily “good” for U.S. cornbelt agriculture since the cost of energy-based inputs is closely related to the price of oil, and this tends to have an inverse relation to the strength of the dollar. Third, simple correlations with publicly available data suggest that real cash rents for U.S. cornbelt agriculture are positively correlated with the real exchange rate for agricultural commodities. Fourth, evidence suggests that one causal link for the above stylized fact is that the purchasing power benefits of a strong dollar improve the net returns from farming additional acres, increasing the demand for cash-rented acres.

However, there are several potential limitations of the econometric results in this essay. For example, the model of the process by which cash rents are negotiated is stylized. The model abstracts from the dynamic and stochastic aspects of crop production. The conclusions are tempered by the fact that the study relies upon aggregated data, which are susceptible to problems with data measurement, and which complicate statistical procedure. These are all reasons to use caution in interpreting the regression results. Nonetheless, the essay has marshaled enough evidence to encourage a rethinking of the idea that a weak dollar is necessarily “good” for export-dependent agriculture. While a weak dollar may raise output prices, it may be associated with a rise in input prices to an extent that the net benefit of a weak dollar is called into question.

References

Batten, D., and M. Belongia. 1986. “Monetary Policy, Real Exchange Rates, and U.S. Agricultural Exports.” *American Journal of Agricultural Economics* 2:422-427.

Berenblut, I. and G. Webb. 1973. “A New Test for Autocorrelated Errors in the Linear Regression Model.” *Journal of the Royal Statistical Society* 35:33-50.

Campa, J., and L. Goldberg. 2001. “Employment Versus Wage Adjustment and the US Dollar.” *Review of Economics and Statistics* 83:477-489.

Carter, C., and D. Pick. 1989. “The J-Curve Effect and the US Agricultural Trade Balance.” *American Journal of Agricultural Economics* 71:712-720.

Chavas, J., and C. Shumway. 1982. “A Pooled Time-Series Cross-Section Analysis of Land Prices.” *Western Journal of Agricultural Economics* 7:31-41.

Cho, G., I. Sheldon, and S. McCorriston. 2002. “Exchange Rate Uncertainty and Agricultural Trade.” *American Journal of Agricultural Economics* 84:931-942.

Clark, J., M. Fulton, and J. Scott. 1993. “The Inconsistency of Land Values, Land Rents, and Capitalization Formulas.” *American Journal of Agricultural Economics* 75:147-155.

Erickson, K., A. Mishra, and C. Moss. 2003. “Cash Rents, Imputed Returns, and the Valuation of Farmland Revisited.” In: C. Moss and A. Schmitz, Eds., *Government Policy and Farmland Markets*. Ames: Iowa State University Press. pp. 223-238.

Featherstone, A.M., and T.G. Baker. 1987. “An Examination of Farm Sector Real Asset Dynamics: 1910-1985.” *American Journal of Agricultural Economics* 69(3):532-546.

Goldberg, L., and J. Tracy. 2000. “Exchange Rates and Local Labor Markets.” In R. Feenstra, ed. *The Impact of International Trade on Wages*. Chicago: The University of Chicago Press, pp. 269-308.

Goodwin, B., A. Mishra, and F. Ortalo-Magné. 2003. “What’s Wrong with Our Models of Agricultural Land Values?” *American Journal of Agricultural Economics* 85:744-752.

Granger, C. 1969. “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods.” *Econometrica* 37:424-438.

Hausman, J. 1978. “Specification Tests in Econometrics.” *Econometrica* 46:1251-1271.

Helmberger, P., and J. Chavas, 1996. *The Economics of Agricultural Prices*. Upper Saddle River, NJ: Prentice Hall.

Iowa State University Extension. 2008. *Farmland Ownership and Tenure in Iowa 2007*. Extension Publication PM1983.

Irwin, S., and P.L. Colling. 1990. “Are Farm Asset Values Too Volatile?” *Agricultural Finance Review* 50:58-65.

Just, R., and J. Miranowski. 1993. “Understanding Farmland Prices.” *American Journal of Agricultural Economics* 75(1):156-168.

Kandilov, I. 2008. “The Effects of Exchange Rate Volatility on Agricultural Trade.” *American Journal of Agricultural Economics* 90:1028-1043.

Krugman, P. 1983. “Oil and the Dollar.” In: J. Bhandari and B. Putnam, eds., *Economic Interdependence Under Flexible Exchange Rates*. Cambridge: Massachusetts Institute of Technology, pp. 179-190.

Krugman, P. 1987. “Pricing to Market When the Exchange Rate Changes.” Ed. S. Arndt, and J. Richardson. *Real-Financial Linkages Among Open Economies*. Cambridge, MA, MIT Press, pp. 48-70.

Lence, S., and A. Mishra. 2003. “The Impacts of Different Farm Programs on Cash Rents.” *American Journal of Agricultural Economics* 85:753-761.

Moss, C. 1997. “Returns, Interest Rates and Inflation: How They Explain Changes in Farmland Values.” *American J. of Agricultural Economics* 79:1311-1318.

Patton, M., P. Kostov, S. McErlean, and J. Moss. 2008. “Assessing the Influence of Direct Payments on the Rental Value of Agricultural Land.” *Food Policy* 33:397-405.

Pick, D. 1990. “Exchange Rate Risk and US Agricultural Trade Flows.” *American Journal of Agricultural Economics* 72:694-700.

Pick, D., and T. Park. 1991. “The Competitive Structure of U.S. Agricultural Exports.” *American Journal of Agricultural Economics* 73:133-141.

Revenga, A. 1992. “Exporting Jobs? The Impact of Import Competition on Employment and Wages in U.S. Manufacturing.” *Quarterly Journal of Economics* 107:255-284.

Roberson, R. 2008. “Input Costs Pushing Farm Risk Levels Higher.” *Southeast Farm Press*. 35:18.

Roberts, M., B. Kirwan, and J. Hopkins. 2003. “The Incidence of Government Program Payments on Agricultural Land Rents: The Challenges of Identification.” *American Journal of Agricultural Economics* 85:762–769.

Ryan, J., C. Barnard, R. Collender, and K. Erickson. 2001. “Government Payments to Farmers Contribute to Rising Land Values.” *Agricultural Outlook* June:22-26.

Schuh, G. 1974. “The Exchange Rate and U.S. Agriculture.” *American Journal of Agricultural Economics* 56:1-13.

Schmitz, A. 1995. “Boom/Bust Cycles and Ricardian Rent.” *American Journal of Agricultural Economics* 77:1110-1125.

Schnitkey, G., and A. Gupta. 2007. “Impacts of Rising Crude Oil Prices on Corn and Soybean Production Costs.” *University of Illinois Extension Publication FEFO* 08-10. pp. 6.

Tsoodle, L., B. Golden, and A. Featherstone. 2006. “Factors Influencing Kansas Agricultural Farm Land Values.” *Land Economics* 82(1):124-139.

USDA (U.S. Department of Agriculture, Economic Research Service). 2009a. “Farm Income and Costs Briefing Room.” www.ers.usda.gov/briefing/farmincome/

USDA (U.S. Department of Agriculture, Economic Research Service). 2009b. “U.S. Fertilizer Imports/Exports.” www.ers.usda.gov/Data/FertilizerTrade/

Weersink, A., S. Clark, C. Turvey, and R. Sarker. 1999. “The Effect of Agricultural Policy on Farmland Values.” *Land Economics* 79(3):425-439.

Table 1. Summary Statistics for Data, 1975-2005

Variable	Mean	Std. dev.	Min	Max
Exchange rate, deflated for. cur. per \$ (e_t)				
U.S. markets agricultural trade*	89.9	11.2	64.3	107.1
U.S. markets corn	92.5	11.2	70.6	112.6
U.S. markets soybeans	86.4	12.3	60.2	106.5
Interest rate, % (INT_t)†	6.6	3.5	1.1	16.4
Share of imports in dom. market (M_t)	0.205	0.096	0.075	0.468
Cash rents, deflated \$ per acre (w_t^i)				
Illinois	102.7	11.5	81.8	123.2
Indiana	90.7	9.9	73.4	109.6
Iowa	102.1	10.9	82.3	121.2
Missouri	57.9	6.9	38.5	70.0
Ohio	70.6	8.3	55.6	88.4
Govt. payments, deflated \$ per acre (G_t^i)				
Illinois	24.9	21.7	0.33	73.1
Indiana	21.0	19.2	0.35	61.8
Iowa	27.3	21.4	0.18	72.4
Missouri	10.7	7.7	0.97	28.9
Ohio	16.0	13.9	0.44	46.5
Share of foreign sales in overall sales (χ_t^i)				
Illinois	0.402	0.089	0.234	0.783

Indiana	0.334	0.045	0.257	0.446
Iowa	0.288	0.039	0.219	0.372
Missouri	0.264	0.028	0.207	0.340
Ohio	0.295	0.039	0.246	0.433
Cost share of imported inputs (α_t^i)				
Illinois	0.068	0.018	0.046	0.108
Indiana	0.061	0.015	0.042	0.095
Iowa	0.051	0.013	0.034	0.082
Missouri	0.064	0.016	0.043	0.096
Ohio	0.063	0.015	0.044	0.099

* All results in the study are based on this ERS-generated exchange rate. The results change little if I use the alternatives specific to corn or soybeans. † This is deflated before final use, as described in the Data Section.

Table 2. Regression Results

		Variant of equation (13)		
Variable	Expected sign	I	II	III
Exchange rate		13.69*	20.01**	20.30**
(Δe_t)	+/-	(-0.05)	(-0.01)	(-0.01)
Export share * exch. rate			0.64	0.69
($\chi_t^i \Delta e_t$)	-	--	(-0.56)	(-0.53)
Import competition * exch. rate			-0.01	0.27
($M_t \Delta e_t$)	-	--	(-0.99)	(-0.77)
Imported inputs * exch. rate			26.63**	25.79**
($\alpha_t^i \Delta e_t$)	+	--	(<0.01)	(-0.01)
Government payments		0.05**	0.06**	0.06**
(ΔG_t^i)	+	(<0.01)	(<0.01)	(<0.01)
Interest rates		1.77		1.46
(ΔINT_t)	+/-	(-0.09)	--	(-0.17)

	Variants		
State level fixed effects	I	II	III
Illinois	0.85	0.59	0.65
	(-0.26)	(-0.43)	(-0.39)
Iowa	1.79**	1.56**	1.61**
	(-0.02)	(-0.04)	(-0.03)
Ohio	0.54	-0.33	0.40
	(-0.48)	(-0.66)	(-0.61)
Indiana	1.57**	1.37*	1.43*
	(-0.04)	(-0.07)	(-0.06)
Missouri	1.22	0.95	1.00
	(-0.11)	(-0.21)	(-0.18)
Number of observations	150	150	150
R^2	0.35	0.38	0.39

Notes: All variables are deflated. *p*-value is in parentheses. The asterisks ** and * denote statistical significance at the 1% and 5% levels, respectively.

Figure 1. Cash rents and the dollar, 1975-2005

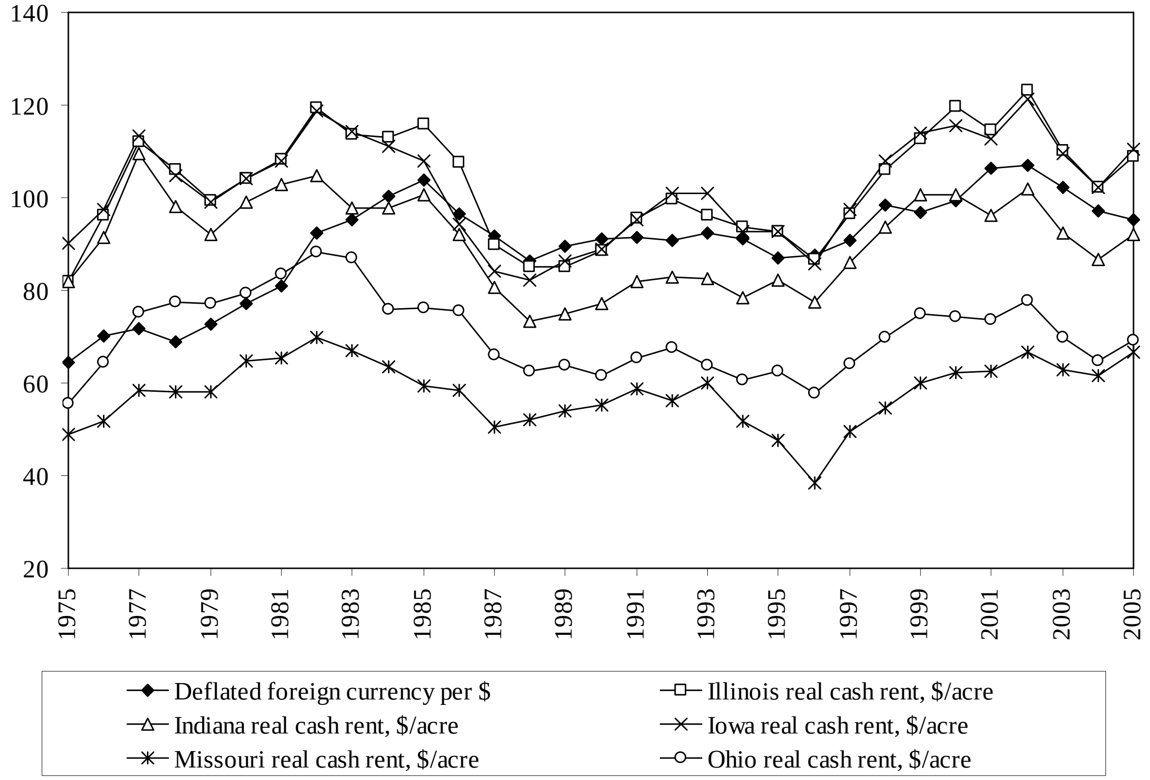
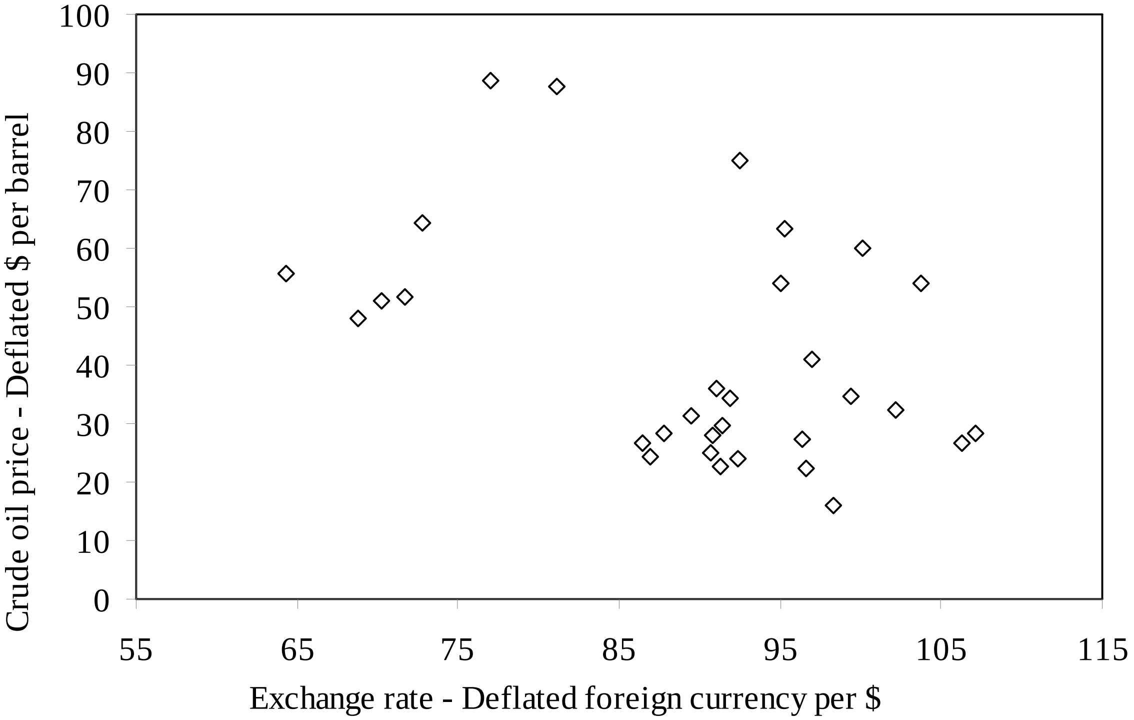


Figure 2. Oil prices and the dollar, 1975-2005



Chapter III: Research Portfolio Choice in Academic Bioscience

Essay II

Sharmistha Nag

Introduction

Relationships between universities and research funding sources have emerged to play a significant role in the development of agricultural biotechnology. Partnerships between private firms and universities, for example, can improve agricultural productivity because they help both groups to gain access to scientific talent, financial support, new opportunities, and cutting edge research techniques (Ervin *et al* 2002). Universities attract industry investments to raise their research productivity (Jaffe 1989), and a major force behind firms' increased investments in academic R&D is to obtain direct access to university labs, students, and staff (Thorn 1996).

US academic institutions performed $48 billion of R&D in 2006 (National Science Board, Chapter 5). Evidence indicates monetary support from all sources for university research increased between 1972 and 2000 but industrial funding declined in 2001 and 2003 and rebounded between 2004 and 2006. Federal support for academic research declined in 2006 as inflation surpassed funding growth. In 2007, the National Institutes of Health sponsored 63% of federally supported academic research, the National Science Foundation provided 13%, the Department of Defense 8%, the National Aeronautics and Space Administration 5 %, Department of Energy 3%, and U.S. Department of Agriculture 2%. States and local governments provided 6% federal support to university research in 2006. Non-profit organizations and voluntary health foundations have spent about 7% of their total budget on academic R&D since 1970s (NSF). Institutional funds (general-purpose or institution-to-institution funds) for university research rose by almost 8% between 1970s and 2000 (Rapoport 2002). Industry's share for academic R&D declined from 7.4% in 1999 to 4.9% in 2004 (Vegso 2006).

Although industry contributes a relatively small fraction of academic research funding, industry support has substantial influence on scientific research in US universities. Monetary awards and in-kind inputs are strong motivating factors for university faculties to engage in industry partnerships (Hall 2004). A survey of 400 university and industry collaborations conducted by Lee (2000) indicates that private partnerships raise university faculties' contributions to patentable scientific discoveries.

The Bayh-Dole Act, passed in December 1980, has played a key role in promoting the commercialization of research and the rate of patent awards to universities (Neumann 2006). Widespread debate has emerged over the commercialization and marketability of university research findings following the Act. University researchers with private funds are more likely to choose commercialization of their research projects than are faculties receiving most of their financial support from public agencies. Research commercialization tends to encourage trade secrets (Blumenthal *et al*, 1986). Commercialization and patentability of scientific findings is a major trend in university bioscience because patents are likely to enhance the academic researchers' professional reputation (Azoulay *et al* 2006).

Professional Values and University Type

The scientific process is driven by professional values or norms. Values regulate conduct within the academic environment and influence scientific practice (Lefkowitz 2003; Howard 1985). Merton (1973) points out that withholding research results prohibits communality of scientific discoveries and limits knowledge utilization (Berardo, 1989). The normative structure of university science has been influenced by industry and political interests (Benner and Sandstorm 2000). A common notion since the US government passed the Bayh-Dohl Act is that public agencies have been encouraging scientists to patent their discoveries. However, Buccola, Ervin, and Yang (2009) do not find any evidence to support the claim that public funds encourage excludable research. Their results do indicate that scientists seeking patents are likely to pursue research with exclusionary goals.

Surveys conducted at various times have depicted gradual shifts among university scientists towards commercial involvement. Reward structures may be a strong motivating factor in such transitions (Stuart and Ding 2006). University environment and policies also influence scientific research (Etzkowitz 1989). Scientists at Land-Grant universities (LGU) are especially inclined to collaborate with industry and perform applied research (Curry and Kenny 1990; Buccola, Ervin, and Yang 2009). LGUs, established under the Morrill Act of 1862 and its 1890 successor, focus primarily on applied research in agriculture, natural resources, and engineering. A survey of administrators at some prominent Land-Grant universities indicates that state budget policies are the rationales behind increased industry partnerships and research commercialization at LGUs (Glenna *et al* 2007). State governments encourage regionally specific applied research that would make a substantial economic contribution at the state level. However, empirical evidence implies that private universities, which often provide an entrepreneurial research environment, draw more financial support from both federal and private sources than do LGUs (Buccola *et al* 2009).

Financial and In-kind Inputs in University Research

A research project's objective is one of the key factors driving funding agencies' R&D investments. Research may be classified as basic or applied. The primary objective of basic research is advancement of knowledge through understanding of the underlying biological mechanism, while applied research aims to solve specific, practical problems through the use of theory and technology. Basic research is driven primarily by scientific curiosity and provides short-term gains but lays the foundation for future advances in science and technology (S & E indicators 2008). The federal government has been spending a greater proportion of its resources on basic research than has the private sector, which tends to invest more in applied research (Klotz-Ingram and Day-Rubenstein 1999). US universities performed about 54% of purely basic research and 33% of translational research in 2004 (NSF 2006). Of the $343 billion spent on total R&D in 2006, investment in basic research was about $62 billion, and in applied research was about $75 billion. Industry funding for academic R&D increased to $2.4 billion in 2006 (National Science Board, Chapter 5). Ervin *et al* (2002) find academic research is strongly affected by private money because private funds tempt university faculties to incline toward applied research. The authors point out that “the average time lag between academic research and marketability of its research findings has been declining over time,” implying that universities are investing more time, effort, and resources into applied research in order to obtain early rewards.

Salter and Martin (2001) find that social and private rates of return on investments in industry-funded applied R&D are larger than on publicly funded basic research. Furthermore, private returns on basic research are less than social returns (Salter and Martin 2001). However, greater public sponsorship of basic research might encourage greater sponsorship of applied research (David and Hall 2000) because progress in basic science improves the productivity of and thus the foundation for applied research. Yet it is ambivalent whether private and federal funds substitute for or complement each other. Empirical evidence in Buccola

(2009) suggests growing industry support “crowds out” government funds and vice versa. A possible explanation of the “crowding-out” effect can be found in Goolsbe’s (1998) study of the labor market impact of federal R&D funding. He finds increased public R&D spending raises the wages of technically skilled workers in private laboratories. Higher government R&D thus increases private-sector labor cost, crowding-out industry funds. Contrary to that result, a time series study by Diamond (1999) suggests public funds stimulate private expenditure on scientific research. He finds a million dollar increase in federal spending on basic research raises industry spending by $ 0.6 million. David, Hall, and Tool (2000) point to several macro-level time series and panel studies on the public-private R&D relationships in the recent literature. All but one of the seven finds that federal R&D expenditures “crowd-in” private R&D investments. Government-sponsored R&D encourages a scientist to boost her time and effort on publication and on communicating her scientific discoveries. Such technical knowledge-sharing resulting from increased public R&D support encourages profit-oriented industries to raise private R&D investments (Leyden and Link 1991; Wang *et al* 2009).

Besides financial grants, in-kind laboratory support often provides an essential component of scientific research. Laboratory equipment and such materials as reagents and cell lines improve the productivity and the quality of academic scientific work (Stephan 2005; Carayol and Matt 2003). A bibliometric study of publication patterns at ten South African universities from 1992 to 1996 shows that, in all branches of science, funding is directly related to research productivity. Yet certain fields (zoology, botany, and microbiology) may exhibit higher productivity than do others in spite of lower funding. However, supplying expensive laboratory equipment may reduce the availability of funds, and reduced cash may have a dampening effect on scientist productivity (Jacobs 2001).

Universities often provide startup capital in order to attract young scientists, who may not have any external funds at the initial phase of their career (Ehrenberg *et al* 2003). A 2002 survey of start-up costs at universities defined startup funds to include laboratory construction or renovation, and materials and equipment, among other expenses. Newly hired academic scientists frequently participate in ongoing research grants or bring in grants that partly contribute to their salaries. In the latter case, universities may use the recovered salaries for materials and equipment, depending on the rules and procedures of the academic institution (Boss and Eckert 2003). Access to well-equipped laboratories facilitates research and improves output (Turner and Mairesse 2002). On a national basis, the proportion of R&D expensed on research equipment declined from 7% to 4% between 1985 and 2006 (National Science Board, Chapter 5).

Recent Trends in Bioscience Research

Cutting-edge research tools, databases, and financial support from prominent funding agencies are widening the breadth of bioscience research. Some bioscience research areas are drawing more grants than others. In the present paper, I ask: to what extent does the size and source of financial support from research funding agencies influence or constrain a scientist's research choice decisions about the object-scale and basic vs. applied content of their laboratory work? In my examination, I include a number of important biotechnology research areas, such as biodiversity, biotechnology, gene therapy, stem cell research, environmental bioremediation, and bioterrorism. (NCABR, NIST, UIMB, 2008).

USDA - CSREES' total estimated funding for biotechnology research stood at $3 billion in 2008. Proteomics, which involves studying protein structures for identifying diseases, is a heavily funded research area at the NIH (Keim 2006). Plant genome research and genome sequencing draw large NSF funding. Grants in integrative organismal systems, which support genome-enabled plant biology research, increased from $160 million to $200 million between fiscal year 2000 and 2004 and has remained stable thereafter. Topics at the frontier of biological sciences drawing large NSF funding include impacts on living organisms of nanostructures dispersed in the environment, interactions of nanomaterials with cellular constituents, infectious diseases of plants and animals, and bioaccumulation, that is toxic-material absorption by living organisms. In general, I classify the above research topic categories according to the scale of the research object and to the basicness of the research question.

In the following, I develop a conceptual framework allowing a scientist to make optimal choices regarding such research-scale and basicness issues. In particular, I develop a model of (a) bioscientists' choices among research topic areas, distinguished in terms of how basic the topics are, and (b) the scale of the research object, distinguished according to whether it is a cell or sub-cellular entity, an organism or organ, or an ecosystem. My hypotheses point to the possibility that, and to the ways in which, money sources matter in scientists' research choices. I control for factors found important in other studies - scientific norms, university infrastructure, and in-kind support.

Conceptual Model

An academic bioscience research program may be characterized by its scientific discipline, field of study within that discipline, sub-specialties within the field, and the program's position on the basic-to-applied research continuum. Discipline refers to theoretical construct, which in biological science includes animal science, biochemistry, cell-biology, genetics, molecular biology, and pathology. Fields, sometimes referred to as sub-disciplines, include plant reproduction, wheat breeding, stress tolerance, and microbial genomics. External financial support expands research possibilities and for many scientists is desirable in its own right and thus a motivating factor to conduct research. My principal focus in this essay is on distinguishing the relative influences of funding and non-funding factors on the research topic choice, characterized by object scale and basicness.

