The Impact of Industrially and Federally Funded R&D on U.S. Manufacturing Growth: A Constrained Translog Model

David S. Saal

March, 2001

Aston Business School
Aston University
Aston Triangle
Birmingham, B4 7ET
United Kingdom

Tel: 44 (0)121 359 3611
Fax: 44 (0)121 333 3474
Email D.S.Saal@aston.ac.uk

THIS IS A DRAFT PAPER ONLY AND MUST NOT BE CITED WITHOUT THE EXPRESSED AGREEMENT OF THE AUTHOR

Abstract

All studies that have previously examined the relationship between federal industrial R&D funding and manufacturing productivity growth with the R&D intensity model have concluded that federal R&D has had an insignificant effect on productivity growth rates. Significantly, these results are often interpreted as indicating that federally financed industrial R&D has been ineffective in stimulating manufacturing productivity growth. However, the previous productivity literature’s failure to employ a simultaneous equations model in order to account for the potentially stimulative effect of federally funded on industrially funded R&D, suggests that these previous results are biased downward.

This paper therefore estimates a constrained translog model of the impact of R&D on manufacturing growth, which not only allows for a potential stimulative effect, but also removes many of the restrictive assumptions of the Cobb-Douglas model underlying the R&D intensity model. Although our results must be interpreted with caution due to some residual econometric problems, they do suggest that the estimated return to federally funded R&D has previously been biased downward. However, in an unexpected finding, this appears to be attributable to the greater flexibility of the translog estimation function, rather than a stimulative effect of federally funded R&D on industrially funded manufacturing R&D.
I. INTRODUCTION

During the Post War era, the U.S. government has been the single largest sponsor of research and development activities (R&D) in the U.S, accounting for 48 percent of all R&D funding between 1953 and 1997. As Cold War priorities dominated the government’s research agenda, most of this funding was allocated to defense related R&D, which on average made up 58 percent of total federal R&D outlays between 1955 and 1998, with this proportion rising as high as 70 percent during periods of high military spending. Moreover, since private weapons contractors carried out much of the research needed to develop high tech weaponry, 51% of all federal R&D funding between 1953 and 1996 actually went to manufacturing industries (NSF, 1998a, 1998b). Nevertheless, all studies that have directly examined the relationship between federal industrial R&D funding and manufacturing productivity growth with the R&D intensity model have concluded that federal R&D has had an insignificant effect on productivity growth rates. (See Terleckyj, 1974; Griliches & Lichtenberg, 1984; Lichtenberg & Siegel, 1991 for examples; and Lichtenberg, 1995 for a survey). Significantly, these results are often interpreted as indicating that federally financed industrial R&D, has been ineffective in stimulating manufacturing productivity growth (Alexander, 1990; Cowan and Foray, 1995).

Despite the consistency of its findings, a careful review of the previous productivity literature reveals theoretical and empirical issues that make it difficult to accept the finding that federally funded industrial R&D has had an insignificant effect on manufacturing productivity growth. Most fundamentally, consideration of a related body of empirical literature reveals mixed evidence that company funded R&D performed in industry increases in response to increased federal R&D funding (Link, 1982; Scott, 1984; Levin & Reiss, 1984; Levy & Terleckyj, 1983, 1995; Lichtenberg, 1984, 1987, 1988; Saal, 1999). As the previous productivity literature based on the
R&D intensity model has consistently failed to build this relationship into the econometric models employed, it almost surely overestimates the productivity return attributable to company funded R&D and underestimates the productivity return of federally funded R&D.

It is therefore possible that the previous literature’s finding of insignificant productivity returns to federally-funded industrial R&D could simply be attributed to the failure to account for a potential simultaneous relationship between federally and industrially-funded R&D expenditures. Moreover, as much of the earlier literature also suggests that federal R&D funding stimulates industrially-funded R&D, the failure to build this relationship into earlier econometric models may result in the overestimation of the returns to industrially-funded R&D and the underestimation of those to federally-funded R&D. Given this hypothesis, this paper will estimate a simultaneous-equations model in which federally-funded R&D is allowed to indirectly influence economic performance through its effect on the level of company-funded R&D.

To accomplish this, Section II first extends a translog model attributable to Verspagen (1995). This not only provides a framework in which to estimate the economic effects of company and federally-funded R&D while simultaneously accounting for the relationship between them: It also provides a flexible functional form, which removes the restrictive assumptions embodied in the Cobb-Douglas production function employed in the previous empirical literature based on the R&D intensity framework. Most significantly, use of the translog model relaxes the highly restrictive assumption that both company and federally-funded R&D have a neutral factor-augmenting impact on productivity growth.

Section III then reviews the empirical implementation of the model for a sample of eight high-tech manufacturing industries with NSF R&D data available from 1957 and economic data drawn from the NBER Manufacturing Productivity Database for 1958-91. Section III next
presents the results, which suggest the existence of a statistically significant positive return to federally-funded R&D, even if the assumed rate of knowledge depreciation has a substantial influence on the estimates. However, as residual econometric problems continue to plague the model, these results must be treated with some caution.

Nevertheless, and in contrast to the paper’s primary hypothesis, the estimated parameters of the model suggest that a stimulative effect of federally-funded R&D on industrially-funded R&D is not directly responsible for the estimated positive return to federally-funded R&D. These results can instead be attributed to the increased flexibility of the translog production function, which allows it to capture the differential impact of industrial and federal R&D funding on the marginal productivity of other factors. Thus, the estimates suggest that federal R&D is labor augmenting, while industrially-funded R&D appears to have a more direct impact on output growth. Given these findings, Section V concludes and offers some suggestions for future research.

