PUBLIC SECTOR PRODUCTION OF AGRICULTURAL KNOWLEDGE

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" ... (Technical Change) gives a name to our ignorance it does not dispel it."

Schultz (1961)

" ... it is necessary to recognize that the economic analysis of inventive activity is seriously handicapped by our present inability to specify the production function for inventive activity with any pretence of precision."

Rosenberg (1976)

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Chapter 1

INTRODUCTION

The sustained use of new agricultural knowledge is an enduring characteristic of American agriculture. But, economists know little about the process by which this knowledge is generated. Some arises from tinkering, on-farm experimentation or 'learning by doing'. Significant amounts are also provided by off-farm sources through private and public sector research and development activity.

There have been renewed efforts by economists to empirically study the inventive activity of firms in the private sector (see Griliches (1984)). Building on this work, the present study applies a simple model of knowledge production to a new and unique data set of research inputs and outputs to explore 'inside the black box' of public sector agricultural research. We begin with a brief and selective synthesis of the informal and often implicit conceptual framework of the antecedent literature on augmented production functions. The conceptual constructs used in these models are broad in nature and generally several steps removed from any 'micro-economic foundation'. Nevertheless, a critical evaluation of this work serves to motivate the narrower focus adopted here.

Economists have been attempting to quantify the output enhancing effects of public sector research and extension spending for over two decades. Several approaches have been used. One measures the average rate of return from research using the supply shifting or index number approach. Examples include Peterson (1966), Lindner and Jarrett (1978) and Edwards and Freebairn (1981).

Another involves econometric estimation of an extended or augmented production function which relates agricultural output to conventional inputs plus research (and extension) variables. Clearly one method constitutes the dual of the other. However, it is argued that the production function approach allows for direct estimation of the marginal internal rate of return to agricultural research and offers the potential to investigate the lag relationship between research spending and agricultural output.

Early attempts to proceed within the augmented production function framework include work by Griliches (1964), Evenson (1968) and Minasian (1969). These studies, and most of the work to follow, have relied little on formal allocative models based on some sort of maximizing behaviour. Despite limiting their scope of analysis to the agricultural sector, they subsume the economic behavior of numerous agents. This includes those who ultimately use the technology (i.e. farmers and producers of intermediate inputs not necessarily 'within' the agricultural sector), those who generate the new technology (i.e. researchers in public and private institutions), and finally those involved in allocative decisions concerning public sector (research) funds (i.e. politicians, research administrators and ultimately producers and consumers).

In principle there is no obstacle to specifying a complete system of equations to capture these effects. In practice, however, our current understanding of the components and linkages of this system are rudimentary, and the data to estimate such a model is currently not available. For these reasons analysts have resorted to the essentially descriptive, aggregate, production function approach described below.

1.1 The Production Function Model:

Consider the production function

$$Y_t = f(\tilde{X}_t, Z_t, \mu_t) \qquad (1.1)$$

where Y_t, an appropriate measure of aggregate agricultural output in period t, is expressed as a function of inputs $\tilde{X}_t$, Z_t and μ_t where $\tilde{X}_t$ is a vector of (quality adjusted) primary inputs such as capital, land and labor; Z_t is a vector of other measured inputs which account for changes in the level of output such as fertilizer, seeds, energy, other purchased inputs and weather and μ_t represents unmeasured influences on output Y.

Partitioning Z_t we can write

$$Z_t = (\tilde{Z}_t, I_t) \qquad (1.2)$$

where

$$I_t = A(L)K_t \qquad (1.3)$$

I_t can be interpreted as the information used in the production of Y_t or alternatively the economically valuable knowledge in use at time period t. K_t represents the existing stock of still (potentially) productive knowledge at time period t and A(L) is a polynomial lag operator so that,

$$A(L)K_t = (a_0 + a_1L + a_2L^2 + \ldots.)K_t = a_0K_t + a_1K_{t-1} + a_2K_{t-2} + \ldots.$$

Clearly not all the productive knowledge in existence at time period t contributes to increases in output as all producing agents, for one reason or another, do not operate on the technically feasible production frontier. Consequently the time shape of the weights in A(L) captures the diffusion process and reflects the outcome of public and private extension activity on the one hand, plus search and screening activity on the part of (potential) adopters on the other[1].

