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Time substitution and network effects with an application to nanobiotechnology policy for US universities

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ABSTRACT

We present a dynamic network model of the knowledge production process for nanobiotechnology research at 25 US universities during 1990–2005. Universities produce knowledge outputs in nanobiotechnology consisting of Ph.D. graduates, research publications, and patents. Inputs include the university's spending on R&D in engineering and the life sciences, and the university's own stock of knowledge measured by past publications in nanobiotechnology. In addition, universities take advantage of the stock of knowledge produced by other universities in previous periods. We simulate the effect of the National Science Foundation being able to optimally allocate research funds for nanobiotechnology research between universities and across time so as to maximize the aggregate amounts of the three knowledge outputs produced by the universities.

1. Introduction

Gordon [1] identifies three industrial revolutions comprising first, steam and railroads, second, electricity, indoor plumbing, communications, and the internal combustion engine, and third, computers, the internet, and mobile phones. However, economic growth has slowed since the middle of the twentieth century and Gordon predicts that the bottom 99% of the income distribution might experience growth of less than one half of 1% in the coming decades.

Although science and research and development of all forms have been responsible for a large proportion of past economic growth, recent federal spending on science and private spending on research and development as a percent of GDP has fallen from about 1.25% in 1976 to approximately 1% in 2009 (Economic Report of the President [2]). One beacon of light has been in the area of nanotechnology. Between 2001 and 2008 the number of inventions in nanotechnology and the number of nanotechnology workers grew at a 25% annual rate, with the worldwide nanotechnology product market reaching $254 billion in sales in 2009 (Roco et al. [3]). The National Science Foundation estimates that nanobiotechnology could become a trillion dollar industry employing more than 800,000 workers by 2015. In this paper we examine science spending for nanobiotechnology research and education at 30 US universities during the period 1990 to 2005. Weber and Xia [4] estimated inefficiency and Morishima elasticities of output substitution for nanotechnology research publications, Ph.D. students, and patents using a stochastic directional distance function. We extend their research in an effort to shed light on two important questions. First, can a reallocation of resources between different universities enhance the university outputs of research, patents, and Ph.D. graduates? If some universities are consistently on the cutting edge of the research frontier then reallocation of resources away from non-frontier universities towards frontier universities could enhance productivity. On the other hand, scale diseconomies might limit the extent of the efficiency gains from reallocating resources. Second, can resources be reallocated across time to enhance productivity? Here, we want to investigate whether it is better for federal agencies to allocate research dollars early in the development stage of new technologies, later in the development stage, or more or less continuously throughout the period.

To investigate these questions we integrate two recent methods using data envelopment analysis: dynamic network production and time substitution. We assume that universities form a network in producing students, research papers, and patents in nanobiotechnology. Changes in the allocation of resources within the network have the potential to enhance productivity. In addition, if the choice were available, each individual university might choose to spend more in a current period by borrowing from a future period so as to maximize production across all periods. Alternatively, individual universities might save resources so as to expand future production. However, to the extent that production by one university in a particular period

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has an effect on the output possibilities of other universities, such a unilateral reallocation might not be Pareto improving. For instance, the accumulation of knowledge often moves in small steps so that if a single step is removed, the process might go down a different path, or stagnate. Thus, we want to account for the fact that research papers written by one university in a given period spill over to other universities in subsequent periods. The idea of knowledge spillovers can be represented Isaac Newton's famous quote: "If I have seen further it is by standing on the shoulders of giants" (op cit. Merton [5]).

Given the potential for knowledge spillovers between universities, coordination of resources between universities and across periods might allow an expansion in production possibilities. To the extent that government agencies already attempt to solve such a problem, any findings of inefficiency in the network might be attributed to the transaction costs associated with acquiring information and providing the proper incentives to the producers to enhance output.

2. Economic returns to science research

The latter part of the 1970s saw the US undergo a period of stagflation. From 1962 to 1976 annual labor productivity growth averaged 2.5% but fell to only 0.5% during 1976 to1980 (Economic Report of the President [2]). Concerns about slow productivity growth led Congress to pass the Bayh–Dole Act in 1980. This Act allowed universities to patent and license research results that had been subsidized through federal funding. Before passage of the Bayh–Dole Act, any inventions that grew out of federally sponsored research became property of the federal government. The Act was not without its critics as some people argued that university research might switch focus from basic research to applied research. For instance, Boldrin and Levine [6] and Just and Huffman [7] presented models showing that when universities are granted monopoly power via patents, the production of new knowledge falls as resources are reallocated toward industrial applications. Weber and Xia [4] found supporting evidence for this theory in the university production of nanobiotechnology patents and publications. Using estimates of the Morishima elasticities of transformation, Weber and Xia [4] found that when the quantity of patents increases relative to publications, the shadow revenue share of publications falls relative to patents. However, other researchers found that university patenting activities tended to complement, rather than substitute for basic research (Thursby and Thursby [8], Azoulay et al. [9], Fabrizio and DeMinin [10]).

One rationale for the public funding of research is that knowledge is a public good – both non-rival and non-excludable – and will be under-produced in private settings since private actors cannot fully capture its returns. Adams [11] presented evidence indicating a time lag of 15 to 20 years between the production of basic research and its embodiment in new technologies. He also suggested that about 15% of the productivity slowdown in the 1970s could be attributed to World War II which siphoned scientists and engineers into the war effort. In a thorough review of the literature on the economic benefits of private and publicly funded basic research Salter and Martin [12] cite evidence that the social returns to private R&D spending tend to be 2–5 times higher than the private returns. In addition, they identify six categories that embody the economic returns to publicly funded research: new knowledge, more skilled workers, new scientific instruments, enhanced network effects and social interactions between researchers and the private sector, an increased capacity to solve new problems, and new firms spawned by the research. To measure potential spillovers from agricultural R&D on agricultural productivity Plastina and Fulginiti [13] estimated a stochastic cost function for 48 states during the 1949–1991 period. Costs are dependent on the state's own R&D stock and the stock of R&D from adjacent states with increases in R&D from neighboring states causing declines in the own state's costs of production. The findings indicate an average 17% internal rate of return for the state's own R&D funding and a 29% social rate of return.

3. The knowledge production process

Various researchers have developed network models of producer performance and models that measure dynamic performance by examining the allocation of resources over multiple periods. Färe and Grosskopf [14] developed a dynamic measure of firm performance where decision-making units determine the amounts of a final output and an intermediate output (capital) to maximize production over multiple periods. Nemoto and Goto [15,16] derived dynamic optimality conditions so that overall producer efficiency can be decomposed into static and dynamic efficiencies. Tone and Tsutsui [17], Fukuyama and Weber [18] and Akther et al. [19] develop a network performance indicator where producers in a first stage of production use exogenous inputs to produce an intermediate output that becomes an input to a second stage of production where final outputs, including an undesirable output are produced. In their model the past production of the undesirable output shrinks the current period's production possibility set. Fukuyama and Weber [20,21] account for the possibility that in the second stage of production a second intermediate output can be produced in lieu of final outputs so as to expand the production possibility set in a future period. Thus, the performance measure compares the observed use of inputs and production of outputs with the potential outputs that could be produced if resources were allocated efficiently across many periods. Sacoto et al. [22] examine university production where various inputs are used to generate an intermediate output of student internships that become an input in the production of job placements—the final output. Fallah-Fini et al. [23] provide a thorough review of dynamic measures of performance.

In this section and the next we present a dynamic network production model that accounts for the potential for the stock of knowledge created in the past to influence the current production of new knowledge. We assume that production takes place by $k=1,\ldots,K$ universities in $t=0,1,\ldots,T$ periods. We follow conventional notation and represent vector valued variables in bold face and scalar variables in italics. The $n=1,\ldots,N$ inputs used by university k in period t are represented by $\mathbf{x}_k^t=(x_{k1}^t,\ldots,x_{kN}^t)\in R_+^N$. In the empirical section of the paper we assume that these inputs include real university R&D expenditures in engineering, the physical sciences, and the life sciences. Another input is derived from grants from the National Science Foundation that have been awarded for the study of nanotechnology. Furthermore, universities harness the existing stock of knowledge as an input to help create new knowledge. The universities use these inputs to produce $m=1,\ldots,M$ knowledge outputs represented by $\mathbf{y}_k^t=(y_{k1}^t,\ldots,y_{kM}^t)\in R_+^M$. Our data set allows us to identify three university outputs in the area of nanobiotechnology: publications (y_1), patents (y_2), and Ph.D. graduates in (y_3).