II. The Model

The model consists of a translog production function along with its first order conditions in a maximization context, and builds on Verspagen (1995). This formulation has two practical advantages. Firstly, it provides a framework in which to estimate the productivity effects of company and federally-funded R&D while simultaneously accounting for the possible stimulative effect of federally-funded R&D on company-funded R&D. Secondly, by providing a flexible functional form, it removes the restrictive assumptions of the Cobb-Douglas production function that has been employed in most previous models analyzing the influence of federally-funded R&D on productivity growth. Most importantly, this removes the assumption that both company and federally-funded R&D result in neutral factor-augmenting technological change and allows the possibility that R&D has biased non-proportional effects on the marginal productivity of factors.
Moreover, the translog function also allows full flexibility in the elasticity of factor substitution. Thus, the increased flexibility of the translog production function, as well as the constrained optimization approach it allows, may generate significant changes, relative to earlier models, in the estimated productivity effects of both company and federally-funded R&D.

Given these potential benefits, I extend Verspagen's (1995) model by separating an industry's total R&D expenditures into industrially-funded R&D and federally-funded R&D. Industrially-funded R&D is then treated as a choice variable in the maximization problem, while federally-funded R&D is treated as an exogenously determined input entering into the industry's production function.¹

Since the model treats R&D as an investment good, current R&D expenditures \( r_t \) do not directly enter an industry's production function but instead contribute to an industry's existing stock of knowledge \( R_t \), which does enter into the production function. Whilst this knowledge stock is unobservable, I assume it is proportional to the accumulated sum of past R&D expenditures. I therefore follow the common practice of constructing the knowledge stocks with the perpetual inventory method (See for example, Griliches (1990). Thus, at time \( t \), the available stocks of knowledge respectively generated by past company and federally-funded R&D expenditures are assumed to be:

\[
\begin{align*}
R_{c,t} &= r_{c,t} + (1 - \delta) R_{c,t-1} \\
R_{f,t} &= r_{f,t} + (1 - \delta) R_{f,t-1}
\end{align*}
\]

¹ This assumption that the level of federally-funded R&D in a given industry is exogenously determined is based on the fact that the interindustry allocation of federal R&D funding as well as intertemporal trends in such funding are primarily determined by the federal government's defense requirements/policies. Therefore, it is reasonable to assume that an industry's decision-makers have little direct control over the level of federal R&D funding received by their industry.
where $\delta$ is an assumed depreciation rate designed to account for the possible depreciation in the economic value of the knowledge stock. As I will discuss below, varying $\delta$ has a substantial influence on the estimation results.\(^2\)

Given these constructed knowledge stocks, it is then possible to specify the following translog production function for output (value added):

$$
\ln Q_{i,t} = \alpha_i + \alpha_{L} \ln L_{i,t} + \alpha_{K} \ln K_{i,t} + \alpha_{R_c} \ln R_{C,i,t} + \alpha_{R_f} \ln R_{F,i,t} + \alpha_T T_i +
$$

$$
\frac{1}{2} \alpha_{L} (\ln L_{i,t})^2 + \alpha_{LK} \ln L_{i,t} \ln K_{i,t} + \alpha_{LR_c} \ln L_{i,t} \ln R_{C,i,t} + \alpha_{LR_f} \ln L_{i,t} \ln R_{F,i,t} + \alpha_{LT} \ln L_{i,t} T_i +
$$

$$
\frac{1}{2} \alpha_{K} (\ln K_{i,t})^2 + \alpha_{KK} \ln K_{i,t} \ln K_{i,t} + \alpha_{KR_c} \ln K_{i,t} \ln R_{C,i,t} + \alpha_{KR_f} \ln K_{i,t} \ln R_{F,i,t} + \alpha_{KT} \ln K_{i,t} T_i +
$$

$$
\frac{1}{2} \alpha_{R_c} (\ln R_{C,i,t})^2 + \alpha_{R_cR_c} \ln R_{C,i,t} \ln R_{C,i,t} + \alpha_{R_cT} \ln R_{C,i,t} T_i +
$$

$$
\frac{1}{2} \alpha_{R_f} (\ln R_{F,i,t})^2 + \alpha_{R_fT} \ln R_{F,i,t} T_i + \frac{1}{2} \alpha_T T_i^2
$$

where output, labor, the capital stock, the company-funded knowledge stock and the federally-funded knowledge stock for each industry are respectively denoted by $Q$, $L$, $K$, $R_c$, and $R_f$. $T$ denotes a time trend designed to capture any other disembodied technological change not attributable to R&D, and $i$ and $t$ are respectively industry and time indexes. Finally, the industry specific constant parameter $\alpha_i$ controls for industry specific effects including variation in the size of industries.

