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Modeling and policy analysis for the U.S. Science Sector

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Modeling and Policy Analysis for the US Science Sector*

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Abstract

This paper analyzes the production process of scientific outputs and its implications on the U.S. economy using variants of a disaggregated Marshallian Macroeconomic Model (MMM). Federal spending on scientific activities produces innovation which we measure using the number of patents awarded. Additionally, this study makes use of the Bass diffusion model to investigate how innovative patents generate new products that attract new firms in existing sectors of the U.S. economy. Firms are assumed to be Bayesian learners while forming expectations about product prices. Using a set of policy simulations, this research provides measured information on how selected science policies may affect sectoral growth of the U.S. economy. Moreover, issues such as bifurcation pertaining to dynamic models are thoroughly addressed in this paper. Among others, our findings suggest that federal spending on applied research has larger short-run growth enhancement effects than spending on development or basic research. The return of current federal spending on applied research depends largely on past spending on basic research, something that is well captured through the lag structure imposed in our model. Recipients of federal grants for basic research often lay foundation for outstanding applied research.

Keywords: *Disaggregated Marshallian Macroeconomic Model; Bass Diffusion Model; Transfer Functions; and Bayesian Learners.*

1 Introduction

If we understand that scientific progress in general and technological innovation in particular constitute pillars for long and sustainable economic development, then more consideration ought to be given to modeling and policy simulations designed to promote and advance the science sector. Scientific research and development is at the core of increased productivity and increased competitive advantage for emerging world market economies. Knowledge-driven production framework has generated incommensurable technological advances that have translated into increased wealth, job creation, substantial improvement in living standard, etc. Advances in science have generated growing demand for skilled labor-force. It is therefore highly relevant to identify and carefully study how scientific knowledge is diffused and how it affects economic performance overall.

Researchers have quite often used historical data to study the impact of federal funding on scientific productivity. Proxies considered in the measurement of scientific productivity vary: the

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most commonly used are 1) the number of publications and their scholarly impact (Adams and Griliches 1998, Payne and Siow 2003), 2) the number of doctoral students trained, 3) patent citations (Huang et al 2006), and 4) the number of patents awarded. Yet, the literature contains major shortcomings that we propose to address in this study.

Market dynamics for products and factors are often ignored in the study of innovation. The structural forms and techniques used in models of innovation are often characterized by an excessive use of dummy variables and a lack of market interaction for innovative outcomes (Arora and Gambarella, 2005). Whether measured using patents or publications, innovative outcomes, like any other production factors in the economy, are equilibrium outcomes determined by the interaction of demand and supply factors. It is common knowledge that equilibrium models are far more informative, produce better fits and predictions than non-equilibrium ones. In this paper, these modeling aspects are implemented in our use of a Marshallian macroeconomic model (MMM) of the U.S. science sector which is described in the next section. Also, in the promotion and commercialization of scientific outputs, patents have played a continuous role. Though, it is widely recognized that patenting alone does not define innovation; see for example, Harper, S. and Becker, S., 2004, or Griliches, Z. 1990, among others. Very often, new ideas and inventions are conceived and patented without necessarily being adapted into new technologies or new products. And even if some patented ideas end up being used for new products, not all of these products are successful in the market place. Although patents are often regarded as the dry preserve for innovative activities, they only form part of the innovation process. Patents numbers can be associated with very valuable inventions leading to successful products or they can be related to inventions of very little value with no success in the market place. Even harsher questions have been asked when it comes to patenting and its impact on innovation. Are patents simply genuine property rights or rather some form of superfluous government interference? Isn't the patent system just a legal cudgel used to smash competition with devastating effects on incremental innovation, something that ironically hinders efforts and incentives to develop superior products? How much do current patents laws and regulations help promote innovative activities in the U.S.? Although not all these questions could be adequately addressed, this paper provides a better understanding of 1) the production process of patentable ideas in the U.S. economy; 2) a good approximation of how patented ideas are transformed into new products; 4) how all that affects sectoral economic growth; and 5) differential effects that various funding schemes have on innovation. Needless to say, innovation usually requires some degree of societal endorsement otherwise it might be creativity or merely productivity. In an economic context, societal endorsement takes the form of some degree of success in the marketplace, i.e. commercialization. For example, the University of Chicago reports that approximately 25 percent of patents are licensed in recent years. If that is typical of other universities, then it is obvious that the total number of patents used to measure innovation should be discounted similarly. Lack of data on better measures of innovation has posed a crucial constraint on this study reason why, as most other studies on innovation, we could only rely on patent numbers. However, as being very concerned by the matter, for future research, we have submitted a complete research proposal to the National Science Foundation where we propose various and improved measures of innovation. At present, in order to address this issue, this study makes use of the growth rate of patents granted while simply assuming that the proportion of approved patents that are commercialized or licensed does not change substantially over years. Although, this is a strong assumption that we propose to investigate in further studies using appropriate data set, e.g. the Association of University Technology Managers. Therefore, the use of growth rate of approved patents in this study helps reduce substantially measurement bias of innovation. Using a model that fits the data reasonable well and provide reliable predictions, we have performed a set of policy simulations that we believe will be of great use to scientists as well as policy makers.

Having completed our introduction, an overview of the rest of the paper is as follows. The second section is devoted to a description of our modeling framework and a discussion on bifurcation boundaries in the MMM. Section III includes fits and forecasts of all the variants of our MMM.

Finally, we implement a set of policy shocks aimed at assessing the impact of raised research spending on the outcome of the U.S. Science sector and the other sectors of the U.S. economy in Section IV and conclude in section V.

2 Modeling framework and data

The modeling of a U.S. science sector includes a product market for innovation proxied by the number of patents granted and markets for the production factors; see Zellner and Ngoie (2011) for a complete development of the MMM. For each of the main inputs, i.e. labor and capital, there is a market with supply, demand and equilibrium dynamics. As regard to capital, innovative activities might include prior information and sample information used through Bayes terms to produce respectively information in posterior distribution of parameters and information in marginal density of observations. Prior information can be measured through the amount of consultancy work the sector makes use of while sample information will be the amount of data and other information such as patent citations available to the researcher. Furthermore, the output as well as input information is priced to get the profit that is maximized. Due to unavailability of such datasets, the present study only includes the traditional inputs: labor and capital.

The science sector affects other sectors of the economy through their factor markets. Output of the science sector, i.e. innovation, constitutes a key input for other sectors. Also, innovative patents lead to new products that are adopted and introduced in the economy. New products can be used as such in existing sectors or they can lead to the creation of brand new sectors. In this paper, we make use of the Bass diffusion model to allow for the introduction and adoption of new products. Therefore, the entry/exit equation of our MMM contains two types of entrants, (1) firms that join the sector while attracted by the profit margin on sales of existing products and (2) firms that have adopted new products and introduce them in the sector. What we call firms here represent production units involved in innovative activities that generate patents which includes private and public labs, universities, private companies, etc.

2.1 Supply, Demandand Entry Equations

We assume a Cobb-Douglas specification of the production function and production units are optimizers in the science sector. Although optimization in the production of patents is not only driven by money, in this study, for simplicity, we do assume that production units involved seek for profit. Patents granted are either commercialized (and later adapted into new products) or directly adapted into new products. In both cases, profit is generated.

The optimization process yields the output function for an individual firm. Multiplying output by the price we obtain the sales supply function for an individual firm and the sector's sales supply function is obtained by multiplying individual sales by the total number of firms within the sector (N).

2.2 Supply Function

$$\begin{aligned} S_{St} \;=\; & N_t.P_t.A_t^{\frac{1}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,\alpha^{\frac{\alpha}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,\beta^{\frac{\beta}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,\sigma^{\frac{\sigma}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,\gamma^{\frac{\gamma}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,r_t^{\frac{-\beta}{1-\alpha-\beta-\gamma-\sigma-\delta}} \\ & w_t^{\frac{-\alpha}{1-\alpha-\beta-\gamma-\sigma-\delta}}\quad Appl_t^{\frac{-\gamma}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,Basic_t^{\frac{-\sigma}{1-\alpha-\beta-\gamma-\sigma-\delta}}\,Dev_t^{\frac{-\delta}{1-\alpha-\beta-\gamma-\sigma-\delta}} \\ & (\alpha+\beta+\gamma+\sigma+\delta)^{\frac{\alpha+\beta+\gamma+\sigma+\delta}{1-\alpha-\beta-\gamma-\sigma-\delta}} \end{aligned} \tag{1}$$

2.3 Demand Function

Similarly, on multiplying both sides of the consumers' demand function for output, we have the following product sales demand function:

$$S_{Dt} = DP_t^{1-\theta} Y_t^{\theta_S} H_t^{\theta_H} \prod_{j=1}^{n} X_{jt}^{\theta_j} \tag{2}$$

In the equations above, the letters represent different variables expressed in real terms such as S_S (product real sales), S_D (product real demand), A (technological factor productivity), P (product price), W (real wage), r (interest rate), H (number of demanders of innovation), X (other demand shifters), π (individual firms profit), *Basic* (share of basic research funding), *Appl* (share of Applied Research funding), *Dev* (share of Development Research funding), P (output price), Y (personal disposable income). The technological factor productivity includes outcomes of previous innovative activities that impact current research efforts.