The stock of productive knowledge can now be written as

$$K_t = B(L)\dot{K}_t^g \qquad (1.4)$$

where $\dot{K}_t^g$ represents increments in the gross stock of knowledge in time period t and B(L) is a polynomial lag operator similar to A(L). In this instance the lag operator function B(L) acts to convert gross increments in the stock of knowledge to net increments then sum them over time into a stock of knowledge measure. The time shape of these weights represents the joint influence of;

(a) biological depreciation -- A peculiarity of biological research is that the productive potential of a unit of $\dot{K}^g$ spontaneously declines whether or not any further research activity is undertaken. This is a tangible depreciation due to the niggardliness of nature. The output enhancing effects of previous research findings can be eroded by the evolution of resistant pests and pathogens, plant varietal deterioration, declining soil fertility and structure, and other factors. Moreover, the notion of maintenance vis-a-vis output enhancing research enters here. If, as Ruttan (1982, p. 60) speculates, the research effort required to maintain productivity is a positive function of the productivity level, then maintenance research will tend to rise as a share of the research budget. This suggests that the weights in B(L) may have a declining structure as yearly additions to the gross stock of knowledge are increasingly dominated by maintenance or replacement research as opposed to output enhancing research.

(b) technological obsolesence--This notion relates to the replacement of old findings or scientific 'truths' by superior or improved findings. Accepting an incremental or evolutionary view of scientific progress it follows that a certain amount of current research activity will confer a degree of obsolesence on the corpus of prior research findings. For instance, letting K_t^T measure the degree of technological obsolesence induced by the current research activity then

$$K_t^T = T(\dot{K}_t^g , K_{t-1}) \qquad (1.5)$$

where it may well be that;

(a) $\delta^2 T / \delta \dot{K}_t^{g\,2} < 0$. i.e. There is a diminishing marginal rate of obsolesence so that it is relatively easy to supersede the first (older) unit of knowledge but becomes harder to supersede (more recent) units, and

(b) $\delta T / \delta K_{t-1} > 0$. i.e. The larger the knowledge base the greater the degree of obsolesence for a given $\dot{K}_t^g$.

The process of technological obsolesence would reinforce the impact of biological depreciation so that we would expect a declining structure of weights in B(L), perhaps after an initial 'shakedown' period of increasing weights. The 'shakedown' effect allows for the possibility that it may take a few years before scientists realize the full significance of their more recent discoveries.

Finally we posit the existence of a knowledge production function whereby

$$\dot{K}_t^g = g(\, C(L)R_t \,,\, v) \qquad (1.6)$$

such that $C(L)R_t$, a weighted sum of current and past research expenditures, is a measure of research 'capital'[2] and v is a vector of other factors which contribute to $\dot{K}_t^g$, and which for the moment we will assume are time invariant. The view that there exists a systematic relationship between research expenditures and knowledge increments has been taken up by numerous authors including Evenson (1968), Minasian (1969), Rosenberg (1976), Pakes (1978), Griliches (1979) and Kamien and Schwartz (1982). It follows naturally from the perception that in general science progresses by a sequence of marginal improvements rather than a series of discrete and essentially sporadic breaksthrough (See Burke (1978)).

By substituting (1.6), (1.4), (1.3) and (1.2) into (1.1) we can write the reduced form version of the augmented production function as

$$Y_t = F(\tilde{X}_t, \tilde{Z}_t, A(L)B(L)g(c(L)R_t), v, \mu_t)$$

$$= F(\tilde{X}_t, \tilde{Z}_t, D(L)R_t, v, \mu_t) \qquad (1.7)$$

where D(L) represents the complex convolution of the three lagged processes A(L), B(L) and C(L)[3]. Generally an appeal to computational convenience or previous estimates of unitary elasticity of substitution between conventional inputs is used to impose the Cobb-Douglas form on F(.) before proceeding with the estimation of equation (1.7). The time invariant factors v are collapsed into the intercept term.

1.2 Some Reservations:

These reduced form augmented production function models, although clearly masking a great deal of complexity with respect to the research-output relationship, have been instructive. However, they have not gone uncriticized. One line of attack centers on the veracity of using ex post rates of return estimates, derived from such production function studies, as a basis for assessing the efficiency of current public investments in agricultural research. This debate lies largely outside the scope of the present research but the recent literature by Ruttan (1980, 1982), Pasour and Johnson (1982) and Fox (1985) highlights some of the issues involved.

A second area of criticism centers on the possible lack of precision of (internal) rates of return estimates due to a variety of measurement and specification errors. To study the more important of these issues broadens our concern beyond questions of accuracy to also aid our interpretation of the estimates derived from models represented by equation (1.7).

From the characterization of the research-output relationship developed in the previous section it is clear that equation (1.7) captures a variety of complex sub-processes including knowledge generation, depreciation, obsolesence and diffusion. With only data on the Y, X, Z and R variables available, the structural coefficients on each of these individual sub-processes cannot be identified. To write the specification as we have here also involves several key, implicit restrictions.