To account for the dynamic process of production we recognize that knowledge produced in the form of publications (y_1) is not lost or sold, but instead becomes an input to the production process in future periods. In addition, university researchers draw not only on their own publications, but on the publications of their colleagues at other universities. The knowledge embodied in publications serves as a spillover input that becomes available to researchers at other universities. It seems reasonable to assume that the stock of past publications generated by the university might have a different marginal effect on the production of new knowledge than the stock of past publications generated by other universities in the same field, since such knowledge might only be tangential to the research and teaching at one's own university. In fact, Salter and Martin (p. 512 [12]) write that "Scientific knowledge is not freely available to all, but only to those who have the right educational background and to members of the scientific and technological networks. The informational view fails to appreciate the extent to which scientific or technical knowledge requires a substantial capability on the part of the user."

Thus, two other inputs are the university's own past cumulative stock of publications and the past cumulative stock of publications from other universities. Knowledge, like other assets, depreciates and becomes obsolete over time as new knowledge is created. In addition, past knowledge become embodied in new knowledge via the publication process as researchers survey the literature, report past findings, and synthesize those findings in new publications. Following Weber and Xia [4] we assume that the previous three years of cumulated publications constitute the knowledge input in the present year used to produce new knowledge outputs. Thus, we define another input as $z_k^t = \sum_{l=1}^{3} y_{k1}^{t-l}$, where $l = 1, 2, 3$ represent the university's own publications from the previous three years. In addition, publications from other universities in the previous three years constitute an additional knowledge input that have the potential to spill-over and enhance the specific university's knowledge production process. The spillover knowledge input is represented as $Y_k^t = \sum_{l=1}^{3} \sum_{k' \neq k}^{K} y_{k'1}^{t-l}$. That is, the cumulative publications produced by all other universities in the previous three years spills over as a knowledge input to university k. In addition to a university's cumulative own publications from the previous three years and the corresponding spillover knowledge input we also consider the cumulative sum of all past own publications and all past publications of other schools, where knowledge depreciates at a constant rate per year. We further describe the formulas for these alternative measures of knowledge inputs, z_k^t and Y_k^t, in Section 5.

The production possibility set for university k in period t is represented by $P^t(\mathbf{x}_k^t, z_k^t, Y_k^t) = \{\mathbf{y} : \ (\mathbf{x}_k^t, z_k^t, Y_k^t) \text{ can produce } \mathbf{y}\}$. Here, the amount of output that can be produced depends on the inputs available from the university and the NSF, past knowledge represented by publications, and past publications at other universities. The DEA constant returns to scale production possibility set for the kth university in period t takes the form

$$P^t(\mathbf{x}_k^t, z_k^t, Y_k^t) = \{\mathbf{y} : \quad y_m \le \sum_{j=1}^{K} \lambda_j^t y_{jm}^t, \quad m = 1, \dots, 3,$$
$$x_{kn}^t \ge \sum_{j=1}^{K} \lambda_j^t x_{jn}^t, \quad n = 1, \dots, N, \quad z_k^t \ge \sum_{j=1}^{K} \lambda_j^t z_j^t, \quad Y_k^t \ge \sum_{k=1}^{K} \lambda_j^t Y_j^t,$$
$$\lambda_j^t \ge 0, \quad j = 1, \dots, K, \quad t = 0, 1, \dots, T\} \tag{1}$$

Efficiency/inefficiency in period t can be measured by either the Shephard output distance function or the directional output distance function. We choose the directional output distance function because it is additive in outputs and will allow us to better model the dynamic network aspects of the technology. Let the directional vector for the M outputs be represented as $\mathbf{g} = (g_1, \dots, g_M)$. The directional output distance function scales the observed outputs along the directional vector to the frontier of the production possibility set. This function takes the form:

$$\vec{D}_{ok}^{\,t}(\mathbf{x}_k^t, z_k^t, Y_k^t, \mathbf{y}_k^t; \mathbf{g}) = \max\{\beta : \quad \mathbf{y}_k^t + \beta \mathbf{g} \in P^t(\mathbf{x}_k^t, z_k^t, Y_k^t)\}. \tag{2}$$

When a university produces on the frontier of the technology its directional distance function takes a value of 0 meaning that it is not possible to expand the set of outputs any further given the directional vector. As such, the directional distance function serves as a measure of inefficiency with larger values indicating greater inefficiency. While a directional technology distance function could also be estimated, this distance function seeks the maximum expansion in outputs and simultaneous contraction in inputs. We choose to hold inputs constant because it allows us to compare the potential output gains given inputs with the potential output gains that might arise from reallocating various university inputs across time. In addition, we want to compare potential outputs holding inputs constant with potential outputs when a particular government agency – The National Science Foundation – reallocates its fixed budget across universities and across time. We take up the problem of reallocation across time in the next section when we address time substitution.

Färe and Grosskopf [24] have shown that under certain conditions, when all producers' inefficiencies are evaluated using a common directional vector, the sum of the directional functions over all producers can serve as a measure of industry inefficiency. Let the sum of the directional distance functions be represented as $D^{\rightarrow t}_{o}(\mathbf{x}^t, \mathbf{z}^t, \mathbf{Y}^t, \mathbf{y}^t; \mathbf{g}) = \sum_{k=1}^{K} D^{\rightarrow t}_{ok}(\mathbf{x}_k^t, z_k^t, Y_k^t, \mathbf{y}_k^t; \mathbf{g})$, where $\mathbf{x}^t = (\mathbf{x}_1^t, \dots, \mathbf{x}_k^t, \dots, \mathbf{x}_K^t)$, $\mathbf{z}^t = (z_1^t, \dots, z_k^t, \dots z_K^t)$, $\mathbf{Y}^t = (Y_1^t, \dots, Y_k^t, \dots Y_K^t)$, and $\mathbf{y}^t = (\mathbf{y}_1^t, \dots, \mathbf{y}_k^t, \dots, \mathbf{y}_K^t)$ are vectors of all producers' outputs and inputs.

The spillover knowledge from all universities to each particular university represented by Y_k^t constitutes one aspect of the network knowledge production process. The second aspect of the network economy acknowledges the fact that some of the private inputs received by university k are grants derived from a particular government agency, in our case, the National Science Foundation, and assumes that those grants can be reallocated among all universities. We partition the input vector, $\mathbf{x}_k^t = (x_{k1}^t, \dots, x_{kN}^t)$, into two sub-vectors: inputs specific to university k represented as $\mathbf{x}_k^t = (x_{k1}^t, \dots, x_{kF}^t)$ and inputs that can be reallocated among universities, $\tilde{\mathbf{x}}_k^t = (\tilde{x}_{kF+1}^t, \dots, \tilde{x}_{kN}^t)$. Let the total amount of each input that is available to be reallocated between universities but not across time be represented as $\overline{\mathbf{x}}^t = \sum_{k=1}^{K} \tilde{\mathbf{x}}_k^t = \left(\sum_{k=1}^{K} \tilde{x}_{kF+1}^t, \dots, \sum_{k=1}^{K} \tilde{x}_{kN}^t \right)$.

The National Science Foundation grant process uses peer review and allocates funds on the basis of merit and broader impacts [25]. The highly competitive nature of the grant process is reflected by the increase in the number of proposals from 31,942 in 2001 to 48,999 in 2013 and the decline in the percent funded declined from 31% to 22% during the same period. However, Cole et al. [26] report on an experiment in which 150 NSF proposals were independently reviewed by a set of external reviewers. The outcome of the experiment suggested that whether a proposal receives funding depended on chance – who reviewed the proposal – even though there was no evidence of systematic bias by NSF reviewer. Furthermore, predicting the success of unproven ideas is fraught with error, with established research areas and researchers favored over fledgling ones (Merton [5], Porter and Rossini [27], Langer [28]). Recently, Congress halted NSF funding of political science proposals unless those proposals could be certified as "promoting national security or the economic interests of the United States" (Prewitt [29]). If the NSF funding is random, subject to a "Matthew effect" (Merton [30]), or based on political expedience, the allocation of NSF funds to universities might be less than optimal and will manifest itself in university performance that is less than that which might have been attained via a grant allocation process with zero transaction costs and perfect foresight. In these cases the level of inefficiency in the network equals the sum of the individual university inefficiencies. However, if the agency can somehow coordinate its funds to maximize output in a given period it could choose to solve a problem like the following:

$$\max_{\beta_k, x^{\sim}{}_k} \sum_{k=1}^{K} \beta_k \text{ subject to}$$
$$\mathbf{y}_k^t + \beta_k \mathbf{g} \in P^t(\mathbf{x}_k^t, \mathbf{x}^{\sim}{}_k^t, z_k^t, Y_k^t) \quad k = 1, \dots, K, \tag{3}$$
$$\sum_{k=1}^{K} \tilde{x}_{kn}^{\,t} \le \overline{x}_n^t, \quad n = F+1, \dots, N, \quad \sim x_{kn}^t \ge 0, \quad k = 1, \dots, K.$$