In a one sector economy with taxes, if there is no money illusion.

2.4 Entry-Exit Function

In our model, we distinguish between two types of firms. First, we have the firms that enter the industry when economic profits are positive and leave the industry when economic profits are negative (N_1). Second, we have the firms that adopt new products generated from innovation and introduce them in the market (N_2).

$$N = f(N_1, N_2)$$

$$\frac{\underset{1t}{\dot{N}}}{N_{1t}} = C_E^{'}(\pi_t^a - \overline{\pi}_t) \tag{3}$$

The market equilibrium profit within a given sector at time t is represented by $\overline{\pi}_t$

A firm's actual profit π_a constitutes a proportion ℓ of its sales supply.

$$\pi_t^a = \ell S_{St}$$

The Bass Diffusion model (Bass, 1990) represented below helps derive the S-shaped cumulative adopter distribution of new products resulting from innovative patents.

$$N_2(t) = \psi m_0 \left[\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \right] \tag{4}$$

With - m_0 number of potential adopters of new products

-ψportion of new adopters joining the sector producing new products

- p the rate of innovation and q the rate of imitation.

Predictive probability density function for expected prices

In our model, we assume that firms or labs are Bayesian learners, they produce based on prices derived from a predictive probability density function that is developed as follo$_{1t}$ws.Predictive probability density function for expected prices

In our model, we assume that firms or labs are Bayesian learners, they produce based on prices derived from a predictive probability density function that is developed as follows.

$$p(P_{T+1}^e | D_T) = \int_{\theta} f(P_{T+1}^e | \theta, D_T) \pi(\theta | D_T) d\theta \tag{5}$$

Where:

- $f(P^e_{T+1}|\theta, D_T)$ represents the pdf;
- $\pi(\theta|D_T)$ is the posterior pdf of θ;
- D_T is the past sample and prior information as of time T;
- θ being the parameter vector included in a parameter space.

Further, we obtain the reduced form dynamic equilibrium function by equating (1) and (2) while replacing N in (1) by (3) and (4). Optimal input costs are obtained from our factor markets optimization (see Zellner and Ngoie, 2011). From the reduced form dynamic equilibrium equations we now derive our transfer equations.

2.5 Transfer functions

We have derived mathematically our transfer functions from the dynamic linear structural equation models referred above. Referring to Quenouille (1957) we can represent a linear multiple time series process as follows (see Zellner and Palm, 2004).

$$H(L) \underset{mx1}{z_t} = \underset{mxm}{F(L)} \underset{mx1}{\varepsilon_t} \tag{6}$$

where (i) $z_t = (z_{1t}, z_{2t}, ..., z_{mt})$ is a vector of random variables, and (ii) $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{mt})$ is the random error vector. $H(L)$ and $F(L)$ are the full rank matrices with polynomial lag operators as elements. Then we allow $z_t = (y_t, x_t)$ with y_t as vector of the endogenous variables and x_t the vector of the exogenous variables. Then (6) becomes

$$\begin{bmatrix} H_{11}(L) & H_{12}(L) \\ H_{21}(L) & H_{22}(L) \end{bmatrix} \begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} F_{11}(L) & F_{12}(L) \\ F_{21}(L) & F_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

Assuming x_t as exogenous, the system can be written as follows.

$$H_{21}(L) = 0, \quad F_{12}(L) = 0 \quad \text{and} \quad F_{21}(L) = 0 \;\; y_t,$$

$$H_{11}(L)y_t + H_{12}(L)x_t = F_{11}(L)\varepsilon_{1t} \tag{7}$$

$$H_{22}(L)x_t = F_{22}(L)\varepsilon_{2t} \tag{8}$$

From the system above, we derive the transfer functions by multiplying both sides of (8) by H_{11}^{-1} to obtain

$$y_t = -H_{11}^{-1}H_{12}(L)x_t + H_{11}^{-1}F_{11}\varepsilon_{1t} \tag{9}$$

From $H_{11}^{-1} = \frac{H_{11}^{adj}}{|H_{11}|}$, (10) can be expressed as

$$|H_{11}|y_t = -H_{11}^{adj}H_{12}(L)x_t + H_{11}^{adj}F_{11}(L)\varepsilon_{1t}$$

Transfer functions for the endogenous variables in our MMM-DA are obtained from (9) with

$$H_{11} = \begin{bmatrix} 1 & -\lambda(L) & -1 \\ 1 & -\gamma(L) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad H_{11}^{-1} = \frac{1}{|H_{11}|} \begin{bmatrix} -\gamma(L) & \lambda(L) & -\gamma(L) \\ -1 & 1 & -1 \\ 0 & 0 & \lambda(L) - \gamma(L) \end{bmatrix}$$

Therefore: $H_{11}^{adj} = \begin{bmatrix} -\gamma(L) & \lambda(L) & -\gamma(L) \\ -1 & 1 & -1 \\ 0 & 0 & \lambda(L) - \gamma(L) \end{bmatrix}$

where $\lambda(L)$ and $\gamma(L)$are polynomial lag operators.

2.6 Data

The model was estimated using data obtained from the Bureau of Economic Analysis (BEA) for economic indicators and the U.S. Patents and Trademark Office (USPTO) for data on patents count. The Bureau of Economic Analysis produces high-quality statistics covering all aspects of the U.S. economic activities with international, domestic, sectoral and industry data that amply satisfied our data needs. Data series on research spending were also obtained from the BEA data base. These simply reflect the nominal spending in dollar amount on the three components: development, applied and basic research.

2.7 Bifurcation boundaries in the MMM

When it comes to bifurcation issues, dynamic models have parameter spaces that are stratified into several subsets while each subset contains a different dynamic solution. At present, regression analysis remains unable to provide parameters with certainty. Therefore, the uncertainty surrounding parameters leads to more uncertainty about bifurcation boundaries linked to the parameter space (Barnett, 2008). Without a clear knowledge of these boundaries, it is unconceivable to understand what happens in the confidence region. It is not possible to determine how much of these boundaries actually cross the confidence region. This causes substantial damages to robustness of inference drawn from dynamic models.

Bifurcation causes major changes in the quality of solutions in dynamic modeling due to changes in parameter values. Usually, quantitative changes in solution features of dynamic models tend to be more acceptable instead of qualitative changes, i.e. convergence (monotonic to non-monotonic, etc). At a point of bifurcation, minor alterations in quantitative features of the solutions are much more sensitive to parameter changes. Henceforth, the use of parameter changes to assess the impact of policy shifts using the model might lead to undependable results.

One of the most common forms of bifurcation impinging on economic models is the Hopf bifurcation. Within a neighborhood of the boundary, point estimation becomes critical due to oscillations.

Let a continuous dynamic system (Barnett et al. 2008, Banerjee 2011).

$$\dot{x} = f(x), x \epsilon \Re^n$$

With x_0 an equilibrium of the system and M, the Jacobian matrix df/dx evaluated at x_0.

Let the numbers of eigenvalues of A with negative real be $n\_$; with zero real be n_0; and with positive real be n_+.

Definition 1

We have an hyperbolic equilibrium when $n_0 = 0$. It means no eigenvalues on the imaginary axis or unit circle.

E.g. Let the following two dynamical systems

$$\dot{x} = f(x, \alpha), x \epsilon \Re^n, \alpha \epsilon \Re^m \tag{10}$$

$$\dot{y} = g(y, \beta), y \epsilon \Re^n, \beta \epsilon \Re^m \tag{11}$$

Definition 2

We can say that (10) is topologically equivalent to (11) if:

- there is existence of a homeomorphism of the parameter space;

$$p : \Re^m \to \Re^m, \beta = p(\alpha)$$

- there is a parameter-dependent homeomorphism of the phase space $h_\alpha : \Re^n \to \Re^n, y = h_\alpha(x)$ which maps the system's orbits at parameter values $\beta = p(\alpha)$ while preserving the time direction.

Definition 3

Presence of topologically non-equivalent phase portrait under variation of parameters is called bifurcation. Also, at the non-hyperbolic points, sufficiently small perturbations of parameters lead to changes in structural stability.

Definition 4

A transcritical bifurcation occurs when a system has non-hyperbolic equilibrium with a geometrically simple zero eigenvalue at the bifurcation point with additional transversality conditions.