For instance equation (1.7) imposes a form of separability between the conventional inputs $\tilde{X}$ (and quality adjusters) and the series of past and present public sector research expenditures, R. This implies that the estimated production elasticities on the research expenditure variable measure the 'partial' contribution of research to output increases holding the level of other quality adjusted inputs (labor, land and capital) constant. The indirect effects of R on Y, through induced changes in $\tilde{X}$, are not captured by the R coefficients in equation (1.7). This conflicts with induced innovation models which posit that research is factor augmenting in nature, not factor neutral, as these models imply.

Generally questions of simultaneity are also glossed over. The traditional supply-push models, implicit in equation (1.7), reflect a science-based view of technical progress where the direction of causality runs from agricultural research expenditures to final agricultural output. Recent work by Guttman (1978) and Rose-Ackerman and Evenson (1982) develop the theme that the economic benefits of (public) agriculture research and extension do not necessarily accrue to the institutions directly involved in the research process but are filtered through a political mechanism. At the aggregate level, the causal relationship suggested by these various demand-pull models runs from agricultural output or sales to research expenditure. To the degree that demand-pull forces are operative, single equation estimation of the parameters in (1.7) may be inappropriate.

From an entirely different perspective Mundlak and Hoch (1965) argue that the production function described by equation (1.7) should be estimated within a multi-equation framework which also includes the factor demand equations derived from first order, profit maximizing conditions. While this seems appropriate for firm-level production functions it is not readily apparent that an aggregate input-output relationship including public sector research expenditures can be usefully dealt with in this framework.

Despite the numerous simplifying assumptions used to construct the reduced form equation (1.7) appropriate estimation procedures are not straightforward. The principal difficulty involves estimating the weights of the polynomial lag structure D(L). The weights are of intrinsic interest in that they summarize the nature of the lag relationship between public sector research expenditure and final agricultural output. The precision with which they are estimated directly effects the confidence intervals we can place on the marginal internal rate of return estimates which are subsequently derived from these coefficients.

Relatively few studies have systematically investigated the nature of the lag relationship between research expenditures and final output. Evenson's 1968 study is one that did and his results have been used repeatedly to justify the estimation procedures adopted by subsequent investigators. For this reason it is worth briefly reviewing his findings.

Two lag forms were estimated. The first was a simple Jorgenson rational lag structure where

$$P_t = (A(L) \; / \; T(L))R_t \tag{1.8}$$

such that A(L) is a zero order polynomial in the lag operator, L, T(L) a second order polynomial, P_t an appropriate agricultural productivity index and R_t represents public sector agricultural research expenditures. The estimating equation was

$$P_t = aR_t + bP_{t-1} + cP_{t-2} \tag{1.9}$$

A non-negative lag distribution for R is implied for values of b and c satisfying the restrictions, $0 < b < 2$, $-1 < c < 1$, $1-b-c > 0$ and $b^2 \geq -4c$.

The advantage of this lag structure is that it admits a variety of possible lag shapes[4]. Setting $c = 0$ gives rise to the Koyck or Geometric Lag. For small values of the root[5], λ, and with $1 > b > c$, $0 < c < 1$ the lag distribution is similar to a (somewhat flattened) exponential, and values of $b^2 = -4c$ gives the Pascal distribution described by Solow (1960). When estimating (1.9) with a weather variable not included Evenson obtained $\hat{b} = .348$ and $\hat{c} = .495$ and with a weather variable included obtained $\hat{b} = .528$ and $\hat{c} = .275$. Both sets of values yield a lag structure of monotonically declining weights.

The difficult question is how to assess the validity of the implied lag structure. Griliches (1967) describes a procedure whereby an approximate joint confidence region can be constructed for (b, c). Evenson's estimates are in fact consistent with a wide range of possible time-shapes. Consequently, from a statistical perspective, the estimated lag structure is not sharply defined. Another means of evaluating the results is to compare the implied weight structure with our prior information on the subject. Unfortunately we have very little to go on in this regard. Evenson argued that a knowledge of the general shape of the lag structure pertaining to each of the sub-processes A(L), B(L) and C(L) places enough restrictions on the time-shape of D(L) (the convolution of the three sub-processes in equation (1.7)) to allow us to reject the weight structure implied by the point estimates of the Jorgenson lag.

In general this is not the case. In Appendix I, using the Pascal distribution, we demonstrate that relatively small changes in the parameters which characterize these various sub-processes gives rise to substantially different convoluted lag distributions. Thus vague priors concerning these sub-processes place relatively few restrictions on the admissible distribution of D(L).

Having 'rejected' the rational lag results Evenson proceeded to estimate a variety of national and regional lag relationships by imposing a DeLeeuw inverted-V lag structure on the data. Similar procedures have since been adopted by numerous studies (See Cline (1975), Davis (1979), Lu et. al. (1979), Hastings (1981), and White and

Havlicek (1981)). They have used a variety of finite lag structures including the inverted-V, (second order) Almon polynomial and Griliches-type lag distributions. All these finite lag structures involve a number of ad hoc, linear constraints.