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Problem (3) represents industry inefficiency in period t when the agency chooses the amounts to allocate to each university so as to maximize the size of the aggregate production possibility set. Let the optimal objective function for (3) be represented as $\sum_{k=1}^{K}\beta_k^{t*}$ and let the optimal vector of NSF inputs allocated to the $k=1,\ \ldots,\ h,\ \ldots,\ K$ universities be $\tilde{\mathbf{x}}^{t*}=(\tilde{x}_k^{t*},\ldots,\tilde{x}_h^{t*},\ldots,\tilde{x}_K^{t*})$. Since the status quo level of $\tilde{x}_k^t$ is feasible, but not necessarily optimal, we have the relation that $\sum_{k=1}^{K}\beta_k^{t*}\geq\vec{D}_o^t(\mathbf{x}^t,\mathbf{z}^t,\mathbf{Y}^t,\mathbf{y}^t;\mathbf{g})=\sum_{k=1}^{K}\vec{D}_{ok}(\mathbf{x}_k^t,z_k^t,Y_k^t,\mathbf{y}_k^t;\mathbf{g})$.

Problem (3) can be estimated as a linear programming problem given the $k=1,\ \ldots,\ K$ production possibility sets in (1). In each period t, the problem is solved as

$$\max_{\lambda_k,\beta_k,\sim x_k}\ \sum_{k=1}^{K}\beta_k^t \text{ subject to}$$

$$\left.\begin{array}{l} y_{1m}^t+\beta_1^t g_m\leq\sum_{j=1}^{K}\lambda_j^t y_{jm}^t,\quad m=1,\ldots,M,\ x_{1n}^t\geq\sum_{j=1}^{K}\lambda_j^t x_{jn}^t,\quad n=1,\ldots,F \\ \sim x_{1n}^t\geq\sum_{j=1}^{K}\lambda_j^t\sim x_{kn}^t, n=F+1,\ldots,N,\ z_k^t\geq\sum_{j=1}^{K}\lambda_j^t z_j^t,\quad Y_k^t\geq\sum_{j=1}^{K}\lambda_j^t Y_j^t, \end{array}\right\}\quad k=1$$

$$\vdots$$

$$\left.\begin{array}{l} y_{hm}^t+\beta_h^t g_m\leq\sum_{j=1}^{K}\lambda_j^t y_{jm}^t,\quad m=1,\ldots,M,\quad x_{hn}^t\geq\sum_{j=1}^{K}\lambda_j^t x_{jn}^t,\quad n=1,\ldots,F, \\ x\sim_{hn}^t\geq\sum_{j=1}^{K}\lambda_j^t\tilde{x}_{jn}^t,\quad n=F+1,\ldots,N,\quad z_h^t\geq\sum_{j=1}^{K}\lambda_j^t z_j^t,\quad Y_h^t\geq\sum_{j=1}^{K}\lambda_j^t Y_j^t, \end{array}\right\}k=h$$

$$\vdots$$

$$\left.\begin{array}{l} y_{Km}^t+\beta_K^t g_m\leq\sum_{j=1}^{K}\lambda_j^t y_{jm}^t,\quad m=1,\ldots,M,\quad x_{Kn}^t\geq\sum_{j=1}^{K}\lambda_j^t x_{jn}^t,\quad n=1,\ldots,F, \\ x\sim_{Kn}^t\geq\sum_{j=1}^{K}\lambda_j^t\tilde{x}_{jn}^t,\quad n=F+1,\ldots,N,\quad z_K^{t-1}\geq\sum_{j=1}^{K}\lambda_j^t z_j^t,\quad Y_K^t\geq\sum_{j=1}^{K}\lambda_j^t Y_j^t, \end{array}\right\}\quad k=K$$

$$\sum_{k=1}^{K}\tilde{x}_{kn}^t\leq x_n^t,\quad \tilde{x}_{kn}^t\geq 0,\quad n=F+1,\ldots,N,\quad k=1,\ldots,K$$

$$\lambda_j^t\geq 0,\quad j=1,\ldots,K,\quad \beta_k^t\geq 0,\quad k=1,\ldots,K. \tag{4}$$

In problem (2) the actual amounts of $\tilde{\mathbf{x}}_k^t$ allocated to each university are taken as given. In contrast, in problem (4) the government agency (agencies) chooses the amounts of the inputs $\tilde{\mathbf{x}}_k^t$, $k=1,\ \ldots,\ K$ to allocate to each university so as to maximize the sum of the distances from each university's own observed outputs to its respective production frontier subject to the constraint that a finite amount of the resource is available. Let the optimal amounts of $\tilde{\mathbf{x}}_k^t$ found as part of the solution to problem (4) equal $\tilde{\mathbf{x}}_k^{t*}$. It is clearly the case that $\sum_{k=1}^{K}\tilde{x}_{kn}^t=\sum_{k=1}^{K}\tilde{x}_{kn}^{t*},\quad n=F+1,\ldots,N$. Again, we assume a common set of scaling variables ($\mathbf{g}=(g_1,g_2,g_3)$) for the three university outputs so that we can interpret the optimal objective function as a measure of industry technical inefficiency in period t. By constraining each $\beta_k^t\geq 0,\quad k=1,\ldots,K$ there is a limit to how much the NSF can reallocate: each university must still be able to produce its observed outputs so that reallocation can only take place from universities that are inefficient under the status quo. Thus, $y_k^t\in P^t(\mathbf{x}_k^t,\tilde{\mathbf{x}}_k^t,z_k^t,Y_k^t)$ under the status quo and $y_k^t\in P^t(\mathbf{x}_k^t,\tilde{\mathbf{x}}_k^{t*},z_k^t,Y_k^t)$ for an optimal reallocation of NSF funds. Problem (4) is solved for each of the $t=0,1,\ldots,T$ periods.

4. Time substitution

The idea of time substitution addresses when inputs should be used and was investigated by Shephard and Färe [31] and then later by Färe and Grosskopf [14], Färe et al. [32], and Färe et al. [33]. In this section we want to incorporate time substitution into our network production model. We consider when the best time is for the National Science Foundation to make inputs available to universities to produce knowledge outputs.

The basic time substitution model assumes that there is at least one input of finite amount that can be reallocated across time. We continue to assume that the first F inputs of the vector $\mathbf{x}_k^t$ are fixed and that the last $F+1,\ \ldots,\ N$ inputs can be reallocated among universities and across time. In actuality, universities might spend resources by hiring lobbyists and professors, purchasing research equipment, adding graduate students, and augmenting library resources so as to influence the NSF funding process, but these potential game theoretic decisions are beyond the scope of the present study. Let the subset of inputs that can be reallocated across time be represented by $\tilde{\mathbf{x}}^t=(\tilde{\mathbf{x}}_{F+1}^t,\ldots,\tilde{\mathbf{x}}_N)$. The finite amount of each of these inputs that can be reallocated among universities and across time equals $\bar{x}_n=\sum_{t=0}^{T}\sum_{k=1}^{K}\tilde{x}_{kn},\quad n=F+1,\ldots,N.$

Consider the timeline depicted in Fig. 1.

The problem of time substitution is to determine when to begin production and for how long production should take place. Let τ represent when to begin production and let Γ represent the number of periods in which production takes place. To account for time preferences we weight each university's distance function by the discount factor δ^t, where $\delta^t=(1+R)^{-t}$ and R is the interest rate. For university k, the time substitution problem can be represented as

$$\begin{aligned} &\max_{\tau,\Gamma,\tilde{x}^\tau}\ \sum_{t=\tau}^{\tau+\Gamma}\delta^t\vec{D}_{ok}^t(\mathbf{x}_k^t,\tilde{\mathbf{x}}_k^t,z_k^t,Y_k^t,\mathbf{y}_k^t;\mathbf{g}) \text{ subject to} \\ &\vec{D}_{ok}^t(\mathbf{x}_k^t,\tilde{\mathbf{x}}_k^t,z_k^t,Y_k^t,\mathbf{y}_k^t;\mathbf{g})\geq 0,\quad t\in[\tau,\tau+\Gamma] \\ &\sum_{t=\tau}^{\tau+\Gamma}\tilde{x}_{kn}^t\leq\bar{x}_{kn},\quad n=F+1,\ldots,N. \end{aligned} \tag{5}$$

In the time substitution problem represented by (5) the individual university chooses when to begin production, τ, when to end production, $\tau+\Gamma$, and how much of the finite input to use in each period, $\tilde{x}_n^t,\quad n=F+1,\ldots,N,\quad t\in[\tau,\tau+\Gamma]$ so as to maximize the sum of the distances from the observed input–output combinations in each period to that period's production possibility frontier. If $\Gamma$is relatively small, production takes place during a short time span and the input is used intensively. When $\Gamma$is relatively large, production takes place over many periods and the input tends to be used less intensively in each period. When technological progress occurs it pays for the producer to delay production so τ tends to be large. In contrast, when technological regress occurs it pays for the producer to begin production earlier resulting in a small τ.