By assuming competitive factor markets and employing Shephard’s Lemma, one can derive the following factor share expressions for the inputs under an industry’s control ($L$, $K$, and $R_c$),

where $S_j$ indicates the share of total costs attributable to factor $j$:

$$
S_{L,i} = \alpha_L + \alpha_{LL} \ln L_{i,t} + \alpha_{LK} \ln K_{i,t} + \alpha_{LR_c} \ln R_{C,i,t} + \alpha_{LR_f} \ln R_{F,i,t} + \alpha_{LT} T_i
$$

$$
S_{K,i} = \alpha_K + \alpha_{LK} \ln L_{i,t} + \alpha_{KK} \ln K_{i,t} + \alpha_{KR_c} \ln R_{C,i,t} + \alpha_{KR_f} \ln R_{F,i,t} + \alpha_{KT} T_i
$$

\(^2\) Continuing to follow the perpetual inventory method, initial stocks of knowledge are generated using
(5) \[ S_{R_c,t} = \alpha_{R_c} + \alpha_{R_c} \ln L_{i,t} + \alpha_{R_c} \ln K_{i,t} + \alpha_{R_c} \ln \ln R_{C,i,t} + \alpha_{R_c} \ln R_{F,i,t} + \alpha_{R_c} T_i \]

Imposing the restriction that \( S_{L,t}+S_{K,t}+S_{R_c,t}=1 \) and then estimating (2), (3), and (4) as a system of equations would yield estimates of all the various \( \alpha \) terms. While these have some limited theoretical interest, the primary interest of this study is the total effect of each factor on output growth. I therefore focus on the elasticity of output with respect to each input, which can be obtained by differentiating the production function (2) with respect to the natural log of each input. This yields equivalent expressions to (3), (4), and (5) for \( L, K, \) and \( R_c \) and a similar expression for \( R_f \) (6). Similarly differentiating with respect to \( T \) yields an expression for the estimated rate of annual growth attributable to disembodied technological change (7). Following Verspagen (1995) these expressions can then be evaluated using mean values of \( \ln L_{i,t}, \ln K_{i,t}, \ln R_{C,i,t}, \ln R_{F,i,t}, \) and \( T_i \); the parameter estimates; and the coefficient covariance matrices to provide elasticity estimates as well as standard errors for these estimates.

(6) \[ e_{Q,R_f} = \alpha_{R_f} + \alpha_{R_f} \ln L_{i,t} + \alpha_{R_f} \ln K_{i,t} + \alpha_{R_f} \ln R_{C,i,t} + \alpha_{R_f} \ln R_{F,i,t} + \alpha_{R_f} T_i \]

(7) \[ e_{Q,T} = \alpha_{T} + \alpha_{T} \ln L_{i,t} + \alpha_{T} \ln K_{i,t} + \alpha_{T} \ln R_{C,i,t} + \alpha_{T} \ln R_{F,i,t} + \alpha_{T} T_i \]

With simple manipulation of the elasticity equations, it is possible to derive estimated returns to the physical capital stock as well as the company and federally-funded R&D capital stocks. These can then be evaluated at the mean levels of output and the capital stocks, yielding the following expressions for the estimated returns to these inputs:

\[ r_K = e_{Q,K} \frac{Q}{K} \]

(8) \[ r_{R_c} = e_{Q,R_c} \frac{Q}{R_c} \]

\( r_{0} = \frac{g}{g+\delta} \) where \( g \) represents an assumed rate of growth equal to .05 as in Verspagen (1995).
\[ r_{Q,F} = \frac{\bar{Q}}{\bar{R}_F} \]

where \( e_{Q,K} \), \( e_{Q,C} \), and \( e_{Q,R} \) respectively denote the elasticity of output with respect to the capital stock and the company and federally-funded knowledge stocks, and \( r_k \), \( r_c \), and \( r_r \) are the resulting estimated returns. These estimates can then be employed to gauge the magnitude of the return to federally-funded R&D relative to that of industrially-funded investments in physical capital and R&D.

III. Empirical Implementation

The implementation of the model requires the availability of a reasonably consistent and complete time series for both company and federally-funded R&D, and I therefore employ NSF data for industries aggregated at the 2 to 2 1/2 SIC level (Appendix Table 1). As census confidentiality requirements have precluded the NSF from publishing a significant number of data points in many of these series, I determined that only 11 industries had sufficiently complete data for both company and federally-funded R&D during the 1957-91 period. This data was then linked with economic data drawn from the NBER Manufacturing Productivity Database.

Unfortunately, estimation of the model across all eleven industries resulted in economically nonsensical parameter estimates, such as a large and statistically significant negative estimate for \( e_{Q,K} \). I attribute this result to the model’s restrictive assumption that all parameter values except for the constant term in the output equation (2) are the same for all industries. I therefore followed Verspagen (1995) and attempted to separately estimate the model for eight high-tech industries and three low-tech industries, on the assumption that parameter values are reasonably similar within these groups. However, the high number of parameters in the model subsequently precluded the estimation of the model for the low-tech industries, and therefore requires the analysis to focus only
on the eight high-tech industries. As the NBER Manufacturing database includes data for the years 1958-91, a maximum of 272 observations is available.

The variable $S_L$ is calculated as the total wage bill divided by value added. In order to calculate $S_K$, I follow Verspagen's (1995) methodology in order to construct rental prices for the physical capital stock. Thus, the rental price of physical capital is assumed to be $P_{l}(\delta_k+r)$ where $P_l$ is an investment price deflator obtained from the NBER Manufacturing productivity database, $\delta_k$ is the assumed rate of depreciation for physical capital (10%) and $r$ is an interest rate, which is assumed to be 5%. $S_K$ is then calculated as $P_{l}(\delta_k+r)K$ divided by value added. A similar methodology is also employed to construct the rental price of the company-funded knowledge stock, which is assumed to equal $P_{R&D}(\delta+r)$ where $P_{R&D}$ is a deflator for R&D costs, which is proxied by the GDP deflator.