For the inverted-V structure these include restrictions on the total and 'mean' lag length plus the nature of the linear relationship between the weights for each 'half' of the inverted-V. The polynomial lag structure involves restrictions on the appropriate lag length and the order of the polynomial distributions of the weights. Judge et. al. (1980, pp. 642f) discuss how an explicit formulation of the restricted least squares nature of the Almon lag can be obtained. Both lag structures may also be estimated subject to endpoint constraints.

Unfortunately systematic testing of these restrictions has not been a feature of the empirical research-on-research literature. For instance most of the studies using polynomial lags have not attempted to test the appropriateness of the second order assumption they have usually adopted. Trivedi and Pagan (1976) have shown that even if the imposed lag length is correct, assuming a polynomial order lower than the true order will always result in a biased polynomial distributed lag estimator[6]. Those studies which have constrained the lag function to a particular form have generally tested the sensitivity of their estimates to various lag lengths on the basis of maximizing $\bar{R}^2$ or equivalently minimizing the sum of squared errors.

Methods for testing either the polynomial degree, the lag length, or both simultaneously are available (see Judge et. al.

(1980) for a summary). However, the estimates generated by these procedures unfortunately have sampling distributions and properties that are unknown as a result of these complicated pretesting schemes. Of course if we are willing to assume the chosen model is the true representation of the lag process under study, appropriate sampling distributions and hence confidence intervals follow directly.

To fully evaluate the worth of these (constrained) estimates we need to know what use is to be made of them. If the purpose is to simply obtain summary measures which characterize the lag distributions then we are in reasonable shape. Davis (1979, pp. 71-73) presented evidence that the sum of the lag coefficients is relatively insensitive to the estimation procedure used. However, virtually none of these studies have reported unconstrained OLS estimates of the lag distribution.

Although multicollinearity problems limit the precision with which each partial production elasticity is estimated, this collinearity can be exploited to obtain quite accurate estimates of some summary measures of the lag distribution. Wallace (1975) and Hatanaka and Wallace (1980) conclude that their form-free method gives a reasonably precise estimate of the long-run response (sum of the coefficients), a fairly precise estimate of the mean lag and less precise estimates of the variance of the lag distribution. These form-free, low-order moments are not only of interest in their own right, but can also be used as a specification check on the results from estimating distributed lags subject to ad hoc, prior restrictions. By varying the number of included lag variables it also gives some information on the problems associated with choosing an inappropriate lag length[7].

It is also possible that in a panel data set the values and relative significance of the partial elasticities will give some hints as to the appropriate lag structure.

If the motivation for estimating D(L) in equation (1.7) is to facilitate estimates of the marginal internal rate of return (MIRR) to research expenditures then the previous discussion offers less comfort. Davis (1979, pp. 108f.) presents evidence that the point estimate of the MIRR to research is quite sensitive to the estimation procedures employed. The computational procedures developed by Cline (1975) and Davis (1979) are also sensitive to the values obtained for the partial research production coefficients, and in particular the values obtained for the early years in the lag distribution.

Consequently, constraining the lag distribution to the class of (exact) second order polynomials or inverted-V structures, as most of the studies have done, may have conferred serious misspecification bias on the estimated lag weights. In particular, the implicit symmetry and smoothness assumptions place restrictions on the nature of the lag relationship which do not seem warranted on the basis of the available prior information.

This leaves analysts with several options. One is to expand the information base on which the estimates are made. For instance, pooling cross-sections of time-series data, which was undertaken to a limited extent by Davis (1979), may inject enough independent variation into the sample to allow a more precise lag distribution to be estimated. Concomitant with this approach less exact priors could formally be incorporated into the estimation procedure, to more realistically reflect our current state of understanding concerning the output-research spending relationship. Specifically, it may be more appropriate to impose stochastic rather than exact linear restrictions on the time subscripted research spending coefficients if we are prepared to accept the notion that the lag weights can be approximated by a relatively smooth and simple curve, rather than fall exactly on a polynomial of a particular degree. The work of Shiller (1973) may be instructive in this area.

An altogether different approach is to seek a better understanding of the nature of the lag relationships inherent in the sub-processes A(L), B(L) and C(L). This could potentially give us more confidence in the priors we can place on D(L). Of course a deeper understanding of these sub-processes is of intrinsic interest as well.

To this end, one line of enquiry has focused on the mechanisms summarized by the lag distribution A(L). Various micro-level (search and screening) models of adoptive behaviour, with implications for the observed macro-level diffusion curves, have been developed and empirically tested (see Lindner (1981), Feder et. al. (1981) and the references contained therein).