Färe et al. [32] also investigated the time substitution problem under different scale economy regimes. Under increasing returns to scale it pays to intensively use the resource in a single period – either early or late in the period – so as to realize the greatest economies of scale. Under decreasing returns to scale an equal quantity of the resource should be employed in each period so as to minimize the effects of dis-economies of scale. Finally, under constant returns to scale the inputs can be used in any quantity during any period and the producer is indifferent concerning the choice of when to begin, τ, and for how long to produce, Γ.

The time substitution problem in this paper is complicated by the knowledge spillovers that occur between universities and across periods. Given the amount of knowledge previously produced by other universities, Y_k^t, what might be an optimal time path for

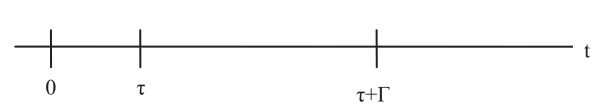

Fig. 1. Timeline of input use.

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resource use by one university, might not be the optimal time path when accounting for the knowledge spillovers. In addition, the government agency (NSF) has control over at least one of the inputs that university k has at its disposal: $\tilde{x}_{kn}^t, \quad n=F+1,\ldots,N,\ t=1,\ \ldots,\ T.$ We will assume that the agency seeks to maximize the sum of the sizes of the university production possibility sets by choosing when (τ) and how long (Γ) to make the input ($\tilde{x}_k^t$) available and which universities are to receive this input subject to the resource scarcity constraint $\sum_{k=1}^{K}\sum_{t=\tau}^{\tau+\Gamma}\tilde{x}_{kn}^t \le \bar{x}_n, \quad n=F+1,\ldots,N.$

Fig. 2 depicts the flow of knowledge outputs over time and between three hypothetical universities—A, B, and C. In period t, university A uses its own inputs, $\mathbf{x}_A^t$, and its knowledge inputs that were produced in a previous period, $z_A^t=y_A^{t-1}$. In addition, the university receives an allocation from the government agency, $\tilde{x}_A^t$, and it can draw on the stock of knowledge that was created at universities B and C in the previous period, $Y_A^t=z_B^t+z_C^t=y_B^{t-1}+y_C^{t-1}$. These four kinds of inputs, $(\mathbf{x}_A^t,\ \tilde{\mathbf{x}}_A^t,\ z_A^t, Y_A^t)$ are used to produce knowledge outputs y_A^t. A similar process is going on at universities B and C which are using inputs $(\mathbf{x}_B^t,\ \tilde{\mathbf{x}}_B^t,\ z_B^t, Y_B^t)$ and $(\mathbf{x}_C^t,\ \tilde{\mathbf{x}}_C^t,\ z_C^t, Y_C^t)$ to produce the knowledge outputs y_B^t and y_C^t. The knowledge outputs produced by the three universities become inputs to each university in the subsequent period. Each university in period $t+1$ draws on its stock of knowledge produced in the previous period, represented as z_A^{t+1}, z_B^{t+1}, and z_C^{t+1}, and in the spillovers they receive from the other two universities: $Y_A^{t+1}=y_B^t+y_C^t$, $Y_B^{t+1}=y_A^t+y_C^t$, and $Y_C^{t+1}=y_A^t+y_B^t$.

The time substitution problem facing the agency can be represented in DEA form as

$$\max_{\tau,\Gamma,\lambda,\tilde{x},\beta}\ \sum_{k=1}^{K}\sum_{t=\tau}^{\tau+\Gamma}\delta^t\beta_k^t\,\text{subjectto}$$

$$\left.\begin{array}{r}
y_{km}^t+\beta_k^t \le \sum_{j=1}^{K}\lambda_j^t y_{jm}^t, \quad m=1,\ldots,M, \quad k=1,\ldots,K\\
z_k^t \ge \sum_{j=1}^{J}\lambda_j^t z_j^t, \quad k=1,\ldots,K\\
Y_k^t \ge \sum_{j=1}^{J}\lambda_j^t Y_j^t, \quad k=1,\ldots,K\\
x_{kn}^t \ge \sum_{j=1}^{K}\lambda_j^t x_{jn}^t, \quad n=1,\ldots,F, k=1,\ldots,K\\
\tilde{x}_{kn}^t \ge \sum_{j=1}^{K}\lambda_j^t \tilde{x}_{jn}^t, \quad \tilde{x}_{kn}^t \ge 0, \quad n=F+1,\ldots,N, \quad k=1,\ldots,K\\
\lambda_j^t \ge 0, \quad j=1,\ldots,K
\end{array}\right\} \quad t=\tau$$

$$\vdots$$

$$\left.\begin{array}{r}
y_{km}^{t+1}+\beta_k^{t+1} \le \sum_{j=1}^{K}\lambda_j^{t+1} y_{jm}^{t+1}, \quad m=1,\ldots,M, \quad k=1,\ldots,K\\
z_k^{t+1}+\beta_k^t \ge \sum_{j=1}^{J}\lambda_j^{t+1} z_j^{t+1}, \quad k=1,\ldots,K\\
Y_k^{t+1}+\sum_{j\ne k}^{K}\beta_j^t \ge \sum_{j=1}^{J}\lambda_j^{t+1} Y_j^{t+1}, \quad k=1,\ldots,K\\
x_{kn}^{t+1} \ge \sum_{j=1}^{K}\lambda_j^{t+1} x_{jn}^{t+1}, \quad n=1,\ldots,F, \quad k=1,\ldots,K\\
\tilde{x}_{kn}^{t+1} \ge \sum_{j=1}^{K}\lambda_j^{t+1} \tilde{x}_{jn}^{t+1}, \quad \tilde{x}_{kn}^{t+1} \ge 0, \quad n=F+1,\ldots,N, \quad k=1,\ldots,K\\
\lambda_j^{t+1} \ge 0, \quad j=1,\ldots,K
\end{array}\right\} \quad t+1=\tau+1$$