While Verspagen (1995) simultaneously estimates production function and share equations by employing 3SLS with lagged (once and twice) values of the variables (including prices) as instruments, the replication of this methodology revealed substantial econometric problems, with significantly autocorrelated errors appearing to be the predominant problem. I therefore implement the following alternative estimation approach, which augments the 3SLS estimator to account for autocorrelation.

An estimate of a common autocorrelation parameters $\rho_L$, $\rho_K$, and $\rho_Q$ is first obtained for the $S_L$, $S_K$, and $\ln Q$ equations, respectively. This is accomplished by following Durbin (1960) who suggested that in a generic setup where $y$ is a dependent variable and $x$ is a vector of explanatory

---

3 The eight high-tech industries are Aerospace, Communication Equipment & Electronic Components, Other Electrical Equipment, Professional & Scientific Instruments, Machinery, Motor Vehicles and Other Transport Equipment, Industrial Chemicals, and Other Chemicals. The Fabricated Metal Products, Petroleum Refining, and Primary Metals Industries are the excluded low-tech industries.
variables, a consistent estimator of an AR (1) autocorrelation parameter is obtained from the coefficient on $y_{t-1}$ in the following regression:

(9) \[ y_t = \rho y_{t-1} + x_t \beta - x_{t-1} (\rho \beta) + \nu_t \]

However, given the constrained optimization embodied in the model, $\ln R_{F,i}$, and $T_i$ are the only right-hand-side variables which are assumed to be exogenous. I therefore obtain estimates of the autocorrelation parameters $\rho_L$ and $\rho_K$, and $\rho_Q$ by employing a 2SLS technique in which twice lagged values of the right-hand-side variables as well as once and twice-lagged values of output and input prices are employed as instruments. This technique has the disadvantage of reducing the available sample size by 2 years for each industry.

(10) \[ y_t - \rho y_{t-1} = (x_t - \rho x_{t-1}) \beta + \varepsilon_t \]

Using $\rho_L$ and $\rho_K$, and $\rho_Q$ I then transform the $S_L$ and $S_K$ and the $ln Q_t$ equations as in (10) and subsequently estimate these transformed versions of (2), (3), and (4). In doing this, I employ 3SLS with once-lagged values of the transformed variables as well as once and twice-lagged values of output and input prices as instruments. For theoretical consistency, I also impose the equality of parameter values across the three equations. Similarly, I impose the following parameter restrictions, derived from (3), (4), and (5), which must be satisfied in order to assume that

\[ S_{Rc} = 1 - S_{L}\bar{\epsilon} - S_{K}\bar{\epsilon} \]

\[ \alpha_{Rc} = 1 - \alpha_L - \alpha_K \]
\[ \alpha_{Rc,L} = \alpha_{LRc} \]
\[ \alpha_{Rc,K} = \alpha_{KRc} \]
\[ \alpha_{Rc,Rc} = -\alpha_{LRc} - \alpha_{KRc} \]
\[ \alpha_{Rc,T} = -\alpha_{LT} - \alpha_{KT} \]
IV. Results

Parameter estimates resulting from the AR augmented 3SLS model are presented in Table 1. Based on the reasonable argument that the depreciation rate of knowledge generated from R&D is close to or equal to zero, this model employs industrially and federally-funded knowledge stocks that were constructed with $\delta$ equal to zero. Nevertheless, as it can be argued that knowledge does depreciate, and since Verspagen (1995) assumed $\delta=0.15$, I present alternative estimates after first considering these results.

As can be seen by the relatively high values of $\rho_L$, $\rho_K$, and $\rho_Q$ that were employed to transform the data, the level of autocorrelation in the models is quite substantial. Unfortunately, even after performing these transformations, significant residual autocorrelation is still evident in the estimating equations. Likewise, further analysis of the residuals, which is not reported here, suggests the presence of heteroscedasticity in the model.

Given these remaining econometric problems, several different approaches were employed in an effort to improve the estimates. However, efforts to specify the model in first differences resulted in economically nonsensical parameter estimates because of the need to estimate the $\alpha_L$, $\alpha_K$, and $\alpha_{Rc}$ parameters in the $\ln Q_{ij}$ equation. Likewise, attempts to respecify the $S_L$ and $S_K$ equations as well as the $\ln Q_{ij}$ equation with an AR (2) transform resulted in the estimation of unstable autocorrelation coefficients. Furthermore, efforts to correct the models for groupwise heteroscedasticity also resulted in economically nonsensical results while weighted least-squares estimation attempting to link the heteroscedasticity to particular explanatory variables had no significant effect on the results or the characteristics of the residuals.

As a result of these failures to improve the model, I have chosen to present my basic model. However, when interpreting the results, the reader is cautioned to note that substantial residual
autocorrelation and heteroscedasticity remains in the estimated models. Similarly, the relatively low explanatory power of the $S_L$ and $S_K$ equations also calls for some caution, although this concern is partially offset by the high explanatory power of the estimated output equation.

While I will focus primarily on the estimated output elasticities and returns to inputs presented below, a brief perusal of the $\alpha$ parameters presented in Table 1 yields some interesting conclusions. Most strikingly, $\alpha_{R_c,R_f}$ is found to be negative and statistically significant. This suggests that increases in federally-funded R&D do not stimulate industrially-funded R&D and may even result in reduced levels. Thus, contrary to our primary hypothesis, the simultaneous-equations approach does not provide evidence that federally-funded R&D indirectly boosted productivity growth by stimulating industry-funded R&D.