Let the reduced form of the one sector MMM (see Zellner and Ngoie, 2011).

$$\frac{\dot{S}_t}{S_t} = b\frac{\dot{S}_t}{S_t} + C_E(S_t - \pi^e_t) + c \tag{12}$$

with

$$\begin{aligned} c \quad = \quad & \frac{\dot{A}_t}{A_t} + \{\alpha[\gamma_h(1-\theta) + \gamma + \gamma_s]/(1+\gamma) + \beta[\phi_h(1-\theta) + \phi + \phi_s]/(1+\phi) - \theta_h\}/\delta(1-\theta) \\ & ... + \alpha\sum_{j=1}^{d}\gamma_j\frac{\dot{z}_j}{z}/\delta_j(1+\gamma) + \beta\sum_{j=1}^{n}\delta_j\frac{\dot{v}_j}{v_j}/\delta(1+\phi) + \sum_{j=1}^{m}[\theta_j/\delta(1-\theta)]\left(\frac{\dot{X}_j}{X_j}\right)[\alpha(\gamma+\gamma_s)/(1+\gamma) \\ & ... + \beta(\phi+\phi_s)/(1+\phi) - 1] \end{aligned} \tag{13}$$

and

$$b = \left\{ \begin{array}{c} 1 - \theta_s - \alpha[(1-\theta)(1-\gamma_s) + (1-\theta)(\gamma+\gamma_s)]/(1+\gamma) \\ -\beta[(1-\theta)(1-\phi_s) + (1-\theta_s)(\phi+\phi_s)]/(1+\phi) \end{array} \right\} /\delta(1-\theta) \tag{14}$$

The logistic equation can be expressed as

$$\frac{dS}{dt} = k_1 S\left(1 - \left(\frac{k_2}{k_1}\right)S\right) \tag{15}$$

$$k_1 = \frac{g - C_E\pi^e}{1-b}$$

$$k_2 = \frac{-C_E}{1-b}$$

We note that (12) has two equilibrium a values $s = 0$ and $S = \frac{k_1}{k_2}$.

Solution $S = \frac{k_1}{k_2}$ is unstable for positive values of k1 and k2.

For constant parameters there are no cyclical movements and for discrete lags there is mixed differential-difference equation that can produce cyclical solutions.

Also, there is a branching point at $(S, k_1) = (0, 0)$

3 Results

In this results' section, we explore the fit as well as forecasting performance of our one-sector MMM of the U.S. science sector, the 16-sector MMM-DA with innovative activities not modeled, and the 17-sector MMM-DA where innovative activities modeled through the science sector included as a separate sector that impact other sectors through their factor markets.

3.1 One-Sector MMM of the U.S. science sector with output measured using the number patents

As described above, the one-sector MMM of the U.S. science sector is modeled using patents as output.As shown in Fig. 3, we make use of the Baxter-King filter to better appraise the salient characteristics of cycles, trends and frequency responses in the total number of patents approved over the years in the U.S.

Although the concept 'cycle' is a misnomer insofar as no sole periodic behavior is observable in a given economy, filtering process are of great use in identifying some of the non-unique periodicities that exist. Fig. 3 depicts the cyclicality of the number of patents and portrays to some large extent regularities of long standing (Zarnowitz, 1992). Indeed, we observe large variations of fluctuations in amplitude, scope and frequency, yet they are persistent and some commonalities that can be extracted. Also, we have obtained satisfactory results for the frequency response function which seems to stabilize over the periods.More measures of productivity related to the science sector are reported using figures in the Appendix.

Fig 4 portrays fits of our transfer function of the one-sector MMM of the U.S. science sector. Fitness in itself can be misleading in macroeconomic modeling. Issues such as overparameterization can lead to remarkable fit even though the model used is unreliable. To this regard, we have performed generic statistical testing and produce forecasts. Below, we made report values of Mean Absolute Forecast Errors (MAFE) and Root Mean Square Forecast Errors (RMSFE) in assessment to the accuracy of our forecasts. The choice between existing measures of accuracy in forecasting is driven by the conception of types and amplitude of errors and how they affect the forecast (see Zarnowitz, 1999). For example, the MAE will be used when the size of the difference between predicted and actual values is the only determinant of the loss. However, if we are more concerned by larger errors (positive or negative), the RMSE is recommended. When both matter, the size of the difference as well as the sign of the errors, the loss function will be asymmetric.

Beside the fact that our MMM of the U.S. science sector fits remarkably well the data, its forecasting performance is commendable. While noting that the forecasting period is relatively short – eight years only - the MAFE and RMSFE are indeed really small and the model is able to forecast 100 percent of all the turning points.

3.2 16-Sector MMM-DA of the US economy without special consideration of the science sector as input to other sectors

The 16-sector MMM-DA is a disaggregated model with 16 sectors of the U.S. economy as per the BEA (Bureau of Economic Analysis) classification. Innovative activities are not modeled here.

a) Fitted transfer equations (see Zellner and Ngoie, 2011)

$$|H_{11}|x_{1it} = -H_{11}^{adj}H_{12}(L)x_{2it} + H_{11}^{adj}F_{11}(L)\varepsilon_{1it}$$

where $x_{1it} = (s_{it}, p_{it}, n_{it})'$ is the vector of endogenous variables, $x_{2it} = (w_{it}, r_{it}, m2_t sp_t,$ $ctax_{it}, y_t, open_t, h_t)'$ is the vector of exogenous variables, and $\varepsilon_{1it} = (\mu_{1it}, \mu_{2it}, \mu_{3it})$ is the vector of error terms. Again, in this study, for our 16-sector MMM-DA we only fit one of the three transfer functions for each sector of the US economy, s_{it}.

Table 1 depicts MAEs and RMAEs obtained from fitting our transfer equations for the 16 sectors of the U.S. economy. Both errors are relatively low indicating a good fit. In Table 2, there errors are compared with the one obtained from the 17-sector MMM-DA. These results prop up our hypothesis that modeling innovative activities improve substantially fits and forecasts of our MMM-DA.

3.3 17-Sector MMM-DA of the US economy with special consideration of the impact of advances in science sector on other sectors of the U.S. economy

For the 17-sector MMM-DA, we have modeled both 16 sectors plus the science sector using seemingly unrelated regressions of the transfer functions. However, outcomes of the science sector, which is the number of patent granted, are adapted into new products, a process captured using the Bass diffusion model. Results obtained using model innovative activities only fit one of the three transfer functions for each sector of the U.S. economy.

Comparing Table 1 and 2, we realize that the use of science as an additional sector that supplies inputs to other sectors of the economy helps reduce forecasting errors for all the sectors of the U.S. economy.

4 Policy shocks per sector

In this section, we have implemented a set of policy shocks aimed at assessing the impact of raised research spending on the outcome of the U.S. Science sector.

In Table 3 we introduce a set of reforms (1 and 5 percentage points increase) on spending for Basic Research, Applied Research and Development and present their impact on the growth rate of the total number of patents approved. As expected, increasing spending on Applied Research produces much larger short-run effects than other increases. Applied Research has faster impact on scientific outputs than other research components. Also, we can see that Corporate Income Tax cut provides large incentive for research development.

In Table 4, we present the effects of increased scientific outputs (one percentage point shock) on other sectors of the U.S. economy. Overall, advances in science have a positive impact on all the sectors of the U.S. economy although the amplitude of the effects differs from one sector to another. Most numbers seem obvious and easy to reconcile with general expectations although further work need to be done to deeper disentangle the pure effects generated by the shocks from other market and non-market adjustment effects.

5 Conclusion

In this paper we have analyzed the production process of scientific outputs i.e. innovation, proxied by the growth rate of approved patents and its implications on the overall U.S. economy using variants of a disaggregated Marshallian Macroeconomic Model (MMM). We have modeled the U.S. science sector using a one-sector MMM that fits the data and provides reliable forecasts. Moreover, we have embedded science as an additional sector in our 17-sector MMM of the overall U.S. economy. We understand the need for a model to include new products that originate from innovative patents. To this regard, we made use of the Bass diffusion model and obtained improved fits and forecasts. Introducing innovation and its effects on adopters of new products significantly improves macroeconomic modeling performance overall. Also, we have assumed that firms use expected product prices and form their expectations as Bayesian learners. Throughout a set of policy simulations, this research provides measured information on how selected science policies i.e. public spending on research (Basic, Applied and Development) versus corporate tax cut, affect the science sector and the U.S. economy overall. Both variants of our MMM have been estimated using transfer functions.

We are aware that further disaggregation of the science sector is much needed for a better investigation of the production process of scientific outputs. Therefore, in future work, we propose to disaggregate the science sector into public versus private operating units, academic versus non-academic based units, etc.