However, surprisingly little work has been done on the research process captured by equation (1.6). Recent studies by Pakes and Griliches (1980), Hausman et. al. (1981) and Hall et. al. (1984) have sought direct estimates of the research lag C(L), or summary measures thereof, for research performed by private firms in the non-agricultural sector. To date there has been no similar analysis of the public sector agricultural research process. This study represents a first step in this direction. It not only will attempt to provide some clues as to the nature of the research spending-research output relationship but will hopefully give some insights into the 'institutional' factors which influence the knowledge generation process.

FOOTNOTES CHAPTER 1

1. This highlights the vexing question concerning the appropriate empirical treatment of extension expenditures in aggregate production functions. Some studies omit the variable altogether, others simply add it to research expenditures and yet others use a variable coefficient specification with the research coefficients being (linear) functions of extension spending.

2. Griliches (1979, p. 7) observes "that nothing tangible corresponds to this notion of R&D 'capital'. It is just an alternative to expensing R&D as a current input. Ideally it would equal the value of the firm's 'know how'...".

3. If g was assumed linear then D(L) would be the convolution [A(L), B(L), C(L)] with the polynomial coefficients in C(L) suitably scaled.

4. Its popularity also arises from the claim that an 'arbitrary' discrete lag distribution can be approximated to any degree of accuracy by certain rational distributions. In practice however Sims (1972) shows, that for distributed lag models, a 'good approximation' from the point of view of least squares fit may not be the same thing as a 'good approximation' from the point of view of the mean lag. Even though the standard error of estimate and associated R^2 of the estimated approximation may approach its optimum value (vis-a-vis the true relation) in an arbitrarily large sample, the estimated mean lag and sum of coefficients may remain arbitrarily far from their true value.

5. Here $\lambda = \frac{b \pm \sqrt{(b^2 + 4c)}}{2}$

6. If the 'true' lag structure follows a sigmoid type distribution (at least in the early stages) as Evenson's (1968, p.31) figure 1 suggests, then a third rather than second order polynomial seems a more 'plausible' a priori lag structure. Cline (1975, p.69) estimated second, third and fourth degree polynomials but claims the second degree specification yielded estimates that 'consistently' gave lower standard errors.

7. Hatanaka and Wallace (1980) note that choosing a lag length which is too small results in biased estimates of the low-order moments, while choosing a lag length which is too large usually increases their variance.

Chapter 2

STATISTICAL MODEL DEVELOPMENT AND ESTIMATION METHODS

2.1 Introduction:

In the following pages a stylized model of the relationship between the research inputs and research outputs of the State Agricultural Experiment Stations (SAES) will be presented. It draws on the approach first sketched by Pakes (1978) and later used by Pakes and Griliches (1980a and b) to study the patent-R & D expenditure relationship in the non-agricultural sector.

The exploratory nature of this study dictates a rather parsimonious approach to modelling the knowledge production process. Consequently the model developed here represents a fairly simplified version of reality. Nevertheless it purports to be a useful framework in which some of the issues raised in the previous chapter can be empirically scrutinized. In particular, the analysis will focus on

(a) The 'quality' of various publication measures as indicators of gross additions to the stock of knowledge,

(b) The nature of the lagged relationship between research expenditures and publication output, and

(c) The degree to which 'institutional' variables can account for state level differences in research 'efficiency'.

2.2 The Statistical Model:

In Chapter (1) we presented the notion of a quite simple knowledge production function (K.P.F) whereby gross scientific knowledge increments , $\dot{K}^g_t$, are primarily a function of current and lagged research expenditures. We wrote[1]

$$\dot{K}^g_t = g(\ c(L)R_t\ ,\ v\ ) \qquad (2.1)$$

where

$\dot{K}^g_t$ = increments in the gross stock of scientific knowledge in time period t,

C(L)R = a weighted sum of current and past research expenditures, and

v = a vector of other factors which contribute to $\dot{K}^g$.

Cognizant of the panel nature of the data used in this study a more explicit version of (2.1) can be written as

$$\dot{K}_{it} = \tilde{\theta} + \sum_{s=0}^{S} \tilde{\beta}_s R_{i,t-s} + \tilde{\mu}_i + \tilde{\lambda}_t + \tilde{w}_{it} \qquad (2.2)$$

$$i=1,2,\ldots.N\ ;\ t=1,2,\ldots.T$$

where

$\tilde{\theta}$ = an intercept term,

$\dot{K}_{it}$ = the gross scientific knowledge increment for state i in time period t,

$\tilde{\mu}_i$ = a state specific (time invariant) variable,

$\tilde{\lambda}_t$ = a time specific (state invariant) variable,

$R_{i,t-s}$ = state level deflated research expenditures lagged s time periods, and

$\tilde{w}_{it}$ = residual influences on $\dot{K}_{it}$ which are assumed to vary over both state and time periods.