Reviewing the other R&D related parameters does however suggest that previous studies employing Cobb-Douglas production functions have failed to properly capture the potentially different effects of industrially and federally-funded R&D on output growth. Thus, for example while both the $\alpha_{KR,f}$ and $\alpha_{KR,1}$ parameters are negative and significant, the statistically significant positive $\alpha_{LR,f}$ and negative $\alpha_{LR,1}$ parameters suggest that federal R&D funding has labor augmenting productivity effects, while industrially-funded R&D appears to generate labor substituting technological change. Similarly, the positive and significant $\alpha_{R,J}$ parameter suggests that the marginal impact of industrially-funded R&D on output growth has become greater over time, while the

---

4 Similar results were obtained and the alternative methods were also rejected when I estimated the series of alternative models employing different values of $\hat{\alpha}$
negative and marginally significant $\alpha_{R_{c},T}$ parameter suggests that output is less responsive to industrial federal R&D funding than it once was.\textsuperscript{6}

Turning next to Table 2 reveals the estimated output elasticities and estimated returns to capital and R&D resulting from the model presented in Table 1. Interestingly, the estimated return to federal R&D ($r_{R_{f}}$) is 0.35 and statistically significant while the estimated return to industrially-funded R&D ($r_{R_{c}}$) is only 0.07. Thus, these results would appear to demonstrate that federally-funded industrial R&D has had a substantial and significant impact on output growth in the eight high-tech manufacturing sectors included in this study. Moreover, the estimate of the return to industrially-funded R&D is below the range of 9% to 51% found in earlier studies employing the traditional R&D intensity model, as well as the estimated return to capital ($r_{K}$) which is found to be 0.34.

However, as Table 3 reveals, these results should be interpreted with some caution because the estimated returns to company and federally-funded R&D are substantially influenced by the assumed depreciation rate of knowledge ($\delta$), with the estimated return to federally-funded R&D undergoing the most dramatic changes.

\textsuperscript{5}$\alpha_{R_{c},R_{f}}$ is negative and significant in 3 of the 4 underlying regression reported below in which I have tested the effects of alternative parameter values for $\delta$. However, when $\delta=0.15$, $\alpha_{R_{c},R_{f}}$ is found to be positive and statistically significant. Given both the residual econometric problems discussed in the text, and the existence of a range of estimates for $\alpha_{R_{c},R_{f}}$, I choose to carefully interpret this coefficient as providing no evidence of a stimulative relationship between company and federally-funded R&D, rather than providing evidence of a negative relationship.

\textsuperscript{6} Some moderate caution is once again required given the residual econometric problems and variance in the estimated values of these coefficients in the alternative regressions reported in Table 3. However, all 4 of the underlying estimates of $\alpha_{R_{c},R_{f}}$ are negative and statistically significant at 95\% or greater, while all 4 estimates of the $\alpha_{R_{f}}$ parameter are positive and statistically significant. Likewise, all 4 of the $\alpha_{R_{c},T}$ parameters are positive and statistically significant, while the estimated values for the $\alpha_{R_{f},T}$ parameter are all negative and statistically significant. Thus, the preponderance of evidence suggests that the impact of federal industrial R&D funding on output growth has not increased over time, and this impact has been labor augmenting, while industrially funded R&D has been capital augmenting.
Thus, Table 3 reveals that increasing the assumed R&D depreciation rate causes a steady increase in the estimated return to federally-funded R&D ($r_{fr}$), to a level of 111% when $\delta$ is equal to 0.15. Similarly, the estimated return to industrially-funded R&D ($r_{ir}$) increases to 15% as $\delta$ increases to 0.10, but then declines substantially when $\delta$ is once again increased to 0.15. Thus, the assumed depreciation rate of the model has a substantial influence on the estimated returns to both company and federally-funded R&D. This reveals a significant weakness of the perpetual inventory method, and suggests that future analysis should allow for the endogenous determination of $\delta$.

Nevertheless, regardless of which rate of depreciation is employed, a positive and significant estimated return to federally-funded R&D is obtained.

V. Conclusions

While the residual autocorrelation and heteroscedasticity found in the models requires a cautious interpretation of the results, the estimation of a constrained translog production function for aggregated manufacturing industries has generated some interesting findings. Most interestingly, the estimation of a negative value for the $\alpha_{c,fr}$ parameter suggests that federally-funded R&D does not have a stimulative effect on industrially-funded R&D. This leads to the rejection of the paper’s primary hypothesis, that previous models have underestimated the return to federally-funded R&D simply because of their failure to properly account for the possible stimulative relationship between federally and industrially-funded R&D.

Despite this finding, the results do suggest that previous models have underestimated the return to federally-funded R&D, even if not for the reasons originally hypothesized. This appears to be the case because employing a translog production function allows for the differential impact of company and federal R&D funding on the marginal productivity of other factors, a characteristic that may result in more accurate estimation of the total return to R&D. As previous models based on the
Cobb-Douglas production function implicitly assume that the factor-augmenting effects of R&D spending must be in the same proportion for all inputs, it would simply be impossible for these models to accurately capture these differential effects.

These results also suggest that while the impact of industrially-funded R&D on output growth has increased over time, the impact of federally-funded R&D has declined. This can be interpreted as indicating that while federal R&D funding had a substantial impact on productivity growth during an earlier formative period for defense-related industries, it later became less effective in generating productivity growth. However, as it is likely that the results of both company and federally-funded R&D are actually embodied into the production process over a period of years, a more accurate estimate of the total returns to R&D funding could be obtained from future research employing a distributed lag approach. Likewise, the impact of the assumed knowledge depreciation rate on the resulting estimated returns to both industrially and company-funded R&D, suggests that future work should pursue the endogenous estimation of this depreciation rate.