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Table 1 - MAEs and RMSEs Forecasted by Industrial Sectors

	Errors Based on Forecasted Values*	
Sector	MAE	RMSE
Arts, entertainment, recreation, accommodation, food service	0.90 %	1.17 %
Construction	2.13 %	3.08 %
Education	1.09 %	1.01 %
Finance, Insurance, Real Estate, Rental, Leasing	0.82 %	1.06 %
Government	0.54 %	0.72 %
Health	1.26 %	1.69 %
Information	2.37 %	2.87 %
Manufacturing	1.45 %	1.79 %
Mining	3.11 %	3.96 %
Other services, except Government	0.79 %	1.07 %
Professional and Business Services	1.13 %	1.55 %
Retail Trade	1.70 %	2.16 %
Transportation and Warehousing	1.02 %	1.26 %
Utilities	3.06 %	3.64 %
Wholesale Trade	2.80 %	3.62 %
Agriculture	5.15 %	5.92 %

Table 2 - MAEs and RMSEs Forecasts by Industrial Sectors

	Errors Based on Fitted Values*	
Sector	MAE	RMSE
Arts, ent., recreation, accommodation, food service	0.89 %	1.21 %
Construction	1.07 %	1.57 %
Education	0.76 %	1.01 %
Finance, Insurance, Real Estate, Rental, Leasing	0.77 %	0.90 %
Government	0.20 %	0.28 %
Health	0.87 %	1.10 %
Information	2.03 %	2.54 %
Manufacturing	0.97 %	1.22 %
Mining	2.83 %	3.28 %
Other services, except Government	0.60 %	0.72 %
Professional and Business Services	1.09 %	1.30 %
Retail Trade	1.66 %	2.08 %
Transportation and Warehousing	1.05 %	1.18 %
Utilities	2.78 %	3.59 %
Wholesale Trade	2.42 %	3.02 %
Agriculture	5.05 %	5.90 %

Table 3 – U.S. Science Total Patents in Growth Terms Resulting from Implemented Reforms

Reform types	Reform Size (percentage point)	No. of patents in growth terms (percentage point after 1 year)
Increase Basic Research	1	1.32 (1.11)
	5	5.71 (1.29)
Increase Applied Research	1	4.69 (1.98)
	5	15.01 (2.11)
Increase Development	1	0.83 (0.91)
	5	4.01 (1.19)
Cut Corporate Income Tax	1	4.01 (1.51)
	5	18.2 (2.05)

Note: Table 3 presents elasticities on the policy variables used for the reform. Estimates have been obtained using the one-sector MMM transfer function of the US economy with the three additional research inputs. The values in parentheses represent the predictive standard errors corresponding to each shock[1].

Table 4 -- Estimated One-Year Effects of Science Output on Sectors of the U.S. Economy: Reforms are implemented in 2007

Sector	Percentage point increase in the sector's annual GDP growth rate
Agriculture	1.16 (0.16)
Arts, entertainment, recreation, accommodation, food service	0.32 (0.26)
Construction	0.39 (0.68)
Education	2.60 (0.31)
Finance, Insurance, Real Estate, Rental, Leasing	1.08 (0.23)
Government	1.47 (1.60)
Health	4.09 (0.36)
Information	9.21 (0.61)
Manufacturing	7.65 (0.39)
Mining	0.77 (0.86)
Other services, except Government	2.58 (0.22)
Professional and Business Services	2.10 (0.33)
Retail Trade	1.03 (0.47)
Transportation and Warehousing	0.78 (0.31)
Utilities	0.29 (0.79)
Wholesale Trade	1.39 (0.43)

Note: These results have been obtained using iterative seemingly unrelated regressions of our 17-sector MMM and values in parentheses represent standard errors.

[1] The predictive standard errors constitute summarized measure of the estimated variance of the equation's residual.

Fig. 1 – Branching of the MMM reduced form

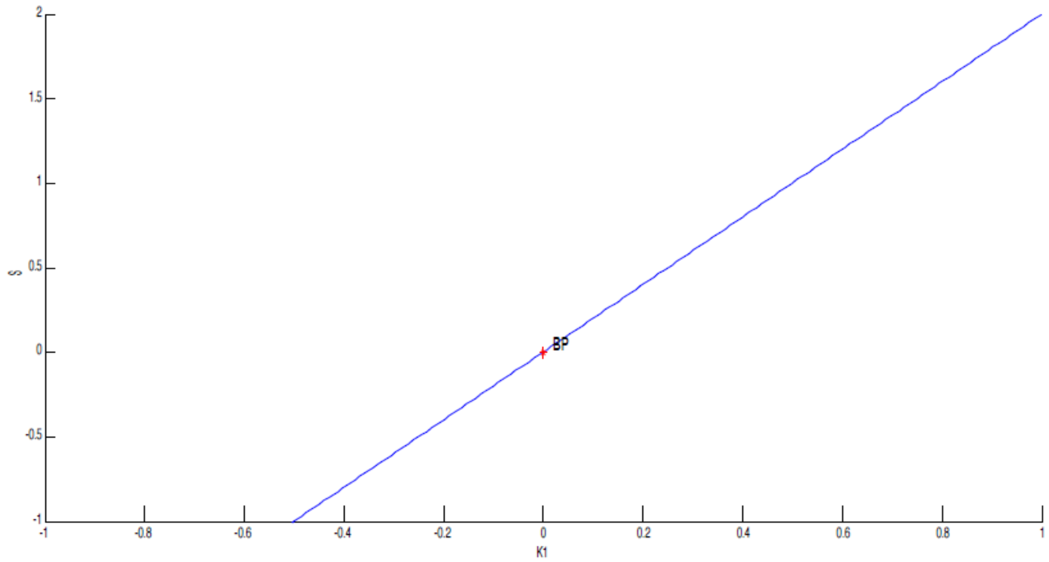


Fig.2 – Stability of equilibrium solutions

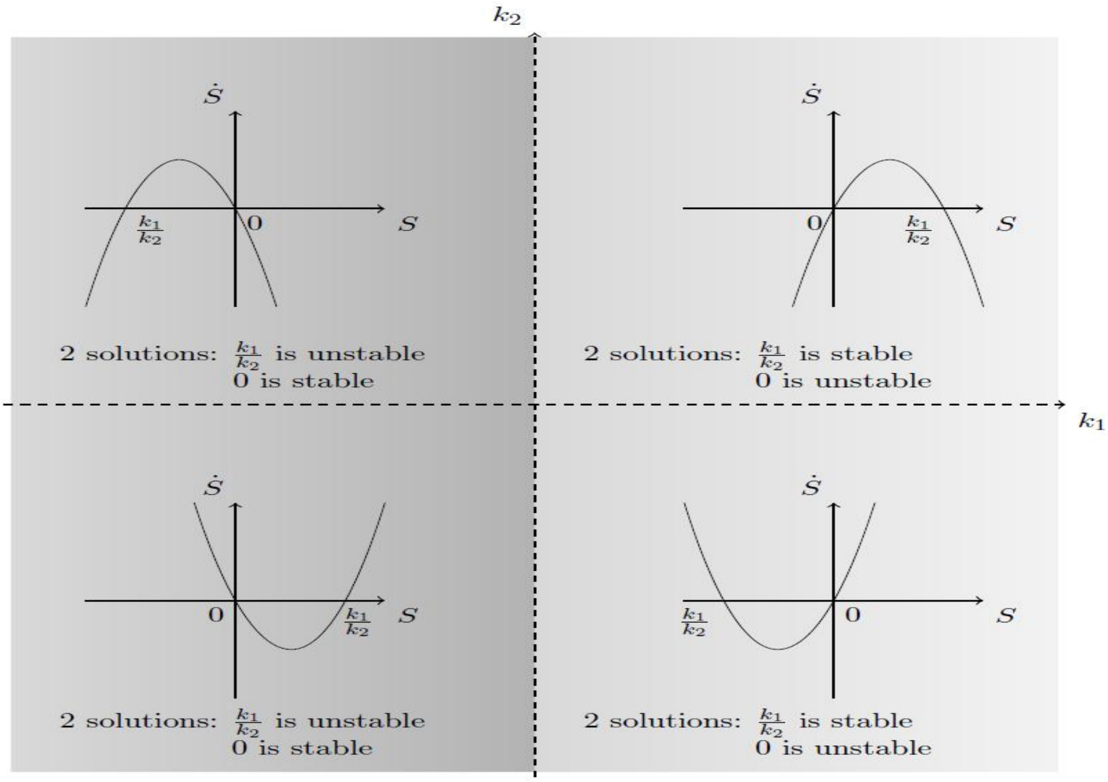


Fig.3 - Trend, Cycle and Frequency Response Function for Total Number of Patents Delivered in the US Economy from 1953 to 2008