The $\tilde{\mu}_i$ variable represents state-specific differences in research efficiency which are assumed to be uncorrelated with time. This interpretation is analogous to similar variables purporting to measure managerial efficiency in more traditional production function studies[2]. At a more fundamental level the variable reflects differences in either the particular research agenda faced by each experiment station (i.e. their technological opportunities) and/or 'institutional' factors which are conducive to a more-or-less productive research effort.

While states clearly share a number of common agricultural production and distribution problems, there is certainly a significant class of problems which is state specific in nature given the varying requirements placed on agricultural production processes by location specific economic, political and geo-climatic influences. For instance plant science problems may on average be a more-or-less difficult 'nut to crack' than animal science problems. To the extent that states' research agendas vary in their plant versus animal science orientation so to will their measured research 'efficiencies'. We will defer further discussion of these aspects, along with the various institutional factors of the SAES which may account for differences in their relative research performance, until chapter (5).

The $\tilde{\lambda}_t$ variable represents time specific shifts in the productivity of the research process. With much agricultural inquiry being of a 'downstream' nature discoveries in the complementary 'core' sciences at the 'upstream' end of the spectrum, along with (non-quantified) improvements in scientific instrumentation and research hardware will act, inter-alia, to enhance the research productivity of the agricultural sciences over time[3]. It is expected that this time specific variable would in general be positively related to $\dot{K}$.

Lastly the $\tilde{w}_{it}$ term is taken to reflect the inherently stochastic nature of the research process or, alternatively, captures the combined influences of omitted time-varying factors specific to the i^{th} state. These three terms, $\tilde{\mu}_i$, $\tilde{\lambda}_t$ and $\tilde{w}_{it}$ jointly represent the variables captured by the v term in equation (2.1).

Given the unobservable nature of $\dot{K}$ we must find a suitable indicator for it in order to make the model operational. State specific increments to the gross stock of scientific knowledge may be directly embodied in a variety of observable outputs. These include publications in scientific journals, patented and non-patented output such as new mechanical innovations and processes or new biological material and finally other publications such as books, station bulletins, newsletters and the like. Of course not all new knowledge is embodied in these indicators. A certain number of findings are extended beyond the laboratory bench via direct contact with potential users either through telephone contact, public media releases and on-farm visits.

For our purposes publications in scientific journals were chosen as an appropriate indicator of scientific knowledge increments generated by public sector research expenditures. The pros and cons of this indicator will be discussed in depth in section (3.1). However, the ability to make some adjustments for variations in 'scientific quality' add substantially to its appeal as a direct measure of scientific output. This represents a significant advance over studies of the patent-R & D expenditure relationship where the ability to make plausible adjustments for quality variations is not as readily available.

The quality adjustments made in this study, which are discussed in section (3.2), give rise to two alternative metrics of research output, namely

(1) raw publication count measures, and

(2) constant quality publication count measures.

The indicator function in which P_{it} represents the (constant quality) publication output of state i in period t is given by

$$P_{it} = \tilde{\tilde{\theta}} + \alpha \dot{K}_{it} + \tilde{\tilde{\varepsilon}}_{it} \qquad (2.3)$$

$$i=1,2,\ldots.N \; ; \; t=1,2,\ldots.T$$

where the error term is decomposed into three components such that

$$\tilde{\tilde{\varepsilon}}_{it} = \tilde{\tilde{\mu}}_i + \tilde{\tilde{\lambda}}_t + \tilde{\tilde{w}}_{it} \qquad (2.4)$$

The $\tilde{\tilde{\mu}}_i$ variable represents state specific differences in the average propensity to publish. The number of publications realized from a particular level of (successful) research activity represents the joint influence of the institutional environment, as it influences the rewards accruing to those who publish, and the (aggregated) utility functions of those who do the research.

For instance, SAES may vary in the emphasis they place on (non-refereed) publication mechanisms for extending the results of their research projects, depending in part on the demands of their clientele groups. This reflects the derived demand aspects of publication output. Furthermore, SAES administrators may vary in the emphasis they place on publication output as an indicator of the research productivity of their research staff. By ultimately affecting their promotion rates, salary scales and tenure status this acts as an incentive or disincentive to generate publications and thereby affects the supply of publication output[4]. As a qualification to these influences it is likely that researchers effectively operate in a national market so that state level differences in publication incentives may not have a strong or measurable impact on the propensity to publish.

The $\tilde{\tilde{\lambda}}_t$ variable captures influences on the propensity to publish which change over time. Finally the $\tilde{\tilde{w}}_{it}$ variable reflects variation in the propensity to publish not accounted for by the time or state specific effects. In this study the total publication output for each state is derived from the publication performance of a stratified random sample of researchers. Consequently $\tilde{\tilde{w}}_{it}$ also captures sampling errors in the measurement of P_{it}.