A Scientist's Utility Maximizing Problem

Consider an academic bioscientist who sets forth goals for achieving a utility maximizing research program. A professional scientist makes significant investments of her time in pursuing the research that maximizes her utility. A scientist addresses research topics that, considered broadly, provide her satisfaction. She obtains financial support to conduct this research. Laboratory infrastructures such as material and equipment supplies affect the quality of output, influencing the scientist's utility both directly and through enhanced publication and fund-raising prospects. In any event, scientists aim to communicate their scientific discoveries by publishing their research results. A new faculty member gains professional recognition and qualifies for academic tenure and promotion by achieving significant research contributions. Ethical norms make a difference in that pursuit. For example, those who think it important to produce technologies with public benefits concentrate less on investigations having potential commercial value. University policies may affect the research environment and thus influence a scientist's research practice. For example, universities that encourage commercialization of research results likely boost the rate of their professors' patentable inventions. We regard these university characteristics as exogenous even though, in a much longer run, they are endogenous because the academic research pursued may influence university policy and culture.

We assume a scientist's utility is a function of the category of her primary object of research **S**; the basic-applied content of the research *M*; amount of grant money **G** received, distinguished by source; the number of publications *P* she produces; her human capital **X**; university type **L**; in-kind support **I**; and her scientific norm vector **V**. The utility function of a scientist thus can be expressed as

$$U = f\ (\mathbf{S}, M, \mathbf{G}, \mathbf{C}) \tag{2}$$

where $\mathbf{C} \equiv (P, \mathbf{X}, \mathbf{L}, \mathbf{I}, \mathbf{V})$. A scientist's research topic decision is depicted in terms of the topic category, in particular by the size or scale **S** of the research object addressed and by the topic's position in the basic-to-applied continuum *M*. As mentioned above, object scales are sorted into three groups: sub-cell or cell, organ or organism, and natural or managed ecosystem.

Based on this assumption, topic choice *T* is a combination of object scale **S** and basicness score *M*. Hence, we can rewrite the utility function as

$$U = f\ (T, \mathbf{G}, \mathbf{C}) \tag{2.1}$$

Exogenous factors are represented by vector **C**. However, although **G** is considered exogenous as well, we include the funding vector as a parameter in the utility function because we are most interested in examining the influence of these financial sources on research portfolio choice.

Equation (2.1) is continuous, monotonically increasing, and convex in *P*, and G_i, $(i = 1, \ldots, k$ indexes funding source). That is,

$$\frac{\partial U}{\partial P}, \frac{\partial U}{\partial G_i} > 0$$

$$\frac{\partial^2 U}{\partial P^2}, \frac{\partial^2 U}{\partial G_i{}^2} < 0$$

We suppose the scientist chooses, among the alternatives available, an object scale category *z* and, likewise, among the alternatives available, the basicness score *m* if they provide her maximum utility. The choices of scale and basicness categories generating optimum utility U_{mz} corresponds to the first-order condition $T(\mathbf{G}, \mathbf{C})$ obtained from maximizing the utility function in equation (2.1) with respect to *T*.

Utility Maximization in a Logistic Framework

We begin by laying out the utility framework developed in the context of random utility maximization, in which the scientist makes optimal choices over research object scales and basicness categories. In such a model, $Y_{mz}{}^{i}$ represents the selected scale category *z* and basicness score *m* of scientist *i* if (dropping subscript *i* for simplicity)

(3)

$$U_{mz} = Max\,(U_{11}, \ldots.., U_{mz})$$

$$= \nu_{mz} + \varepsilon_{mz} > \nu_{nl} + \varepsilon_{nl}$$

$$= Max\;(U_{11}, \ldots.., U_{nl}) = U_{nl},\;\; m \neq n\,;\, z \neq l\,;\, m, n\;\xi\; M\;;\;\; z, l\;\xi\; Z;$$

Because we do not observe the scientist's utility, we decompose it as $U_{mz} = v_{mz} + \varepsilon_{mz}$, where U_{mz} is unobservable indirect utility consisting of a deterministic component v_{mz} and a random component ε_{mz}. Variable v_{mz} depends on the unknown attributes $\mathbf{X}$, that is the exogenous predictors in the model. Based on the above discussion, equation (2) implies a scientist optimally selects scale category *z* and basicness score *m* over an alternative scale category *l* and basicness score *n* because *z* and *m* provide higher utility.

The logit function is commonly used in discrete choice modeling. The joint density of random error ε_{mz} is denoted $f(\varepsilon_{mz})$. With this density we can make the following probabilistic statements about the scientist's choice:

The probability that a scientist selects scale category *z* and basicness score *m* is:

(4)

$$P(Y_{mz} \mid \mathbf{X}) = P(U_{mz} > U_{nl}) = P(v_{mz} + \varepsilon_{mz} > v_{nl} + \varepsilon_{nl})$$

$$= P(v_{mz} - v_{nl} > \varepsilon_{nl} - \varepsilon_{mz}) = \int_{\varepsilon} I(\varepsilon_{nl} - \varepsilon_{mz} < v_{mz} - v_{nl}) f(\varepsilon).\, d\varepsilon$$

where $I(.)$ is the indicator function taking the value one if $I(\varepsilon_{nl} - \varepsilon_{mz} < v_{mz} - v_{nl})$ and zero otherwise. In a logit model, ε follows the logistic cumulative distribution function $\Lambda(\varepsilon) = \frac{1}{1+e^{-\varepsilon}}$ and density function

$\Lambda'(\varepsilon) = f(\varepsilon) = \dfrac{e^{-\varepsilon}}{(1+e^{-\varepsilon})^2}$. The probability $P(Y_{mz} \mid \mathbf{X})$ that each random term ε is less than the observed deterministic component of the indirect utility v is a cumulative probability function which we denote by $\Lambda(\mathbf{X}, \boldsymbol{\beta})$, where $\boldsymbol{\beta}$ is the vector $\mathbf{X}$ of parameters of the scientist and university attributes.

A scientist's decision to pursue research falling into a given object scale and basicness score is specified as a one-zero binary variable, unity indicating she chooses that object scale and score, zero otherwise. Thus, the research choice model is defined over discrete alternatives. In particular, our discrete choice analysis predicts an individual's choice based on the relative utilities associated with the competing alternatives:

$$Y_{mz} = \begin{cases} 1 & \text{if the scientist selects category } z \text{ and basicness score } m \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The probability that research choice (z, m) is optimal is given by (dropping the subscripts for simplicity)

$$\begin{aligned} P(Y=1 \mid \mathbf{X}) &= \Lambda(\mathbf{X}, \boldsymbol{\beta}) = \frac{1}{1+e^{-\mathbf{X}\boldsymbol{\beta}}} \\ P(Y=0 \mid \mathbf{X}) &= 1-\Lambda(\mathbf{X}, \boldsymbol{\beta}) = \frac{e^{-\mathbf{X}\boldsymbol{\beta}}}{1+e^{-\mathbf{X}\boldsymbol{\beta}}} \end{aligned} \tag{6}$$

which are the basic equations defining a logistic model.

$P(Y_{mz} = 1 | \mathbf{X})$ is the joint probability that the scientist will choose category *z* and basicness level *m*. The set of factors included in **X** influence her decision; that is, $\boldsymbol{\beta}$ reflects impacts of the changes in **X** on the probabilities of given research choices.

Following equation (6),

$$\text{(7)} \qquad \frac{P\,(Y=1)}{1-P\,(Y=1)} = \frac{\Lambda\,(\mathbf{X},\boldsymbol{\beta})}{1-\Lambda\,(\mathbf{X},\boldsymbol{\beta})} = e^{\mathbf{X}\boldsymbol{\beta}},$$

Equation (7) measures the odds of the event (Y) occurring relative to its not occurring.[1] An odds ratio exceeding 1 implies the event will occur; that is, the scientist will select scale category z and basicness score *m*.

The logit transformation, which is the main idea behind logistic regression, linearizes the regression model. Take the log of equation (7) to yield

$$\text{(8)} \qquad \ln\frac{P}{1-P} = \ln\frac{\Lambda\,(\mathbf{X},\boldsymbol{\beta})}{1-\Lambda\,(\mathbf{X},\boldsymbol{\beta})} = \mathbf{X}\boldsymbol{\beta} = L$$

Equation (8) implies that $\frac{\partial L}{\partial X_i} = \beta_i$, where, coefficient β_i in vector $\boldsymbol{\beta}$ gives the logarithmic odds of the response of interest.

The marginal effect of the *i*th element of **X** on the probability of Y is given by [following equation (6)],

(9)

$$\frac{\partial P\,(Y=1|X_i)}{\partial X_i} = \beta\,\frac{e^{-X\beta_i}}{(1+e^{-X\beta_i})^2} = \beta\,[P\,(Y=1)\,(1-P\,(Y=1)]$$

By computing these marginal joint probabilities, we observe the magnitudes of the impacts of scientist, funding-source, and university attributes on laboratory choices.

Hypotheses

As discussed earlier, funding sources probably influence research choices, public sources likely encouraging basic research and private sources applied research. Universities' collaborative research efforts with private firms appear from the literature to promote commercialization of scientific discoveries. Scientists' ethical norms and university cultures likely influence scientific practice as well.

I hypothesize that the source and size of financial support strongly motivates the bioscientist's choices among research object scale and basicness categories. Apart from testing the above hypothesis, we can use our model to determine whether a scientist's rank, professional norms, university type, or in-kind support affect those same choices.

Non-monetary research inputs include sponsoring agencies' provisions of laboratory materials and equipment such as cell lines, genomic databases, and software. In a research proposal, funding applicants are required to list expected materials, equipment, and personnel costs needed to accomplish the research objectives. Providing more expensive laboratory equipment might reduce the funder's willingness to provide research cash. By the same token, greater monetary support may reduce the agency's willingness to provide material inputs because total resources are limited. Besides, through in-kind support, an agency provides value to the scientist, so that scientists receiving more in-kind inputs may be willing to accept less cash. In-kind and cash would then be partial substitutes for each other. Grant funders are motivated to provide scientists in-kind inputs rather than cash if they can provide the former more cheaply than other suppliers can. Furthermore, scientists may be unable to obtain in-kind inputs with their monetary support in the event of supply shortages of laboratory equipment and reagents. For instance, in the wake of Mad Cow disease in the US, aprotinin, a vital reagent extracted from bovine lung tissue and used in R&D laboratories for the manufacture of biologic drugs, faced supply shortage (www.in-pharmatechnologist. com/Materials-Formulation).

Furthermore, as we have said, just as the source and size of financial support may influence a scientist's research decisions, her research choices may influence the source and size of the funds obtained. Hence, cash support, non-cash support, and research choice are likely jointly determined. However, in spite of such arguments of possible simultaneity between in-kind support, financial grants, and research decisions, we treat material inputs and funding as exogenous. Endogenizing them would complicate estimation by requiring several sets of in-kind support equations in addition to funding equations. It is difficult to use instrumental variable estimation to solve the simultaneity problem between research choice, funding, and in-kind support because, as explained below, we would have an under-identified system of equations in this analysis.

We have six funding variables distinguished by the following sources: National Institutes of Health, US Department of Agriculture, state government, industry, private foundations, and other funding agencies such as the Department of Defense and Department of Energy. Three categories of in-kind support variables are employed: materials (biomaterial or reagents), capital (databases, equipment, and software), and services (student internships or staff support). Suppose we consider three sets of equations - one explaining research choice *Y*, one explaining funding support vector **G**, and one defining in-kind support vector **K**, where research choice, funding, and in-kind support are endogenous variables. We would find that the number of exogenous predictors excluded from an equation is less than the number of endogenous variables included in that equation less one. This violates the order condition of identifiability. Mathematically, consider

$$(a)\quad Y = f_1\,(\mathbf{G}, \mathbf{I}_1, \mathbf{X}, \mathbf{K})$$

$$(b)\quad \mathbf{G} = f_2\,(Y, \mathbf{I_2}, \mathbf{X}, \mathbf{K})$$

$$(c)\quad \mathbf{K} = f_3\,(Y, \mathbf{G}, \mathbf{I_3}, \mathbf{X})$$

In research choice equation (a) *Y*, which would have nine endogenous regressors (six funding variables and three in-kind support variables), we also include three norm variables influencing Y but not $\mathbf{G}$ and $\mathbf{K}$. These identifying variables are denoted by $\mathbf{I}_1$. We also include two academic rank and two university-type variables (denoted **X**) in equation (a). Including four additional norm variables as identifying variables in the equation system, that is the variables represented in $\mathbf{I}_2$ and $\mathbf{I}_3$ -- which are assumed to be exogenous predictors in the funding and in-kind equations (b) and (c) – would leave four instruments excluded from research choice equation (a), less than the number of endogenous variables minus one in that equation. Thus, equation (a) is under-identified and cannot be estimated. At the same time, on account of data limitations, we are unable to find identifying variables for each funding source variable.

Survey Data

A national survey of 1067 bioscientists employed at 80 randomly selected major US research universities comprises much of the individual-level data for this study. Respondents provided answers to questions related to their discipline, field, and research topic; how basic the research is; their professional norms and academic rank; the type of university at which they are employed; the sources and sizes of financial support they receive; and the non-monetary inputs received from grant funders.

We represent a scientist's research choice decision by the category of topic she selects, in particular by the size or scale of the research object she addresses. We are also interested, separately, in how basic or applied the topic is, measured in a manner to be discussed in the present section.

Research Object Scale Classification

We classify a scientist's topic based in terms of the scale (z) of the primary object of her research. The scales on which we focus are: sub-cell or cell, organ or organism, and natural or managed ecosystem. A scientist's scale choice is indicated by a binary choice variable, unity implying she chooses a given scale and zero implying she does not. That is, we have

$$z_i = \begin{cases} 1 \text{ if the research topic falls in category } i \\ \\ 0 \text{ otherwise} \end{cases}$$

Data were collected on all six scale categories. We combine sub-cell and cell scale categories into a "cellular" category, organ and organism into an "organism" category, and natural and managed ecosystems into an "ecosystem" category. Based on these classifications, we find that 43 percent of the bioscientists conduct research at the cellular scale, 37 percent at the organism scale, and 20 percent at the ecosystem scale.

Research Basicness Classification:

The survey document describes basicness as follows:

> "Purely basic means experimental or theoretical discoveries that add to fundamental science and engineering knowledge (for example: fundamental genomics)."
>
> "Purely applied means research that draws from basic or other applied research to create new products (for example: transgenic plant)."

The scientist was asked to indicate the basicness of her research on a one-to-six Likert scale – one indicating "purely basic" and six indicating "purely applied". To simplify modeling, we combine basicness scores one, two, and three and refer to it as "basic", and four, five, and six and refer to it as "applied". m_j is measured by a binary variable, one indicating that the topic is associated with a basicness score j and zero indicating that it is not. That is,

$$m_j = \begin{cases} 1 \text{ if the research topic has score } j \\ 0 \text{ otherwise} \end{cases}$$

Fifty-one percent of the respondents pursue relatively basic research and 49 percent relatively applied research.

Interacting Object Scale and Basicness Classifications

We develop a measure of the scientist's joint object-scale and basicness choice by interacting the object scale and basicness classifications. Let T be the joint set of topics classified by research scale category (z) and basicness score (m). T is a zero-one binary variable, one indicating the scientist chooses a given object scale and basicness score and zero indicating that she does not. That is, $T = z_i \cap m_j$.

Twenty-nine of the respondents pursue basic research at the cellular scale, and 14 percent applied research at the cellular scale. Sixteen percent pursue basic research at the organism scale and 21 percent applied research at the organism scale. Six percent pursue basic research at the ecosystem scale and 14 percent applied research at the ecosystem scale.

Research Funding Sources

Bioscientists were asked to estimate their annual total research budgets and the proportions of that budget derived from the alternative sources: federal government (National Science Foundation, National Institutes of Health, US Department of Agriculture, and other federal sources), state government, individual firms, trade or commodity associations, foundations or non-profit organizations, and miscellaneous sources. We combine grant shares from individual firms and trade or commodity associations into a single “industry” grant share, and grant shares from other federal and miscellaneous sources into a single “other funding” share. The six alternative funding sources used in the final analysis therefore are: National Science Foundation, National Institutes of Health, US Department of Agriculture, state government, industry, foundations, and miscellaneous sources. Total funding G_i received from the i^{th} agency is obtained by multiplying the annual budget H by the share of money S_i contributed by the i^{th} agency. That is,

$G_i = S_i\ H$, where $i = 1,...,k$ indexes funding source, $H = \sum_{i=1}^{k} S_i\ H$, and $\sum_{i=1}^{k} S_i = 1$.

Grant shares S_i are expressed as percentages by multiplying them by 100, such that $\sum_i S_i\ 100 = 100$. We use the NSF share as the base category.

University Type

Scientists were asked whether they were employed in a public Land-Grant (LG), public non-Land-Grant (PNLG), or private university. We measure university type l_k with a binary variable: one indicating she belongs to university l_k and zero indicating she does not, where $k = \text{LG}\ , \text{PNLG}\ , \text{private university}$. Private University is used as the base dummy.

Academic Rank

A scientist indicated her academic position by stating whether she was an assistant (assis), associate (assoc), or full professor (prof). Academic rank x_r is indicated by a zero-one dummy, where one implies the scientist holds rank x_r and zero implies she does not, and $r = \text{assis, assoc, or prof.}$ Assistant professor is used as the base category.

In-Kind Support

Scientists were asked whether they received non-monetary inputs from grant funders in addition to financial support. In-kind support is divided into (a) materials (bio-materials or reagents), (b) capital (databases, equipment, or software), and (c) services (student internships or staff support). We measure in-kind support k with binary variables; one indicating that the scientist receives the k^{th} category of in-kind input and zero that she does not. Only capital in-kind inputs were included in the final analysis.

Professional Norms

Scientists were asked, on a Likert scale, to indicate how important the following criteria ought to be in their choice of research problems:

(a) Potential contribution to scientific theory, where 1 is “not important” and 7 is “very important.”

(b) Potential contribution to public (non-excludable) benefits, where 1 is “strongly agree” and 6 is “do not know.”

(c) Potential to patent and license the research findings, where 1 is “not important” and 7 is “very important.”

The survey document defines completely “public” or “non-excludable” research as the situation in which it is infeasible to exclude anyone from using the findings of that research. Measures of research non-excludability were drawn from the survey responses but are not employed in the present study.

We model scientists' research topic choices, namely the product of three scale groups and two basicness categories, using six different regression equations. In particular, we model the choice of basic and applied research at the cellular scale, of basic and applied research at the organism scale, and of basic and applied research at the ecosystem scale.

Empirical Results

We estimate equations (8) and (9), that is of the probabilities that the scientist will choose a topic at a given research object-scale and basicness classification, using Limdep/Nlogit 4.0. Our sample consists of 720 observations. The applied-cellular and basic-organism category combinations generated very low R-squares, 0.06 and 0.07 respectively, implying they explain less than 10% of the total variation in choice probability. This possibly is because cellular research tends to fall at the relatively fundamental, and organism topics at the relatively applied end, of the research spectrum. We therefore primarily consider the basic-cellular, basic-ecosystem, applied-organism, and applied-ecosystem combinations in the following analysis.

We begin by discussing the diagnostic tests performed in connection with logistic model equations (8) and (9). We then discuss our empirical results of the impact on a scientist's research choice of money source, scientist norms, academic rank, university type, and in-kind support.

The Hosmer-Lemeshow test, a diagnostic test for binary logit models, tests for the differences between observed and predicted values of the response variable. Low chi-square values imply that the null hypothesis is true, that is, observed and predicted values of the response variable do not differ greatly from one another and the model fits the data well. The respective Hosmer-Lemeshow chi-square values of 2.56, 7.67, 10.05, and 12.22, for the basic-cellular, basic-ecosystem, applied-organism, and applied-ecosystem specifications turn out to be nonsignificant at the 10%, 5%, and 1% level, implying we cannot reject the null hypothesis and that therefore the model provides a reasonably good fit.

In addition to the Hosmer-Lemeshow statistic, we compute in each logistic regression the likelihood ratio chi-square values. The chi-square is used to test whether the inclusion of a variable reduces the badness-of-fit measure. The greater the difference between the likelihood function of the full model and of the restricted model, the higher is the chi-square statistic. Restriction is imposed on the model by eliminating variables from it in an iterative process. We find the respective chi-square values of 129.58, 59.09, 125.77, and 96.58 in the basic-cellular, basic-ecosystem, applied-organism, and applied- ecosystem regressions to be significant at the 1% level, implying the restriction does matter. In other words, including a variable improves the model’s goodness-of-fit. The Hosmer-Lemeshow and chi-square tests results are suggestive of good model fits despite the low R-squares. The respective R-squares from the logistic regression of the basic- cellular, basic-ecosystem, applied-organism, and applied-ecosystem categories are 0.16, 0.21, 0.18, and 0.18.

Summary statistics in table 1 show that the representative scientist received 56% of her annual funding from federal agencies and 32% from non-federal agencies. In percentage terms, the National Science Foundation, state governments, and the US Department of Agriculture contribute, on average, almost equal shares of research money. Most scientists in the sample believed contributing to scientific theory should be an important research choice criterion. The theoretical-contribution norm's mean score on a 7-point Likert scale was 6.05.   The representative respondent thought creating scientific discoveries with public (non-excludable) benefits, and patenting of scientific discoveries, ought to be relatively lower research criteria (means 3.97 and 1.98 on 6-point and 7-point Likert scales respectively). Almost 50 % of the bioscientists in the survey sample held professor rank and 50% were employed at Land-Grant universities. Forty percent of the respondents received in-kind support.

Results of estimating equations (8) and (9) are shown in tables 2 – 5. Equation (7) and (8) estimates give us, respectively, the marginal impacts of the given explanatory variable on the log-odds and marginal probability that the representative scientist will choose a topic in a given classification. An odd is the ratio of the probability density function to the cumulative distribution function of the distribution. Tables 2 - 5 suggest that the scientist's aggregate budget has no significant impact on the marginal probability of choosing either basic-cellular, basic-ecosystem, or applied-ecosystem research. However, it does have a statistically significant effect on the marginal probability of pursuing applied research at the organism scale (t = 2.35). Table 3 implies that a $1000 increase in aggregate agency funding increases the scientist's chance of pursuing applied research at the organism scale by 0.01%, controlling for funding source, rank, university type, and in-kind input. In short, the magnitude of aggregate financial support itself has little or no effect on research topic choice. We now examine whether the *source* of funding affects a scientist's research choices. Table 2 suggests that neither the National Institutes of Health nor other funding agencies have any significant impact on the choice of basic research at the cellular scale. However, state, industry, and USDA funds do reduce the odds of pursuing basic-cellular research (i.e. ratio of the probability of conducting basic-cellular research to the probability of not conducting it). That is, more state, industry, and USDA grants make it less likely that a researcher will choose a basic-cellular topic.

Table 2, showing the probabilities of the choices of basic research at the cellular scale, clearly indicates that industry funds discourage basic-cellular research more than does funding from any other source. A one percentage point increase in industry funding and an equivalent decline in NSF funding reduces the probability of pursuing basic research at the cellular scale by only one percentage point (t = - 4.80). We find from tables 2 and 5 (the latter showing the probabilities of topic choice at the basic-ecosystem category) that a one percentage point increase in state funding reduces the probability of choosing basic-cellular research by a mere 0.2 percentage points, and basic-ecosystem research by a mere 0.1 percentage point (t_{cell} = - 2.00; t_{eco} = - 2.40). This implies that cellular and ecosystem research scales make no substantial difference to the impact of state support on scientist's topic choice. We find, in proportional terms, that a 1% increase in state funding, respectively, reduce basic research at the cellular and ecosystem scale by 0.12% and 0.46%.

Tables 3 and 4 respectively show the probability of choosing applied-organism and applied-ecosystem research. A one-percentage point rise in state funds, accompanied by a decline in NSF funds by one percentage point, increase the probabilities of pursuing applied research at the organism scale by just 0.4 percentage points (t = 4.31) and of applied research at the ecosystem scale by only 0.1 percentage point (t = 3.05). Table 5 shows that state money reduces the chance of choosing basic-ecosystem research by 0.1 percentage point (t = 3.05).

The above results have two implications: (a) scientists have slightly higher chances of choosing organism than ecosystem topics when state funding is higher, and (b) state grants are more likely to support applied than basic research. The state funding elasticities of applied-organism and applied-ecosystem research are respectively, 0.36 and 0.24. Although state grants do not substantially impact scientists' choices of applied research at the organism or ecosystem scale, we do notice a positive and significant effect of state money on these research choices. Consistent with this result is that state government research budgets are geared heavily toward encouraging regionally specific applied research. The California State University Agricultural Research Institute has, for example, in collaboration with industry, funded agricultural biotechnology research with special reference to such topic areas as bioactive animal products, plant and animal disease resistance, herbicide tolerant crops, and cropping systems, most of which appear to be at the organism scale (http://ari.calpoly.edu). In FY 2007-2008, the Colorado state government allocated approximately $5 million to Colorado universities and research institutes in support of bioscience commercialization. Reports suggest the Washington Technology Center, in collaboration with the University of Washington, plans in 2009 to sponsor applied biomedical research on micro-fluidic imaging technology, leading to the development of new drugs and tools for the treatment of diseases and generating economic benefits for the state (WTC, 2009).

Tables 3 and 4 also suggest that a one percentage point increase in industry grants lifts the probabilities of conducting applied research at the organism and ecosystem scales by only 0.4 and 0.1 percentage points (t_{org} = 4.64, t_{eco} = 2.50) respectively. We can thus infer that industry money is, by a small extent, more likely to motivate scientists to choose an organism than an ecosystem topic. The corresponding elasticity estimates are 0.25 and 0.15, respectively. Again, although we obtain low marginal probabilities, the positive and significant t values on the marginal probability estimates suggest industry funding tends to encourage applied research at both the organism and ecosystem scale. A recent example of industry support for ecosystem research is Conoco Philips' announcement of a $22.5 million grant to Iowa state University researchers toward a bio-renewable fuel research program (Carpenter, 2008).

Tables 2 and 3 imply that contributions from non-federal agencies such as foundations increase the chances of choosing applied-organism research. Raising foundation support and reducing NSF support by one percentage point lifts the marginal probability of pursuing applied research at the organism scale by a mere 0.2 percentage points (t = 1.92). A positive and significant t statistic on the marginal probability estimate indicates that private foundations do encourage applied-organism research, even though their impact is not substantial. Foundations and non-profit organizations support a substantial amount of applied-organism research – such as plant hybridization, genetics, and breeding – for developing crop varieties as means to improve food production (www.jeffersoninstitute.org; www.AgBioworld.org). The need for applied plant breeding for the development of high yielding, pest-resistant, and drought-resistant crop varieties is expanding worldwide (Stelly and Yencho 2009). Several non-profit foundations are also closely linked to bioscience industries for the provision of commercially oriented research through industry partnerships (Hisrich 2003).