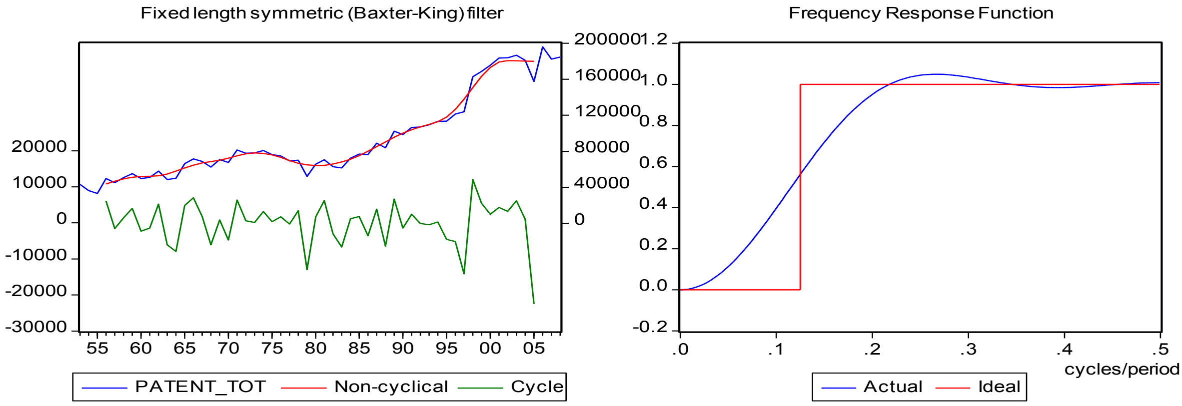


Fig. 4 - Actual, Fit and Residuals of the one-sector MMM of the U.S. science sector, 1988-2008
No. of patents (growth rate)

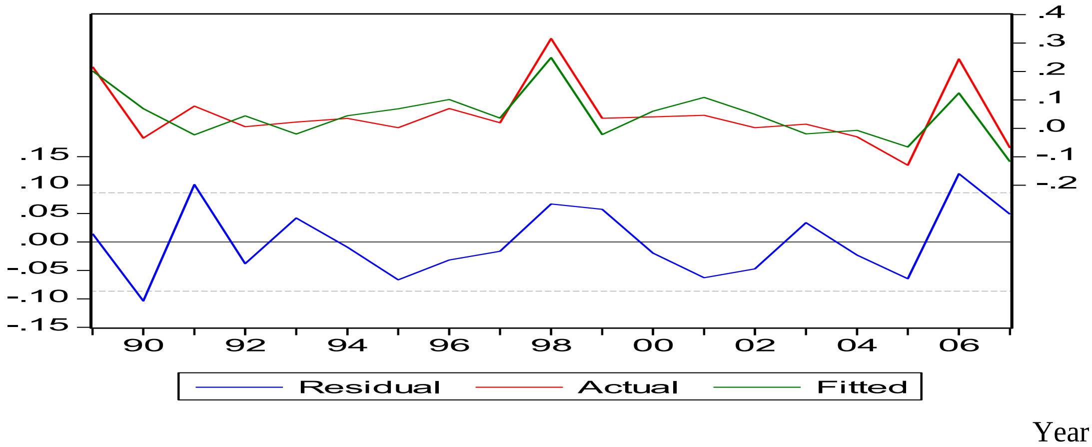
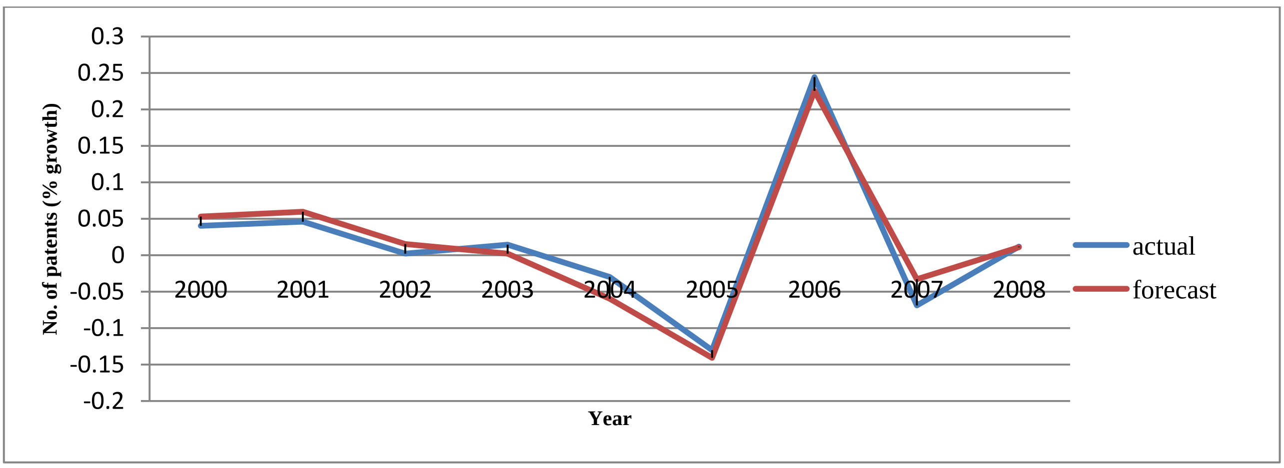


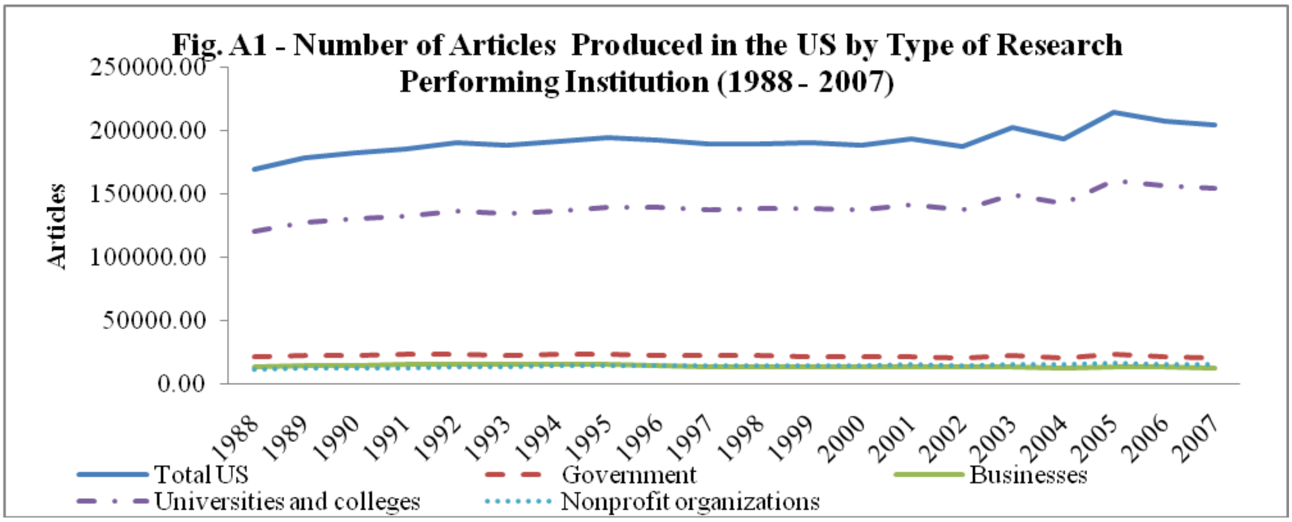
Fig. 5 - One-Year Ahead Forecast of the one-sector MMM of the U.S. science sector, 2000 – 2008



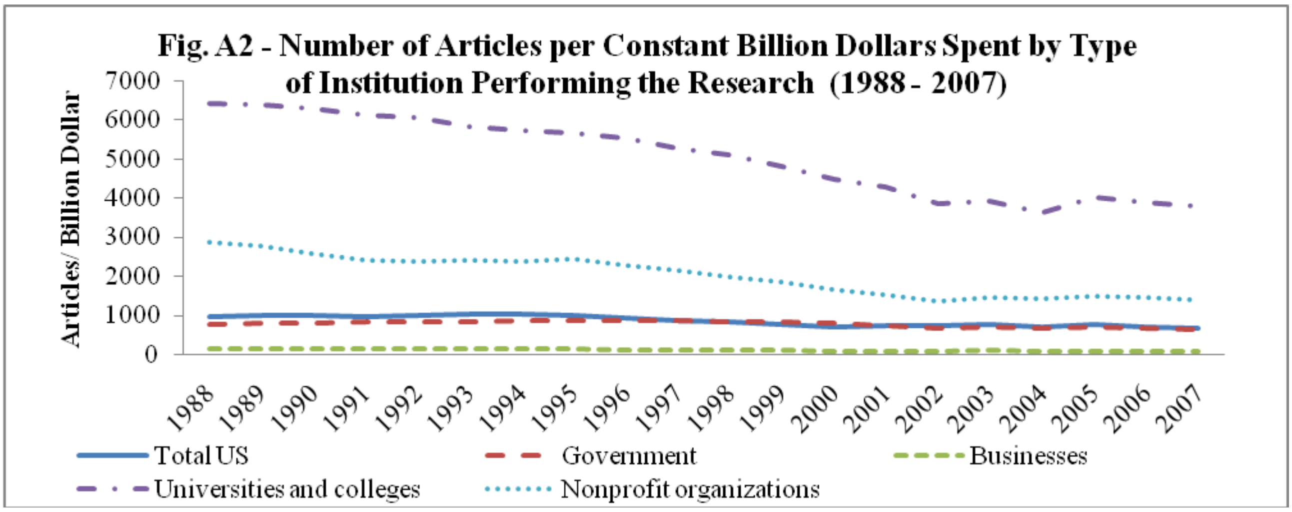
MAFE = 1.63 percentage points
RMSFE = 1.91 percentage points