From the orthogonality condition imposed on the $\dot{K}$ and $\tilde{\tilde{\varepsilon}}_{it}$ variables we will assume also that the $\tilde{\tilde{\mu}}_i$, $\tilde{\tilde{\lambda}}_t$ and $\tilde{\tilde{w}}_{it}$ components of $\tilde{\tilde{\varepsilon}}_{it}$ are also uncorrelated with the determinants of $\dot{K}$ given by (2.2). Substituting (2.2) and (2.4) into (2.3) gives the reduced form equation relating lagged research expenditures to publication output such that

$$P_{it} = \theta + \sum_{s=0}^{S} \beta_s R_{i,t-s} + \mu_i + \lambda_t + w_{it} \qquad (2.5)$$

$$i=1,2,\ldots.N \ ; \ t=1,2,\ldots.T$$

where

$$\theta = (\tilde{\tilde{\theta}} + \alpha\tilde{\theta})$$

$$\mu_i = (\tilde{\tilde{\mu}}_i + \alpha\tilde{\mu}_i)$$

$$\lambda_t = (\tilde{\tilde{\lambda}}_t + \alpha\tilde{\lambda}_t)$$

$$\beta_s = \alpha\tilde{\beta}_s$$

$$w_{it} = (\tilde{\tilde{w}}_{it} + \alpha\tilde{w}_{it})$$

$$i=1,2,\ldots,N \; ; \; t=1,2,\ldots,T$$

The state specific term μ_i represents the weighted sum of both knowledge production and subsequent publication performance influences which are specific to the various states. Likewise the λ_t variable represents the weighted sum of these same influences which are of a time specific nature. When estimating equation (2.5) it is clear that the response of $\dot{K}$ to a unit change in research expenditure, R, cannot be identified given the information contained in this model. Nevertheless, the form of the distributed lag linking $\dot{K}$ to R can be investigated by normalizing the estimated lag coefficients to obtain $\tilde{\beta}_s/\Sigma\tilde{\beta}_s = \beta_s/\Sigma\beta_s$ for all s.

The research production process, represented by equation (2.5) or variants thereof constitutes the primary focus of the subsequent empirics.

2.3 Panel Data Estimation Procedures and Analytical Results:

(i) An overview

To date we have not made explicit the nature of the state and time specific variables in equation (2.5). There has been much recent analytical and empirical work on the pooling of time-series, cross-section data. It is centered on the assumptions made concerning the state and time specific variables and the related, but separate, issue concerning the relationship between these effects variables and the other regressors.

Assuming the μ's and λ's are both fixed parameters gives rise to the covariance or fixed effects model. Assuming both the μ's and λ's are random variables gives rise to the variance components or random effects models. Another class of models which allows the slope coefficients to vary over time and/or states, with the slope parameters themselves being considered fixed or random, have also been developed. However, given the exploratory nature of this study, combined with the relatively truncated panel data set available to us, the hypothesis of constant slope coefficients in the time dimension will generally be maintained.

To understand these various models more fully we can rewrite (2.5) in more standard matrix notation to give,

$$Y = X\beta + \varepsilon \qquad (2.6)$$

where Y is an ordered NTX1 vector[5], X is an NTXK matrix of K variables (which in this case consists of an intercept term along with current and lagged research expenditure), β is a KX1 vector of parameters to be estimated and ε is an NTX1 vector of composite residuals such that

$$\varepsilon_{it} = \mu_i + \lambda_t + w_{it} \qquad (2.7)$$

$$i=1,2,\ldots.N \; ; \; t=1,2,\ldots.T$$

Various implications of this model can be explored depending on the assumed form of the variance-covariance structure of the residuals. Following the conventional specification we consider that

$$\mu_i \sim N(0,\sigma_\mu^2)$$

$$\lambda_t \sim N(0,\sigma_\lambda^2) \qquad (2.7a)$$

$$w_{it} \sim N(0,\sigma_w^2)$$

where

$$E(\mu_i\lambda_t) = E(\mu_i w_{jt}) = E(\lambda_t w_{is}) = 0 \quad \text{for all } i,\ j,\ t \text{ and } s$$

$$E(\mu_i\mu_j) = 0 \quad \text{for } i\neq j$$

$$\qquad (2.7b)$$

$$E(\lambda_t\lambda_s) = 0 \quad \text{for } t\neq s$$

$$E(w_{it}w_{js}) = 0 \quad \text{for } i\neq j \text{ or } t\neq s$$

Several implications flow from the nature of the relationship between the components of ε_{it} and the explanatory variables in X. For the moment we will assume they are uncorrelated but will discuss this point at some length in the following section. Writing out the NTXNT residual variance covariance matrix implied by these assumption we get

$$E(\varepsilon\varepsilon') = \begin{bmatrix} \sigma_\mu^2 A & \sigma_\lambda^2 I_T & \cdots & \sigma_\lambda^2 I_T \\ \sigma_\lambda^2 I_T & \sigma_\mu^2 A & & \\ & & \ddots & \\ \sigma_\lambda^2 I_T & \cdots & \cdots & \sigma_\mu^2 A \end{bmatrix} \qquad (2.7c)$$