Boosting USDA funds and reducing NSF funds by one percentage point increases the probability of pursuing applied research at the organism scale by 0.2 (t = 2.45) and at the ecosystem scale by 0.1 percentage points (t = 1.79) only.

Hence, the object-scale induces little or no difference in the topic choice probabilities resulting from an increase in USDA support. Although these are low marginal probabilities, the significant *t* values indicate that USDA funds do encourage applied-organism and -ecosystem research. Recent USDA-sponsored projects include research on drought and stress tolerance and on identifying useful genetic variations in plants. For example, USDA - CSREES funds supported scientists at UC - Davis in identifying wheat genes that could improve tolerance to freezing temperatures and thus boost crop yields. USDA - CSREES also announced, in 2009, that 15 universities and states across the country will be awarded $11 million for livestock genomic research aiming to protect livestock and promote food safety (www.genomeweb.com). The National Institutes of Food and Agriculture (NIFA), a federal agency under the USDA, supports natural and managed ecosystem research to improve human welfare. The current (2009) NIFA budget for promoting agricultural ecosystem services relating to climate change, water availability, pests, weed and invasive species management, and soil and land degradation, stands at $4.5 million (http://www.csrees.usda.gov).

Tables 3 and 4 show that a one percentage point increase in NIH money increases the chances of pursuing applied-organism and reduces the chances of choosing applied-ecosystem research by 0.2 percentage points (t_{org} = 3.06, t_{eco} = -3.61), all else constant. And table 5 shows that a one percentage point increase in NIH support, accompanied by an equivalent decline in NSF support, reduces the probability of choosing *basic* ecosystem research by 0.1 percentage point (*t* = -

3.65). NIH's mild impacts on ecosystem research at both the applied and basic level suggest it does not have strong preferences for ecosystem research. Nevertheless, the estimates, significant at the 1% level as noted above, are suggestive of NIH's support for applied-organism research.

A shift in NIH funding from basic to product-oriented research, observed since early 2000, has been fueling scientists' fears about the future of basic science (Dove, 2004). Figures reported by Fong (2009) indicate NIH funding on proteomics-related fundamental research dropped by almost 3% during FY 2008 alone. NIH is making substantial investments in biomedical research and supporting commercialization of basic research findings. Model organisms used in NIH-sponsored academic biomedical research include arabidopsis, neurospora (filamentous fungus), daphnia (water flea), rerio (zebra fish), and elegans (round worm) (www.nih.gov/science/models).

We find that scientists' norms, in particular their ethics regarding the achievement of theoretical contributions and the patenting of scientific discoveries, have prominent effects on research choice. Tables 2 – 5 suggest that, all else held constant, a one-point increase in the Likert indicator through which the scientist expresses a valuation of theoretical contributions to her field increases the probability of her choosing basic- cellular research by 0.05 points (t = 3.619) and basic-ecosystem research by 0.01 points (t = 2.18). It reduces the probability of conducting applied research at the organism and ecosystem scales by about 0.02 points (t_{org} = - 3.06, t_{eco} = - 3.01).

In tables 2 – 5, the corresponding elasticities of the theory-norm impacts are respectively, 1.54, 2.78, 1.07 and 1.36. That is, a 1% increase in the strength of the scientist's theory norm increases the probability of her choosing basic-cellular topics by 1.54% and basic-ecosystem topics by 2.78%, while reducing the probability of choosing applied-organism and -ecosystem topics by 1.08% and 1.36%, respectively. On the other hand, the norm that scientists should pursue knowledge or technology with public benefits shows no significant impact on the probability of research choice.

Next we discuss the impact on topic choice of the ethic that a scientist ought to pursue patentable research. We find, from tables 2 – 5, that a 1% increase in the norm indicating a scientist's valuation for patent production increases her chances of choosing applied research at the organism scale by 0.38% while reducing her chances of pursuing basic research at the cellular and ecosystem scale by 0.25% and 0.6% respectively. The scientists' preference for patents reduces her chances of choosing basic-cellular research while increasing her chances of pursuing applied-organism and applied-ecosystem research, possibly because researchers think of patents as restricting the usefulness of basic research discoveries in product development (National Genome Research Institute, NIH). Dasgupta and David (1994) suggest that patents encourage scientists to select research projects generating commercial benefits and therefore discourage fundamental research.

Neither academic rank, university infrastructure, nor in-kind support appear to affect a scientist's research object scale or basicness choices. However, table 3 shows that all else constant, Land-Grant and non-Land-Grant scientists are more likely, respectively by 27 and 17 percentage points (t_{lg} = 3.88 and t_{pnlg} = 2.03), to choose applied-organism research than are private university scientists. Table 5 also shows that scientists employed at Land-Grant universities are by 27 percentage points

(t_{lg} = - 1.76), and at non-Land-Grant universities by 21 percentage points (t_{pnlg} = - 1.89), less likely to pursue basic research at the ecosystem scale than are private university scientists. This corroborates earlier findings that Land-Grant scientists invest more time in applied research than do private university scientists (Buccola *et al*, 2009). And our results imply that the availability of in-kind research support – such as genomic databases, software, and laboratory equipment – increases the incidence of basic-cellular research by six percentage points (t = 1.92). This is consistent with the fact that cellular biotechnology research tends to be capital-intensive, involving expensive, high-technology equipment.

Overall, we find that the source and size of financial support have a statistically significant but mild impact on the intention and direction of university biotechnology research. That is, a scientist's choices over the scale and basicness of her research do not seem strongly influenced or constrained by the sources of her monetary support. University culture, including university missions, academic contacts, and governing rules, appears to have a much larger influence. Kulakowski and Chronister (2006) buttress this conclusion by pointing out that university consortia – research partnerships with public or private agencies – play a major role in identifying research projects and priorities. Supplies of in-kind inputs, also, are relatively important in scientists' research choices. The statistically significant impact of in-kind laboratory inputs on research choice implies funding agents have comparative advantage in producing or accessing these very inputs, as the funder otherwise would simply provide the money for the scientist to buy them. In many cases, the funder virtually is the only one who can produce such inputs at reasonable cost, possibly because of its intellectual property rights over the equipment or cell-line. Scientists wishing to pursue particular research topics often need those unique inputs. Proprietary cell lines are a good example.

Conclusions and Policy Implications

We have developed a model to explain a bioscientist's research choices regarding the object scale and basicness of research. We have been particularly interested in examining whether the source and size of financial support influences these choices. Results in tables 2 – 5 suggest that support from the U.S. Department of Agriculture, state governments, and private agencies tends to encourage scientists to choose organism and ecosystem topics at the translational and applied end of the research spectrum. In contrast to this, the National

Institutes of Health appears to show no preference for ecosystem research. Additional support from non-profit foundations, as from states and industries, boosts the chances that our representative scientist will select applied organism topics.

The model also provides information about whether scientist norms, academic rank, or university type or culture influence research choices. We find that lower valuations of theoretical contributions and stronger preferences of patents incline researchers to select relatively applied topics at the organism and ecosystem scale. Academic rank itself does not appear to have any significant impact on research topic choice. However, employment at public Land-Grant and non-Land-Grant universities does substantially encourage scientists to pursue applied-organism research, while to a large extent reduces the incidence of basic-ecosystem research. Our results also imply that availability of in-kind support boosts the chances a scientist will be found choosing basic-cellular topics.

Nevertheless, funding sources little affect scientists’ research choices over object scale and basicness classifications, implying that academic scientists tend to develop their research orientations independently of the financial support they might receive for it. Such decisions are, to a much larger extent, determined by the type of university that employs them and by the content of in-kind inputs accompanying a grant. For example, universities encouraging faculties to patent and license their inventions likely motivate scientists to pursue research with wide commercial applications (Azoulay *et al*, 2006; Blumenthal *et al*, 1996; Neumann, 2006).

My results broadly imply that funding agents' direct impacts – through the magnitudes of grants to individual scientists – on academic scientists' research choices are, if not exactly incorrect, exaggerated. Efforts to re-direct academic bioscience research objectives instead should be concentrated on the scientist's cultural and technical environment. Scientists' research choice trends suggest that Land-Grant and public non-Land-Grant universities tend to focus more on entrepreneurial research than private universities do. Although this is contrary to our expectations that public universities conduct research on public (non-rival and non-excludable) innovations, close ties with firms and industries may be changing research trends in public universities.

References

Academic Research and Development, National Science Board, Chapter 5, National Science Foundation *www.nsf.gov.*

American Society of Microbiology *http://www.asm.org/Awards/index.asp?bid=14942.*

"Aprotinin from Plants could end Supply Shortage" *Materials and Formulation, www.in-pharmatechnologist.com/Materials-Formulation/Aprotinin-from-plants-could-end-supply-shortage* January 2004.

Arizona Bioscience News, January 30, 2008. "BIO5 receives $ 50 million NSF grants." *http://www.flinn.org/news/601*.

Argyres, N. S., J. P. Liebeskind, 1998. "Privatizing the intellectual commons: university and the commercialization of biotechnology." *Journal of Economic Behavior and Organization 35(4):427-454.*

Azoulay, P., W. Ding, and T. Stuart, 2006. "The Determinants of Faculty Patenting Behavior: Demographics or Opportunities?" *Journal of Economic Behavior and Organization 63:573-576.*

Barham, B, J. Foltz, and Kwansoo Kim, 2002. "Trends in University Ag-Biotech Patent Production". *Review of Agricultural Economics*, 24: 294-308.

Berardo, F.M. 1989. "Scientific Norms and Research Publications: Issues and Professional Ethics." *Sociological Enquiry 59 (3):119-141.*

Bhattacharjee, Y, 2008. “Industry Shrinks Academic Support”. *www.sciencemag.org, October, 2008.*

Bioregion News, May 05, 2008. *http://www.genomeweb.com/bioregionnews/florida-economic-development-bill-colorado%E2%80%99s-bioscience-research-grant-program-m.*

Blumenthal, D., N. Causino, E. Campbell, K. Louis, 1996. “Relationships between academic institutions and industry in the life sciences – an industry survey.” *The New England Journal of Medicine 334(6): 368-374.*

Blumenthal, D., Gluck, M., Louis, K. S., Stoto, M. A., Wise, D., 1986.”University-Industry Research Relationships in Biotechnology: Implications for the University.”*Science 232:1361-1366.*

Buccola, S., David Ervin, and H. Yang. 2009. “Research Finance and choice in University Bioscience.” *Southern Economic Journal 75 (4):1238-1255*.

Carpenter, S., 2008. “Finding Industry Funding.” *“http://sciencecareers.sciencemag.org/career_magazine/previous_issues/articles/2008_03_14/caredit.a0800040.*

Carraro, C., D. Siniscalco, 2006. “Science versus Profit in Research.” *Journal of the European Economic Association 1(2-3):576-590.*

Cole, S., 1979. “Age and Scientific Performance.” *American Journal of Sociology 84(4):958-977*.

Co-operative State Research, Extension, and Education Service, (CSREES), USDA. *www.csrees.usda.gov.*

Curry, J., M. Kenney, 1990. "Land-Grant University-Industry Relationships in Biotechnology: A comparison with the Non-Land-Grant research Universities." *Rural Sociology 55(1):44-57.*

Dasgupta, P., P. A. David, 1994. "Towards a new economics of science." Research Policy 23(5): 487-521.

David, P. A., B. Hall, A. Toole, 2000. "IS public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence" R*esearch Policy 29:497-529.*

Diamond, A. M., 1999. "Does Federal funding "Crowd-in" Private Funding of Science?" *Contemporary Economic Policy 17(4):423-431.*

Gel3LSDigest, Alberta, *http://www.genomealberta.ca/files/ge3ls/digest/07January15.pdf.*

Genome Web staff Reporter, March 2, 2009. "USDA grants $11 million for livestock genomics.*" http://www.genomeweb.com/usda-grants-11m-livestock-genomics.*

Glenna, L., W.B. Lacy, R. Welsh, D. Biscotti, 2007. "University Administrators, Agricultural Biotechnology, and Academic Capitalism: Defining the Public good to promote university-industry Relationships." *The Sociological Quarterly 48:141-163.*

Greene, W. "Econometric Analysis - 5th Edition" *Prentice Hall*.

Gulsbrandsen, M., J. Smeby, 2005. “Industry funding and university professors’ research performance.” *Research Policy 34(6):932-950.*

Hall, B., A. N. Link, J. T. Scott, 2000. “Universities as research partners” *NBER Working paper Series number 7643.*

Hisrich, M. 2003. “Scientific Community backs AgBiotech*.” AgBio world 3(12):15*

Hosmer, D., S. Lemeshow, “Applied Logistic Regression – Second Edition” *Wiley Series in Probability and Statistics*.

Jaffe, A. 1986. “Technological Opportunity and Spillovers of R&D: Evidence from firms’ patents, profits, and market value.” *American Economic Review 76(5): 984-1001*.

Jaffe, A. 1989. “Real Effects of Academic Research.” *American Economic Review 79(1):957-970*.

Kintisch, E., 2007. “How to make bio-fuels truly poplar?” *Science 315(5813):781.*

Kjelstrup, S., 2001. “Basic and Applied research in the University- have they changed?” *OECD workshop on basic research: Policy relevant definitions and measurement, Oslo, Norway, October 29-30, 2001.*

Klotz-Ingram, C., K. Day-Rubenstein, 1999. “The Changing Agricultural Research Environment: what does it mean for public-private innovation?” *AgBio Forum 2(1):24-32.*

Kulakowski, E., L. Chronister, 2006. “Research Administration and Management.”*Published by Jones and Bartlett, MA.*

Lefkowitz, J. 2003. “Ethics and Values in Industrial-Organizational Psychology” Book.

Leyden, Dennis P, A. N. Link, 1991. “Why are Governmental R&D and private R&D complements?” *Applied Economics 23:1673-1681*.

Logit, Likelihood Ratio Test, Odds Ratios *users.rcn.com/alancm/pp605/12_**Logit**_LR**test**_Odds_Ratio.pdf.*

Logistic Regression *http://luna.cas.usf.edu/~mbrannic/files/regression/Logistic.html.*

National Human Genome Research Institute, Intellectual Property and Genomics *http://www.genome.gov/19016590*

National Institute of health, US Department of Health and Human Services, *www.nih.gov*

National Institutes of Standard and Technology, *www.nist.gov.*

National Institute of Health News, May 5, 2009. “NIH grants $ 122 million in institutional development grants” *http://www.nih.gov/news/health/may2009/ncrr-05.htm*

Neumann, C., “The Bayh-Dohl Act: the basis for US technology transfer.” *Office of Science and Technology www.ostina.org.*

Rapoport, A. I., 1998. “What are the sources of funding for academically performed R&D” *National Science Foundation, Directorate for Social, Behavioral and Economic Sciences.*

Salter, L., B. Martin, 2001. “The Economic Benefits of Publicly Funded Basic Research: A critical Review.” *Research Policy 30 (3):509-532.*

Santoro, M. D., A. Chakrabarti, 1999. “Building industry-university research centers: some strategic considerations.” *International Journal of Management Reviews 1(3):225-244*.

Schimmelpfennig, D., and Heisey, P., 2009. “US Public Agricultural Research, changes in funding sources and shifts in emphasis, 1980-2005.” *USDA ERS Economic Information Bulletin No. 45, March 2009*.

Science and Engineering Indicators, *2008* Chapter 4.

Shackelford. B., 2004. “US R&D projected to have grown marginally in 2003.” *National Science Foundation, Division of Science Resource Statistics.*

Smith, Jason Owen, 2002. “From separate systems to a hybrid order: Across accumulative advantage of public and private science at Research One Universities.” *Research Policy 32:1081-1104.*

Stelley, D. M., G. C. Yencho. “Plant Breeding - A Key for Excellence and Relevance of US Science & Technology”.

Stuart, T., W. W. Ding, 2006. “When do scientists become entrepreneurs?”*American Journal of Sociology 112:97-144.*

Thorn, C. A. 1996. “Building expertise in High Technology: New Dynamics of R&D Funding at US Research Universities” *http://ieeexplore.ieee.org*.

Thomas Jefferson Agricultural Institute *http://www.jeffersoninstitute.org/*.

United States Department of Agriculture, *www.usda.gov*.

University of California, State Oath of Allegiance, Patent Policy, and Patent Acknowledgement.

Vegso, J. 2006 “Decline of Industrial Support for Academic R&D.” NSF info brief Academic Research and Development Expenditures, CRA bulletin, *http://www.cra.org/wp/index.php?cat=11*.

Yang, H., S. Buccola, 2003. “University-Industry Relationships and the Design of Biotechnology Research.” *Paper prepared for presentation at the AAEA Annual Meetings, Montreal, Canada, July 27-30, 2003*.

Zucker, L.G., M. Darby, and Marilyn B Brewer, 1998. “Intellectual Human capital and the Birth of U.S. Biotechnology Enterprises.” *American Economic Review 88(1):291-306*.

Table 1: Summary Statistics (*N* = 720)

Variable	Mean	Std Dev	Min	Max
Funds	273.487	394.250	0	4500
NSF Funds (%)	15.161	29.741	0	100
Other Funds (%)	27.255	33.607	0	100
NIH Funds (%)	26.090	38.994	0	100
USDA Funds (%)	14.595	26.168	0	100
State Funds (%)	14.075	24.307	0	100
Industry Funds (%)	9.5311	20.942	0	100
Foundation Funds (%)	7.975	18.786	0	100

Variable	Mean	Std Dev	Min	Max
Theoretical contribution Norm	6.059	1.4498	1	7
Non-excludability Norm	3.9786	1.077	0	5
Probability of Patenting Norm	1.988	1.466	1	7
Capital Input	0.398	0.490	0	1
Professor	0.486	0.500	0	1
Associate Professor	0.247	0.431	0	1
Land Grant University	0.488	0.500	0	1
Non-Land Grant University	0.354	0.478	0	1

Table 2: Logistic Estimates of Cell-Level Basic Research

	LOGIT		MARGINAL		
Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Constant	-1.985	-2.517	-0.329	-2.562	
Funds	-0.000	-0.659	-0.000	-0.657	-0.038
Other Funds (%)	-0.001	-0.351	-0.000	0.000	-0.350
NIH Funds (%)	0.004	1.364	0.000	1.357	0.091
USDA Funds (%)	-0.008	-1.690	-0.001	-1.670	-0.097
State Funds (%)	-0.010	-2.034	-0.002	-2.007	-0.115
Industry Funds (%)	-0.057	-3.847	-0.010	-4.802	-0.438
Foundation Funds (%) Base: NSF	0.000	0.013	0.000	0.013	0.000

Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Norms: Theoretical contribution Norm	0.322	3.560	0.053	3.619	1.541
Non-excludability Norm	-0.061	-0.683	-0.010	-0.683	-0.191
Probability of Patenting Norm	-0.163	-2.105	-0.027	-2.085	-0.255
Capital Input	0.375	1.965	0.064	1.922	0.121
Professor	-0.009	-0.038	-0.001	-0.038	-0.003
Associate Professor (Base: Assistant Prof)	-0.181	-0.685	-0.029	-0.704	-0.034
Land Grant University	-0.045	0.157	-0.007	-0.157	-0.018
Non-Land Grant University (Base: Private Univ)	-0.087	-0.329	-0.014	-0.332	-0.024

R square: 0.16

Table 3: Logistic Estimates of Organism-Level Applied Research

	LOGIT		MARGINAL		
Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Constant	-4.804	-4.611	-0.060	-5.382	
Funds	0.000	2.330	0.000	2.354	0.144
Other Funds (%)	0.022	2.885	0.003	3.088	0.230
NIH Funds (%)	0.019	2.850	0.002	3.061	0.437
USDA Funds (%)	0.017	2.318	0.002	2.450	0.217
State Funds (%)	0.028	3.945	0.004	4.312	0.346
Industry Funds (%)	0.031	4.282	0.004	4.645	0.259
Foundation Funds (%)	0.016	1.856	0.002	1.920	0.110

Base: NSF

Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Norms: Theoretical contribution	-0.209	-3.107	-0.026	-3.062	-1.079
Non-excludability	0.107	0.992	0.013	0.991	0.366
Probability of Patenting	0.224	3.281	0.028	3.261	0.378
Capital Input	-0.233	-1.047	-0.029	-1.062	-0.078
Professor	0.092	0.356	0.012	0.355	0.038
Associate Professor (Base: Assistant Prof)	-0.122	-0.397	-0.015	-0.405	-0.025
Land Grant University	2.104	3.790	0.275	3.881	0.928
Non-Land Grant University (Base: Private Univ)	1.223	2.206	0.177	2.037	0.419

R square: 0.18

Table 4: Logistic Estimates of Ecosystem-Level Applied Research

	LOGIT		MARGINAL		
Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Constant	-0.859	-0.924	-0.061	-0.917	
Funds	0.000	0.565	0.000	0.567	0.048
Other Funds (%)	0.012	1.992	0.001	1.940	0.136
NIH Funds (%)	-0.026	-2.819	-0.002	-3.612	-0.609
USDA Funds (%)	0.012	1.830	0.001	1.791	0.160
State Funds (%)	0.018	3.052	0.001	2.832	0.244
Industry Funds (%)	0.017	2.657	0.001	2.502	0.151
Foundation Funds (%) Base: NSF	0.010	1.443	0.001	1.425	0.078

Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Norms: Theoretical contribution	-0.243	-3.374	-0.017	-3.009	-1.358
Non-excludability	-0.011	-0.090	-0.001	-0.090	-0.040
Probability of Patenting	-0.204	-2.225	-0.014	-2.130	-0.373
Capital Input	-0.117	-0.453	-0.008	-0.456	-0.043
Professor	0.451	1.455	0.032	1.412	0.205
Associate Professor (Base: Assistant Prof)	0.611	1.799	0.050	1.548	0.159
Land Grant University	-0.524	-1.038	-0.037	-1.025	-0.242
Non-Land Grant University (Base: Private Univ)	0.025	0.051	0.002	0.051	0.008

R square: 0.18

Table 5: Logistic Estimates of Ecosystem-Level Basic Research

	LOGIT		**MARGINAL**		
Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Constant	-2.271	-1.279	-0.054	-1.310	
Funds	-5E-04	-0.606	-0.000	-0.605	-0.135
Other Funds (%)	-0.020	-2.596	-0.000	-2.237	-0.239
NIH Funds (%)	-0.036	-4.315	-0.001	-3.655	-0.906
USDA Funds (%)	-0.008	-1.027	-0.000	-0.978	-0.110
State Funds (%)	-0.033	-2.506	-0.001	-2.406	-0.467
Industry Funds (%)	-0.020	-1.495	-0.000	-1.437	-0.184
Foundation Funds (%) Base: NSF	-0.012	-1.441	-0.000	-1.351	-0.097

Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Norms: Theoretical contribution Norm	0.471	2.017	0.011	2.184	2.777
Non-excludability Norm	-0.088	-0.530	-0.002	-0.533	-0.342
Probability of Patenting Norm	-0.308	-1.697	-0.007	-1.699	-0.595
Capital Input	0.006	0.016	0.000	0.016	0.002
Professor	-0.256	-0.591	-0.006	-0.586	-0.121
Associate Professor (Base: Assistant Prof)	-0.443	-0.906	-0.010	-0.976	-0.096
Land Grant University	-1.105	-2.053	-0.027	-1.761	-0.557
Non-Land Grant University (Base: Private Univ)	-0.959	-1.898	-0.021	-1.898	-0.296

R square: 0.21

APPENDIX: Table 6: Logistic Estimates of Organism-Level Basic Research

	LOGIT		MARGINAL		
Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Constant	-1.404	-1.607	-0.167	-1.623	
Funds	-7E-04	-1.411	-0.000	-1.427	-0.155
Other Funds (%)	-0.010	-1.959	-0.001	-1.967	-0.109
NIH Funds (%)	0.001	0.282	0.000	0.282	0.231
USDA Funds (%)	-0.007	-1.287	-0.001	-1.287	-0.092
State Funds (%)	-0.020	-2.890	-0.002	-3.002	-0.249
Industry Funds (%)	-0.012	-1.581	-0.001	-1.590	-0.097
Foundation Funds (%) Base: NSF	-0.005	-0.866	-0.001	-0.866	-0.037

Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Norms:					
Theoretical contribution Norm	0.183	1.846	0.022	1.878	0.958
Non-excludability Norm	-0.095	-0.970	-0.011	-0.971	-0.327
Probability of Patenting Norm	-0.08	-0.892	-0.009	-0.894	-0.136
Capital Input	-0.303	-1.326	-0.035	-1.355	-0.103
Professor	-0.127	-0.464	-0.015	-0.465	-0.053
Associate Professor (Base: Assistant Prof)	-0.010	-0.033	-0.001	-0.033	-0.002
Land Grant University	-0.046	-0.136	-0.006	-0.136	-0.020
Non-Land Grant University (Base: Private Univ)	0.106	0.345	0.013	0.341	0.033

R square: 0.07

Table 7: Logistic Estimates of Cell-Level Applied Research

	LOGIT		**MARGINAL**		
Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Constant	-3.902	-3.917	-0.407	-4.136	
Funds	7E-05	0.257	0.000	0.257	0.017
Other Funds (%)	0.014	2.037	0.001	2.108	0.158
NIH Funds (%)	0.011	1.780	0.001	1.834	0.258
USDA Funds (%)	0.021	3.037	0.002	3.202	0.279
State Funds (%)	0.015	2.167	0.002	2.247	0.198
Industry Funds (%)	0.016	2.110	0.002	2.183	0.136
Foundation Funds (%) Base: NSF	0.009	1.088	0.001	1.102	0.067

Variable	Coefficient	*t* - Value	Coefficient	*t* - Value	Elasticity
Norms: Theoretical contribution Norm	0.028	0.341	0.003	0.341	0.150
Non-excludability Norm	0.051	0.436	0.005	0.436	0.180
Probability of Patenting Norm	0.250	3.528	0.026	3.554	0.437
Capital Input	0.311	1.314	0.033	1.287	0.113
Professor	-0.152	-0.529	-0.016	-0.530	-0.065
Associate Professor (Base: Assistant Prof)	0.086	0.264	0.009	0.260	0.019
Land Grant University	-0.349	-0.875	-0.036	-0.874	-0.153
Non-Land Grant University (Base: Private Univ)	-0.395	-1.034	-0.039	-1.081	-0.117

R square: 0.06

Chapter IV: Fund-Raising and Productivity in Academic Bioscience

Essay III

Sharmistha Nag

Introduction

Academic science traditionally has specialized in relatively basic, public-good research. One of its primary goals, however, is fund-raising because funding expands research opportunities. Another major goal is the publication of the scientist's research results. Publication leads to professional advancement (Woolf 1986). It also allows other researchers to evaluate and use one's laboratory results for their own further work. Financial reward and publications influence one another. On the one hand, a scientist with a good publication record likely will be awarded more grant money. On the other hand, financial support may motivate and enable scientists to pursue high-quality research and publish their discoveries.