APPENDIX

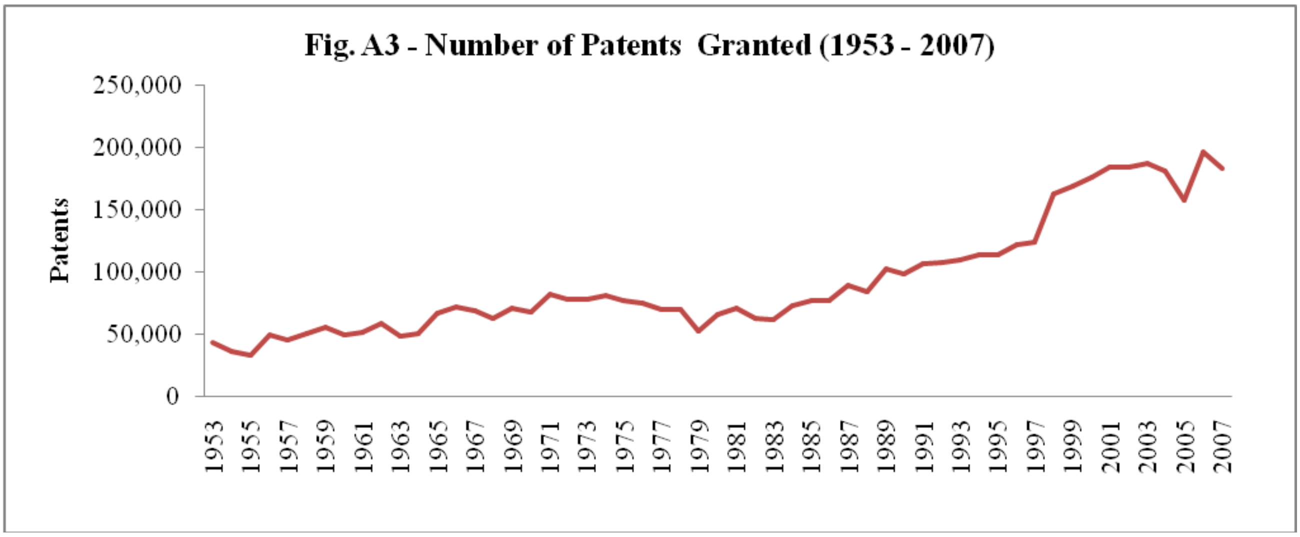
SOME MEASURES OF PRODUCTIVITY OF THE SCIENCE SECTOR IN THE US



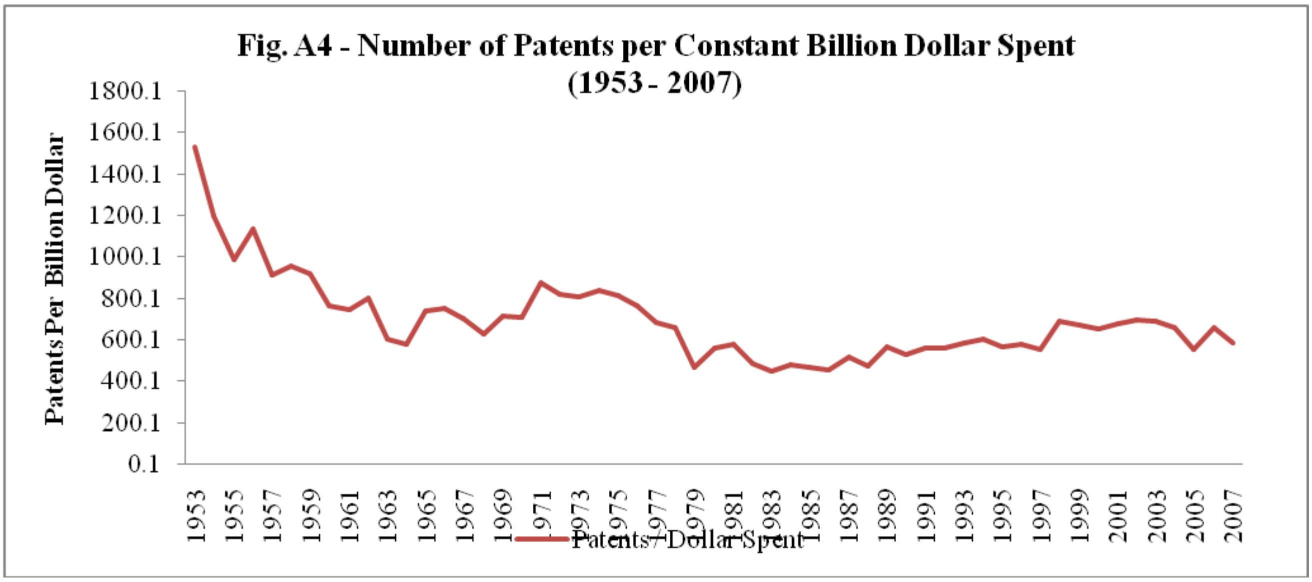
Source: NSF
Description: The graph shows the number of articles in Science and Engineering produced in the US between 1998 and 2007 by type of institution performing the research.



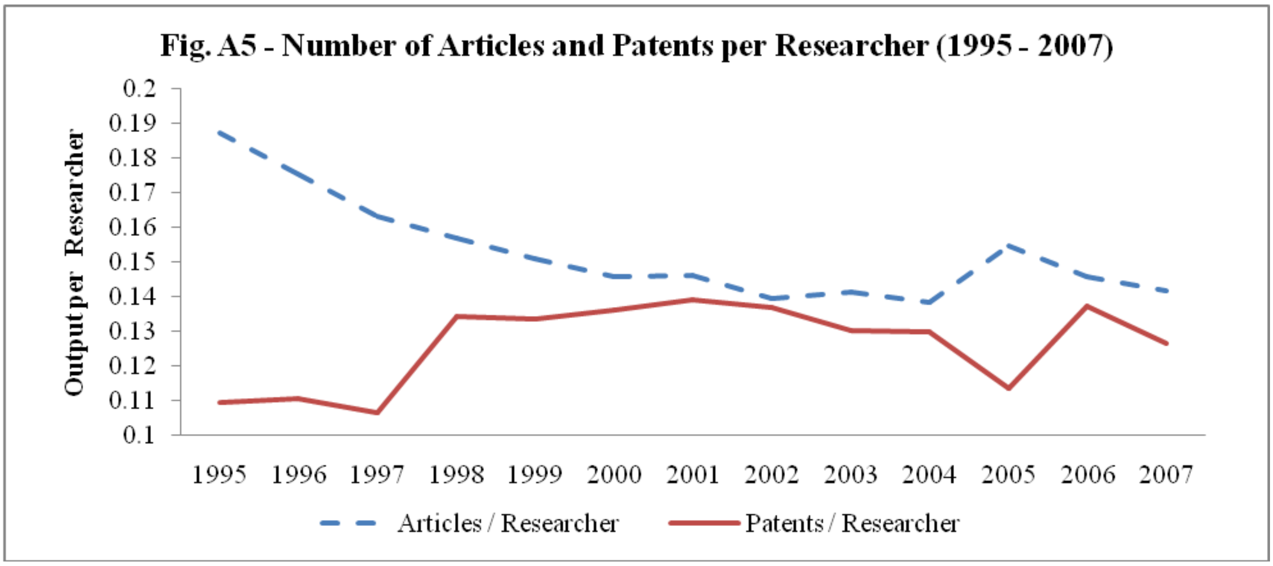
Source: NSF
Description: The graph shows the number of articles in Science and Engineering produced in the US per billion dollars (constant dollars of 2000) spent on research between 1998 and 2007 by type of institution performing the research.



Source: United States Patent and Trademark Office
Description: The graph shows the total number of patents awarded to US institutions/citizens between 1953 and 2007.