The challenge of such a research agenda would be to both maintain a flexible functional form such as the translog function and increase the model's sophistication by estimating a distributed lag model with endogenous depreciation rates, while simultaneously finding an econometric approach that corrects for the econometric problems that plague the existing model. While this task would be exceedingly difficult to accomplish, the benefit of further improving our understanding of the effects of federal industrial R&D funding on manufacturing performance would make the effort worthwhile.
REFERENCES


### Table 1 Estimated Parameters Assuming $\delta=0$
(Sample Period 1960-91, 8 Industries)

#### $S_L$ Equation

<table>
<thead>
<tr>
<th>Estimate</th>
<th>T-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_L$</td>
<td>-0.235**</td>
</tr>
<tr>
<td>$a_K$</td>
<td>1.169**</td>
</tr>
<tr>
<td>$a_Rc$</td>
<td>0.066**</td>
</tr>
<tr>
<td>$a_Rf$</td>
<td>0.547**</td>
</tr>
<tr>
<td>$a_T$</td>
<td>0.0003</td>
</tr>
<tr>
<td>$a_{LL}$</td>
<td>-0.070**</td>
</tr>
<tr>
<td>$a_{LK}$</td>
<td>0.080**</td>
</tr>
<tr>
<td>$a_{LRc}$</td>
<td>-0.010**</td>
</tr>
<tr>
<td>$a_{LRf}$</td>
<td>-0.040**</td>
</tr>
<tr>
<td>$a_{LT}$</td>
<td>0.059**</td>
</tr>
<tr>
<td>$a_{L}$</td>
<td>-0.235**</td>
</tr>
</tbody>
</table>

#### $S_K$ Equation

<table>
<thead>
<tr>
<th>Estimate</th>
<th>T-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{LL}$</td>
<td>-0.070**</td>
</tr>
<tr>
<td>$a_{LK}$</td>
<td>0.080**</td>
</tr>
<tr>
<td>$a_{LRc}$</td>
<td>-0.010**</td>
</tr>
<tr>
<td>$a_{LRf}$</td>
<td>-0.040**</td>
</tr>
<tr>
<td>$a_{LT}$</td>
<td>0.059**</td>
</tr>
<tr>
<td>$a_{L}$</td>
<td>-0.235**</td>
</tr>
</tbody>
</table>

#### $S_{Rc}$ Equation

<table>
<thead>
<tr>
<th>Estimate</th>
<th>T-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{LL}$</td>
<td>-0.070**</td>
</tr>
<tr>
<td>$a_{LK}$</td>
<td>0.080**</td>
</tr>
<tr>
<td>$a_{LRc}$</td>
<td>-0.010**</td>
</tr>
<tr>
<td>$a_{LRf}$</td>
<td>-0.040**</td>
</tr>
<tr>
<td>$a_{LT}$</td>
<td>0.059**</td>
</tr>
<tr>
<td>$a_{L}$</td>
<td>-0.235**</td>
</tr>
</tbody>
</table>

#### Industry Dummy Variables

- Professional & Scientific Instruments: 0.141** 3.38
- Industrial Chemicals: 0.156** 5.44
- Other Chemicals: 0.416** 6.29
- Communication Equipment & Electronic Con: -0.104** 2.77
- Other Electrical Equipment: -0.051 1.38
- Motor Vehicles and Other Transport Equipm: -0.085 1.27
- Aerospace: 0.049** 3.58
- $\rho_Q$: 0.91
- $\rho_K$: 0.93
- $\rho_{Q}$ between Obs. and Pred.: 0.13
- Standard Error: 0.018
- Residual autocorrelation: 0.40
- $R^2$ between Obs. and Pred.: 0.12
- Standard Error: 0.015
- Residual autocorrelation: 0.41

** indicate statistical significance at the 95% level
* indicate statistical significance at the 90% level
Table 2 Estimated Output Elasticities and Returns Assuming $\delta=0$

<table>
<thead>
<tr>
<th>Input</th>
<th>Elasticity</th>
<th>T-Stat</th>
<th>Est. Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>0.32**</td>
<td>15.45</td>
<td>0.36</td>
</tr>
<tr>
<td>Rc</td>
<td>0.06**</td>
<td>25.31</td>
<td>0.07</td>
</tr>
<tr>
<td>Rf</td>
<td>0.35**</td>
<td>2.96</td>
<td>0.34</td>
</tr>
<tr>
<td>L</td>
<td>0.62**</td>
<td>28.24</td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>-0.64</td>
<td>0.64</td>
<td></td>
</tr>
</tbody>
</table>

** indicates statistical significance at the 95% level
* indicates statistical significance at the 90% level

Table 3 Estimated Returns to Capital and R&D at Various Values of $\delta$

<table>
<thead>
<tr>
<th>Assumed Knowledge Depreciation Rate ($\delta$)</th>
<th>0.00</th>
<th>0.05</th>
<th>0.10</th>
<th>0.15</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_K$</td>
<td>0.36**</td>
<td>0.38**</td>
<td>0.39**</td>
<td>0.38**</td>
</tr>
<tr>
<td></td>
<td>(15.45)</td>
<td>(14.60)</td>
<td>(13.21)</td>
<td>(11.31)</td>
</tr>
<tr>
<td>$r_{Rc}$</td>
<td>0.07**</td>
<td>0.13**</td>
<td>0.15**</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(25.31)</td>
<td>(22.74)</td>
<td>(16.21)</td>
<td>(1.37)</td>
</tr>
<tr>
<td>$r_{Rf}$</td>
<td>0.34**</td>
<td>0.73**</td>
<td>0.98*</td>
<td>1.11**</td>
</tr>
<tr>
<td></td>
<td>(2.96)</td>
<td>(2.16)</td>
<td>(1.86)</td>
<td>(3.47)</td>
</tr>
</tbody>
</table>