In the US, Science and Engineering research publications grew at an average annual rate of 0.6% between 1995 and 2005, compared to 1.8% in the European Union (EU) and 6.6% in the ten Asian countries (National Science Board, chapter 5). The US share of total world article output dropped from 34% to 29% during the same period. In the shorter period 2000 - 2005, US article output grew at an average annual rate of 1.3%, less than the 6.3 % growth rate in the ten Asian countries during the same period

(National Science Board, chapter 5). The rise in scientists' publication rates in foreign countries has also reduced the US share of the world's more influential articles, as measured by citation rates. Although the US share of global article output has declined in recent years, research articles from authors in US institutions are among the most widely cited worldwide (National Science Board, Chapter 5). However, we do not account for co-authorships or citation rates in our analysis.

Several factors influence or constrain a scientist's publication rates. David Blumenthal (1996) finds that academic scientists with financial support from private firms tend to be more interested in commercial outcomes of their research than they are in publications. And scientists who tend to choose commercially-oriented research topics are more likely to delay or withhold publication (Hartford 1999). In general, industry funds tend to motivate scientists to emphasize research patents and commercial applications. Reports from the US Patents and Trademarks Office indicate patent grants to US universities have declined since 2002, but that patent filings by academic institutions increased between 2003 and 2005 (National Science Board, Chapter 5). Intellectual property protections of scientific discoveries often involve publication postponement (Stephan 2005).

Between 1996 and 2006, the life science field experienced, of all science and engineering fields, the largest share of investment in academic R&D. The federal government provided 63% of its total research funding to academic R&D in 2006. The industry and state share of expenditures on academic R&D remained at 5% and 6%, respectively, during the same period (National Science Board, chapter 5). Institutional investments, that is general-purpose funds or institution-to-institution funds for academic research, increased from 12% to 19% between 1972 and 2006. Finally, non-profit foundations provided about 7% of their funding to academic R & D in 2006.

The premise of the present paper is that bioscientist output, measured in terms of publications, is strongly affected by the source and size of financial support, and that the latter are influenced by publication output rates. In the process of examining these questions, we are interested as well in how other important factors – research topic choice, in-kind support, ethical norms, human capital, and university characteristics – affect scientists' output and funding. To our knowledge, no published study has examined such a two-way causal interaction between laboratory productivity and laboratory funding.

Determinants of Scientific Productivity

Scientists present their work to the world through publications and gain status through publications, patents, and intellectual property rights of research discoveries. The essential ingredient for publication is innovative and rigorous research. A good publication record professionally benefits academic researchers, while an insufficient record may derail their careers because scientists' skills are most often judged by their peer-reviewed published papers (Kelner 2007).

Scientist Age

Several studies point to the role of age and status in scientists' productivity. Some researchers suggest that striving for publication is more prevalent among young scientists than among senior faculty members because an impressive publication record is a primary criterion for academic tenure and promotion. Age and experience have a diminishing marginal effect on scientific productivity (Besar and Pema 2004). Most scientists lose their motivation and drive to achieve as age progresses (Pelz and Andrews 1976). The average annual numbers of a scientist's publications rises during the initial phase of his career and declines thereafter (Weiss and Lillard 1982; Mairesse and Turner 2002). According to Lehman (1953), a scientist's contribution reaches its peak in his late 30s or early 40s. However, Carayol and Matt (2003) find junior researchers occupying assistant professor positions have low publication performance, possibly on account of low experience, high teaching assignments, and involvements in administrative activities. Scientific productivity is also related to the research program's position on the basic-to-applied continuum. Lehman finds that scientists engaged in applied science become more productive during relatively later parts of their career than do scientists working in the theoretical sciences (Bozeman and Lee 2003).

Collaborative Research

Alison and Long (1990) analyzed the effect of job changes on scientist productivity. The results conform to an earlier study by Crane (1965), which suggests that scientists working at prestigious institutions show higher publication rates than do scientists working at smaller, less prestigious schools. Researchers find evidence that social interactions among peers, and proper guidance from senior faculty members, enhance scientist productivity. Major institutions provide better opportunities for establishing contacts with the scientific community than do smaller institutions. Scientists working with other reputed scientists in the same field make greater productivity gains than do those working with students and junior scientists (Bozeman and Lee 2003). Collaborative networks among scientists are viewed as transfers of scientific and technical human capital. Collaborative practices in scientific research, especially between academic colleagues and firms, raise scientists' publication rates. However, not all collaborations are successful; evidence suggests that scientific projects fail to succeed on account of co-ordination failure among collaborators (Bozeman and Lee 2003).

Rising collaboration among scientists at different US institutions appears to have increased co-authored article output, from 32% to 41% of all articles, during the 1988 - 2005 period (National Science Board, chapter 5), where co-authored articles are defined as more than one institutional address in the byline. Using a panel of the top 110 US research universities over the period 1981 - 1999, Adams *et al* (2005) find that federally funded R&D projects tend to encourage large scientific team sizes, measuring team size by the number of authors per paper. Further evidence suggests that scientific collaborations with foreign institutions are rising faster than team size. Co-authorship with international authors increased by 9 % among academic and federal researchers between 1995 and 2005 (National Science Board, Chapter 5). Rapid technological development in telecommunications networks is one of the primary factors leading to such foreign collaborations. Increases in co-authorships are an implication of division of labor: by enabling researchers to concentrate on narrower specialized tasks, greater divisions of labor tend to raise scientific productivity (Adam *et al* 2005; Becker and Murphy 1992).

Scientific Norms, University Type, and Financial Support

Scientific practice is likely driven heavily by professional values or norms. Values regulate conduct within the academic environment and influence scientific practice (Lefkowitz 2003; Howard 1985). Blumenthal *et al* (1986) argue that university faculties using privately-sourced funds are more likely to commercialize the outputs of their research projects than are those with financial support from public agencies only. Furthermore, research commercialization involves holding back research results to some extent. Merton (1973) argues that withholding research results prohibits communality of scientific discoveries and limits knowledge utilization (Berardo 1989). The pressure on university scientists to publish more research papers may undermine good scientific practice and promote research misconduct (Wheeler 1989; Berardo 1993). It can distort the quality of a researcher’s work (Berardo 1989). A national survey report indicates that pressure for publication and recognition, and demands for external funds, are some of the primary factors that encourage unethical and fraudulent practices among academic scientists (Broome *et al*).

University policies encouraging financial support from external sources may provide scientists a strong impetus to enhance their publication output. By providing a more entrepreneurial environment than do public universities, private universities appear to attract more grant money, and scientists' publication rates seem to influence the grants they receive (Buccola *et al* 2009). Empirical evidence suggests that higher publication rates draw more public funds into scientists' research budgets than private support does. A study conducted of forty-seven UK universities during two separate time periods (1989-90 and 1992-93) suggests that institutions drawing more public money than average appear to show substantially greater scientific productivity than average. Guena (1997) finds that universities which tried to partially counterbalance the large cuts in state support with industry funds experienced a declining scientific productivity. This conforms with studies by Blumenthal (1996), Hartford (1999), and Stephan (2005), who suggest that universities' reliance on private grants reduce scientists' publication rates.

However, Boumahdi *et al* (2003) find that private funds enhance academic scientists' publication performance. In a time-series study of 76 research laboratories in a Strasbourg, France University, Boumahdi *et al* show that publication output has a positive and significant impact on the volume of private contractual funding. However, their evidence suggests active laboratories with significantly higher publication records than others draw less private support. A possible explanation of this public funding crowd-out of private funding can be found in Goolsbe's (1998) study of the labor market impact of federal R&D funding. Goolsbe finds that higher public R&D spending raises the wages of the technically skilled workers in private laboratories. So by boosting private sector labor cost, higher government R&D expenses tend to crowd-out industry funds. The technology-effect of government financed research, as opposed to the wage-effect, however, shows that public R&D expenses crowd-in private R&D funds. Technological opportunities created through public investment in life sciences research tend to encourage profit-oriented industries to boost private R&D financing (Wang *et al* 2009).

Boosting external funds in turn seems to raise universities' institutional investments. Using a panel of 195 US universities over a twelve-year time period, Connolly (1997) finds that total funding from both public and private sources increases internal support for universities. In recent years the federal government has demanded "matching" institutional money for submitted research proposals, so that obtaining external funds puts pressure on universities to raise their share of internal funds (Ehrenberg *et al* 2003). Brehdahl *et al* (1980) suggest that an efficient mix of resource allocation from both internal and external sources boosts scientific productivity.

Non-monetary Laboratory Inputs

In addition to financial grants, in-kind support often forms an essential component of scientific research. Laboratory equipment and such materials as reagents and cell lines improve the productivity and the quality of academic scientific work (Stephan 2005; Carayol and Matt 2003). A bibliometric study of publication patterns at ten South African universities from 1992 to 1996 shows that funding is directly related to research productivity in all branches of science. Yet certain scientific fields (zoology, botany, and microbiology) may exhibit higher productivity than do others in spite of lower funding. However, supplying expensive laboratory equipment may reduce the availability of funds, and reduced cash may have a dampening effect on scientist productivity (Jacobs 2001). Universities provide startup capital in order to attract young scientists, who may not have any external funds at the initial phase of their career (Ehrenberg *et al* 2003). A 2002 survey of start-up costs at universities defined startup funds to include laboratory construction or renovation, and materials and equipment, among other expenses. Newly hired academic scientists frequently participate in ongoing research grants or bring in grants that partly contribute to their salaries. In the latter case, universities may use the recovered salaries for materials and equipment, depending on the rules and procedures of the academic institution (Boss and Eckert 2003). Access to well-equipped laboratories facilitates research and improves output (Turner and Mairesse 2002). On a national basis, the proportion of R&D budget invested in research equipment declined from 7% to 4% between 1985 and 2006, thus indicating a decline in non-monetary research inputs (National Science Board, Chapter 5).

In the present study, I contribute to the extensive literature on the factors affecting scientific productivity by examining the causality between academic scientists' publication rates and financial aid. I also am interested in determining how scientists' academic rank, professional norms, and university characteristics affect publication success.

Conceptual Model

In the market for research, scientists conduct research with certain characteristics to obtain funding, while funding agents provide financial aid to scientists in exchange for the research they conduct. An academic bioscience research program may be characterized by its scientific discipline, field of study within that discipline, sub-specialties within the field, and the program's position on the basic-to-applied research continuum. Discipline refers to theoretical construct, which in biological science includes animal science, biochemistry, cell-biology, genetics, molecular biology, and pathology. Fields, sometimes referred to as sub-disciplines, include plant reproduction, wheat breeding, stress tolerance, and microbial genomics. External financial support expands research possibilities and for many scientists is desirable in its own right and thus a motivating factor to conduct research. In any event, scientists clearly aim to communicate their scientific discoveries by publishing their research results. In this essay, I focus on whether university bioscience productivity simultaneously determines, and is determined by, the sizes and sources of grant funds.

Funding agencies can be considered as demanders and scientists as suppliers of research products. Alternatively, funding agencies can be seen as providers and scientists as seekers of funds. I lay out a utility framework based on the former approach.

Utility Maximizing Problem

Consider an academic bioscientist who sets forth goals for achieving a utility maximizing research program. A professionally dedicated scientist makes significant investments of her time in pursuing the research that maximizes her utility. A scientist addresses research topics that, considered broadly, provide her satisfaction. She obtains financial support to conduct this research. Laboratory infrastructures such as material and equipment supplies affect the quality of output, influencing the scientist's utility both directly and through enhanced publication and fund-raising prospects. A scientist aims to make her scientific discoveries available through publication of the research results. A new faculty member, through significant research contributions, gains professional recognition and qualifies for academic tenure and promotion. Scientists presumably comply – or seek to comply – with their own ethical norms in pursuing the research. For example, those who think it is important to produce technologies with public benefits concentrate less on investigations with potential commercial value. University policies may affect the research environment and thus influence a scientist's research practice. For example, universities that do not undertake sponsored projects exerting what they regard as undue control over the content of publication may reduce their faculties' patent production rates. We regard these characteristics as exogenous even though, in a much longer run, they are endogenous because the academic research pursued may influence university policy and culture.

The conceptual framework of this analysis is to consider an academic scientist who solves the funding that maximizes her utility. That is,

$$\begin{aligned} &\underset{\mathbf{G}}{Max}\ U\,(P, \mathbf{G}, \mathbf{V}, \mathbf{A}) \\ (1) \qquad & \\ &s.t.\ \ P = P\,(\mathbf{G}, \mathbf{V}, \mathbf{A}) \\ &and\ \mathbf{G} = G\,(P, \mathbf{V}, \mathbf{A}) \end{aligned}$$

where $\mathbf{A} \equiv (T, \mathbf{C}, \mathbf{L}, \mathbf{K})$. We represent the exogenous factors by vector **A**. However, although scientific norms are considered exogenous as well, we include the norm vector **V** as a separate parameter set because they serve as identifying variables in the simultaneous model, which will be discussed in one of the subsequent sections.

A scientist's utility is a function of the research topics *T* she chooses, amount of grant money **G** received, distinguished by source; the number *P* of publications she produces; her scientific norms **V**; human capital **C** (proxied by her academic rank); university characteristics **L**; and in-kind support vector **K**. The utility function in equation (1) implies that both grant support and publication rate directly influence utility. The publication-success and fund-raising behavioral constraints in (1) suggest that publication and funding successes in turn influence each other.

The publication constraint, which is also the laboratory production function, of research implies that the number of publications produced would depend not only on the scientist’s effort in achieving publication success but also the journal’s willingness to accept the articles. At the same time, the availability of grants would not only depend on the funding agent’s willingness to supply funds but also on the scientist’s effort in obtaining the money. So research demand and supply, inevitably, have characteristics of reduced-form equations. Similarly, some of the explanatory variables in research and funding supply and demands, namely those observable by both scientist and funding agent, have reduced-form characteristics. For example, human capital and university type may each be both demand and supply factors. The professor’s rank (a measure of her human capital) and the kind of university at which she is employed may not only influence her research choices, that is her supply of research and demand for research money, but also funding agencies’ decisions about whom to supply with such funds.

Equation (1) is continuous, monotonically increasing, and convex in *P*, and G_i $(i = 1, ..., k$ indexes funding source$)$. That is,

$$\frac{\delta U}{\delta P}, \frac{\partial U}{\partial G_i} > 0 \text{ and}$$

$$\frac{\partial^2 U}{\partial P^2}, \frac{\partial^2 U}{\partial G_i^{\ 2}} < 0 .$$

Maximizing the utility function $U(.)$ in equation (1) subject to the constraints gives the following first-order conditions yielding the optimum quantities of **G** and *P*:

$$\mathbf{G} = f_1\ (P, T, \mathbf{C}, \mathbf{L}, \mathbf{V}, \mathbf{K}) \tag{2}$$

$$P = f_2\ (\mathbf{G}, T, \mathbf{C}, \mathbf{L}, \mathbf{V}, \mathbf{K}) \tag{3}$$

Equation (2) implies that funding agencies' demand for research, that is, the amount of funds supplied, depend upon research topic choice, publication rate, human capital, university type, and scientific norms. Equation (3) implies that topic choice, funds obtained, human capital, university type, and norms affect publication success, that is scientists' research supplies. Research choice may, on the one hand, influence funding agents' willingness to provide grant support, and on the other hand affect publication rates. For example, pursuing applied research at the organism scale may attract more financial support from state governments than it does from federal agencies such as the National Science Foundation. And as discussed before, industry-sponsored applied research with potential commercial value, as opposed to basic research, may affect publication rate.

Evidence of continued productivity likely is another important determinant of money supply. Funding agents' provision of research support might also affect publication rates. Academic position, an indicator of scientists' reputation and experience, could on the one hand influence the grant awards funding agencies make, and on the other hand help achieve publication success. University infrastructural policies, such as assistance in securing funds, can facilitate financial support. Through its partial determination of the research environment, university culture may influence the scientist’s research effectiveness and thus publication success. Professional norms, serving as proxies for the scientist’s unobserved fund-raising and research efforts, therefore may also influence grant support as well as publication success. As discussed earlier, higher in-kind support may reduce grant availability. At the same time, the laboratory infrastructure improvements provided by in-kind inputs can enhance scientific productivity.

Resource Allocation and Productivity

The size of the scientist’s laboratory may affect her scientific output. We measure laboratory size by the number of employees working in the laboratory – post-doctorates, graduate students, and technicians. Research performance is closely related to universities’ higher education policies. For instance, incorporating research into classroom teaching enhances students’ knowledge base by linking research to relevant theory, posing significant questions for future investigations, and replicating and generalizing findings across studies (Heirdsfield, Ruthven 2004; Shavelson and Towne). Incorporating research into teaching may improve students’ future research performance while at the same time assisting current research. Accounting for the number of employees together with funding support **G** provides a test for allocative efficiency, that is, whether scientists spend their resources efficiently on labor inputs (Xia and Buccola 2005). Suppose, a scientist’s publication rate is specified as

$$P = g_1\,(PD, T, \mathbf{G}, \mathbf{C}, \mathbf{L}, \mathbf{V}, \mathbf{K}) \tag{4}$$

where, *PD* indicates the number of postdoctoral fellows employed. A scientist's total research budget *H* can be decomposed into post-doctoral (*PD*) and non-post-doctoral (*NPD*) inputs such that

$$(5) \qquad H = \sum_{i=1}^{k} S_i \; H = \sum_{i=1}^{k} G_i = r_{pd} PD \; + \; r_{npd} NPD$$

where $i = 1, ..., k$ indexes funding source, S_i is the share of funding obtained from the i^{th} agency, $\sum_{i=1}^{k} S_i = 1$ and; r_{pd} and r_{npd} are input prices.

The total change in *H* is given by $dH = r_{pd} .dPD + r_{npd} .dNPD.$ Holding *H* fixed, that is $dH = 0,$ we have $r_{pd} dPD = - r_{npd} dNPD.$ That is, an increase in expenditure on postdoctoral inputs is equal to the decrease in expenditure on non-postdoctoral inputs, assuming budget remains fixed. The marginal effect on publication output $\frac{dP}{dPD} |_{H_0}$ of employing an additional postdoctoral fellow can be decomposed as [from the total differentiation of $P = u_1 (PD, NPD)$, and using $r_{pd} \; dPD = - r_{npd} \; dNPD$]

$$(6) \qquad \frac{dP}{r_{pd} dPD} |_{H_0} = \frac{\partial P}{r_{pd} \partial PD} |_{NPD_0} - \frac{\partial P}{r_{npd} \partial NPD} |_{PD_0}$$

Multiplying both sides by r_{pd}, we have

$$\frac{dP}{dPD}\Big|_{H_0} = \frac{\partial P}{\partial PD}\Big|_{NPD_0} - \frac{r_{pd}}{r_{npd}}\frac{\partial P}{\partial NPD}\Big|_{PD_0} \tag{7}$$

Postdoctoral and non-post-doctoral inputs are allocatively efficient if

$$\begin{gathered}\frac{\dfrac{\partial P}{\partial PD}\Big|_{NPD_0}}{\dfrac{\partial P}{\partial NPD}\Big|_{PD_0}} = \frac{r_{pd}}{r_{npd}} = \frac{MP_{PD}}{MP_{NPD}} \\ \Rightarrow \frac{MP_{PD}}{r_{pd}} = \frac{MP_{NPD}}{r_{npd}}\end{gathered} \tag{8}$$

The last line implies that the last dollar spent on each input, *PD* and *NPD*, yields the same output increase. This efficiency condition holds when, and only when, $\frac{dP}{dPD}\Big|_{H_0} = 0$. That is, if budget is to be minimized, publication rate must be unaffected by any change in the allocation of inputs between post-doctorates and non-post-doctorates. Or in other words, when the coefficient estimate of *PD* in equation (4) is not significantly different from zero, academic scientists distribute resources optimally between post-doctoral and non-post-doctoral laboratory workers. If the coefficient estimate instead is positive (negative) and significant, too few (many) postdoctoral fellows are employed in the research laboratory. Mathematically,

$$\frac{\frac{\partial P}{\partial PD}\big|_{NPD_0}}{\frac{\partial P}{\partial NPD}\big|_{PD_0}} > \frac{r_{pd}}{r_{npd}} \Rightarrow \frac{MP_{PD}}{MP_{NPD}} > \frac{r_{pd}}{r_{npd}}$$

$$\Rightarrow \frac{MP_{PD}}{r_{pd}} > \frac{MP_{NPD}}{r_{npd}}$$

$\frac{MP_{PD}}{r_{pd}} > \frac{MP_{NPD}}{r_{npd}}$ when $\frac{dP}{dPD}\big|_{H_0} > 0$. $\frac{MP_{PD}}{r_{pd}} > \frac{MP_{NPD}}{r_{npd}}$ implies that post-doctorates have higher marginal productivity per dollar than do non-post-doctorates. So output (publication rate) can be increased by shifting resources in their favor. In other words, $\frac{\partial P}{\partial PD}\big|_{H_0} > 0$ implies that scientists are hiring too few post-doctorates or under-investing in them, holding research budget fixed. This situation is depicted in figure 1 [page 156].

We measure post-doctorates along the horizontal and non-post-doctorates along the vertical axis. Scientists minimize costs at point E, where the iso-budget line CD is tangent to the isoquant. PD* and NPD* are the cost-minimizing choice of inputs to achieve output $q_{0.}$ However, suppose scientists operate at point A, using PD^E and NPD^E, at which $\frac{MP_{PD}}{MP_{NPD}} > \frac{r_{pd}}{r_{npd}}$. At A, scientists are employing too few post-doctorates and too many non-post-doctorates than optimal at fixed expenditure CD, thus achieving an output q_1 that is lower than possible. Moving downward along the iso-budget line from A to E redirects resources from non-labor factors to post-doctorates and thereby achieves a higher output level q_0.

We may test for the allocative efficiency of graduate students and technicians with similar means. In the present study, I employ human resource levels – post-doctorates, graduates, and technicians – as determinants of scientists' publication rates in addition to funding, human capital, university type, professional norms, and in-kind inputs.

Other Productivity Factors

Following our earlier discussion on relations between government and private funding, public and private funding may substitute for or complement each other. Higher federal R&D expenditures may attract or repel private R&D investments. The crowding-in or -out phenomenon is affected by the scarcity of the scientist's time. Attracting federal funds requires investing in the time to, among other things, develop the necessary professional relationships. That time is unavailable for pursuing private funds, so that federal support would tend to replace private support. However, if the inherent complementarities between federal and private funds outweigh the time effect, we would expect federal funds to crowd-in private funds. Fundamental scientific discoveries form the basis of applied research. So as Wang (2009) notes, federal investment in basic science, leading to fundamental scientific advancement, tends to attract R&D support toward profit-oriented industries that wish to make extensive use of the basic discoveries for producing applied technologies.

As discussed above, the supply of financial support and non-monetary inputs may affect each other as well. In a research proposal, funding applicants are required to list expected materials, equipment, and personnel costs needed to accomplish the research objectives. Because resources are limited, more financial support may reduce the availability of non-monetary inputs and vice-versa. And because in-kind support provides value to the scientist, those receiving more in-kind inputs may be willing to accept less research cash: the two are partial substitutes for one another. Grant funders will provide a research input in kind rather than cash if the former is cheaper for them than the latter is. That would occur, for example, if the grant provider is a biotechnology firm which produces the input, such as a cell line, in the course of its own work. Funders might also acquire laboratory equipment at discounted rates.

A scientist’s rank and publication rate may also influence one another. On the one hand, because publication rate is a determinant of academic promotion and tenure, it may affect the rank a scientist achieves. On the other hand, academic position may, following our earlier discussion on age and scientific productivity, influence publication rates as well. Furthermore, just as a scientist’s research decision may influence the volume of financial support, the financial support obtained may influence her research choice. For example, a scientist performing basic research at the cellular level may be more likely to receive higher federal than non-federal funding; at the same time, higher federal support may incline a scientist to conduct cellular-level basic research. Hence, cash support, non-cash support, research choice, rank, and publications are likely jointly determined. In spite of the possible simultaneities among research topic choice, financial awards, in-kind support, scientist rank, and publication rate, we nevertheless hold research choice, in-kind support, and academic rank exogenous. Endogenizing them would complicate estimation by requiring several sets of topic choice, in-kind-support, and academic-rank equations and their associated instrumental variables in addition to funding and publication rate equations.

We therefore estimate the following equations depicting the causal relationship between financial support and scientific productivity, using instrumental variables.

$$P = g_2\,(\,\mathbf{G}, T, \mathbf{HR}, \mathbf{C}, \mathbf{L}, \mathbf{V}, \mathbf{K}\,) \tag{4}$$

$$\mathbf{G} = g_3\,(\,P, T, \mathbf{C}, \mathbf{L}, \mathbf{V}, \mathbf{K}) \tag{5}$$

where **HR** denotes the number of post-doctorates, graduate students, and technicians.

Identifying Variables

In attempting to estimate the causal effect of publication rate (funding) on the availability of funds (publication rate), we use identifying variables which affect publication rate and not funding (funding and not publication rate). More specifically, identifying variables are exogenous variables uniquely associated with each equation, that is affecting the dependent variable in that equation. In the publication equation (4), human resource vector **HR** influencing scientific productivity serves as the identifying variables. As indicated above, human resource factors may affect publication rates. But recruiting more laboratory workers does not directly influence funding agents to award more grants. Engaging employees, however, would depend on the availability of funds. Therefore, just as labor inputs may affect a scientist's publication rate, scientific output may in turn influence labor force recruitment by way of the influence of publication rate on financial support. Hence, we expect vector **HR** to be endogenous, requiring instrumentation in a manner to be discussed in the results section. Similarly, identifying variables need to be found for funding equation (5) in order to estimate the causality between publication and fund availability.

We thus hypothesize that scientific norms influence grant support from federal and non-federal sources. Professional norms likely influence the unobservable efforts a scientist allocates in order to succeed in receiving grants from various sources (Buccola *et al*, 2009). Therefore, a scientist who especially values public research support, and thus especially recognizes the importance of scientist panels in setting university research agendas, would be most likely to allocate her fund-raising efforts toward receiving federal grants. A scientist who thinks industries should have an especially significant role in setting research agendas, or whose ethic is most oriented toward commercializing her discoveries, would be most likely to try to secure industry or state grants.