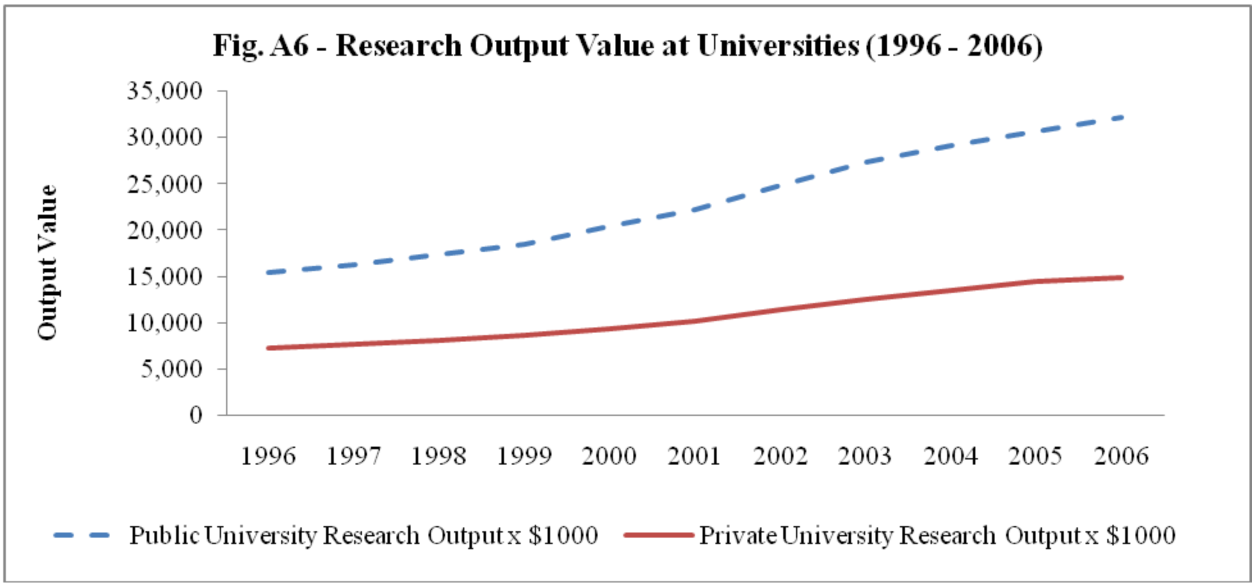


Source: United States Patent and Trademark Office, NSF
Description: The graph shows the total number of patents awarded to US institutions/citizens per dollar spent on research (constant dollars of 2000) between 1953 and 2007.

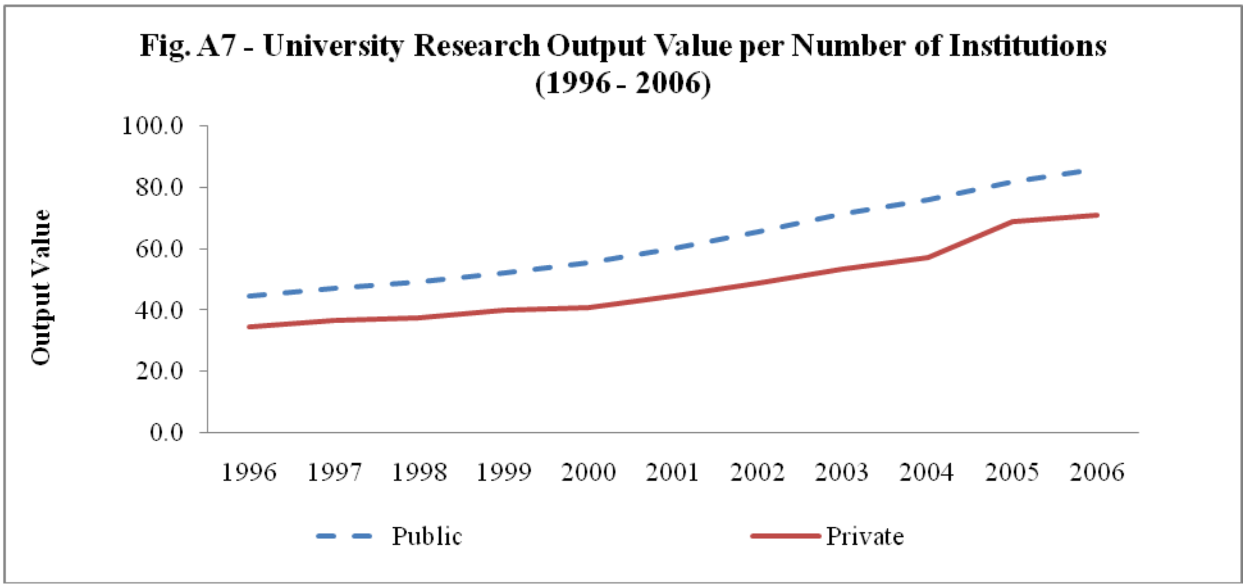


Source: United States Patent and Trademark Office, NSF
Description: The graph shows the total number of patents awarded to US institutions/citizens and the number of Science & Engineering Journal Articles produced in the US between 1995 and 2007 per researcher. The number of researchers is calculated as FTE employees.

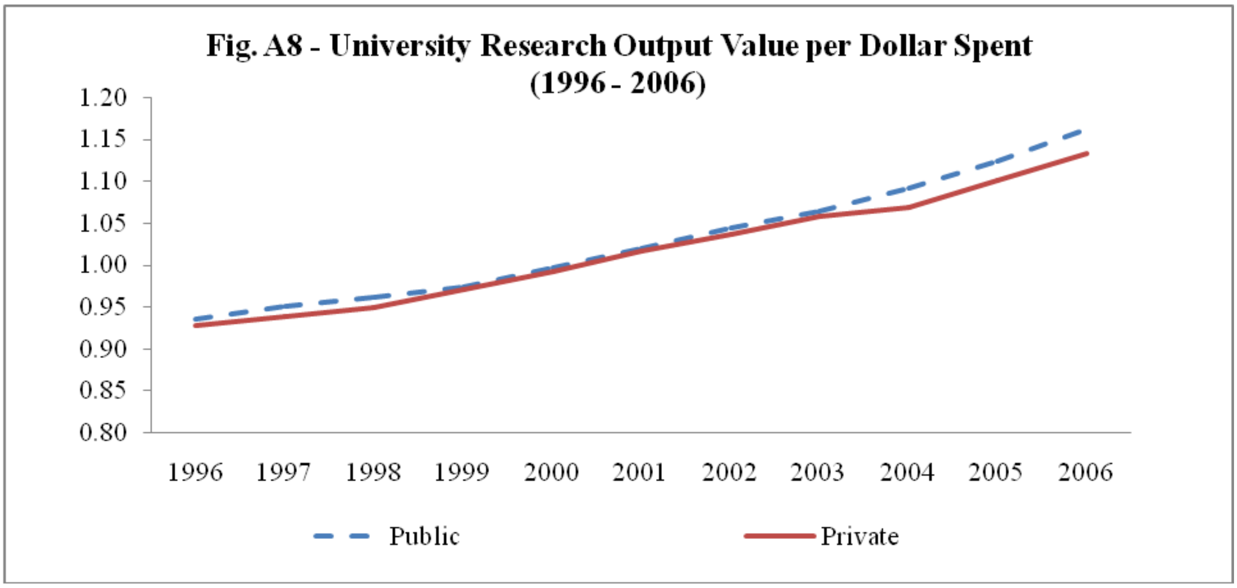
PRODUCTIVITY OF THE SCIENCE SECTOR IN US UNIVERSITIES PUBLIC vs PRIVATE



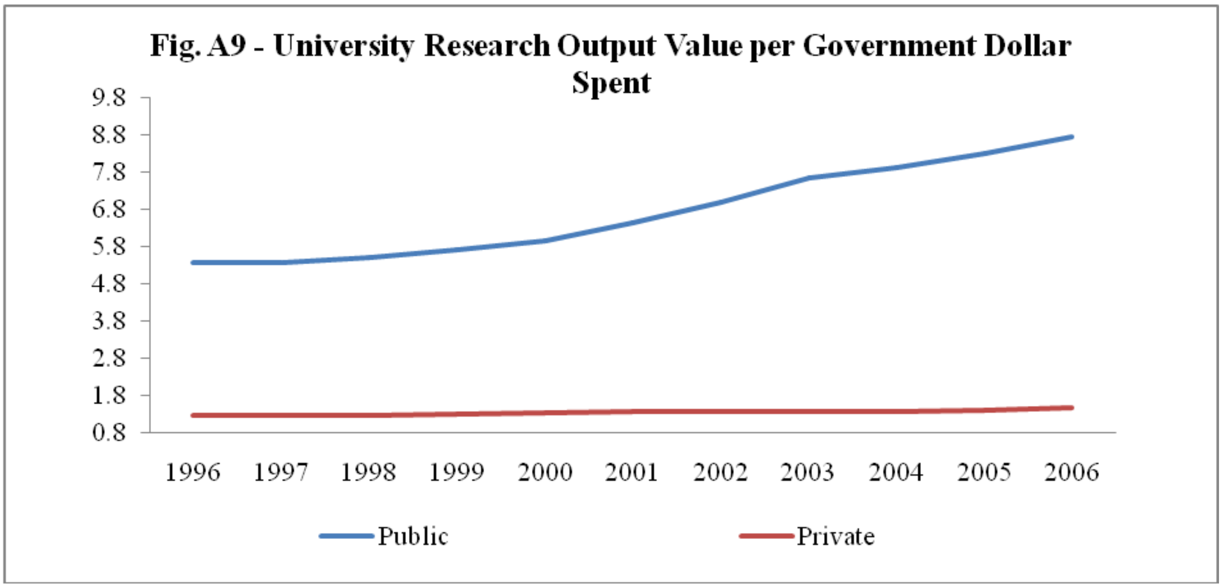
Source: Center for Measuring University Performance
Description: The graph shows the value of the research produced by public and private universities between 1996 and 2006.