$$\vdots$$

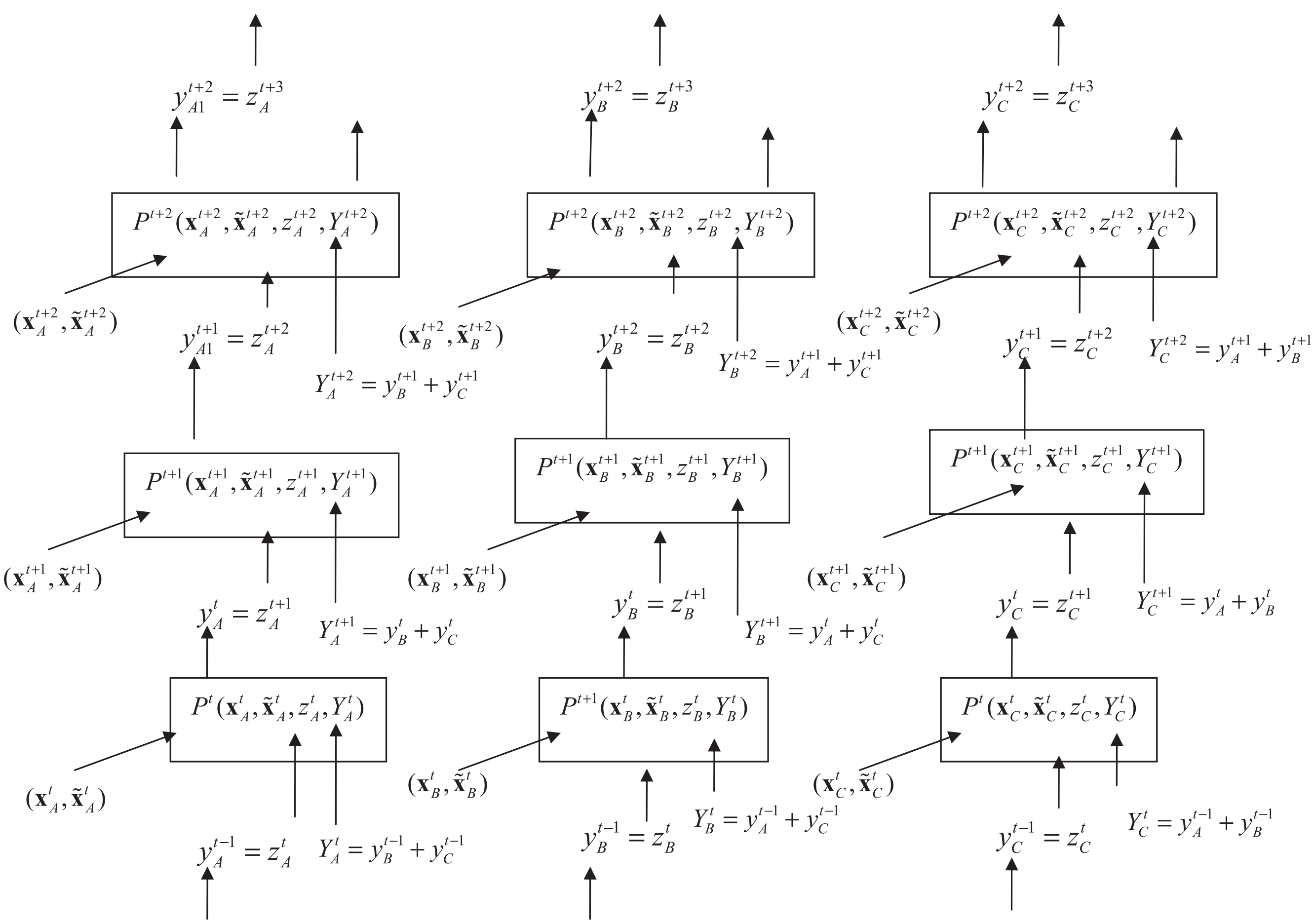

Fig. 2. Network production with knowledge spillovers $\tilde{\mathbf{x}}_A^\tau+\tilde{\mathbf{x}}_B^\tau+\tilde{\mathbf{x}}_C^\tau+\cdots+\tilde{\mathbf{x}}_A^{\tau+\Gamma}+\tilde{\mathbf{x}}_B^{\tau+\Gamma}+\tilde{\mathbf{x}}_C^{\tau+\Gamma}\le\bar{\mathbf{x}}$.

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$$\left.\begin{aligned} y_{km}^{t+\Gamma}+\beta_k^{t+\Gamma} &\le \sum_{j=1}^{K}\lambda_j^{t+\Gamma}y_{jm}^{t+\Gamma}, \quad m=1,\dots,M, \quad k=1,\dots,K \\ z_k^{t+\Gamma}+\beta_k^{t+\Gamma-1} &\ge \sum_{j=1}^{J}\lambda_j^{t+\Gamma}z_j^{t+\Gamma}, \quad k=1,\dots,K \\ Y_{k1}^{t+\Gamma}+\sum_{j\neq k}^{K}\beta_j^{t+\Gamma-1} &\ge \sum_{j=1}^{J}\lambda_j^{t+\Gamma}Y_j^{t+\Gamma}, \quad k=1,\dots,K \\ x_{kn}^{t+\Gamma} &\ge \sum_{j=1}^{K}\lambda_j^{t+\Gamma}x_{jn}^{t+\Gamma}, \quad n=1,\dots,F, \quad k=1,\dots,K \\ \tilde{x}_{kn}^{t+\Gamma} &\ge \sum_{j=1}^{K}\lambda_j^{t+\Gamma}\tilde{x}_{jn}^{t+\Gamma}, \quad \tilde{x}_{kn}^{t+\Gamma}\ge 0, \quad n=F+1,\dots,N, \quad k=1,\dots,K \\ \lambda_j^{t+\Gamma} &\ge 0, \quad j=1,\dots,K \end{aligned}\right\} \quad t+\Gamma=\tau+\Gamma$$

$$\sum_{k=1}^{K}\sum_{t=\tau}^{\tau+\Gamma}\tilde{x}_{kn}^{\tau}\le \overline{x}_n, \quad \tilde{x}_{kn}^{\tau}\ge 0, \quad n=F+1,\dots,N, \quad k=1,\dots,K$$

$$\beta_k^t \ge 0, \quad k=1,\dots,K, \quad t=1,\dots,T. \tag{6}$$

The choice variables in (6) include when the universities should begin production, τ, for how long production should occur, Γ, the amount of NSF funds to allocate to each university in each period, $\tilde{x}_k^t$, and the intensity variables that determine the frontier in each period, λ_k^t, so as to maximize the weighted sum of the distances to the frontier across universities and periods. We note that in the period that production begins, past knowledge outputs enter the problem as pure inputs in the two sets of equations $z_k^t \ge \sum_{j=1}^{J}\lambda_j^t z_j^t, \quad k=1,\dots,K$ and $Y_k^t \ge \sum_{j=1}^{J}\lambda_j^t Y_j^t, \quad k=1,\dots,K$. Then, in every subsequent period, those past knowledge outputs are expanded given the amount of inefficiency in the previous period. For instance, in period $t+1$, the university's own past knowledge outputs are an input, but those inputs are expanded by the amount of inefficiency from the previous period so the set of equations is modified as $z_k^{t+1}+\beta_k^t \ge \sum_{j=1}^{J}\lambda_j^{t+1}z_j^{t+1}, \quad k=1,\dots,K$. Similarly, the stock of knowledge outputs produced by other universities in the previous period becomes an input in the subsequent period and those spillover knowledge outputs are again augmented by the inefficiencies of all universities in the preceding period so the set of equations is $Y_k^{t+1}+\sum_{j\neq k}^{K}\beta_j^t \ge \sum_{j=1}^{J}\lambda_j^{t+1}Y_j^{t+1}, \quad k=1,\dots,K$. The university's own stock of knowledge (y_{k1}^t) is an intermediate output which serves as an input in the subsequent period (z_k^{t+1}) and is augmented by the university's own inefficiency in the previous period, β_k^t. Similarly the spillover input (Y_k^{t+1}) is augmented by the preceding period's inefficiencies of other universities, $\sum_{j\neq k}^{K}\beta_j^t$. Adding to both knowledge inputs relaxes the two inequality constraints and expands the production possibility set.

5. Data and estimates

We employ a unique panel data set comprising 25 universities that were engaged in nanobiotechnology knowledge production during the period 1990–2005. Three knowledge outputs are produced by universities: nanobiotechnology journal publications (y_1), nanobiotechnology patents (y_2), and Ph.D. graduates in nanobiotechnology (y_3). The production of knowledge outputs is generally not confined to a single year, but occurs over several years. We follow Weber and Xia [4] and take a three year moving average of the three outputs. Thus, the first year we have data for the three year moving average is 1992. Foltz et al. [34] use a similar framework for defining the outputs of 98 research universities. Since knowledge outputs produced in one period become inputs to a subsequent period's production technology, our model can be estimated for the 13 year period 1993 to 2005. Using the GDP deflator with a base year of 2005, total real university spending in engineering, life sciences, and physical sciences comprise one of the university inputs (x_1). The other university inputs are lagged own publications (z), lagged publications of other universities (Y), and real grants in nanotechnology from the National Science Foundation ($\tilde{x}$).

We consider two different ways of measuring the stock of lagged own publications and lagged publications of other universities. In model 1, lagged own publications (z) equal the sum of the university's own publications in nanobiotechnology in the previous three years. Similarly, the spillover knowledge output (Y) consists of the sum of all other universities' publications in the previous three years. In model 2, we employ a perpetual inventory method to construct the total stock of previous knowledge produced by the university in all previous periods as the own stock of knowledge and the total stock of previous knowledge produce by other universities in all previous periods as the spillover knowledge output. Like physical capital, knowledge can depreciate and become obsolete (see Park et al. [35] and Grubler and Nemet [36]) because of human capital turnover (researchers move to other institutions) and because of rapid innovation and creative destruction. Given a depreciation rate of θ, the universities own stock of knowledge embodied in past publications is $z_k^t = z_k^{t-1}(1-\theta)+y_{k1}^{t-1}$ with the year 1990 serving as the first year in which publications can occur[1]. For model 2, the spillover knowledge output consists of the sum of all other universities' depreciated publications from all previous years: $Y_k^t = Y_k^{t-1}(1-\theta)+\sum_{j\neq k}^{K}y_j^{t-1}$.