An econometrically estimable form of the full model would look like

(6) $$P = j_1 \,(G_{fed}, G_{nonfed}, R, \mathbf{HR}, \mathbf{C}, \mathbf{L}, \mathbf{K}, \mathbf{V})$$

(7) $$G_{fed} = j_2 \,(G_{nonfed}, P, R, \mathbf{C}, \mathbf{L}, \mathbf{K}, \mathbf{V}_1)$$

(8) $$G_{nonfed} = j_3 \,(G_{fed}, P, R, \mathbf{C}, \mathbf{L}, \mathbf{K}, \mathbf{V}_2)$$

where **HR** is the number of graduate students, post-doctorates, technicians – labor variables identifying publication equation, $\mathbf{V}_1$ are the norm variables identifying federal funds equation, and $\mathbf{V}_2$ are norm variables identifying non-federal funds equation, to be discussed in the following section in detail.

Solving equations (6) – (8) for the endogenous variables yields the following reduced-form system of equations.

(9) $$P = m_1 \,(R, \mathbf{HR}, \mathbf{C}, \mathbf{L}, \mathbf{K}, \mathbf{V}, \mathbf{V}_1, \mathbf{V}_2)$$

(10) $$G_{fed} = m_2 \,(R, \mathbf{HR}, \mathbf{C}, \mathbf{L}, \mathbf{K}, \mathbf{V}, \mathbf{V}_1, \mathbf{V}_2)$$

(11) $$G_{nonfed} = m_3 \,(R, \mathbf{HR}, \mathbf{C}, \mathbf{L}, \mathbf{K}, \mathbf{V}, \mathbf{V}_1, \mathbf{V}_2)$$

These equations are not sufficient for the present analysis because they hide the effects of the endogenous variables on one another. Reduced-form equations express only the exogenous variables' total or net effects on the endogenous variables. Equations (6), (7), and (8) are estimated simultaneously using two-stage and three-stage least-square methods. Equations (9), (10), and (11) are estimated with ordinary least squares.

Survey Data

We use the same cross-sectional survey data, collected from US academic bioscientists, as in Essay 2. We use similar measures for research object-scale and basicness classifications, academic rank, university type, and in-kind support, as explained in essay 2. Below I discuss the variables that differ from those used in essay 2**,** such as funding sources, and those used in the present essay only, such as full-time employees and publication rate.

Research funding sources

In the present essay we combine the total funding obtained from the National Science Foundation (NSF), National Institutes of Health (NIH), US Department of Agriculture (USDA), and other federal sources, along with private foundations, to form the "federal" category, while state governments and industry funds comprise the "non-federal" category:

$$\begin{aligned} \mathbf{G}_{fed} &= G_{nsf} + G_{nih} + G_{usda} + G_{othfed} + G_{found} \\ \mathbf{G}_{nonfed} &= G_{state} + G_{industry} \end{aligned}$$

Recall from essay 2 that $G_i = S_i\ H$, where $i = 1, \ldots, k$ indexes funding source,

$$H = \sum_{i=1}^{k} S_i \; H, \, and \, \sum_{i=1}^{k} S_i = 1,$$

so that the total funding G_i received from the i^{th} agency is obtained by multiplying the annual budget H by the share of money S_i contributed by the i^{th} agency.

Publication Rates and Laboratory Employees

Scientists were asked to specify the number of articles they have published as authors or co-authors in refereed journals. They also indicated how many of each of the research staff categories – post-doctoral fellows (*PD*), graduate students (*Grad*), technicians (*Tech*) and others – they support. We denote the number of full-time employees by **HR**. $\mathbf{HR} \equiv PD, Grad, Tech$ are used as the identifying variables (discussed in the previous section) in equation (6).

Professional Norms

Scientists were asked, on a Likert scale, to indicate how important the following criteria ought to be in their choice of research problems:

(a) Availability of public (state and federal) funding, where 1 is “not important and 7 is “very important.”

(b) Potential marketability of final product, where 1 is “not important and 7 is “very important.”

(c) Public-good nature of the research problem, where 1 is “not important and 7 is “very important.”

(d) Scientist panels set public research scientists’ agendas, where 1 is ‘strongly agree” and 6 is “do not know.”

(e) Industry plays a central role in public research scientists’ agendas, where 1 is ‘strongly agree” and 6 is “do not know.”

Norms (a) and (d), indicated by vector $\mathbf{V}_1$, are used as the identifying variables in equation (7) determining federal funding success. Norms (b) and (e), indicated by vector $\mathbf{V_2}$, are used as the identifying variables in equation (8) determining non-federal funding success. However, while modeling for funding success from federal sources only, we consider norms (a) and (c) as the identifying variables.

Empirical Results

We estimate structural equations (6), (7), and (8) in linear form with two and three stage least squares, and reduced-form equations (9), (10), and (11) with ordinary least squares (SAS Institute Inc. Cary, NC). Research topic choice and in-kind inputs are dropped from these equations due to very low *t* values. The attempt to use certain norms in the publication-rate equation, in addition to the number of graduate students, post-doctorate fellows, and technicians, as identifying variables also generated low *t* values and were eliminated from publication equation (6).

We begin by discussing the results when using the total sample, followed by the results obtained after disaggregating the total population into three subsamples. The first such subsample, referred to as S_1, excludes scientists receiving financial support from non-federal sources alone. The second, referred to as S_2, eliminates scientists receiving funds from federal sources alone. And the third, S_3 , includes scientists getting federal funds exclusively. That is,

S_1 = scientists receiving federal grants or grants from both federal and non-federal sources;

S_2 = scientists receiving non-federal grants or grants from both federal and non-federal sources;

S_3 = scientists receiving federal grants only.

Before discussing the estimation results, we discuss some of the diagnostic tests performed in connection simultaneous model [equations (6), (7), (8)], namely the Hausman specification test and the over-identification test. The Hausman test evaluates the significance of an estimator versus an alternate estimator. The over-identification test determines the validity of the instruments used to estimate the simultaneous system of equations. We discuss these tests below.

As we shall show, the Hausman specification test (1978), a statistical test to determine the presence of two-way causality between the dependent and one or more independent variables, indicates causality between publication rate and funding availability in equations (6) – (8). That is, publication rate and volume of financial support affect each other. More technically, the funding magnitudes in publication equation (6), the publication and non-federal quantities in federal equation (7), and the federal and publication rates in non-federal equation (8) are correlated with the respective error terms in those equations. Consider two estimators of b, namely b_0 obtained with OLS, and b_1 obtained with instrumental variables. Under the null hypothesis of the Hausman test, both b_0 and b_1 are consistent. Under the alternate hypothesis, only b_1 is consistent.

$$(a) \qquad Y_1 = f\ (Y_2, Y_3, \mathbf{I}_1, \mathbf{X})$$

$$(b) \qquad Y_2 = f_1\ (\mathbf{Z}, \mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3, \mathbf{X}) \Rightarrow \quad residual\ \hat{e}_2$$

$$(c) \qquad Y_3 = f_2\ (\mathbf{Z}, \mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3, \mathbf{X}) \Rightarrow \quad residual\ \hat{e}_3$$

$$(d) \qquad Y_1 = f_3\ (Y_2, Y_3, \mathbf{I}_1, \mathbf{X}, \hat{e}_2, \hat{e}_3)$$

Equation (a) depicts the model in which Y_2 and Y_3 are the endogenous regressors, $\mathbf{I}_1$ is the vector of identifying variables, and **X** is the vector of exogenous factors. Equation (a) corresponds to the publication equation (6) in the conceptual model section, where Y_2 and Y_3 respectively refer to federal and non-federal funding and Y_1 refers to publication rate. In the first-stage of the Hausman test, we regress the endogenous regressors Y_2 and Y_3 on $\mathbf{Z}$, $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3$, and **X** and derive the residuals $\hat{e}_2$ and $\hat{e}_3$, as shown by equations (b) and (c) above, where **X** denotes the exogenous factors, $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3$, correspond to the variables respectively identifying equations (6), (7), and (8), and **Z** refers to the exogenous variables used as first-stage instruments but not included in the second-stage. In the second-stage, we use OLS to regress the first endogenous variable Y_1 on residuals $\hat{e}_2$ and $\hat{e}_3$ along with endogenous regressors Y_2 and Y_3, identifying variables $\mathbf{I}_1$, and exogenous factors **X** as shown in equation (d). Finally, we perform a *t* test on the residuals $\hat{e}_2$ and $\hat{e}_3$. A significant *t* value would indicate Y_2 and Y_3 are correlated with the errors $\hat{e}_2$ and $\hat{e}_3$, thus revealing simultaneity between Y_1 and regressors Y_2 and Y_3. The exogenous variables $\mathbf{X}$, $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3,$ and $\mathbf{Z}$ are known as instrumental variables or instruments. We may test for simultaneity, following the same procedure, considering each of the two funding equations (7) and (8).

Hausman test results indicate rejection of the null hypothesis, implying that OLS estimates are inconsistent, in the total population as well as in the subsamples $\mathrm{S}_1, \mathrm{S}_2,$ and S_3. In the total sample, the *t* values on the residuals of federal and nonfederal funding, that is $\hat{e}_2$ and $\hat{e}_3$ in regression equation (d) showing the determinants of publication rate, are respectively - 2.52 and - 0.93, the former significant at the 5% level as shown in table 2.1. In equation (d_2), $Y_2 = f_4\ (Y_1, Y_3, \mathbf{I}_2, \mathbf{X}, \hat{e}_1, \hat{e}_3),$ measuring federal funding, the *t* values on residual $\hat{e}_1$ of publication rate Y_1 and on $\hat{e}_3$ of non-federal funding Y_3 are respectively - 5.28 and 3.38 (both significant at the 1% level), as shown in table 3.1. In equation (d_3) $Y_3 = f_5\ (Y_1, Y_2, \mathbf{I}_3, \mathbf{X}, \hat{e}_1, \hat{e}_2),$ measuring non-federal funding, the *t* values on residual $\hat{e}_1$ of publication rate and on $\hat{e}_2$ of federal funding Y_2, are respectively - 2.32 and 3.65 (the former significant at the 5 % level and the latter significant at 1% level), as shown in table 4.1.

In subsample S_1, the *t* values on residuals $\hat{e}_2$ and $\hat{e}_3$ in equation (d) are respectively - 2.26 (significant at 5% level) and -1.02. The *t* values on residuals $\hat{e}_1$ and $\hat{e}_3$ in equation (d_2) are respectively - 4.92 (significant at 1% level) and 3.33 (significant at 5% level), and those on the residuals $\hat{e}_1$ and $\hat{e}_2$ in equation (d_3) are respectively - 2.56 and

3.46 (both significant at 5% level) as shown in tables 6.1, 7.1, and 8.1. In subsample S_3, the corresponding *t* statistics on $\hat{e}_2$ and $\hat{e}_3$ in equation (d) are respectively - 2.22 (significant at 5% level) and - 0.68; the *t* values on $\hat{e}_1$ and $\hat{e}_3$ in equation (d_2) are respectively - 3.19 and 2.49 (both significant at 5% level); and those on $\hat{e}_1$ and $\hat{e}_2$ in equation (d_3) are respectively - 1.18 and 2.46 (significant at 5% level), as shown in tables 10.1, 11.1, and 12.1.

Finally, in equation (d_4) $Y_1 = f_6\,(Y_2, \mathbf{I}_1, \mathbf{X}, \hat{e}_2),$ measuring publication rate, the *t* value on residual $\hat{e}_2$ of federal funding in subsample S_3 is - 0.83 and the *t* value on residual $\hat{e}_1$ of publication rate in equation (d_5) $Y_2 = f_7\,(Y_1, \mathbf{I}_2, \mathbf{X}, \hat{e}_1),$ measuring federal funding, is - 2.58 (significant at 5% level), as shown in tables 14.1 and 15.1. Significant *t* statistics on the disturbance terms imply that simultaneity bias could not be rejected in any of the equations [(6) – (8)]. Hence, we use the two-stage and three-stage least square methods to estimate the regression equations.

In the first-stage of the two-stage least-squares method, we regress the endogenous regressors on the exogenous variables of the model, as shown by equations (b) and (c) above. In the second-stage, we replace the endogenous regressors by their fitted values. That is, we estimate equation (d), replacing Y_2 and Y_3 by their predicted values obtained from the estimation of equations (b) and (c) but dropping residuals $\hat{e}_2$ and

$\hat{e}_3$. Since the new (fitted) variables are created from the exogenous ones, they should not be correlated with the disturbance term and can be considered exogenous.

We use the number of graduate students, post-doctorates, and technicians as identifying variables in the equation showing the determinants of publication rate, that is equation (6), because we hypothesize that they influence scientific productivity. As we have reasoned above, publication rate ought to influence, and be influenced by, research source and amount, and the size and composition of laboratory labor would depend on research grants received. Thus, by way of grant funding, we expect scientists' publication rates to affect the use of graduate students (*GRAD*), post-doctorates (*PD*), and laboratory technicians (*TECH*). We test for this possible simultaneity between publication rate and laboratory employment with the Hausman specification test. That is we estimate equation (k_1), $Y_1 = f_8\,(GRAD, PD, TECH, \mathbf{X}, \hat{e}_{GRAD}, \hat{e}_{PD}, \hat{e}_{TECH}),$ with the respective residuals $\hat{e}_{GRAD}, \hat{e}_{PD}$, and $\hat{e}_{TECH}$ as explanatory variables, obtained from the first-stage regressions of $\mathbf{Z}$, $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3$ and $\mathbf{X}$ on each of the three variables *GRAD*, *PD*, and *TECH*. Unsurprisingly we find that simultaneity in publication equation (k_1) cannot be rejected in any of the four samples. In the whole sample, the *t* values of - 2.01, 2.85, and - 3.60 respectively on $\hat{e}_{GRAD}, \hat{e}_{PD}$, and $\hat{e}_{TECH}$ are significant at the 5%, 5% and 1% levels respectively. In subsample S_1, the *t* values on $\hat{e}_{GRAD}, \hat{e}_{PD}$, and $\hat{e}_{TECH}$ are respectively, -2.08, 3.03, 3.35, all of which are significant at the 5% level. The corresponding *t* statistics in subsample S_2 are respectively - 1.12, 1.64 (significant at 10%), and - 2.40 (significant at

5%). Finally, the respective *t* values on the $\hat{e}_{GRAD}, \hat{e}_{PD}$, and $\hat{e}_{TECH}$, in subsample S_3 are - 1.47, 2.19 (significant at 5%), and - 1.93 (significant at 5%). Hence, as discussed earlier, the significant *t* statistics on the laboratory labor variables, indicating simultaneity, require instrumentation to correct for the simultaneity bias.

Further, we perform the Hausman test on the instrumented endogenous regressors to verify whether instrumentation, that is replacement of the endogenous regressors with their fitted values, has been successful in removing the simultaneity bias in each of equations (6) – (8). First, we regress the fitted values of the endogenous regressors $\hat{Y}_2$ and $\hat{Y}_3$ - obtained from equations (b) and (c) above – on exogenous variables **Z**, $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3$, **X**, save the residuals $\hat{\hat{e}}_2$ and $\hat{\hat{e}}_3$, and conduct OLS regressions on each equation, using the respective residuals as explanatory variables. Mathematically,

$$(e) \qquad \hat{Y}_2 = h_1\,(\mathbf{Z}, \mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3, \mathbf{X}) \Rightarrow \quad \textit{residual}\ \hat{\hat{e}}_2$$

$$(f) \qquad \hat{Y}_3 = h_2\,(\mathbf{Z}, \mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3, \mathbf{X}) \Rightarrow \quad \textit{residual}\ \hat{\hat{e}}_3$$

$$(g) \qquad Y_1 = h_3\,(\hat{Y}_2, \hat{Y}_3, \mathbf{I}_1, \mathbf{X}, \hat{\hat{e}}_2, \hat{\hat{e}}_3)$$

We then perform a *t* test on the residuals of the fitted values of endogenous regressors $\hat{Y}_2$ and $\hat{Y}_3$. Insignificant *t* values imply the predicted value of the endogenous regressor is not correlated with the error term; that is, we accept the null of no simultaneity.

We find, in the total sample, that the *t* values on residual $\hat{\hat{e}}_2$ of the predicted value of federal funding $\hat{Y}_2$ and on $\hat{\hat{e}}_3$ of the predicted value of non-federal funding $\hat{Y}_3$ in equation (g) are respectively 0.77 and 0.32 (both insignificant). In equation (g_2) $Y_2 = h_4\ (\hat{Y}_1, \hat{Y}_3, \mathbf{I}_2, \mathbf{X}, \hat{\hat{e}}_1, \hat{\hat{e}}_3)$, measuring federal funding, the *t* values on residual $\hat{\hat{e}}_1$ of the predicted value of publication rate $\hat{Y}_1$ and on residual $\hat{\hat{e}}_3$ of $\hat{Y}_3$, are respectively, - 0.85 and - 1.27. In equation (g_3) $Y_3 = h_5\ (\hat{Y}_1, \hat{Y}_2, \mathbf{I}_3, \mathbf{X}, \hat{\hat{e}}_1, \hat{\hat{e}}_2)$, measuring non-federal funding, the *t* values on residuals $\hat{\hat{e}}_1$ and $\hat{\hat{e}}_2$ of $\hat{Y}_1$ *and* $\hat{Y}_2$, are respectively 0.47 and - 0.34, all of which turn out to be insignificant at the 10%, 5% and 1% level. In subsample S_1, the *t* values on residuals $\hat{\hat{e}}_2$ of $\hat{Y}_2$ and $\hat{\hat{e}}_3$ of $\hat{Y}_3$ in equation (g) are respectively - 1.20 and - 0.31; the *t* values on the residuals $\hat{\hat{e}}_1$ of $\hat{Y}_1$ *and* $\hat{\hat{e}}_3$ *of* $\hat{Y}_3$ in equation (g_2) are respectively 1.39 and - 1.58; and those on residuals $\hat{\hat{e}}_1$ and $\hat{\hat{e}}_2$ of $\hat{Y}_1$ *and* $\hat{Y}_2$ in equation (g_3) are respectively - 0.03 and 0.52. All these statistics are insignificant. The corresponding *t* statistics in equations (g), (g_2) and (g_3) in subsample S_2 are respectively 1.02 and - 1.03; - 1.73 and 1.77; and 0.21 and - 0.18. Although the respective *t* values of 1.73 and 1.77 on residuals $\hat{\hat{e}}_1$ and $\hat{\hat{e}}_3$ are significant at 10% level, their significance levels decline upon instrumentation (the earlier *t* values on the residuals of publication rate and federal funds being - 3.19 and 2.49 respectively). Finally, in equation (g_4), $Y_1 = h_6\ (\hat{Y}_2, \mathbf{I}_1, \mathbf{X}, \hat{\hat{e}}_2)$, measuring publication rate in subsample S_3, the *t* value on residual

$\hat{\hat{e}}_2$ of the predicted value of federal funding $\hat{Y}_2$ is - 0.54, and in equation (g_5) [$Y_2 = h_7\ (\hat{Y}_1, \mathbf{I}_2, \mathbf{X}, \hat{\hat{e}}_1)$] measuring federal funding, the *t* value on the residual $\hat{\hat{e}}_1$ of the predicted value of publication rate $\hat{Y}_1$ is 1.10, both of which are insignificant. 2SLS is therefore appropriate and provides us consistent estimates of publication rate and the size of federal and non-federal funding.

Next we discuss the over-identification test. An over-identified simultaneous model has more instruments than are needed to identify an equation. We conduct the over-identification test to determine the validity of the additional instruments used to estimate the endogenous regressors – publication rate, volume of federal and non-federal funding, and number of graduate students, post-doctorates, and technicians - in the first-stage of the 2SLS. When the number of instruments excluded from an equation is greater than the number of endogenous regressors in the model less one, the equation is over-identified. Recall, in the second-stage of 2SLS, that we use fitted values of the endogenous regressors $\hat{Y}_2$ and $\hat{Y}_3$, along with identifying variables $\mathbf{I}_1$ and other predetermined variables **X**, to estimate Y_1, as shown by equation (h) below. We obtain $\hat{Y}_2$ and $\hat{Y}_3$ from the first-stage of the two-stage method by regressing Y_2 and Y_3 respectively on $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3$, **X**, and **Z**, where **Z** refers to exogenous variables used as first-stage instruments. To determine whether the **Z**s are valid, that is uncorrelated with the error term, we regress the second-stage residual $\hat{e}$ on $\mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3$, **Z**, and **X**, as shown by equation (*i*), and compute the chi-square statistics. Mathematically,

$$(h) \qquad Y_1 = n_1\,(\hat{Y}_2, \hat{Y}_3\,, \mathbf{I}_1, \mathbf{X}\,) \Rightarrow \quad residual\ \hat{e}$$

$$(i) \qquad \hat{e} = n_2\,(\,\mathbf{Z}, \mathbf{I}_1, \mathbf{I}_2, \mathbf{I}_3, \mathbf{X}\,)$$

If the critical chi-square value with degrees of freedom equal to the number of over-identifying restrictions turns out to be greater than the calculated chi-square, the instruments are uncorrelated with the error terms. We find the over-identification test statistics of 38.23 and 71.56 in the total sample are insignificant at the 1% level. This confirms the validity of the first-stage instruments **Z**. However, when regressed against the exogenous variables, the residual generated from the second-stage estimation of the non-federal funds equation (8) gives a test statistic of 102.38, which is significant at the 1% level. Nevertheless, we do not exclude any instrument from this equation, as they are part of the simultaneous system and they pass the over-identifying test in two of the three equations in this model.

The over-identification test statistics in equations (6), (7) and (8) in subsample S_1 are respectively 35.82, 71.97, and 94.16. The corresponding test statistics in subsample S_2 are respectively 42.10, 62.56, and 71.93. Finally, in the subsample S_3 the over-identification test statistics in the publication-rate and federal-funding equations are 47.49 and 50.33 respectively. We find, in all the subsamples $S_1 - S_3$, that the chi square values obtained are insignificant at the 1% level. Therefore, based upon the test results, we can infer that the diagnostic checks performed validate the model specification represented by equations (6) – (8). We next proceed to discuss the descriptive statistics, followed by the model estimates.

Descriptive Statistics

Summary statistics reported in table 1 (*N* = 720) suggest that an average scientist publishes about 3 articles annually and receives $227,310 of federal and $46,180 of non-federal support annually. Most scientists in the sample believe scientist panels should set university research agendas (mean 3.51 on a 5-point scale, where 1 indicates “strongly agree” and 5 indicates “strongly disagree”), and that industries should have a significant role in setting research agendas (mean 1.92 on a 5-point scale). Availability of public funds ought to be an important research criterion to sampled scientists (mean 5.6 on a 7-point scale where 1 indicates “not important” and 7 indicates “very important”), while commercialization of produced knowledge/technology ought to be less important (mean 2.60 on a 7-point scale). An average scientist employs about two graduate students, one post-doctorate, and one technician in her laboratory. Forty-nine percent of the scientists surveyed held professor rank and 25 percent held associate professor rank. Fifty percent of the bioscientists are employed at Land-Grant universities, 35 percent are employed at non-Land-Grant universities, and 15 percent at private universities.

Regression Results – Whole Sample

Table 2 shows the 3SLS estimation results for the whole sample, consisting of 720 observations. R-squares obtained from the first-stage regressions of both publication rate and federal funding volume on the instruments are 0.30, of non-federal funding volume on the instruments is 0.26, and of the number of graduate students, post-doctorates, and technicians on the instruments, respectively 0.16, 0.44 and 0.24. The first-stage R-squares are, besides the Hausman specification test, an indication of the predictive power of the instruments in removing the simultaneity bias. In other words, first-stage R-squares reflect the extent to which predicted values of the endogenous regressors are correlated with the original endogenous variables. R-squares obtained here are not inconsiderable for cross-sectional data. The F test of the joint significance of the excluded instruments in the regression equations (6), (7), and (8) explaining publication rate, federal funding, and non-federal funding are 22.35, 20.87, and 11.42, respectively, compared to the tabled values F (9, 1000) = 3.13 and F (8, 1000) = 2.66 at the 1% level of significance. These results point to the relevance of my instruments and to a decent model fit.

Laboratory Employees and Publication Rates

Three-stage estimation results in tables 2 suggest that funding size does not have a significant impact on scientists' publishing success. As discussed above, earlier research by Blumenthal *et al* (1996) and Godin (1998) find that industry funding boosts publication productivity. We find, in table 2, that recruiting graduate students and technicians increases scientists' average publication rates by about one article per year ($t_{grad} = 5.15$, $t_{tech} = 2.56$). However, we do not find post-doctorates to have any significant impact on publication rates. Following our earlier discussion of laboratory resource allocation, this non-significance implies that scientists allocate post-doctorate resources efficiently, that is they hire a cost-minimizing number of post-doctorates. Recall we hypothesize that, by means of grant funding, the number of graduate students, post-doctorates, and laboratory technicians, would also affect publication rate. We therefore can infer that financial support, through its impact on higher labor recruitment, influences publication rate. Hence also, table 2 reinforces Blumenthal *et al* and Godin's conclusions.

On the other hand, positive and significant *t* statistics on the graduate and technician variables imply that scientists do not allocate these two resources efficiently in the production of scientific output. In particular it implies, controlling for research budget, that scientists hire too few graduate students and technicians even though (given those inoptimal levels) an optimal number of post-doctorates. It is notable that the reduced-form equation (9) estimates in table 31 shows that the number of post-doctoral fellows have, in addition to the number of graduate students and technicians, a positive and significant impact on scientists' publication rates (t_{grad} = 3.81, $t_{postdoc}$ = 1.97, t_{tech} = 4.10). Thus, when mutual interactions among publication rate and federal and non-federal funding are equilibrated, we find that scientists hire too few of all three labor types to minimize the cost of a given publication output.

As discussed earlier, resources are allocated efficiently when the last dollar spent on labor inputs yields the same output increase as does the last dollar spent on non-labor inputs, that is when any change in the resource allocation does not affect publication rate, assuming budget remains fixed. However, if an additional dollar invested in laboratory workers boosts output more than does an additional dollar spent on non-labor factors, scientists do not distribute their resources efficiently between labor and non-labor inputs. That is, they do not operate at an allocatively efficient point on the isoquant, illustrated in figure 1. In other words, a higher per-dollar labor than non-labor productivity indicates that scientists hire too few workers. As discussed above, such inefficiency is detected when, controlling for the total budget, recruiting an additional graduate student or technician increases the scientist's publication rate. Thus, positive and significant coefficients on the number of graduate students and technicians imply that scientists hire few graduates and technicians, indicating that scientists under-invest in them.

This brings us to the question why the representative scientist recruits an optimal number of post-doctorates but too few graduates and technicians. A possible reason is that post-doctorates are better experienced and trained than graduate students and technicians are and, unlike graduate students who must split time between research and study, can devote all their time for research. Resource misallocation could also result from inflexibilities in university hiring policies (Xia and Buccola 2005). Fee structures and reputational concerns in many universities could result in hiring restrictions (Denton *et al* 1997). Labor shortages may induce under-investment in human resource factors as well. For example, a strong economy that generates many job opportunities would lead fewer people to attend school and hence a shortfall in university laboratory employees. In proportional terms, we find that a scientist's additional publication success from taking in one more graduate student (elasticity = 0.61) is greater than that from taking in another laboratory technician (elasticity = 0.25). This possibly is because scientists work jointly with graduate students in co-authoring articles.