** indicates statistical significance at the 95% level
* indicates statistical significance at the 90% level

Figures in Brackets are T-Statistics

(T-Statistics are the same as for the underlying output Elasticities, because the rate of return is equal to the elasticity divided by the average factor output ratio, which is taken as nonstochastic)
### Appendix Table 1: Summaries of Manufacturing R&D Funding by Source and Industry: 1958-1991

(All data are expressed as percentages)

<table>
<thead>
<tr>
<th>Industry</th>
<th>Avg. Annual Funded R&amp;D/Sales Ratio</th>
<th>Avg. Annual Federally Funded R&amp;D/Sales Ratio</th>
<th>Avg. Annual Total Funded R&amp;D/Sales Ratio</th>
<th>Avg. annual share of all company funded R&amp;D</th>
<th>Avg. annual share of all federally funded R&amp;D</th>
<th>% of Ind. Funds from Federal Gov. 1958-91</th>
<th>% of Ind. Funds from Federal Gov. 1958-68</th>
<th>Estimated Growth Rate in Company Funded R&amp;D</th>
<th>Estimated Growth Rate in Total R&amp;D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerospace</td>
<td>3.72, 376</td>
<td>4.03</td>
<td>1.68</td>
<td>21.15</td>
<td>5.80</td>
<td>28.92</td>
<td>78.98</td>
<td>87.04</td>
<td>4.27</td>
</tr>
<tr>
<td>Comm. Equip &amp; Electronic Components</td>
<td>366, 367</td>
<td>7.26</td>
<td>8.83</td>
<td>16.09</td>
<td>12.11</td>
<td>17.60</td>
<td>14.46</td>
<td>49.91</td>
<td>66.89</td>
</tr>
<tr>
<td>Communication Equipment (1)</td>
<td>366</td>
<td>8.28</td>
<td>6.64</td>
<td>14.45</td>
<td>8.79</td>
<td>14.04</td>
<td>10.27</td>
<td>43.62</td>
<td>NA</td>
</tr>
<tr>
<td>Electronic Components (2)</td>
<td>367</td>
<td>5.23</td>
<td>1.69</td>
<td>6.84</td>
<td>4.40</td>
<td>2.21</td>
<td>3.54</td>
<td>24.69</td>
<td>NA</td>
</tr>
<tr>
<td>Other Electrical Equipment</td>
<td>361-5, 369</td>
<td>3.13</td>
<td>3.32</td>
<td>6.44</td>
<td>5.62</td>
<td>8.75</td>
<td>7.43</td>
<td>42.67</td>
<td>59.01</td>
</tr>
<tr>
<td>Radio &amp; TV Receiving Equipment (3)</td>
<td>365</td>
<td>3.52</td>
<td>NA</td>
<td>3.67</td>
<td>0.65</td>
<td>NA</td>
<td>0.39</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Electrical Equipment NEC (4)</td>
<td>361-4, 369</td>
<td>2.22</td>
<td>NA</td>
<td>6.68</td>
<td>3.32</td>
<td>NA</td>
<td>8.64</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Prof. and Science Instruments</td>
<td>38</td>
<td>5.81</td>
<td>1.59</td>
<td>7.40</td>
<td>6.61</td>
<td>2.35</td>
<td>5.04</td>
<td>21.45</td>
<td>36.80</td>
</tr>
<tr>
<td>Scientific &amp; Mechanical Measuring Equip. (5)</td>
<td>381-2</td>
<td>5.17</td>
<td>1.19</td>
<td>4.59</td>
<td>2.15</td>
<td>0.71</td>
<td>1.20</td>
<td>25.66</td>
<td>39.60</td>
</tr>
<tr>
<td>Optical, Surgical, &amp; Photographic Equip. (5)</td>
<td>383-87</td>
<td>6.48</td>
<td>2.29</td>
<td>8.49</td>
<td>4.49</td>
<td>1.67</td>
<td>2.98</td>
<td>26.15</td>
<td>32.72</td>
</tr>
<tr>
<td>Machinery (includes Computers)</td>
<td>35</td>
<td>3.40</td>
<td>0.70</td>
<td>4.10</td>
<td>16.38</td>
<td>4.79</td>
<td>11.94</td>
<td>18.22</td>
<td>30.64</td>
</tr>
<tr>
<td>Computers (6)</td>
<td>357</td>
<td>28.94</td>
<td>11.17</td>
<td>60.09</td>
<td>13.68</td>
<td>4.19</td>
<td>8.95</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Nonelectrical Machinery (7)</td>
<td>35-1-6, 358-9</td>
<td>1.47</td>
<td>NA</td>
<td>NA</td>
<td>5.16</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Mot. Vehicles and Other Transport Equip.</td>
<td>371, 373-379</td>
<td>2.70</td>
<td>0.73</td>
<td>3.43</td>
<td>14.12</td>
<td>5.51</td>
<td>10.44</td>
<td>20.88</td>
<td>26.75</td>
</tr>
<tr>
<td>Motor Vehicles (8)</td>
<td>371</td>