Clearly, the rate at which journal publications (knowledge) depreciate affects the values of z_k^t and Y_k^t. Hall [37] finds that knowledge depreciation rates vary depending on whether a production function approach or market value approach is used to measure depreciation. Darr et al. [38] find extremely high rates of depreciation of service firms' own stock of knowledge. Grubler and Nemet [36] find similarly high rates of depreciation (on the order of 100% per year) in service industries due to staff turnover. In contrast, Alston et al. [39] find depreciation rates of less than 10% for agricultural R&D. Park et al. [33] estimate an average depreciation rate of 13.3% for technological knowledge across various industries during the period 1985 to 1999. We choose a depreciation rate of $\theta = 0.15$. This depreciation rate gives a half-life for a publication slightly greater than four years.

Fig. 3 graphs the number of total number of publications, patents, and Ph.D. students in nanobiotechnology for the period 1990 to 2005. In 1990, there were only six publications among the 25 universities in our sample, but by 2005 that number had increased to 723. Patents and Ph.D. graduates grew less rapidly during the period. In 1990 there were 28 patents and 10 Ph.D. graduates. By 2005 universities patented 162 inventions and graduated 179 Ph.D. graduates in nanobiotechnology. Given the large increase in publications it is possible that the quality of publications changed during the period or that the value of a publication relative to a patent or Ph.D. graduate changed. However, without price data on the three outputs and with no data on citations which might serve as a measure of quality we are unable to measure changes in the relative values of the three outputs. Instead, our model partially controls for the increasing number of publications in that we control for past publications in the form of the university's own stock of knowledge and the spillover stock of

[1] For instance, for the years 1994 and 1995 the variable z_k^t is defined as $z_k^{1994} = z_k^{1993}(1-\theta)+z_k^{1992}(1-\theta)^2+z_k^{1991}(1-\theta)^3+y_k^{1993}$ and $z_k^{1995} = z_k^{1994}(1-\theta)+y_k^{1994}$.

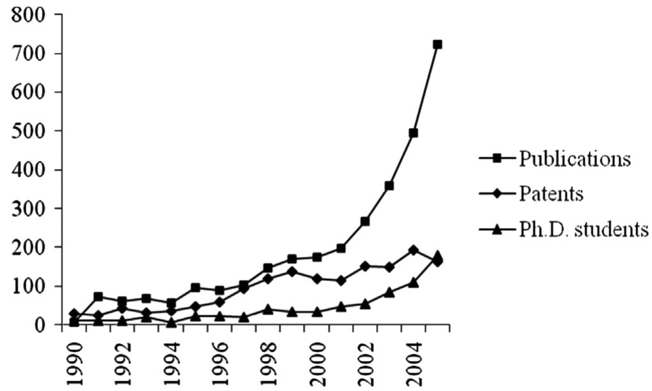

Fig. 3. University knowledge outputs in nanoikbiotechnology.

Table 1
Descriptive Statistics.

Variable	Mean	Std	Minimum	Maximum
Publications $= y_1$	6.63	6.63	0.3	45.3
Patents $= y_2$	3.38	3.26	0	17
Ph.D.s $= y_3$	1.49	1.65	0	11
University research dollars $= x_1$ (millions of \$, base = 2005)	251.68	133.58	19.5	662.7
NSF funds $= \tilde{x}$ (millions of \$, base = 2005)	3.13	4.65	0	32.5
Lagged other publications $= Y_k^t = \sum_{l=1}^{3} \sum_{k' \neq k}^{K} y_{k'1}^{t-l}$	419.23	267.06	124	1112
Lagged Own publications $z_k^t = \sum_{l=1}^{3} y_{k1}^{t-l}$	16.08	14.87	1	100

knowledge from other universities. Since both of these knowledge inputs are increasing it seems reasonable to expect the production of new knowledge will also increase.

Table 1 reports descriptive statistics for the three outputs and four inputs. The three year moving average of publications is 6.6 and ranges from 0.3 at several universities to 45.3 at Harvard University in 2005. Patents average 3.4 and several universities had no patents in at least one year and the University of Michigan had 17 nanobiotechnology related patents in 2005. The universities produced a three year moving average of 1.5 Ph.D. graduates ranging from 0 at several universities to 11 at Cornell University in 2005. The three year moving average of university research dollars allocated to engineering, physical sciences, and life sciences averaged \$252 million and ranged from \$19.5 million at Rice University in 1995 to \$663 million at UCLA in 2004. NSF grants averaged \$3.1 million and ranged from \$0 to \$32.5 million at Cornell University in 2001.

We report the model 1 and model 2 estimates of university performance found by solving problems (2), (4), and (6) in Table 2, but focus our discussion on the model 1 results. The numbers of frontier universities are reported in Table 3 and the actual and optimal amounts of NSF funds are reported in Table 4. To estimate the network performance of universities we chose a directional vector $\mathbf{g} = (g_1, g_2, g_3) = (1, 1, 1)$ to scale the three knowledge outputs to the frontier. Thus, the interpretation of the estimate for the directional distance function for a university, β_k^t, is that it gives the simultaneous unit expansion in the three outputs that would be feasible if the university were to adapt the best-practices of the most efficient universities. Other directional vectors could also be chosen. Another directional vector that is common to all universities would to use the average output quantities of all universities: $\mathbf{g} = (\bar{y}_1, \bar{y}_2, \bar{y}_3)$. In this case, the estimate of university performance, β_k^t, would be the expansion in the three outputs as a proportion of their mean. As an example of a directional vector that is university specific would be $\mathbf{g_k} = (y_{k1}, y_{k2}, y_{k3})$. With this directional scaling vector the value of the directional output distance function in a specific period, β_k^t, would give the proportional expansion in the three outputs. However, with a university specific directional vector an indicator of aggregate performance cannot be obtained as the sum of the individual university performance indicators (Färe and Grosskopf [24]).

In problem (2) we assume that all inputs, including grants from the NSF ($\tilde{x}$), are fixed and estimate the directional distance function for each university in a given period. That is, we allow for the production frontier to shift from period to period. Average university inefficiency equals $\vec{D}_o^t(\mathbf{x}_k^t, z_{k1}^t, Y_k^t, \mathbf{y}_k^t; \mathbf{1}) = 0.20$ in 1993. Thus, the typical university could have achieved 0.2 more patents, publications, and Ph.D. graduates if it realized greater efficiency and produced on the frontier in 1993. In this model, the sum of the individual university directional distance functions equals aggregate university technical inefficiency reported in column 3 of Table 2. From 1993 to 1997 aggregate inefficiency moves in a zig-zag pattern ranging from a low of 4.05 in 1994 to a maximum of 5.74 in 1995. Beginning in 1998, aggregate inefficiency increases to 6.04 and ends at 12 in 2005. Table 3 reports the number of universities that produced on the frontier which ranged from a low of 13 in 1996 to a high of 19 in 1997. The sum of discounted aggregate inefficiency over the 13 year period is 72.12 where we use an interest rate of $R = 3.43\%$. This interest rate equals the real interest rate calculated as the difference between the 20 year Treasury bond rate and the rate of inflation measured by the consumer price index.

We also used the perpetual inventory method to measure the stock of a university's own publications and the spillover input of other university's publications (model 2) when there is no reallocation of NSF funds across universities or time. The estimates resulted in the same general pattern of aggregate inefficiency, with inefficiency lowest in 1994 and greatest in 2004. The sum of discounted aggregate inefficiency for the 13 year period was higher, 93.3 compared to 72.12. Furthermore, as seen in Table 3, the model 2 estimates show fewer universities to be on the frontier in each period compared to model 1.

Our data set has a relatively small number of observations (25 universities) for which to estimate a technology with three outputs and four inputs and thus might suffer from what is called the curse of dimensionality. That is, it is likely that most universities are compared to themselves when evaluating efficiency which is evident from the large number of frontier universities. One possible method for addressing the dimensionality problem is by reducing the number of inputs or outputs to evaluate (see Avkiran [40] for an example), although theory gives us little guidance of which outputs or inputs to eliminate and would be akin to the problem that the error term captures the effect of missing variables in classical regression analysis. As an alternative, the researcher could combine PCA (principal components analysis) with DEA (data envelopment analysis) following Adler and Golany [41] to get more power to discriminate among the producers. However, the dynamic network structure of our knowledge production problem complicates the use of PCA with DEA. Instead, we estimated the principal components of the three outputs and the four inputs and estimated a simple DEA model with no network and no dynamic effects. The results are reported in Table 4. As expected, the model that uses the principal components of the outputs and principal components of the inputs estimates greater inefficiency in each year and fewer universities on the frontier relative to the actual data on inputs and outputs. To get even greater discriminatory power we further constrained the model to the top two principal components of the three outputs and the top two principal components of the four inputs. The top two principal components accounted for 93% of the variance of

Table 2
Estimates of Inefficiency for 25 universities.

a. Model 1 Results[1,2]