Impact of Publication Rates on Research Support

Tables 2, showing the estimated determinants of federal and non-federal funding success, clearly indicate that publication rate affects grant availability. All else constant, another published article per year increases federal support by about $128,000 ($t$ = 7.65). However, it increases non-federal support by only $24000 ($t$ = 4.40), implying state and industry funding allocation decisions do not, as judged by the marginal effects, depend upon scientists' publication success to a great extent. The corresponding elasticity estimates are 1.65 and 1.55. It is consistent with the relative sizes of these positive effects that the official purposes of federal support are to foster scientific discoveries and encourage their communication in the form of publications and patents.

In a time-series study of the input versus output orientation of government funding of university research in five OECD countries, Himanen *et al* (2009) find that output-driven funding allocations, that is research grants allocated mostly on the basis of the scientist's already-observed publications and degrees awarded, lead to competitive university funding environments. Their results imply that government funding in British, Australian, and Finnish universities is largely output-oriented and lead to improved productivity. Many state funds, in contrast, are formula or input-oriented funds, allocated to universities for such infrastructures as buildings, equipment, and staff salaries, and therefore are less conditional on publication rates. State governments and private firms are interested in commercializing research findings that generate profits, as these provide economic benefits. As Ziman (1996) points out, industry-sponsored research appears to be "firm-specific" – research best serving the firms' interest – and thus less focused on producing knowledge with non-market benefits (Ziman 1996; Nieminen 2005). My results in table 2 confirm this conjecture that state and private funds discourage publication of university research results, with the purpose, in the case of private funding, of preventing scientific discoveries from being available to the market competitors. More publications in a scientist's vitae do lead to more non-federal research money. But they may be associated with fewer patents in her vitae, for which we do not account and which presumably lead to less non-federal research money.

Impact of Norms on Research Productivity and Funding

Table 2 shows that the more scientists value the role of scientist panels in determining academic research agendas, the greater is their grant support from federal sources. Private and state funding prospects, on the other hand, are higher for scientists who believe that industries ought to play an important part in setting university research agendas. All else held constant, a one-point increases in the Likert indicator in which the scientist expresses a valuation of scientist-panel influence and industry influence, respectively, over research programs increases her federal and non-federal funding success by \$32,000 and \$16,000 (t = 2.66; t = 4.20) . Scientists who value the commercialization of scientific discoveries, indicated by “marketability of final product” in table 2 regression results, also receive higher non-federal than federal funds (t = 3.18). Presumably this is because they exert greater effort in obtaining these funds. The corresponding elasticities are 0.5 and 0.27, and 0.7 and 0.4 respectively. The estimate of the non-federal-funding reduced-form equation (11) in table 18 implies that one Likert-point increase in the scientist’s valuation of an industry role in setting university research agendas increases the volume of non-federal support by \$17,000 (t = 4.09). This increase in non-federal support is a combined result of norms’ direct effects on funding, and their indirect effects caused by their impacts on publication rate and federal funding, which in turn affect non-federal funding.

Crowding-out Effects of Funding

Our results in table 2 clearly indicate that federal and non-federal funds crowd each other out: a $1000 increase in federal grants reduces the success rate in attracting non-federal funds by $1000 (*t* = - 3.34). And a $1000 increase in non-federal funds reduces the success rate in attracting federal grants by $110 (*t* = - 3.44). At sample means, a 1% rise in federal funds reduces the success rate in drawing non-federal funds by 0.54%, while a 1% rise in non-federal funds reduces the success rate in drawing federal funds by 0.22%. In other words, public and private money substitute for one another. The evidence of crowding-out phenomena is also found in earlier studies by Goolsbe (1998) and Buccola, Ervin, and Yang (2009). The latter study suggests that scientific norms, a proxy for scientist effort, may explain the crowding-out. Diamond (1999) suggests that efficient management of private funds might lower the damaging effect of the crowding-out of federal grants.

Elsewhere in the literature, there is evidence that government support encourages privately sponsored R&D, that is that federal funds crowd-in private funds (Robson, 1993; Khanna *et al*, 1995; Diamond 1999; Payne, 2001). Toole (1999) finds evidence that, with a lag, publicly supported basic research stimulates privately sponsored research. The crowding-in phenomenon is prevalent primarily when government supports fundamental research and private agencies sponsor applied research (Buccola *et al* 2009). By providing the foundation for producing applied scientific knowledge and technology, advancement in basic sciences tends to draw private investment if complementarities between federal and private funds outweigh the scarcity of scientists' time. We should expect to see crowd-out unless the *presence* of federal money in the scientist's portfolio makes it *easier* for him to attract non-federal money, or vice versa. Investing more time to attract federal funds takes away the time she allots to obtain non-federal funds. If increases in non-federal money lead to lower reductions in federal money than increases in federal money lead to reductions in non-federal money, which is what our results imply, it follows that federal sources tend to like to see non-federal money in the scientist's portfolio. Perhaps that is because federal agencies use the presence of non-federal money as a sign that the scientist is connected to cell lines and important research problems through his connections to private industry. Hence, although the scarcity of a scientist's time has the *ceteris paribus* effect that federal and non-federal funds substitute for one another, the magnitude of the crowding-out appears to be lower when it is the non-federal funds.

Table 2 shows public non-Land Grant scientists have, on average, one-half fewer publications per year than do private-university scientists (t = - 1.78), all else constant. And Land Grant and public non-Land Grant scientists receive, respectively, \$159,000 (t = - 3.03) and \$118,000 (t = - 2.23) less federal support than do private university scientists. It is intuitive to compare these structural equation estimates – equation (8) – with the corresponding reduced-form ones – equation (10). The reduced-form estimates of equation (10) in table (32) suggest that scientists employed at Land Grant and non-Land Grant universities receive \$200,000 (t = - 3.63) and \$172,000 (t = - 3.20) less federal funding than do scientists at private universities. These reduced-form estimates are a combined result of the fact that university characteristics directly affect funding success as well indirectly through changes in publication rates and grant support. Both structural and reduced-form estimates show similar trends, suggesting it is the entrepreneurial environments in private universities that facilitate this superior grant support (Buccola *et al* 2009). Although we do not find any evidence of university characteristics influencing the availability of private as well as federal funds, earlier research suggests that private universities receive more private R&D support than do public universities (Payne 2001).

Academic rank by itself does not appear to have any significant impact on research funding. However, tables 2 and 31, showing the results of the structural and reduced-form equations (6) and (9) respectively, indicate *ceteris paribus* that professors achieve higher publication rates than do assistant professors. In both the structural and reduced-form model a full professor publishes, on average, one more article (t_{str} = 4.67, t_{red} = 4.63) than do assistant professors. As Carayol (2003) points out, teaching and administrative responsibilities at the initial phase of their careers, could, besides weak experience, result in lower publication performance simply because of the fixity of a scientist's time. A high teaching load can result in research crowding-out (Himanen *et al*, 2009).

Regression Results – Scientists Receiving either Federal Grants or Grants from both Federal and Non-Federal Sources

We now discuss the results of the subsample that eliminates the population of scientists receiving only non-federal funds, that is that considers scientists receiving either federal grants only or those from both federal and non-federal sources – subsample S_1. The F statistics, in the second-stage, of the joint significance of the instruments excluded respectively from the publication rate, federal funds, and non-federal funds regression equations [equations (6) – (8)] are 20.96, 17.77, and 11.27, compared to the tabled values F (9, 1000) = 3.33 and F (8, 1000) = 2.66 at the 1% level of significance. This confirms the validity of our instruments. The second-stage R-squares in the three equations are 0.26, 0.21, and 0.15 respectively, low but perhaps not unduly so for cross-sectional data. They do indicate the relative difficulty of modeling non-federal funding success. Table 4 shows the estimation results from this sample, consisting of 649 observations.

The table 4 results do not differ largely from the full-sample table 2. As earlier, we find that laboratory budget has no significant impact on publication rate. However, our hypothesis that publication record is an important factor in financial awards is strongly confirmed. All else constant, an additional published article per year draws \$132,000 more federal ($t = 7.31$) and \$24000 ($t = 4.81$) more non-federal funds. Table 4 shows that one more graduate student and technician in the laboratory increases the mean scientist's publication rate by approximately two articles ($t_{grad} = 5.21$, $t_{tech} = 2.27$). Table

34, showing the estimation of reduced-form equation (9), suggests that in contrast another graduate student and technician respectively increase the average scientist's publication rate by about one-quarter (*t* = 4.12) and three-quarters (*t* = 4.03). These results again indicate a crowding-out effect. Tables 7 and 8 estimates together show that the magnitude of the crowding-out effect is greater when initiated by an increased non-federal than by an increased federal grant. In particular, similar to that obtained from the total sample, we find that the next $1000 inflow of federal funds crowds out about $1000 (*t* = - 3.27) of non-federal funds, while an additional $1000 from state governments and industry crowds out $104 (*t* = - 3.31) of federal government grants, controlling for other factors.

As earlier, the structural as well as reduced-form estimates suggest that scientists from both Land Grant and non-Land Grant universities obtain less federal support than do those from private universities. We also find that scientific productivity increases with academic rank. Both tables 4 – structural equation (6) estimates – and table 34 – reduced-form equation (9) estimates – say the average professor publishes about one journal article per year (t_{str} = 4.61, t_{red} = 4.56) more than does the average assistant professor, consistent with the full-sample results. The impacts on grant support of the scientist-norm effects in the present sample are also quite close to those in the whole population. For example, at sample means, a 1% rise in a scientist's expression of his ethical valuation of public-fund support increases his access to federal support by 0.22%, compared to a 0.27 elasticity in the total sample.

Regression Results – Scientists Receiving either Non-Federal Grants or Grants from both Federal and Non-Federal Sources

We next discuss the results of the subsample, consisting of 392 observations, that excluding scientists who receive funds from only federal sources, namely that includes scientists receiving either non-federal funds alone or those from both federal and non-federal sources – subsample S_2. The F statistics of the joint significance in the second-stage, of the instruments excluded from the publication rate, federal funds, and non-federal funds regression equations [equations (6) – (8)] are 13.76, 9.34, and 5.73, respectively, compared to the tabled values F (9, 500) = 3.16 and F (8, 500) = 3.33 at 1% level of significance. This confirms the validity of using instruments. We conclude that the second-stage R-squares in the three equations are respectively 0.27, 0.18, and 0.12, not inconsiderable for cross-sectional data. Table 6 shows the results of this restricted sample.

Model estimates of equations (6) – (8) in table 6 are similar to those in the unrestricted (total) sample and in the sample excluding scientists who receive non-federal funds alone – subsample S_1. However, we find two differences in the present restricted sample: laboratory post-doctorates have a significant marginal impact on publication rate (t = 2.18) while the number of technicians does not. And, university characteristics significantly reduce scientific productivity. This implies that Land-Grant and Non-Land-Grant scientists receiving financial support predominantly from state government and industry tend to publish fewer articles, possibly because university policies motivate them to emphasize research patents and commercial applications, which often involve publication postponement.

As indicated above, a positive and significant *t* value on the number of graduates and post-doctorates implies an allocatively inefficient laboratory, that is scientists do not distribute resources optimally between labor and non-labor inputs. However, because the number of technicians here is not significantly different from zero, scientists in this subsample do appear to hire an optimal number of laboratory technicians. Thus, positive and significant coefficients on the number of graduate students and post-doctorates imply that scientists hire fewer graduates and post-doctorates than they should in order to minimize the cost of achieving a given publication rate. In other words, they under-invest in research personnel and over-invest in non-labor factors such as genomic databases, software, cell lines, and reagents, assuming a constant research budget. All else constant, an average Land Grant (LG) and non-Land Grant (PNLG) university scientist publishes one less article (t_{lg} = - 1.86 and t_{pnlg} = - 1.91) than does a private university scientist. This estimate is similar to the one in table 37, which gives the reduced-form results, equation (9).

Regression Results - Scientists Receiving Federal Grants Only

Finally, we discuss the results of the subsample, consisting of 308 observations, which includes scientists receiving funds from federal sources only – subsample S_3. The *F* statistics of the joint significance in the second-stage of the instruments excluded from the publication rate and federal funds regression equations [equations (6) and (7)] are 13.41 and 11.02 respectively, compared to the tabled values *F* (9, 500) = 3.16 and *F* (8, 500) = 3.33 at 1% level of significance, suggestive of the significance of the model's instruments. The 2nd stage R-squares in the two equations are 0.31 and 0.25 respectively, not unduly low for cross-sectional data. Table 8 shows the estimates obtained for this sample that is restricted to federal funds.

As earlier, table 8 shows that, all else constant, one more publication per year increases a scientist's federal support by $112,000 ($t$ = 4.49). We also find, similar to the estimates obtained with the earlier samples, that Land Grant and non-Land Grant scientists draw less financial support than do private university scientists. Structural equation estimates, in table 8, of the equation determining federal-funding success [equation (7)] show that a Land Grant scientist draws $228,000 ($t$ = - 3.24) less federal funds than does a private university scientist. The corresponding reduced-form estimation results in table 41 implies that a Land Grant scientist receives $158,000 ($t$ = - 2.25) less federal support than does a private university scientist. Table 8 [structural equation (6) estimates] and 40 [reduced-form equation (9) estimates] show that professors, on average, publish one more article (t_{str} = 4.34, t_{red} = 4.60) than do assistant professors, controlling for other factors. We drop from this specification the norm representing a scientist's belief that peer-review panels should determine research agendas because, unlike state and industry grants, most federal awards are determined largely by peer-review panels. Instead we include, as an identifying variable in the federal funds equation, a scientist's Likert-scale valuation for producing research with public benefits. All else held constant, a one-point increase in the Likert indicator measure of this public-good norm increases federal support by $36,000 ($t = 2.32$), close to the corresponding reduced-form estimate of $33,000 ($t = 2.17$). We therefore find that as public goods become more valuable, so that scientists presumably exert more effort in producing knowledge with public benefits, their access to federal support rises.

Our attempt to model the population of scientists receiving grants from non-federal sources alone fails, possibly because the sample size is very small ($N = 51$) relative to the population ($N = 720$). The F statistics of the joint significance in the second-stage of the instruments excluded from the publication rate and non-federal funding regression equations [equations (6) and (8)] are, respectively, 0.96 and 2.08 compared to the tabled values $F(8, 50) = 4.00$ and $F(7, 50) = 4.22$, at 1% level of significance. These low F values serve to undermine our confidence in the instruments we use for estimating the nonfederal-funds-only simultaneous model.

In summary, we can infer that 3SLS results in table 2 are broadly robust to the disaggregation of the total population into subsamples connected to sources of financial support. Federal research grants substitute for non-federal ones, and federal grants crowd-out non-federal ones, rather than complement one another. Scientists over-invest in equipment and materials and generally under-invest in skilled labor. That is, they hire fewer research personnel than they ought in order to minimize the cost of producing given publication output. Scientific norms, a proxy for unobserved fund-raising effort, play a significant role in attracting funds from both federal and non-federal sources. Although academic rank does not appear to influence research financing, professors do on average achieve higher publication success than do assistant professors.

Conclusions

We have developed a simultaneous model of causal interactions between the scientific productivity, measured by publication rates, and the financial support of academic bioscientists employed at major US universities. In this study, the National Science Foundation, National Institutes of Heath, U. S. Department of Agriculture, and other federal sources such as Department of Energy and Department of Defense, are combined along with private foundations to form the “federal” category while state governments and private firms comprise the “non-federal” category.

Earlier research has examined the role of financial agencies in influencing academic productivity, but none have done so in a way that accounts for the simultaneous influence of funding on productivity. That has been my goal in the present essay. I have paid particular attention to the differences in this respect between federal and non-federal funding.

Hausman Specification test results, in the total population as well as the subsamples, indicate simultaneity between publication and research support. Hence we use three-stage least square procedures to estimate the models. We find, under *ceteris paribus* conditions, that a scientist’s publication rates greatly affect research funding success. Yet federal agencies' funding decisions are more publication-rate-affected than are state government and private-firm funding decisions. Universities' reliance on external funding sources has encouraged them to undertake a wide range of activities, from increasing their scientific capacities to collaborating with financial agencies and marketing research findings. Federal sources publicly endorse the value of disseminating scientific discoveries through publications. They recognize the need for broad utilization of university research for the general public benefit and therefore encourage the researchers they fund to publish their results in peer-reviewed journals. Non-federal sources' and, to perhaps a slightly smaller extent state governments, are on the other hand more motivated by commercial benefits. Because they are primarily interested in sponsoring research that can be commercialized, they often encourage withholding or delaying the publication of potentially profitable research results (Niemann, 2005).

Our results also imply that funding from federal and non-federal sources substitute for rather than complement one another. The fact that a scientist has a limited amount of time to apply for grant money implies, to that extent, that federal and non-federal money substitute for one another, that is crowd each other out. We model the hypothesis that on the one hand laboratory size, measured by employee numbers, influences scientific productivity, but that scientific productivity on the other hand influences – through grant success – labor recruitment. By including the number of laboratory workers together with funding volumes, our model provides a test of allocative efficiency, that is whether scientists distribute their resources efficiently across types of inputs. Importantly, we find that the average scientist misallocates resources between labor and non-labor inputs, recruiting too few research personnel and overusing such non-labor factors as laboratory equipment, cell lines, and reagents. Expressed differently, the per-dollar marginal productivity of labor inputs is higher than that of non-labor inputs. This is suggestive of the importance of human resources in influencing research productivity. Despite high labor productivity, scientists and universities appear to over-invest in equipment and buildings, possibly because they believe such infrastructure is valuable in attracting students, faculty, and research financial support.

References

Adams, J. D., G. C. Black, J. R. Clemmons, P. E. Stephan, 2005. “Scientific teams and institutional collaborations: Evidence from US universities, 1981-1999.” *Research Policy 34(3): 259-285.*

Alison, P. D., J. S. Long. 1990. “Departmental Effects on Scientific Productivity.” *American Sociological Review 55:469-478.*

Baser, O., E. Pema, “Publications over the Academic Life-Cycle: Evidence for Academic Economists.” *Economics Bulletin 1(1):1-8.*

Becker, G. S., K. Murphy, 1992. “The Divisions of Labor, Co-ordination costs, and knowledge.” *Quarterly Journal of Economics, 107(4):1137-1160.*

Berardo, F.M. 1989. “Scientific Norms and Research Publications: Issues and Professional Ethics.” *Sociological Enquiry 59 (3):119-141.*

Blumenthal, D., M. Gluck, K. Louis., M. A. Stoto, D. Wise, 1986.”University-Industry Research Relationships in Biotechnology: Implications for the University.”*Science 232:1361-1366.*

Blumenthal, D., N. Causino, E. Campbell, and K. Louis, 1996. “Relationships between academic institutions and industry in the life sciences – an industry survey.” *The New England Journal of Medicine 334(6): 368-374.*

Boss, J. M, S. H. Eckert, 2003. “Academic Scientists at Work: Navigating the Biomedical Research Center” *Springer-Verlag New York, LLC 2nd edition.*

Boumahdi, R., N. Carayol, P. Llerena, 2008. “The Private Contractual Funding of Academic Laboratories: A Panel Data Analysis.” *Applied Economics Letters 15(6):465-468.*

Bozeman, B., S. Lee, 2003. “The Impact of Research Collaboration on Scientific Productivity.” *Paper prepared for presentation at the AAAS Annual Meetings, Colorado, Denver, February, 2003*.

Bredhal, M., W.K. Bryant, V. W. Ruttan. 1980. “Behavior and Productivity Implications Of Institutional And Project Funding Of Research.” *American Journal of Agricultural Economics 62(3):371-383.*

Buccola, S., David Ervin, and H. Yang. 2009. “Research Finance and choice in University Bioscience.” *Southern Economic Journal 75 (4):1238-1255*.

Carayol, N., M. Matt. 2004. “Does Research Organization Influence Academic Production: Laboratory Evidence from a Large European University.” *Research Policy 33(8):1081-1102*.

Connolly, L. S. 1997. “Does External Funding of Academic Research Crowd out Institutional Support? *Journal of Public Economics 64:389-406*.

David, P. A., B. H. Hall, A. Toole, 1999. “Is Public R&D a complement or substitute for Private R&D? A Review of the Econometric Evidence.” Prepared for the special issue of *Research Policy* on technology policy issues forthcoming in the year 2000.

Denton, F. T., C. Feaver, B. G Spencer, 1997. “Student Enrollment and Faculty Renewal: The Response of a Tenure-based University System to Demographic and Budgetary shocks.” *Journal of Economic Behavior and Organization 34 (1):101-127.*

Diamond, A. M. 1999. “Does Federal Funding crowd-in Private Funding in Science?” *Contemporary economic Policy* 17(4):423-431.

Ehrenberg, R. G., M. J. Rizzo, G. H. Jacubson. 2003. “Who Bears the Growing Cost of Science at Universities?” *ILR collections working papers*.

Ellison, G., 2002. “The Slowdown of the Economics Publishing Process.” *Journal of Political Economy 110(5): 947-993.*

Guena, A., 1997. “Allocation of funds and Research Output: The Case of UK universities.” *Revue d’Economie Industrielle.*

Gulsbranden, M., J. C. Smeby. 2005 “Industry Funding and University professors’ Research Performance.”*Research Policy 34(6):932-950.*

Gupta, H. M., J. R. Campanha, R. A. G. Pesce, 2005. “Power – Law Distributions for citation Index of scientific publications and scientists.” *Brazilian Journal of Physics, 35(4A): 981-986.*

Himanen, L., O. Auranen, H. M. Puska, M. Nieminen, 2009. “Influence of Research Funding and Science Policy on University Research Performance: a comparison of five countries.” *Science and Public Policy.*

Kelnar, K. 2007. “3 skills for the Academic Scientist” *dx.doi.org/10.1126/science. Caredit.a0700046.*

Lefkowitz, J. 2003. “Ethics and Values in Industrial-Organizational Psychology” Book

National Science Board. 2008 “Academic Research and Development.” *Science and Engineering Indicators Chapter 5.*

Nieminen, M. 2005. “Academic Research in Change: Transformation of Finnish university Policies and University Research during the 1990s.” *Finnish Society of Sciences and Letters.*

Payne, A. 2001. “Measuring the Effects of Federal Research funding on Private Donations at Research Universities: Is Federal Research funding more than a substitute for Private Donations?” *International Tax and Public Finance, 8(5-6):731-751.*

Shavelson, R., L. Towne. “On Scientific Research in Education: Questions not Methods should Drive the Enterprise.” *http://www.stanford.edu/dept/SUSE/SEAL/Reports_Papers/On%20Scientific%20Research%20in%20Education_Questions%20.doc.*

Stephan, P., 2005. “Job Market Effects on Scientific Productivity.” *Paper built on the presentation at the conference “The Future of Science” Venice, Italy, September, 2005.*

Toole, A. 1999. “Public Research, Public Regulation and Expected Profitability: The Determinants of Pharmaceutical Research and Development Investment.” *Stanford Institute for Economic Policy Research Working Paper*.

Turner, L., J. Mairesse, 2003. “Individual Productivity Differences in Public Research: How important are Non-individual Determinants - An Econometric Study of French Physicists Publications (1986-1997). *NBER working papers*.