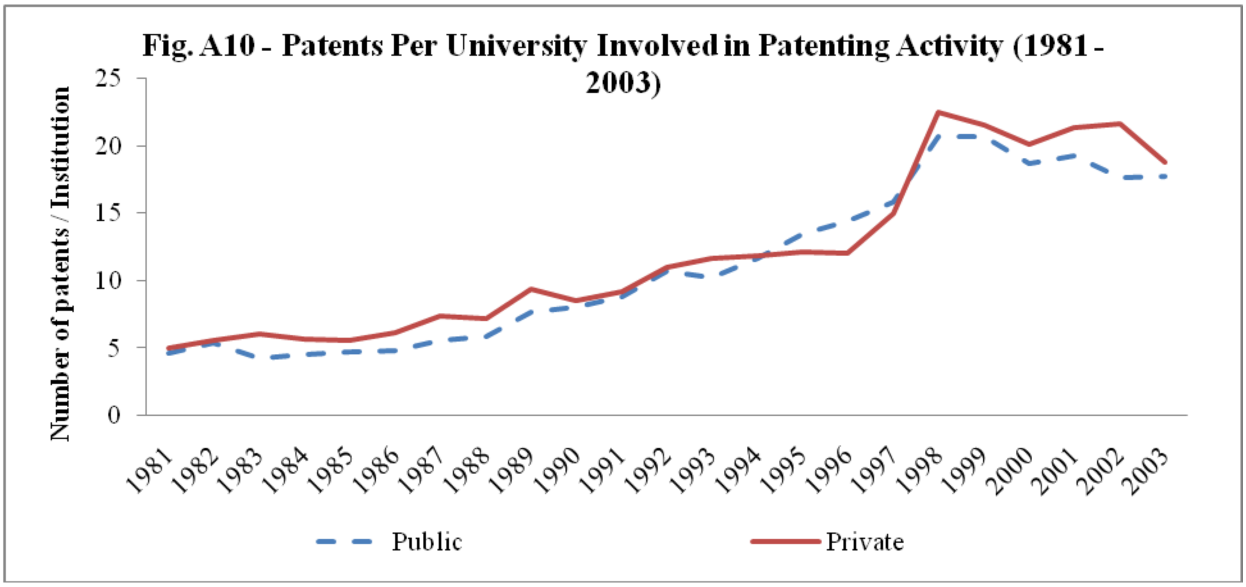
Source: Center for Measuring University Performance
Description: The graph shows the value of the research produced by public and private universities per institution reporting any research activity between 1996 and 2006.



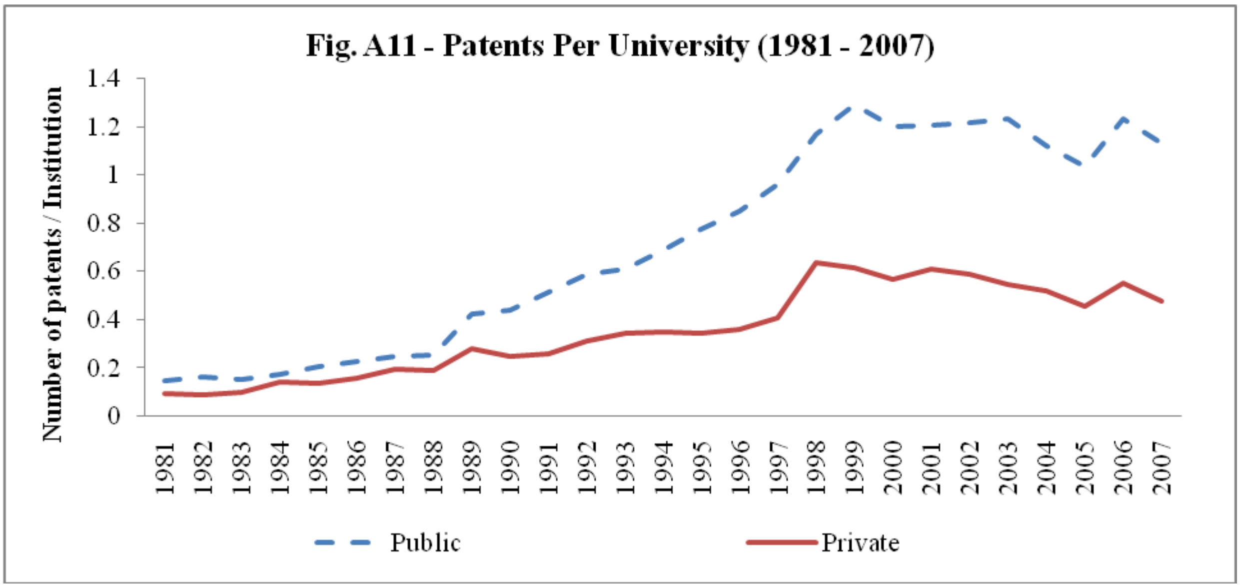
Source: Center for Measuring University Performance, NSF
Description: The graph shows the value of the research produced by public and private universities per billion dollars spent on research (constant dollars of 2000) between 1996 and 2006.



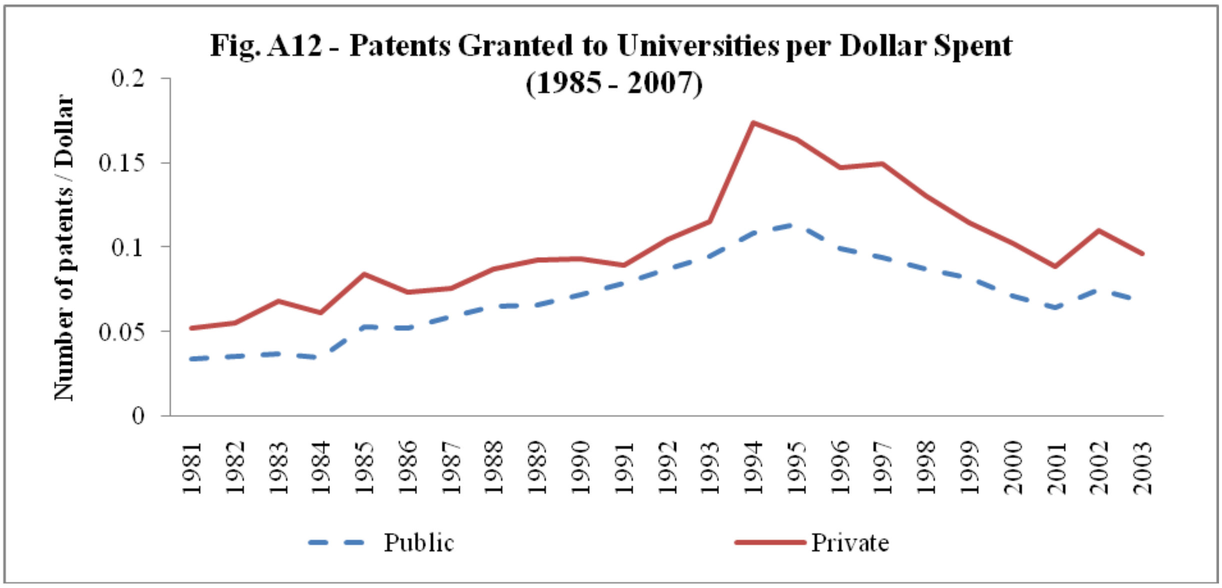
Source: Center for Measuring University Performance, NSF
Description: The graph shows the value of the research produced by public and private universities per billion dollars spent on research funded by the government (constant dollars of 2000) between 1996 and 2006.



Source: United States Patent and Trademark Office, NSF
Description: The graph shows the number of patents per institution reporting patenting activity by public and private universities between 1981 and 2003.



Source: United States Patent and Trademark Office, NSF
Description: The graph shows the number of patents per existing institution by public and private universities between 1981 and 2007.



Source: United States Patent and Trademark Office, NSF
Description: The graph shows the number of patents per billion dollar spent (constant dollars of 2000) by public and private universities between 1985 and 2007.