Year	No reallocation of NSF funds ($\tilde{x}$) $\overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	No reallocation of NSF funds ($\tilde{x}$) Sum over all universities $\sum_{k=1}^{K} \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	Reallocation between universities, but not across time $\sum_{k=1}^{K} \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	Reallocation between universities and across time $\sum_{k=1}^{K} \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$
1993	0.20	4.91	5.90	5.38
1994	0.16	4.05	6.11	7.52
1995	0.23	5.74	7.01	9.66
1996	0.22	5.50	8.51	10.86
1997	0.17	4.29	6.69	10.00
1998	0.24	6.04	10.02	13.07
1999	0.23	5.75	9.00	14.61
2000	0.30	7.51	11.50	19.15
2001	0.38	9.53	15.01	23.02
2002	0.16	4.06	6.57	16.86
2003	0.40	9.94	17.04	26.41
2004	0.47	11.74	16.13	44.95
2005	0.48	12.00	15.31	45.95
$\sum_{t=0}^{T}\sum_{k=1}^{K} \delta^t \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1}) =$		72.12	106.61	188.88

b. Model 2 Results[3]

Year	No reallocation of NSF funds ($\tilde{x}$) $\overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	No reallocation of NSF funds ($\tilde{x}$) Sum over all universities $\sum_{k=1}^{K} \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	Reallocation between universities, but not across time $\sum_{k=1}^{K} \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	Reallocation between universities and across time $\sum_{k=1}^{K} \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$
1993	0.20	4.91	5.90	5.42
1994	0.16	3.98	7.00	7.40
1995	0.22	5.51	7.03	8.04
1996	0.20	5.10	7.57	8.29
1997	0.22	5.39	6.71	7.70
1998	0.28	7.00	10.84	11.65
1999	0.32	7.88	10.78	12.14
2000	0.40	9.90	17.05	18.35
2001	0.51	12.64	19.27	20.15
2002	0.34	8.61	15.11	15.67
2003	0.55	13.85	24.76	28.77
2004	0.75	18.70	24.42	37.95
2005	0.67	16.65	27.92	36.74
$\sum_{t=}^{T}\sum_{k=1}^{K} \delta^t \overrightarrow{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1}) =$		93.30	142.39	166.74

Note:

1. The network input/output is the three year sum of lagged own publications: $z_k^t = \sum_{l=1}^{3} y_{k1}^{t-l}$ and the spillover input is the three year sum of all other universities' publications: $Y_k^t = \sum_{l=1}^{3}\sum_{k' \neq k}^{K} y_{k'1}^{t-l}$.
2. The discount rate is $\delta^t = (1+R)^{-t}$, where $R = 0.0343$.
3. The network input output is the depreciated sum of all own past publications: $z_k^t = z_k^{t-1}(1-\theta) + y_{k1}^{t-1}$,. The spillover input is the depreciated sum of all other universities' past publications: $Y_k^t = Y_k^{t-1}(1-\theta) + \sum_{k' \neq k}^{K} y_{k'}^{t-1}$. The depreciation rate is $\theta = 0.15$.

outputs and 79% of the variance of the four inputs. With this model we estimated even greater inefficiency and fewer universities on the frontier. Although the curse of dimensionality might truly exist with our data set, we argue that the large number of frontier universities should not be unexpected in the nascent nanobiotechnology research that is taking place among some of the top US research universities.

When the NSF can reallocate the input it gives to universities, aggregate inefficiency as estimated by problem (4) increases in every year. This result was expected because the status quo allocation by the NSF is feasible, but not necessarily optimal so that $\sum_{k=1}^{K} \beta_k^{t*} \geq \overrightarrow{D}^t_o(\mathbf{x}^t, z^t, Y^t, \mathbf{y}^t; \mathbf{1})$, where $\overrightarrow{D}^t_o(\mathbf{x}^t, z^t, Y^t, \mathbf{y}^t; \mathbf{1})$ represents aggregate inefficiency under the status quo allocation of the NSF input and $\sum_{k=1}^{K} \beta_k^{t*}$ represents aggregate inefficiency when the NSF can reallocate its nanotechnology grants to universities in a given year. The difference between $\sum_{k=1}^{K} \beta_k^{t*}$ and $\overrightarrow{D}^t_o(\mathbf{x}^t, z^t, Y^t, \mathbf{y}^t; \mathbf{1})$ equals the extra publications, extra patents, and extra Ph.D. graduates that could have been produced given an optimal reallocation of NSF funds, $\tilde{x}_k^t, \quad k = 1, \ldots, K$, if the universities were to use their resources efficiently and produce on the production possibility frontier. As shown in the fourth column of Table 2 this difference (5.90–4.91) ranged from about 1 extra publication, 1 extra patent, and 1 extra Ph.D. graduate in 1993 among the 25 universities to 7.1 extra publications, 7.1 extra patents, and 7.1 extra Ph.D. graduates in 2003. We can also see in Table 3 that optimal reallocation of NSF funds reduces the number of universities that produce on the frontier relative to the status quo allocation of NSF funds in every year except 2004. Further analysis of this result showed that the NSF would have taken just enough of their allocation away from an inefficient university and reallocated it to other universities so that the loss of potential output from the inefficient university was less than the potential gain to the other universities. In addition, the loss of funds turned the inefficient university into one of the efficient producers. Using the specification of the knowledge outputs for model 2 and where the NSF reallocates funds across universities but not across time again results in higher levels of inefficiency with inefficiency rising from 1997 to 2003, a slight decline in 2004, and then greater inefficiency in 2005. However, the number of frontier universities increases in every year relative to the status quo allocation. Again, this result occurs because the NSF takes money away from inefficient universities shifting their production frontiers inward toward their observed outputs and reallocates the money to universities where potential outputs can increase more than the loss of potential output at the inefficient universities.

In problem (6) we allow the NSF to reallocate its grants between universities and across time. We calculated the real risk-free interest rate as the return on 20 year treasury bonds and the inflation rate, where the inflation rate equals the percent change in the consumer price index. From 1993 to 2005 this real risk-free interest rate averaged 3.43% and we use that rate as the weight or discount rate for problem (6): $\delta^t = (1+.0343)^{-t}$, $t = 0, 1, \ldots, T$. Discounted aggregate inefficiency summed over time increases relative to when NSF can only reallocate funds between universities in a given period. However, we see that for 1993, aggregate inefficiency (or potential output gains) actually declines relative to when NSF can only reallocate between universities in a given period. This result occurs because using the money in a future period can result in larger potential output gains than is lost by taking the money away from 1993. There is a rising trend in aggregate inefficiency throughout the 13 year period. In addition, the sum of discounted aggregate inefficiency over the 13 year period is more than twice as high when NSF can optimally reallocate its funds across universities and time relative to the status quo estimate of discounted aggregate inefficiency. The number of frontier universities reported in the last column of Table 3 declines in every period relative to the status quo.

Table 5 reports the means for actual and optimal NSF grants and these provide us with an explanation for why aggregate inefficiency is less in 1993 when the NSF can reallocate resources across time, than when it can only reallocate resources across universities. Since fewer NSF grants would have been given in 1993 than were actually given, the sum of the sizes of the production possibility sets for the 25 universities shrinks when NSF can reallocate across time. In fact, mean optimal NSF grants are smaller in 1993 and 1995 to 2002, but the decline in those years is offset by increases in 1994 and the period 2003 to 2005. Such intertemporal reallocation of NSF funds increases the number of publications, patents, and Ph.D. graduates that could have been feasibly produced if universities were able to increase their

Table 3
Number of Frontier universities.

Year	No reallocation of NSF funds ($\tilde{x}$)	Reallocation between universities, but not time	Reallocation between universities and across time
Model 1			
1993	16	15	15
1994	16	11	8
1995	15	13	7
1996	13	9	5
1997	19	14	8
1998	14	10	5
1999	15	12	4
2000	15	13	5
2001	16	12	7
2002	17	14	7
2003	15	12	5
2004	14	15	4
2005	17	12	3
Model 2			
Year	No reallocation of NSF funds ($\tilde{x}$)	Reallocation between universities, but not time	Reallocation between universities and across time
1993	15	15	15
1994	7	16	8
1995	12	14	6
1996	10	13	7
1997	11	16	7
1998	10	14	8
1999	11	15	7
2000	10	13	8
2001	12	16	11
2002	8	14	10
2003	9	13	6
2004	8	12	5
2005	9	14	3

Table 4
Principal Components Analysis with DEA.