Wang, C., Y. Xia, S. Buccola, 2009. “Public Investment and Industry Incentives in Life-Science Research.” *American Journal of Agricultural Economics 91(2):374-388.*

Wheeler, A. G., 1989. “The Pressure to Publish Promotes Disreputable Science.” *The Scientist July 10, 1989.*

Wooldridge, J. M, 2001. “Econometric Analysis of Cross-section and Panel Data” published by the *MIT Press*

Xia, Y., S. Buccola. 2005. “University Life Science Programs and Agricultural Biotechnology.” *American Journal of Agricultural Economics 87(1):229-243.*

Ziman, J. 1996. “Post-Academic Science”: Constructing knowledge with Networks and Norms.” *Science Studies 9(1):67-80.*

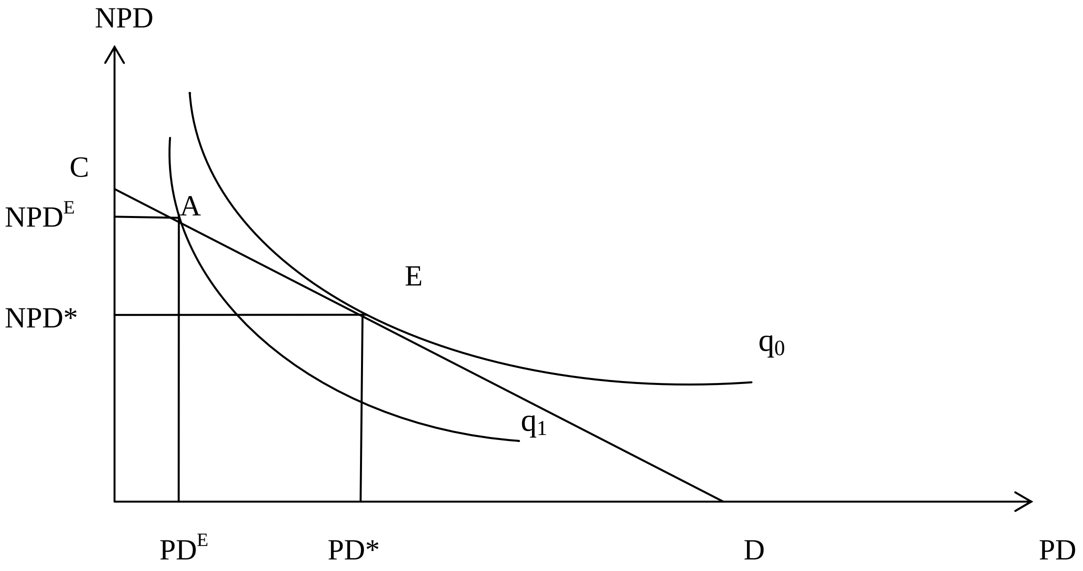


Figure 1: Allocative Efficiency Between Labor and Non-Labor inputs

TABLE 1: Summary Statistics (Whole Sample *N* = 720)

Variable	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Publication Rate	2.836	2.337	0	27.5
Federal Funding	227.309	365.635	0	4500
Nonfederal Funding	46.178	105.243	0	1050
Laboratory Employees				
No. of Graduates	2.424	2.238	0	26
No. of Post Doctorates	1.400	2.295	0	29
No. of Technicians	1.158	1.353	0	15
Scientist Norms				
Panel Agenda	3.512	1.251	0	5
Public Fund	5.572	1.709	1	7
Industry Agenda	1.925	1.015	0	5
Market Final Product	2.603	1.813	1	7
Academic Rank				
Prof	0.486	0.500	0	1
Assoc	0.247	0.431	0	1
Univ Type				
Land-Grant Univ	0.488	0.500	0	1
Non-Land Grant Univ	0.354	0.478	0	1

TABLE 2: Factors Influencing Publication Rate, Federal Funding, and Non-federal Funding (Whole Sample)

	Publication Rate		Federal Fund		Non-Federal Fund	
Variable	Parameter	*t*	Parameter	*t*	Parameter	*t*
Constant	0.479	1.18	-112.20	-1.2	-48.63	-2.43
Publication Rate			129.296	7.65	24.604	4.40
Federal Funding	0.000	0.75			-0.11	-3.44
Non-Federal Funding	-0.002	-1.22	-1.069	-3.34		
Laboratory Employees						
No. of Graduates	0.547	5.15				
No. of Post Doctorates	0.129	1.36				
No. of Technicians	0.611	2.56				
Laboratory Employees						
Scientific Norms						
Panel Agenda			32.133	2.66		
Public Funds			11.107	1.32		
Industry Agenda					16.818	4.20
Market Final Product					7.161	3.18

Variable	Parameter	*t*	Parameter	*t*	Parameter	*t*
Academic Rank (Base :Assistant Prof)						
Professor	1.044	4.67	-36.060	-0.84	-8.290	-0.70
Associate Professor	0.376	1.56	-24.840	-0.60	-12.480	-1.09
Univ Type (Base: Private Univ)						
Land-Grant Univ	-0.423	-1.21	-159.80	-3.03	13.327	0.87
Non-Land-Grant Univ	-0.607	-1.78	-118.60	-2.23	4.299	0.28
R square:	**0.26**		**0.22**		**0.13**	

TABLE 3: Summary Statistics (Receivers of Federal Funding or Federal-and-Nonfederal Funding *N* = 649)

Variable	Mean	Std Dev	Minimum	Maximum
Publication Rate	2.954	2.373	0	27.5
Federal Funding	252.176	376.904	2	4500
Nonfederal Funding	45.303	107.898	0	1050
Laboratory Employees				
No. of Graduates	2.554	2.290	0	26
No. of Post Doctorates	1.524	2.378	0	29
No. of Technicians	1.206	1.382	0	15
Scientist Norms				
Panel Agenda	3.534	1.245	0	5
Public Fund	5.637	1.665	1	7
Industry Agenda	1.925	1.034	0	5
Market Final Product	2.593	1.802	1	7
Academic Rank				
Prof	0.496	0.500	0	1
Assoc	0.249	0.433	0	1
Univ Type				
Land-Grant Univ	0.488	0.500	0	1
Non-Land Grant Univ	0.348	0.476	0	1

TABLE 4: Factors Influencing Publication Rate, Federal Funding, and Non-federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

	Publication Rate		Federal Fund		Non-Federal Fund	
Variable	Parameter	*t*	Parameter	*t*	Parameter	*t*
Constant	0.435	1.03	-119.60	-1.18	-60.26	-2.91
Publication Rate			131.608	7.23	26.78	4.79
Federal Funding	0.000	0.91			-0.105	-3.31
Non-Federal Funding	-0.000	-0.87	-1.131	-3.27		
Laboratory Employees						
No. of Graduates	0.547	5.21				
No. of Post Doctorates	0.131	1.42				
No. of Technicians	0.544	2.27				
Laboratory Employees						
Scientific Norms						
Panel Agenda			31.749	2.40		
Public Funds			12.132	1.28		
Industry Agenda					16.274	3.86
Market Final Product					7.407	3.02

Variable	Parameter	*t*	Parameter	*t*	Parameter	*t*
Academic Rank (Base :Assistant Prof)						
Professor	1.102	4.61	-37.06	-0.78	-9.111	-0.71
Associate Professor	0.469	1.81	-26.9	-0.58	-8.977	-0.72
Univ Type (Base: Private Univ)						
Land-Grant Univ	-0.497	-1.39	-149.9	-2.66	17.917	1.14
Non-Land-Grant Univ	-0.589	-1.71	-112.5	-2.02	5.700	0.37
R square:	**0.26**		**0.21**		**0.15**	

TABLE 5: Summary Statistics (Receivers of Non-Federal Funding or Federal-and-Nonfederal Funding *N* = 392)

Variable	Mean	Std Dev	Minimum	Maximum
Publication Rate	2.92	2.638	0	27.5
Federal Funding	177.784	363.425	0	3800
Nonfederal Funding	84.817	130.698	0.9	1050
Laboratory Employees				
No. of Graduates	2.668	2.525	0	26
No. of Post Doctorates	1.145	2.224	0	29
No. of Technicians	1.222	1.492	0	15
Scientist Norms				
Panel Agenda	3.300	1.251	0	5
Public Fund	5.580	1.740	1	7
Industry Agenda	2.094	1.055	0	5
Market Final Product	3.150	1.948	1	7
Academic Rank				
Prof	0.527	0.499	0	1
Assoc	0.219	0.414	0	1
Univ Type				
Land-Grant Univ	0.711	0.453	0	1
Non-Land Grant Univ	0.22	0.419	0	1

TABLE 6: Factors Influencing Publication Rate, Federal Funding, and Non-federal Funding (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

	Publication Rate		Federal Fund		Non-Federal Fund	
Variable	Parameter	*t*	Parameter	*t*	Parameter	*t*
Constant	1.566	2.10	-127.3	-0.87	7.706	0.19
Publication Rate	0.000	0.50	89.112	5.00	19.04	3.04
Federal Funding	-0.000	-0.69			-0.082	-1.98
Non-Federal Funding			-0.623	-1.93		
Laboratory Employees						
No. of Graduates	0.439	3.55				
No. of Post Doctorates	0.302	2.18				
No. of Technicians	0.397	1.41				
Laboratory Employees						
Scientific Norms						
Panel Agenda			42.992	2.66		
Public Funds			15.343	1.36		
Industry Agenda					25.417	4.10
Market Final Product					4.541	1.40

Variable	Parameter	*t*	Parameter	*t*	Parameter	*t*
Academic Rank (Base :Assistant Prof)						
Professor	1.058	3.15	22.582	0.41	4.624	0.25
Associate Professor	0.584	1.55	0.432	0.01	-16.07	-0.83
Univ Type (Base: Private Univ)						
Land-Grant Univ	-1.263	-1.86	-156.3	-1.58	-37.9	-1.14
Non-Land-Grant Univ	-1.373	-1.91	-148.0	-1.41	-14.79	-0.42
R square:	**0.27**		**0.19**		**0.12**	

TABLE 7: Summary Statistics (Receivers of Federal Funding only $N = 308$)

Variable	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Publication Rate	2.823	1.931	0.25	3.313
Federal Funding	305.100	363.754	6	4500
Laboratory Employees				
No. of Graduates	2.201	1.823	0	10
No. of Post Doctorates	1.791	2.384	0	17
No. of Technicians	1.120	1.180	0	9
Scientist Norms				
Public Fund	5.602	1.626	1	7
Public Good	5.149	1.505	1	7
Academic Rank				
Prof	0.445	0.497	0	1
Assoc	0.288	0.453	0	1
Univ Type				
Land-Grant Univ	0.230	0.421	0	1
Non-Land Grant Univ	0.500	0.500	0	1

TABLE 8: Factors Influencing Publication Rate and Federal Funding (Receivers of Federal Funding only)

	Publication Rate		Federal Fund	
Variable	Parameter	*t*	Parameter	*t*
Constant	0.75	1.79	-64.16	-0.52
Publication Rate			115.868	4.49
Federal Funding	0.000	1.36		
Laboratory Employees				
No. of Graduates	0.371	3.06		
No. of Post Doctorates	0.073	0.83		
No. of Technicians	0.332	1.63		
Laboratory Employees				
Scientific Norms				
Public Fund			3.826	0.28
Public Good			36.927	2.36
Academic Rank (Base: Assistant Prof)				
Professor	1.122	4.34	-33.42	-0.51
Associate Professor	0.270	1.00	-23.63	-0.38
Univ Type (Base: Private Univ)				
Land-Grant Univ	-0.074	-0.22	-227.9	-3.24
Non-Land-Grant Univ	-0.355	-1.23	-147.00	-2.42
R square:		**0.31**		**0.25**

Table 2.1: Hausman Test Result: Publication Rate (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	2.300	1.235	1.86
Federal Funds	0.006	0.002	3.11
Non-Federal Funds	0.015	0.006	2.51
Graduate	1.005	0.141	7.13
Post doctorate	1.485	0.161	9.19
Technician	0.421	0.252	1.67
Professor	3.251	0.739	4.40
Associate Professor	1.287	0.801	1.61
Land Grant University	0.441	1.111	0.40
Non-Land Grant University	-0.260	1.0765	-0.24
Residual of federal funds	-0.005**	0.002	-2.52
Residual of non-federal funds	-0.006	0.0067	-0.93

Table 3.1: Hausman Test Result: Federal Funding (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	-128.800	91.420	-1.41
Publication	33.584	4.0870	8.22
Non-Federal Funds	-0.671	0.311	-2.15
Panel Agenda	31.971	12.027	2.66
Public Funds	9.210	8.3769	1.10
Professor	-48.070	41.107	-1.17
Associate Professor	-25.320	39.881	-0.63
Land Grant University	-164.900	50.712	-3.25
Non-Land Grant University	-110.700	50.920	-2.17
Residual of Publication	-23.610***	4.471	-5.28
Residual of non-federal funds	1.189**	0.351	3.38

Table 4.1: Hausman Test Result: Non-federal Funding (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	-64.090	19.211	-3.34
Publication	6.395	1.366	4.68
Federal Funds	-0.085	0.0313	-2.71
Industry Agenda	17.003	3.9791	4.27
Market Final Goods	7.527	2.2414	3.36
Professor	-13.650	11.343	-1.2
Associate Professor	-14.510	10.945	-1.33
Land Grant University	23.609	14.686	1.61
Non-Land Grant University	13.898	14.422	0.96
Residual of Publication	-3.378**	1.454	-2.32
Residual of federal funds	0.122***	0.033	3.65

Table 6.1: Hausman Test Result: Publication Rate (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	2.479	1.264	1.96
Federal Funds	0.005	0.002	2.82
Non-Federal Funds	0.016	0.006	2.72
Graduate	0.974	0.147	6.61
Post doctorate	1.491	0.163	9.11
Technician	0.409	0.263	1.55
Professor	3.430	0.788	4.35
Associate Professor	1.444	0.857	1.69
Land Grant University	0.064	1.126	0.06
Non-Land Grant University	-0.31	1.085	-0.29
Residual of federal funds	-0.005**	0.002	-2.26
Residual of non-federal funds	-0.007	0.006	-1.02

Table 7.1: Hausman Test Result: Federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-130.000	99.082	-1.31
Publication	33.601	4.408	7.62
Non-Federal Funds	-0.709	0.337	-2.10
Panel Agenda	32.258	13.185	2.45
Public Funds	10.010	9.473	1.06
Professor	-47.510	45.501	-1.04
Associate Professor	-28.520	44.235	-0.64
Land Grant University	-157.80	54.242	-2.91
Non-Land Grant University	-106.300	53.507	-1.99
Residual of Publication	-23.800***	4.835	-4.92
Residual of non-federal funds	1.269**	0.381	3.33

Table 8.1: Hausman Test Result: Non-federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-76.370	19.795	-3.86
Publication	6.885	1.359	5.06
Federal Funds	-0.077	0.030	-2.48
Industry Agenda	16.416	4.184	3.92
Market Final Goods	7.767	2.439	3.18
Professor	-14.88	12.178	-1.22
Associate Professor	-11.14	11.842	-0.94
Land Grant University	28.672	14.953	1.92
Non-Land Grant University	15.329	14.631	1.05
Residual of Publication	-3.727**	1.457	-2.56
Residual of federal funds	0.115***	0.033	3.46

Table 10.1: Hausman Test Result: Publication Rate (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	3.889	2.309	1.68
Federal Funds	0.005	0.002	2.13
Non-federal Funds	0.011	0.006	1.63
Graduate	0.992	0.191	5.20
Post doctorate	2.002	0.245	8.17
Technician	0.417	0.364	1.15
Professor	3.246	1.086	2.99
Associate Professor	2.006	1.221	1.64
Land Grant University	-1.474	2.101	-0.7
Non-Land Grant University	-2.040	2.233	-0.91
Residual of federal funds	-0.006**	0.002	-2.22
Residual of non-federal funds	-0.005	0.007	-0.68

Table 11.1: Hausman Test Result: Federal Funding (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-202.300	138.94	-1.46
Publication	23.478	4.240	5.54
Non-federal funds	-0.092	0.313	-0.30
Public Goods	42.207	15.938	2.65
Public Funds	12.472	11.193	1.11
Professor	5.6114	50.871	0.11
Associate Professor	-0.845	53.369	-0.02
Land Grant University	-107.700	92.734	-1.16
Non-Land Grant University	-108.600	98.484	-1.10
Residual of Publication	-15.200**	4.766	-3.19
Residual of non-federal funds	0.895**	0.360	2.49

Table 12.1: Hausman Test Result: Non-federal Funding (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-26.770	37.781	-0.71
Publication	5.125	1.496	3.42
Federal Funds	-0.022	0.040	-0.54
Industry Agenda	24.923	6.082	4.10
Market Final Goods	4.935	3.216	1.53
Professor	-7.977	17.280	-0.46
Associate Professor	-21.230	17.878	-1.19
Land Grant University	-9.311	30.960	-0.30
Non-Land Grant University	14.836	33.070	0.45
Residual of Publication	-1.958	1.664	-1.18
Residual of federal funds	0.110**	0.0448	2.46

Table 14.1: Hausman Test Result: Publication Rate (Receivers of Federal Funding only)

Variable	Coefficient	Std Error	*t* - Value
Constant	3.775	1.363	2.77
Federal Funds	0.004	0.002	1.82
Graduate	0.907	0.210	4.31
Post doctorate	0.943	0.205	4.59
Technician	0.524	0.331	1.58
Professor	4.057	0.938	4.32
Associate Professor	0.886	0.990	0.90
Land Grant University	0.481	1.239	0.39
Non-Land Grant University	-0.640	1.027	-0.62
Residual of federal funds	-0.002	0.002	-0.83

Table 15.1: Hausman Test Result: Federal Funding (Receivers of Federal Funding only)

Variable	Coefficient	Std Error	*t* - Value
Constant	-89.560	120.72	-0.74
Publication	31.562	6.3456	4.97
Public Goods	35.942	15.423	2.33
Public Funds	4.1303	13.626	0.30
Professor	-47.200	64.326	-0.73
Associate Professor	-28.080	60.466	-0.46
Land Grant University	-219.800	69.013	-3.18
Non-Land Grant University	-136.300	59.676	-2.28
Residual of Publication	-19.220**	7.457	-2.58

Table 16: Reduced Form: Factors Influencing Publication Rate (Whole Sample)

Variable	Coefficient	Std Error	*t* - value
Constant	0.976*	2.249	1.74
Graduate	0.428***	0.449	3.81
Post Doctorate	0.188**	0.382	1.97
Technician	0.762***	0.744	4.10
Panel Agenda	-0.099	0.297	-1.33
Public Funds	0.016	0.203	0.32
Industry Agenda	-0.036	0.364	-0.39
Market Final Goods	-0.017	0.210	-0.33
Professor	1.013***	0.874	4.63
Associate Professor	0.414*	0.963	1.72
Land Grant University	-0.549*	1.305	-1.68
Non-Land Grant University	-0.675**	1.278	-2.11

R square: 0.25

Table 17: Reduced Form: Factors Influencing Federal Funding (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	23.997	94.849	0.25
Graduate	6.985	18.930	0.37
Post Doctorate	38.987**	16.115	2.42
Technician	144.14***	31.372	4.59
Panel Agenda	17.798	12.528	1.42
Public Funds	16.015*	8.5697	1.87
Industry Agenda	-20.350	15.349	-1.33
Market Final Goods	-8.607	8.8604	-0.97
Professor	68.360	36.855	1.85
Associate Professor	39.555	40.633	0.97
Land Grant University	-199.800**	55.030	-3.63
Non-Land Grant University	-172.600**	53.889	-3.20

R square: 0.23. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 18: Reduced Form: Factors Influencing Non-Federal Funding (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	-23.570	26.168	-0.90
Graduate	10.540**	5.222	2.02
Post Doctorate	-4.573	4.445	-1.03
Technician	34.081***	8.655	3.94
Panel Agenda	-5.510	3.456	-1.59
Public Funds	-5.916**	2.364	-2.50
Industry Agenda	17.316***	4.234	4.09
Market Final Goods	5.5256**	2.444	2.26
Professor	5.513	10.168	0.54
Associate Professor	-4.421	11.210	-0.39
Land Grant University	26.084*	15.182	1.72
Non-Land Grant University	8.426	14.868	0.57

R square: 0.16

Table 19: Reduced Form: Factors Influencing Publication Rate (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	1.004*	2.372	1.69
Graduate	0.447***	0.434	4.12
Post Doctorate	0.171*	0.379	1.81
Technician	0.769***	0.763	4.03
Panel Agenda	-0.099	0.318	-1.25
Public Funds	0.003	0.222	0.06
Industry Agenda	-0.115	0.382	-0.30
Market Final Goods	-0.029	0.229	-0.44
Professor	1.068***	0.937	4.56
Associate Professor	0.493*	1.037	1.90
Land Grant University	-0.623*	1.340	-1.86
Non-Land Grant University	-0.678**	1.305	-2.08

R square: 0.26

Table 20: Reduced Form: Factors Influencing Federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	51.267	102.590	0.50
Graduate	5.0422	18.763	0.27
Post Doctorate	33.615**	16.393	2.05
Technician	153.95***	32.997	4.67
Panel Agenda	15.789	13.758	1.15
Public Funds	14.843	9.6371	1.54
Industry Agenda	-21.650	16.524	-1.31
Market Final Goods	-8.272	9.907	-0.83
Professor	67.961*	40.492	1.68
Associate Professor	40.174	44.854	0.90
Land Grant University	-204.200**	57.970	-3.52
Non-Land Grant University	-170.400**	56.428	-3.02

R square: 0.23. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 21: Reduced Form: Factors Influencing Non-Federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-33.210	27.801	-1.19
Graduate	13.029**	5.084	2.56
Post Doctorate	-3.596	4.442	-0.81
Technician	32.735***	8.941	3.66
Panel Agenda	-4.410	3.728	-1.18
Public Funds	-6.765**	2.611	-2.59
Industry Agenda	16.572**	4.477	3.70
Market Final Goods	5.666	2.684	2.11
Professor	8.079	10.973	0.74
Associate Professor	1.759	12.155	0.14
Land Grant University	26.932*	15.709	1.71
Non-Land Grant University	6.851	15.291	0.45

R square: 0.16

Table 22: Reduced Form: Factors Influencing Publication Rate (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	2.399**	3.669	2.62
Graduate	0.371**	0.545	2.72
Post Doctorate	0.323**	0.569	2.27
Technician	2.670**	0.912	2.93
Panel Agenda	-0.667**	0.440	-2.12
Public Funds	0.003	0.322	0.04
Industry Agenda	-0.099	0.548	-0.72
Market Final Goods	-0.015	0.278	-0.21
Professor	3.765**	1.339	2.81
Associate Professor	0.941	1.491	1.64
Land Grant University	-1.266*	2.692	-1.88
Non-Land Grant University	-1.433**	2.832	-2.02

R square: 0.28. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 23: Reduced Form: Factors Influencing Federal Funding (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-3.555	137.860	-0.03
Graduate	7.872	20.505	0.38
Post Doctorate	40.370*	21.386	1.89
Technician	121.59**	34.281	3.55
Panel Agenda	16.864	16.567	1.02
Public Funds	15.532	12.121	1.28
Industry Agenda	-22.310	20.611	-1.08
Market Final Goods	-4.545	10.452	-0.43
Professor	73.715	50.311	1.47
Associate Professor	67.380	56.036	1.20
Land Grant University	-173.300*	101.170	-1.71
Non-Land Grant University	-199.500*	106.440	-1.87

R square: 0.19. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 24: Reduced Form Results: Factors Influencing Non-Federal Funding (Receivers of Non-Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	45.228	45.854	0.99
Graduate	3.351	6.820	0.49
Post Doctorate	1.622	7.113	0.23
Technician	45.619***	11.402	4.00
Panel Agenda	-8.878	5.510	-1.61
Public Funds	-6.545	4.031	-1.62
Industry Agenda	22.919**	6.855	3.34
Market Final Goods	2.335	3.476	0.67
Professor	6.555	16.734	0.39
Associate Professor	-4.854	18.638	-0.26
Land Grant University	-22.660	33.649	-0.67
Non-Land Grant University	-7.286	35.402	-0.21

R square: 0.17

Table 25: Reduced Form: Factors Influencing Publication Rate (Receivers of Federal Funds only)

Variable	Coefficient	Std Error	*t* - Value
Constant	0.431	2.268	0.76
Graduate	0.405**	0.472	3.43
Post Doctorate	0.156**	0.318	1.97
Technician	0.460**	0.712	2.58
Public Fund	0.039	0.250	0.62
Public Good	0.164	0.282	0.58
Professor	0.041***	1.017	4.60
Associate Professor	0.236	1.089	0.87
Land Grant University	-0.237	1.297	-0.73
Non-Land Grant University	-0.467*	1.086	-1.72

R square: 0.31. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 26: Reduced Form: Factors Influencing Federal Funding (Receivers of Federal Funds only)

Variable	Coefficient	Std Error	*t* - Value
Constant	-105.300	123.090	-0.86
Graduate	34.758	25.547	1.36
Post Doctorate	52.757**	17.269	3.06
Technician	102.55**	38.700	2.65
Public Fund	9.332	13.585	0.69
Public Good	33.377**	15.356	2.17
Professor	56.472	55.121	1.02
Associate Professor	-17.700	59.202	-0.30
Land Grant University	-158.700**	70.502	-2.25
Non-Land Grant University	-121.100**	59.001	-2.05

R square: 0.30. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 27: OLS Result: Factors Influencing Publication Rate (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	0.887***	0.903	3.93
Federal Funds	0.000*	0.001	1.92
Non-Federal Funds	0.000*	0.003	1.90
Graduate	0.246***	0.132	7.45
Post doctorate	0.379***	0.149	10.19
Technician	0.218***	0.217	4.01
Professor	0.932***	0.656	5.68
Associate Professor	0.289	0.738	1.57
Land Grant University	-0.076	0.830	-0.37
Non-Land Grant University	-0.203	0.846	-0.96

R square: 0.45

TABLE 28: OLS Result: Factors Influencing Federal Funding (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	44.159	66.303	0.67
Publication	54.400***	1.489	9.13
Non-Federal Funds	0.300**	0.125	2.37
Panel Agenda	20.480**	10.160	2.02
Public Funds	15.628**	7.337	2.13
Professor	56.084*	31.382	1.79
Associate Professor	22.543	34.606	0.65
Land Grant University	-238.565***	37.049	-6.44
Non-Land Grant University	-172.120***	38.486	-4.47

R square: 0.24

TABLE 29: OLS Result: Factors Influencing Federal Funding (Whole Sample)

Variable	Coefficient	Std Error	*t* - Value
Constant	-71.359***	14.462	-4.93
Publication	10.724***	0.457	5.86
Federal Funds	0.027**	0.011	2.35
Industry Agenda	16.107***	3.800	4.24
Market Final Goods	8.617***	2.158	3.99
Professor	-5.324	9.377	-0.57
Associate Professor	-4.213	10.382	-0.41
Land Grant University	44.386***	11.338	3.91
Non-Land Grant University	26.886**	11.643	2.31

R square: 0.16. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 30: OLS Result: Factors Influencing Publication Rate (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	0.889**	0.963	3.69
Federal Funds	0.000*	0.000	1.73
Non-Federal Funds	0.000**	0.003	2.07
Graduate	0.241***	0.138	7.02
Post doctorate	0.378***	0.151	10.00
Technician	0.219***	0.226	3.88
Professor	0.985***	0.703	5.60
Associate Professor	0.331*	0.791	1.67
Land Grant University	-0.126	0.869	-0.58
Non-Land Grant University	-0.187	0.887	-0.84

R square: 0.46

TABLE 31: OLS Result: Factors Influencing Federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	76.560	72.953	1.05
Publication	52.984***	1.615	8.20
Non-Federal Funds	0.328**	0.134	2.45
Panel Agenda	19.124*	11.139	1.72
Public Funds	15.049*	8.245	1.83
Professor	56.086	34.665	1.62
Associate Professor	16.652	38.129	0.44
Land Grant University	-246.799***	39.866	-6.19
Non-Land Grant University	-173.995***	41.467	-4.20

R square: 0.23

TABLE 32: OLS Result: Factors Influencing Non-Federal Funding (Receivers of Federal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-78.318***	15.441	-5.07
Publication	11.568***	0.483	5.98
Federal Funds	0.029**	0.012	2.47
Industry Agenda	15.722***	4.005	3.93
Market Final Goods	8.902***	2.343	3.80
Professor	- 4.154	10.166	-0.41
Associate Professor	0.791	11.255	0.07
Land Grant University	44.913**	12.020	3.74
Non-Land Grant University	24.651**	12.333	2.00

R square: 0.17. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 33: OLS Result: Factors Influencing Publication Rate (Receivers of Nonfederal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	1.404**	1.847	3.04
Federal Funds	0.000	0.001	0.47
Non-Federal Funds	0.000	0.003	0.59
Graduate	0.246***	0.179	5.51
Post doctorate	0.480***	0.234	8.21
Technician	0.274***	0.296	3.70
Professor	1.050***	0.969	4.33
Associate Professor	0.480*	1.140	1.69
Land Grant University	-0.769*	1.726	-1.78
Non-Land Grant University	-0.905*	1.872	-1.93

R square: 0.50. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 34: OLS Result: Factors Influencing Federal Funding (Receivers of Nonfederal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-74.321	103.722	-0.72
Publication	46.960***	1.801	6.52
Non-Federal Funds	0.538***	0.134	4.03
Panel Agenda	30.995**	13.770	2.25
Public Funds	17.683*	9.777	1.81
Professor	56.193	41.631	1.35
Associate Professor	27.448	47.801	0.57
Land Grant University	-179.370**	71.675	-2.50
Non-Land Grant University	-191.895**	77.711	-2.47

R square: 0.26

TABLE 35: OLS Result: Factors Influencing Non-Federal Funding (Receivers of Nonfederal or Federal-and-Nonfederal Funding)

Variable	Coefficient	Std Error	*t* - Value
Constant	-37.224	31.992	-1.16
Publication	12.484***	0.688	4.54
Federal Funds	0.075***	0.019	3.94
Industry Agenda	21.671***	6.127	3.54
Market Final Goods	5.500*	3.296	1.67
Professor	-7.989	15.710	-0.51
Associate Professor	-4.720	17.992	-0.26
Land Grant University	10.367	26.995	0.38
Non-Land Grant University	34.664	29.308	1.18

R square: 0.19. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

TABLE 36: OLS Result: Factors Influencing Publication Rate (Receivers of Federal Funds only)

Variable	Coefficient	Std Error	*t* - Value
Constant	1.099***	1.119	3.93
Federal Funds	0.000**	0.001	2.24
Graduate	0.219***	0.199	4.40
Post doctorate	0.287***	0.184	6.25
Technician	0.097	0.325	1.19
Professor	0.935***	0.894	4.18
Associate Professor	0.191	0.950	0.81
Land Grant University	0.031	1.061	0.03
Non-Land Grant University	-0.091	0.898	-0.40

R square: 0.39

TABLE 37: OLS Result: Factors Influencing Federal Funding (Receivers of Federal Funds only)

Variable	Coefficient	Std Error	*t* - Value
Constant	37.405	97.295	0.38
Publication	58.388***	2.687	5.43
Public Goods	38.193**	12.925	2.95
Public Funds	2.982	11.860	0.25
Professor	55.823	48.963	1.14
Associate Professor	-6.484	50.897	-0.13
Land Grant University	-222.549***	55.713	-3.99
Non-Land Grant University	-158.727***	46.622	-3.40

R square: 0.23. The asterisks ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Chapter V: Conclusion

I can make four basic points based upon the results obtained from the first essay in which I look at how the dollar tends to affect land rental prices in US cornbelt agriculture. First, that the exchange rate is over-looked as a potential causal factor in studies of agricultural rents; indeed, it would be surprising if this macroeconomic variable did not have some effect, particularly in the case of U.S. cornbelt agriculture, which is export dependent and makes intensive use of energy-based inputs. Second, a weak dollar is not necessarily “good” for U.S. cornbelt agriculture since the cost of energy-based inputs is closely related to the price of oil, and this tends to have an inverse relation to the strength of the dollar. Third, simple correlations with publicly available data suggest that real cash rents for U.S. cornbelt agriculture are positively correlated with the real exchange rate for agricultural commodities. Fourth, evidence suggests that one causal link for the above stylized fact is that the purchasing power benefits of a strong dollar improve the net returns from farming additional acres, increasing the demand for cash-rented acres stylized fact is that the purchasing power benefits of a strong dollar improve the net returns from farming additional acres, increasing the demand for cash-rented acres.