<td>3.33</td>
<td>0.47</td>
<td>3.62</td>
<td>13.52</td>
<td>4.06</td>
<td>10.40</td>
<td>13.02</td>
<td>NA</td>
</tr>
<tr>
<td>Other Transport Equipment (9)</td>
<td>373-5, 375</td>
<td>0.87</td>
<td>0.44</td>
<td>0.76</td>
<td>0.42</td>
<td>0.65</td>
<td>0.40</td>
<td>54.15</td>
<td>NA</td>
</tr>
<tr>
<td>Rubber &amp; Plastic Products</td>
<td>30</td>
<td>1.33</td>
<td>0.51</td>
<td>1.96</td>
<td>1.78</td>
<td>0.73</td>
<td>1.50</td>
<td>24.34</td>
<td>22.56</td>
</tr>
<tr>
<td>Textiles and Apparel</td>
<td>22.23</td>
<td>0.16</td>
<td>0.02</td>
<td>0.16</td>
<td>0.45</td>
<td>0.06</td>
<td>0.31</td>
<td>10.30</td>
<td>19.19</td>
</tr>
<tr>
<td>Fabricated Metal Products</td>
<td>34</td>
<td>0.48</td>
<td>0.08</td>
<td>0.56</td>
<td>1.84</td>
<td>0.39</td>
<td>1.21</td>
<td>12.88</td>
<td>18.61</td>
</tr>
<tr>
<td>Chemicals-Industrial</td>
<td>281-2, 286</td>
<td>3.86</td>
<td>0.65</td>
<td>4.51</td>
<td>8.59</td>
<td>1.91</td>
<td>5.65</td>
<td>13.69</td>
<td>17.98</td>
</tr>
<tr>
<td>Chemicals-Pharmaceuticals &amp; Nonindustrial</td>
<td>283-5, 287-9</td>
<td>3.61</td>
<td>0.16</td>
<td>3.77</td>
<td>8.23</td>
<td>0.35</td>
<td>5.21</td>
<td>4.86</td>
<td>12.92</td>
</tr>
<tr>
<td>Pharmaceuticals (10,11)</td>
<td>283</td>
<td>7.51</td>
<td>0.18</td>
<td>7.78</td>
<td>6.19</td>
<td>0.07</td>
<td>2.76</td>
<td>NA</td>
<td>2.31</td>
</tr>
<tr>
<td>Nonindustrial Chemicals (10,11)</td>
<td>284-5, 287-9</td>
<td>1.49</td>
<td>0.71</td>
<td>1.56</td>
<td>2.83</td>
<td>0.95</td>
<td>1.50</td>
<td>NA</td>
<td>30.57</td>
</tr>
<tr>
<td>Nonferrous Metals(12)</td>
<td>333-36</td>
<td>0.67</td>
<td>0.06</td>
<td>0.73</td>
<td>1.06</td>
<td>0.15</td>
<td>0.71</td>
<td>8.61</td>
<td>11.80</td>
</tr>
<tr>
<td>Petroleum Refining &amp; Related Industries</td>
<td>13.29</td>
<td>1.37</td>
<td>0.08</td>
<td>1.37</td>
<td>4.69</td>
<td>0.42</td>
<td>2.77</td>
<td>5.72</td>
<td>7.76</td>
</tr>
<tr>
<td>Lumber, Wood Products, and Furniture</td>
<td>24.25</td>
<td>0.17</td>
<td>0.00</td>
<td>0.17</td>
<td>0.36</td>
<td>0.00</td>
<td>0.22</td>
<td>1.95</td>
<td>6.38</td>
</tr>
<tr>
<td>Stone, Clay, and Glass Products</td>
<td>32</td>
<td>0.96</td>
<td>0.04</td>
<td>0.91</td>
<td>1.50</td>
<td>0.09</td>
<td>0.93</td>
<td>4.63</td>
<td>3.88</td>
</tr>
<tr>
<td>Food, Kindred, Tobacco</td>
<td>20.21</td>
<td>0.26</td>
<td>0.00</td>
<td>0.26</td>
<td>2.18</td>
<td>0.03</td>
<td>1.29</td>
<td>1.35</td>
<td>3.16</td>
</tr>
<tr>
<td>Ferrous Metals (12)</td>
<td>331-2, 3398-9</td>
<td>0.46</td>
<td>0.04</td>
<td>0.50</td>
<td>1.32</td>
<td>0.12</td>
<td>0.89</td>
<td>4.36</td>
<td>1.89</td>
</tr>
<tr>
<td>Paper &amp; Allied Products</td>
<td>26</td>
<td>0.63</td>
<td>0.00</td>
<td>0.63</td>
<td>1.46</td>
<td>0.01</td>
<td>0.87</td>
<td>0.93</td>
<td>5.03</td>
</tr>
<tr>
<td>Manufacturing Industries NEC</td>
<td>NEC</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>All Manufacturing</td>
<td>1.79</td>
<td>1.25</td>
<td>3.04</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>40.60</td>
<td>55.08</td>
<td>4.28</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation From: Research and Development in Industry: Various Annual Reports, NSF and Manufacturing Productivity Database, NBER
Appendix Table 1: Summaries of Manufacturing R&D Funding by Source and Industry: 1958-1991-

2. company R&D estimates 1972-91, federal & total R&D estimates 1972-1990. Company and federal R&D data unavailable for 1975-
7. company R&D estimates 1977-91, insufficient data for federal and total R&D estimates
11. company funded average for 1980-91 was 10.5% for pharmaceuticals and 2.08% for other chemicals