	Actual **y**and **x**[1]		All Principal Components of **y**and **x**		Top 2 Principal components of**y**and **x**	
Year	$\sum_{k=1}^{K} \vec{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	# on frontier	$\sum_{k=1}^{K} \vec{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	# on frontier	$\sum_{k=1}^{K} \vec{D}^t_{ok}(\mathbf{x}, z, Y, \mathbf{y}; \mathbf{1})$	# on frontier
1993	4.91	16	9.54	10	33.06	4
1994	4.04	15	8.62	10	37.98	3
1995	5.76	15	14.93	9	46.53	4
1996	5.50	12	17.83	5	66.70	3
1997	4.28	19	14.30	9	62.73	2
1998	6.03	14	11.72	7	53.99	4
1999	5.79	14	14.10	10	65.40	3
2000	7.50	14	17.17	9	82.85	3
2001	9.54	15	16.15	11	80.30	2
2002	4.07	17	18.78	10	104.15	3
2003	9.95	15	16.11	13	94.98	3
2004	11.75	13	22.77	12	108.83	2
2005	12.01	16	30.23	12	129.06	2

Note:
1. The output vector is $\mathbf{y} = (y_1, y_2, y_3)$ and the input vector is $\mathbf{x} = (x_1, \tilde{x}, z, Y)$.

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Table 5
Mean Actual ($\tilde{x}$) and Optimal ($\tilde{x}^*$) National Science Foundation Grants (std.dev.).

		Model 1		Model 2	
		Reallocation between universities but not across time	Reallocation between universities and across time	Reallocation between universities but not across time	Reallocation between universities and across time
Year	Actual NSF $\tilde{x}$	Optimal NSF $\tilde{x}^*$	Optimal NSF $\tilde{x}^*$	Optimal NSF $\tilde{x}^*$	Optimal NSF $\tilde{x}^*$
1993	0.725	0.725	0.521	0.725	0.535
	(1.724)	(1.764)	(1.704)	(1.760)	(1.702)
1994	1.342	1.342	1.716	1.342	1.725
	(2.829)	(2.805)	(2.905)	(1.874)	(2.906)
1995	1.112	1.112	1.035	1.112	0.869
	(1.871)	(1.882)	(1.821)	(1.879)	(1.606)
1996	1.636	1.636	1.107	1.636	1.014
	(2.631)	(1.678)	(1.542)	(2.224)	(1.558)
1997	1.123	1.123	0.667	1.123	0.683
	(1.734)	(1.098)	(0.428)	(1.616)	(0.507)
1998	1.380	1.380	1.234	1.380	1.202
	(1.648)	(1.039)	(0.722)	(0.986)	(0.772)
1999	1.455	1.455	1.106	1.455	1.127
	(1.782)	(1.531)	(0.747)	(1.739)	(0.753)
2000	3.439	3.439	2.248	3.439	2.264
	(5.288)	(3.867)	(0.924)	(3.931)	(0.987)
2001	4.985	4.985	3.626	4.985	3.558
	(6.660)	(6.049)	(2.079)	(2.134)	(2.212)
2002	6.180	6.180	6.200	6.180	6.385
	(6.183)	(5.539)	(3.226)	(3.258)	(4.355)
2003	5.780	5.780	6.370	5.780	6.501
	(5.162)	(3.712)	(3.462)	(2.779)	(3.531)
2004	5.970	5.970	8.853	5.970	8.339
	(6.080)	(5.992)	(6.644)	(4.957)	(5.656)
2005	5.603	5.603	5.955	5.603	6.527
	(5.107)	(4.845)	(4.610)	(4.698)	(4.655)

efficiency to that of the frontier universities. The last row of Table 2 reports the sum of discounted aggregate inefficiencies over the 13 year period, 1993–2005. Relative to the status quo level of discounted aggregate inefficiency of 72 extra publication, 72 extra patents, and 72 extra Ph.D. students, if the NSF were to optimally reallocate across universities but not time, each of the three knowledge outputs could increase by 34 from 72 to 106. If the NSF were able to optimally reallocate its grants across universities and time each of the three knowledge outputs could increase by 82 (from 106.6 to 188.8) if universities were to employ those resources efficiently.

Table 6 reports the universities that would gain the most NSF funding and those that would lose the most NSF funding if NSF funds were optimally reallocated for the model 1 specification of inputs and outputs. When NSF funds can be reallocated between universities but not across time, Northwestern from 1993 to 1995, Cornell from 1996 to 2001, UCLA from 2002 to 2004, and Wisconsin in 2005 would lose the most funds. The biggest gainers in NSF funds include UCLA in 1993, Washington University (St. Louis) in 1994, 2002, and 2005, Michigan in 1995, Ohio State in 1996, Case Western from 1997 to 2001, and the University of Washington in 2003 and 2004. When resources can also be reallocated across time, Pennsylvania State University replaces Northwestern as losing the most NSF funds, but the remainder of the list is the same except for Cornell replacing UCLA in 2002. The list of universities that would gain the most in NSF funds changes to include Maryland in 1994, Tufts in 1998 and 2000, Virginia in 1999, and Stanford in 2005. Case Western University, which would have gained the most in NSF funding in the years 1997 to 2001, now only gains the most in 2001. In addition, except in 1993, 1994, and 2004, the maximum losses of NSF funding are greater than the maximum gains suggesting that the optimal NSF distribution of funds is more equal. The more even distribution of

Table 6
Gainers and Losers in NSF funding.

	Reallocation between universities but not across time		Reallocation between universities and across time	
Year	Loss of NSF Grants$=(\tilde{x}_k^{t*}-\tilde{x}_k^t)$	Gain of NSF grants$=(\tilde{x}_k^{t*}-\tilde{x}_k^t)$	Loss of NSF Grants$=(\tilde{x}_k^{t*}-\tilde{x}_k^t)$	Gain of NSF grants$=(\tilde{x}_k^{t*}-\tilde{x}_k^t)$
1993	−1.62	2.64	−1.62	2.04
	(Northwestern)	(UCLA)	(Northwestern)	(UCLA)
1994	−1.87	0.76	−0.31	6.11
	(Northwestern)	(Washington U.)	(Penn State)	(Maryland)
1995	−1.46	1.56	−1.41	0.46
	(Northwestern)	(Michigan)	(Northwestern)	(Washington U.)
1996	−8.15	2.80	−10.11	2.18
	(Cornell)	(Ohio State U.)	(Cornell)	(U. of Washington)
1997	−6.90	5.21	−7.20	1.57
	(Cornell)	(Case Western)	(Cornell)	(U. of Washington)
1998	−5.81	4.44	−6.28	1.25
	(Cornell)	(Case Western)	(Cornell)	(Tufts)
1999	−5.74	7.50	−5.61	0.65
	(Cornell)	(Case Western)	(Cornell)	(Virginia)
2000	−24.58	20.13	−24.49	1.87
	(Cornell)	(Case Western)	(Cornell)	(Tufts)
2001	−28.94	31.77	−29.34	2.92
	(Cornell)	(Case Western)	(Cornell)	(Case Western)
2002	−6.52	3.33	−17.99	7.71
	(UCLA)	(Washington U.)	(Cornell)	(Washington U.)
2003	−13.75	4.66	−13.58	5.48
	(UCLA)	(U of Washington)	(UCLA)	(U. of Washington)
2004	−10.88	11.15	−8.50	13.00
	(UCLA)	(U of Washington)	(UCLA)	(U. of Washington)
2005	−4.47	2.69	−4.21	3.43
	(Wisconsin)	(Washington U.)	(Wisconsin)	(Stanford)

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funding is also seen in the lower standard deviations of the optimal NSF grants ($\tilde{x}^*$) relative to actual NSF grants ($\tilde{x}$) reported in Table 6, especially in the latter part of the period.

6. Summary

The production of knowledge at a university can enhance its future production possibilities and spillover and enhance the production possibilities of other universities. In this paper we developed three DEA production models to examine the potential gains in three knowledge outputs in the area of nanobiotechnology: publications, patents, and Ph.D. graduates. During 1993 to 2005, the 25 universities in our sample could have produced an additional 72 publications, 72 patents, and 72 Ph.D. graduates by reducing inefficiency. Allowing the NSF to optimally redistribute its grants in nanotechnology among the 25 universities in each given time period could have resulted in an extra 34 publications, 34 patents, and 34 Ph.D. graduates if the 25 universities had produced efficiently. Allowing the NSF to optimally redistribute among the 25 universities and across the 13 year period 1993–2005 could have resulted in an additional 82 publications, 82 patents, and 82 Ph.D. graduates. Given that the NSF grant process is highly competitive and subject to peer review our findings of inefficiency suggest that the transactions costs of NSF acquiring the necessary information and overcoming political obstacles are fairly high. This lack of information might be expected given the fledgling nanobiotechnology industry and might also be part of the costs of funding basic and applied research in science.

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