However, there are several potential limitations of the econometric results in this essay. For example, the model of the process by which cash rents are negotiated is stylized. The model abstracts from the dynamic and stochastic aspects of crop production. The conclusions are tempered by the fact that the study relies upon aggregated data, which are susceptible to problems with data measurement, and which complicate statistical procedure. These are all reasons to use caution in interpreting the regression results. Nonetheless, the essay has marshaled enough evidence to encourage a rethinking of the idea that a weak dollar is necessarily “good” for export-dependent agriculture. While a weak dollar may raise output prices, it may be associated with a rise in input prices to an extent that the net benefit of a weak dollar is called into question.

In the second essay, where I estimate a logit model to examine how the source and size of financial support affect scientists’ research choice decisions, I find that funding sources little affect scientists’ research choices over object scale and basicness classifications, implying that academic scientists tend to develop their research orientations independently of the financial support they might receive for it. Such decisions are, to a much larger extent, determined by the type of university that employs them and by the content of in-kind inputs accompanying a grant. My results broadly imply that funding agents’ direct impacts – through the magnitudes of grants to individual scientists – on academic scientists’ research choices are, if not exactly incorrect, exaggerated. Efforts to re-direct academic bioscience research objectives instead should be concentrated on the scientist’s cultural and technical environment. Scientist’s research choice trends suggest that Land-Grant and public non-Land-Grant universities tend to focus more on entrepreneurial research than private universities do. Although this is contrary to our expectations that public universities conduct research on public (non-rival and non-excludable) innovations, close ties with firms and industries may be changing research trends in public universities.

In the third essay I have developed a simultaneous model of causal interactions between the scientific productivity, measured by publication rates, and the financial support of academic bioscientists employed at major US universities. We find, under *ceteris paribus* conditions, that a scientist's publication rates greatly affect research funding success. Yet federal agencies' funding decisions are more publication-rate-affected than are state government and private-firm funding decisions. Federal sources publicly endorse the value of disseminating scientific discoveries through publications. They recognize the need for broad utilization of university research for the general public benefit and therefore encourage the researchers they fund to publish their results in peer-reviewed journals. Non-federal sources' and, to perhaps to a slightly smaller extent state governments, are on the other hand more motivated by commercial benefits.

Our results also imply that funding from federal and non-federal sources substitute for rather than complement each other. The fact that the scientist has a limited amount of time to apply for grant money implies, to that extent, that federal and non-federal money substitute for one another, that is crowd each other out. We hypothesize that on the one hand laboratory size, measured by employee numbers, influences scientific productivity; but that on the other hand, scientific productivity influences – by means of grant success – labor recruitment. By including the number of laboratory workers together with funding volumes, our model provides a test of allocative efficiency, that is whether scientists distribute their resources efficiently across types of inputs. Importantly, we find that the average scientist misallocates resources between labor and non-labor inputs, recruiting too few research personnel and overusing such non-labor factors as laboratory equipment, cell lines, and reagents. Expressed differently, the per-dollar marginal productivity of labor inputs is higher than that of non-labor inputs. This is suggestive of the importance of human resources in influencing research productivity. Despite high labor productivity, scientists and universities appear to over-invest in equipment and buildings, possibly because they believe such infrastructure is valuable in attracting students, faculty, and research financial support.

Final Bibliography

Batten, D., and M. Belongia. 1986. "Monetary Policy, Real Exchange Rates, and U.S. Agricultural Exports." *American Journal of Agricultural Economics* 2:422-427.

Berenblut, I. and G. Webb. 1973. "A New Test for Autocorrelated Errors in the Linear Regression Model." *Journal of the Royal Statistical Society* 35:33-50.

Campa, J., and L. Goldberg. 2001. "Employment Versus Wage Adjustment and the US Dollar." *Review of Economics and Statistics* 83:477-489.

Carter, C., and D. Pick. 1989. "The J-Curve Effect and the US Agricultural Trade Balance." *American Journal of Agricultural Economics* 71:712-720.

Chavas, J., and C. Shumway. 1982. "A Pooled Time-Series Cross-Section Analysis of Land Prices." *Western Journal of Agricultural Economics* 7:31-41.

Cho, G., I. Sheldon, and S. McCorriston. 2002. "Exchange Rate Uncertainty and Agricultural Trade." *American Journal of Agricultural Economics* 84:931-942.

Clark, J., M. Fulton, and J. Scott. 1993. "The Inconsistency of Land Values, Land Rents, and Capitalization Formulas." *American Journal of Agricultural Economics* 75:147-155.

Erickson, K., A. Mishra, and C. Moss. 2003. "Cash Rents, Imputed Returns, and the Valuation of Farmland Revisited." In: C. Moss and A. Schmitz, Eds., *Government Policy and Farmland Markets*. Ames: Iowa State University Press. pp. 223-238.

Featherstone, A.M., and T.G. Baker. 1987. "An Examination of Farm Sector Real Asset Dynamics: 1910-1985." *American Journal of Agricultural Economics* 69(3):532-546.

Goldberg, L., and J. Tracy. 2000. "Exchange Rates and Local Labor Markets." In R. Feenstra, ed. *The Impact of International Trade on Wages*. Chicago: The University of Chicago Press, pp. 269-308.

Goodwin, B., A. Mishra, and F. Ortalo-Magné. 2003. “What’s Wrong with Our Models of Agricultural Land Values?” *American Journal of Agricultural Economics* 85:744-752.

Granger, C. 1969. “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods.” *Econometrica* 37:424-438.

Hausman, J. 1978. “Specification Tests in Econometrics.” *Econometrica* 46:1251-1271.

Helmberger, P., and J. Chavas, 1996. *The Economics of Agricultural Prices*. Upper Saddle River, NJ: Prentice Hall.

Iowa State University Extension. 2008. *Farmland Ownership and Tenure in Iowa 2007*. Extension Publication PM1983.

Irwin, S., and P.L. Colling 1990. “Are Farm Asset Values Too Volatile?” *Agricultural Finance Review* 50:58-65.

Just, R., and J. Miranowski. 1993. “Understanding Farmland Prices.” *American Journal of Agricultural Economics* 75(1):156-168.

Kandilov, I. 2008. “The Effects of Exchange Rate Volatility on Agricultural Trade.” *American Journal of Agricultural Economics* 90:1028-1043.

Krugman, P. 1983. “Oil and the Dollar.” In: J. Bhandari and B. Putnam, eds., *Economic Interdependence Under Flexible Exchange Rates*. Cambridge: Massachusetts Institute of Technology, pp. 179-190.

Krugman, P. 1987. “Pricing to Market When the Exchange Rate Changes.” Ed. S. Arndt, and J. Richardson. *Real-Financial Linkages Among Open Economies*. Cambridge, MA, MIT Press, pp. 48-70.

Lence, S., and A. Mishra. 2003. “The Impacts of Different Farm Programs on Cash Rents.” *American Journal of Agricultural Economics* 85:753-761.

Moss, C. 1997. “Returns, Interest Rates and Inflation: How They Explain Changes in Farmland Values.” *American J. of Agricultural Economics* 79:1311-1318.

Patton, M., P. Kostov, S. McErlean, and J. Moss. 2008. “Assessing the Influence of Direct Payments on the Rental Value of Agricultural Land.” *Food Policy* 33:397-405.

Pick, D. 1990. “Exchange Rate Risk and US Agricultural Trade Flows.” *American Journal of Agricultural Economics* 72:694-700.

Pick, D., and T. Park. 1991. “The Competitive Structure of U.S. Agricultural Exports.” *American Journal of Agricultural Economics* 73:133-141.

Revenga, A. 1992. “Exporting Jobs? The Impact of Import Competition on Employment and Wages in U.S. Manufacturing.” *Quarterly Journal of Economics* 107:255-284.

Roberson, R. 2008. “Input Costs Pushing Farm Risk Levels Higher.” *Southeast Farm Press*. 35:18.

Roberts, M., B. Kirwan, and J. Hopkins. 2003. “The Incidence of Government Program Payments on Agricultural Land Rents: The Challenges of Identification.” *American Journal of Agricultural Economics* 85:762–769.

Ryan, J., C. Barnard, R. Collender, and K. Erickson. 2001. “Government Payments to Farmers Contribute to Rising Land Values.” *Agricultural Outlook* June:22-26.

Schuh, G. 1974. “The Exchange Rate and U.S. Agriculture.” *American Journal of Agricultural Economics* 56:1-13.

Schmitz, A. 1995. “Boom/Bust Cycles and Ricardian Rent.” *American Journal of Agricultural Economics* 77:1110-1125.

Schnitkey, G., and A. Gupta. 2007. “Impacts of Rising Crude Oil Prices on Corn and Soybean Production Costs.” *University of Illinois Extension Publication FEFO* 08-10. pp. 6.

Tsoodle, L., B. Golden, and A. Featherstone. 2006. “Factors Influencing Kansas Agricultural Farm Land Values.” *Land Economics* 82(1):124-139.

USDA (U.S. Department of Agriculture, Economic Research Service). 2009a. “Farm Income and Costs Briefing Room.” www.ers.usda.gov/briefing/farmincome/

USDA (U.S. Department of Agriculture, Economic Research Service). 2009b. “U.S. Fertilizer Imports/Exports.” www.ers.usda.gov/Data/FertilizerTrade/

Weersink, A., S. Clark, C. Turvey, and R. Sarker. 1999. “The Effect of Agricultural Policy on Farmland Values.” *Land Economics* 79(3):425-439.

Academic Research and Development, National Science Board, Chapter 5, National Science Foundation *www.nsf.gov.*

American Society of Microbiology *http://www.asm.org/Awards/index.asp?bid=14942.*

"Aprotinin from Plants could end Supply Shortage" *Materials and Formulation, www.in-pharmatechnologist.com/Materials-Formulation/Aprotinin-from-plants-could-end-supply-shortage* January 2004.

Arizona Bioscience News, January 30, 2008. "BIO5 receives $ 50 million NSF grants." *http://www.flinn.org/news/601*.

Argyres, N. S., J. P. Liebeskind, 1998. "Privatizing the intellectual commons: university and the commercialization of biotechnology." *Journal of Economic Behavior and Organization 35(4):427-454.*

Azoulay, P., W. Ding, and T. Stuart, 2006. "The Determinants of Faculty Patenting Behavior: Demographics or Opportunities?" *Journal of Economic Behavior and Organization 63:573-576.*

Barham, B, J. Foltz, and Kwansoo Kim, 2002. "Trends in University Ag-Biotech Patent Production". *Review of Agricultural Economics*, 24: 294-308.

Bhattacharjee, Y, 2008. "Industry Shrinks Academic Support". *www.sciencemag.org, October, 2008.*

Bioregion News, May 05, 2008. *http://www.genomeweb.com/bioregionnews/florida-economic-*

development-bill-colorado%E2%80%99s-bioscience-research-grant-program-m.

Blumenthal, D., N. Causino, E. Campbell, K. Louis, 1996. “Relationships between academic institutions and industry in the life sciences – an industry survey.” *The New England Journal of Medicine 334(6): 368-374.*

Blumenthal, D., Gluck, M., Louis, K. S., Stoto, M. A., Wise, D., 1986.”University-Industry Research Relationships in Biotechnology: Implications for the University.”*Science 232:1361-1366.*

Buccola, S., David Ervin, and H. Yang. 2009. “Research Finance and choice in University Bioscience.” *Southern Economic Journal 75 (4):1238-1255*.

Carpenter, S., 2008. “Finding Industry Funding.”
“http://sciencecareers.sciencemag.org/career_magazine/previous_issues/articles/2008_03_14/caredit.a0800040.

Carraro, C., D. Siniscalco, 2006. “Science versus Profit in Research.” *Journal of the European Economic Association 1(2-3):576-590.*

Cole, S., 1979. “Age and Scientific Performance.” *American Journal of Sociology 84(4):958-977*.

Co-operative State Research, Extension, and Education Service, (CSREES), USDA. *www.csrees.usda.gov.*

Curry, J., M. Kenney, 1990. “Land-Grant University-Industry Relationships in Biotechnology: A comparison with the Non-Land-Grant research Universities.” *Rural Sociology 55(1):44-57.*

Dasgupta, P., P. A. David, 1994. “Towards a new economics of science.” Research Policy 23(5): 487-521.

David, P. A., B. Hall, A. Toole, 2000. “IS public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence” R*esearch Policy 29:497-529.*

Diamond, A. M., 1999. “Does Federal funding “Crowd-in” Private Funding of Science?” *Contemporary Economic Policy 17(4):423-431.*

Gel3LSDigest, Alberta, *http://www.genomealberta.ca/files/ge3ls/digest/07January15.pdf.*

Genome Web staff Reporter, March 2, 2009. “USDA grants $11 million for livestock genomics.*” http://www.genomeweb.com/usda-grants-11m-livestock-genomics.*

Glenna, L., W.B. Lacy, R. Welsh, D. Biscotti, 2007. “University Administrators, Agricultural Biotechnology, and Academic Capitalism: Defining the Public good to promote university-industry Relationships.” *The Sociological Quarterly 48:141-163.*

Greene, W. “Econometric Analysis - 5th Edition” *Prentice Hall.*

Gulsbrandsen, M., J. Smeby, 2005. “Industry funding and university professors’ research performance.” *Research Policy 34(6):932-950.*

Hall, B., A. N. Link, J. T. Scott, 2000. “Universities as research partners” *NBER Working paper Series number 7643.*

Hisrich, M. 2003. “Scientific Community backs AgBiotech*.” AgBio world 3(12):15*

Hosmer, D., S. Lemeshow, “Applied Logistic Regression – Second Edition” *Wiley Series in Probability and Statistics*.

Jaffe, A. 1986. “Technological Opportunity and Spillovers of R&D: Evidence from firms’ patents, profits, and market value.” *American Economic Review 76(5): 984-1001.*

Jaffe, A. 1989. “Real Effects of Academic Research.” *American Economic Review 79(1):957-970.*

Kintisch, E., 2007. “How to make bio-fuels truly poplar?” *Science 315(5813):781.*

Kjelstrup, S., 2001. “Basic and Applied research in the University- have they changed?” *OECD workshop on basic research: Policy relevant definitions and measurement, Oslo, Norway, October 29-30, 2001.*

Klotz-Ingram, C., K. Day-Rubenstein, 1999. “The Changing Agricultural Research Environment: what does it mean for public-private innovation?” *AgBio Forum 2(1):24-32.*

Kulakowski, E., L. Chronister, 2006. “Research Administration and Management.”*Published by Jones and Bartlett, MA.*

Lefkowitz, J. 2003. "Ethics and Values in Industrial-Organizational Psychology" Book.

Leyden, Dennis P, A. N. Link, 1991. "Why are Governmental R&D and private R&D complements?" *Applied Economics 23:1673-1681*.

Logit, Likelihood Ratio Test, Odds Ratios *users.rcn.com/alancm/pp605/12_**Logit**_LR**test**_Odds_Ratio.pdf.*

Logistic Regression *http://luna.cas.usf.edu/~mbrannic/files/regression/Logistic.html.*

National Human Genome Research Institute, Intellectual Property and Genomics *http://www.genome.gov/19016590*

National Institute of health, US Department of Health and Human Services, *www.nih.gov*

National Institutes of Standard and Technology, *www.nist.gov.*

National Institute of Health News, May 5, 2009. "NIH grants $ 122 million in institutional development grants" *http://www.nih.gov/news/health/may2009/ncrr-05.htm*

Neumann, C., "The Bayh-Dohl Act: the basis for US technology transfer." *Office of Science and Technology www.ostina.org.*

Rapoport, A. I., 1998. "What are the sources of funding for academically performed R&D" *National Science Foundation, Directorate for Social, Behavioral and Economic Sciences.*

Salter, L., B. Martin, 2001. “The Economic Benefits of Publicly Funded Basic Research: A critical Review.” *Research Policy 30 (3):509-532.*

Santoro, M. D., A. Chakrabarti, 1999. “Building industry-university research centers: some strategic considerations.” *International Journal of Management Reviews 1(3):225-244.*

Schimmelpfennig, D., and Heisey, P., 2009. “US Public Agricultural Research, changes in funding sources and shifts in emphasis, 1980-2005.” *USDA ERS Economic Information Bulletin No. 45, March 2009.*

Science and Engineering Indicators, *2008* Chapter 4.

Shackelford. B., 2004. “US R&D projected to have grown marginally in 2003.” *National Science Foundation, Division of Science Resource Statistics.*

Smith, Jason Owen, 2002. “From separate systems to a hybrid order: Across accumulative advantage of public and private science at Research One Universities.” *Research Policy 32:1081-1104.*

Stelley, D. M., G. C. Yencho. “Plant Breeding - A Key for Excellence and Relevance of US Science & Technology”.

Stuart, T., W. W. Ding, 2006. “When do scientists become entrepreneurs?”*American Journal of Sociology 112:97-144.*

Thorn, C. A. 1996. “Building expertise in High Technology: New Dynamics of R&D Funding at US Research Universities” *http://ieeexplore.ieee.org*.

Thomas Jefferson Agricultural Institute *http://www.jeffersoninstitute.org/*.

United States Department of Agriculture, *www.usda.gov*.

University of California, State Oath of Allegiance, Patent Policy, and Patent Acknowledgement.

Vegso, J. 2006 “Decline of Industrial Support for Academic R&D.” NSF info brief Academic Research and Development Expenditures, CRA bulletin, *http://www.cra.org/wp/index.php?cat=11*.

Yang, H., S. Buccola, 2003. “University-Industry Relationships and the Design of Biotechnology Research.” *Paper prepared for presentation at the AAEA Annual Meetings, Montreal, Canada, July 27-30, 2003*.

Zucker, L.G., M. Darby, and Marilyn B Brewer, 1998. “Intellectual Human capital and the Birth of U.S. Biotechnology Enterprises.” *American Economic Review 88(1):291-306*.

Adams, J. D., G. C. Black, J. R. Clemmons, P. E. Stephan, 2005. “Scientific teams and institutional collaborations: Evidence from US universities, 1981-1999.” *Research Policy 34(3): 259-285.*

Alison, P. D., J. S. Long. 1990. “Departmental Effects on Scientific Productivity.” *American Sociological Review 55:469-478.*

Baser, O., E. Pema, “Publications over the Academic Life-Cycle: Evidence for Academic Economists.” *Economics Bulletin 1(1):1-8.*

Becker, G. S., K. Murphy, 1992. “The Divisions of Labor, Co-ordination costs, and knowledge.” *Quarterly Journal of Economics, 107(4):1137-1160.*

Berardo, F.M. 1989. “Scientific Norms and Research Publications: Issues and Professional Ethics.” *Sociological Enquiry 59 (3):119-141.*

Blumenthal, D., M. Gluck, K. Louis., M. A. Stoto, D. Wise, 1986.”University-Industry Research Relationships in Biotechnology: Implications for the University.”*Science 232:1361-1366.*

Blumenthal, D., N. Causino, E. Campbell, and K. Louis, 1996. “Relationships between academic institutions and industry in the life sciences – an industry survey.” *The New England Journal of Medicine 334(6): 368-374.*

Boss, J. M, S. H. Eckert, 2003. “Academic Scientists at Work: Navigating the Biomedical Research Center” *Springer-Verlag New York, LLC 2nd edition.*

Boumahdi, R., N. Carayol, P. Llerena, 2008. “The Private Contractual Funding of Academic Laboratories: A Panel Data Analysis.” *Applied Economics Letters 15(6):465-468*.

Bozeman, B., S. Lee, 2003. “The Impact of Research Collaboration on Scientific Productivity.” *Paper prepared for presentation at the AAAS Annual Meetings, Colorado, Denver, February, 2003*.

Bredhal, M., W.K. Bryant, V. W. Ruttan. 1980. “Behavior and Productivity Implications Of Institutional And Project Funding Of Research.” *American Journal of Agricultural Economics 62(3):371-383.*

Buccola, S., David Ervin, and H. Yang. 2009. “Research Finance and choice in University Bioscience.” *Southern Economic Journal 75 (4):1238-1255*.

Carayol, N., M. Matt. 2004. "Does Research Organization Influence Academic Production: Laboratory Evidence from a Large European University." *Research Policy 33(8):1081-1102*.

Connolly, L. S. 1997. "Does External Funding of Academic Research Crowd out Institutional Support? *Journal of Public Economics 64:389-406*.

David, P. A., B. H. Hall, A. Toole, 1999. "Is Public R&D a complement or substitute for Private R&D? A Review of the Econometric Evidence." Prepared for the special issue of *Research Policy* on technology policy issues forthcoming in the year 2000.

Denton, F. T., C. Feaver, B. G Spencer, 1997. "Student Enrollment and Faculty Renewal: The Response of a Tenure-based University System to Demographic and Budgetary shocks." *Journal of Economic Behavior and Organization 34 (1):101-127.*

Diamond, A. M. 1999. "Does Federal Funding crowd-in Private Funding in Science?" *Contemporary economic Policy* 17(4):423-431.

Ehrenberg, R. G., M. J. Rizzo, G. H. Jacubson. 2003. "Who Bears the Growing Cost of Science at Universities?" *ILR collections working papers*.

Ellison, G., 2002. "The Slowdown of the Economics Publishing Process." *Journal of Political Economy 110(5): 947-993.*

Guena, A., 1997. "Allocation of funds and Research Output: The Case of UK universities." *Revue d'Economie Industrielle.*

Gulsbranden, M., J. C. Smeby. 2005 “Industry Funding and University professors’ Research Performance.”*Research Policy 34(6):932-950.*

Gupta, H. M., J. R. Campanha, R. A. G. Pesce, 2005. “Power – Law Distributions for citation Index of scientific publications and scientists.” *Brazilian Journal of Physics, 35(4A): 981-986.*

Himanen, L., O. Auranen, H. M. Puska, M. Nieminen, 2009. “Influence of Research Funding and Science Policy on University Research Performance: a comparison of five countries.” *Science and Public Policy.*

Kelnar, K. 2007. “3 skills for the Academic Scientist” *dx.doi.org/10.1126/science. Caredit.a0700046.*

Lefkowitz, J. 2003. “Ethics and Values in Industrial-Organizational Psychology” Book

National Science Board. 2008 “Academic Research and Development.” *Science and Engineering Indicators Chapter 5.*

Nieminen, M. 2005. “Academic Research in Change: Transformation of Finnish university Policies and University Research during the 1990s.” *Finnish Society of Sciences and Letters.*

Payne, A. 2001. “Measuring the Effects of Federal Research funding on Private Donations at Research Universities: Is Federal Research funding more than a substitute for Private Donations?” *International Tax and Public Finance, 8(5-6):731-751*.

Shavelson, R., L. Towne. "On Scientific Research in Education: Questions not Methods should Drive the Enterprise." *http://www.stanford.edu/dept/SUSE/SEAL/Reports_Papers/On%20Scientific%20Research%20in%20Education_Questions%20.doc.*

Stephan, P., 2005. "Job Market Effects on Scientific Productivity." *Paper built on the presentation at the conference "The Future of Science" Venice, Italy, September, 2005*.

Toole, A. 1999. "Public Research, Public Regulation and Expected Profitability: The Determinants of Pharmaceutical Research and Development Investment." *Stanford Institute for Economic Policy Research Working Paper.*

Turner, L., J. Mairesse, 2003. "Individual Productivity Differences in Public Research: How important are Non-individual Determinants - An Econometric Study of French Physicists Publications (1986-1997). *NBER working papers*.

Wang, C., Y. Xia, S. Buccola, 2009. "Public Investment and Industry Incentives in Life-Science Research." *American Journal of Agricultural Economics 91(2):374-388.*

Wheeler, A. G., 1989. "The Pressure to Publish Promotes Disreputable Science." *The Scientist July 10, 1989.*

Wooldridge, J. M, 2001. "Econometric Analysis of Cross-section and Panel Data" published by the *MIT Press*

Xia, Y., S. Buccola. 2005. “University Life Science Programs and Agricultural Biotechnology.” *American Journal of Agricultural Economics 87(1):229-243*.

Ziman, J. 1996. “Post-Academic Science”: Constructing knowledge with Networks and Norms.” *Science Studies 9(1):67-80.*