Where A is a TXT matrix defined as

$$A = \begin{bmatrix} \frac{\sigma^2}{\sigma_\mu^2} & 1 & 1 & \cdots & 1 \\ 1 & \frac{\sigma^2}{\sigma_\mu^2} & & & \\ & & \ddots & & \\ 1 & 1 & \cdots & \cdots & \frac{\sigma^2}{\sigma_\mu^2} \end{bmatrix} \qquad (2.7d)$$

and $Var(\varepsilon_{it}) = \sigma^2 = \sigma_\mu^2 + \sigma_\lambda^2 + \sigma_\omega^2$ for all i,t.

From these covariance matrices it is clear that, in contrast to the usual serial correlation assumptions, this model restricts the correlation of the disturbances over time to remain unchanged across all time horizons for a given cross-sectional unit. Kmenta (1971) presents a series of panel data models with alternative stochastic specifications.

With non-zero, off-diagonal elements in the pooled variance-covariance (error) matrix, (2.7c), applying OLS directly to (2.6) (i.e. ignoring the error components detailed in (2.7)) will give unbiased but inefficient estimates of the β parameters[6]. In fact Wallace and Hussain (1969) have shown that such OLS estimators have unbounded asymptotic variances (i.e. they have zero efficiency in the limit).

Treating μ_i and λ_t as fixed variables the resulting covariance model can be estimated by adding separate time and state specific dummy variables to equation (2.6) and applying OLS. This least squares dummy variable (LSDV) estimation technique not only gives unbiased and efficient estimates of β but also gives direct estimates of each time and state specific effect which are unique up to a normalization. However this procedure completely ignores the between state (and time) variation and consequently eliminates a major portion of the variation among both the explained and explanatory variables if the between effects variation is large.

To incorporate the between effects information into the estimation procedure we can treat the time and state specific effects as random variables (as described in (2.7a) and (2.7b)), giving rise to the variance components model. This generates an error structure which is no longer independent and identically distributed so that a generalized least squares (GLS) procedure is required in order to obtain unbiased and efficient estimates of the β's. With this approach we estimate, instead of the (N-1) μ's and (T-1) λ's of the covariance model, only two parameters for each effect, namely their mean and variance.

As Maddala (1971) shows, the variance component estimator of the β's can be expressed as a weighted sum of both the within and between group variance in the dependent and independent variables.

Consequently it can be viewed as a compromise between the OLS estimator which utilized all of the between group variation and the LSDV estimator which completely ignores this source of variation in the variables. For known variances Wallace and Hussain (1969) show that, under the usual assumption of nonstochastic X's which repeat in repeated samples, both the finite and asymptotic variance of the variance component estimator is smaller than the equivalent variance of the covariance estimator.

However in our case the variances of the error components detailed in (2.7a) are unknown. Thus a two stage estimation technique which parallels Zellner's seemingly unrelated procedure can be employed. The first step provides consistent estimates of the parameters of the distribution of the variance components and the second step uses them to perform generalized least squares on the original equation. The resulting β's are called estimated generalized least squares (EGLS) estimators.

A variety of variance estimators have been described in the literature including those based on OLS residuals (Wallace and Hussain(1969)), those based on LSDV residuals (Amemiya(1971)) and finally those derived from the fitting of constants method (Fuller and Battese(1974)). Details of the method employed in this study are given in section (iv) below.

The properties of the resulting EGLS estimators have also been explored by several writers. Swamy and Arora (1972) show that for finite samples the EGLS estimator could have larger variances than the OLS estimators if the variances σ_μ^2 and σ_λ^2 are small, and again larger variances than the LSDV estimator if σ_μ^2 and σ_λ^2 are very large. This result however rests on the assumption that both σ_{μ}^{2} and σ_{λ}^{2} are strictly greater than zero. Fuller and Battese (1974) relax this and other assumption and derive the conditions under which the EGLS estimator is unbiased and asymptotically equivalent to the GLS estimator.

(ii) Fixed versus Random Effects Models

Before discussing the computational procedures used to estimate these various models the efficacy of choosing fixed versus random time and state effects deserves attention. Imposing a fixed versus random assumption on the time-series, cross-section model has both theoretical and practical implications. From an analytical perspective we noted that GLS estimators under a random effects specification will be more efficient than LSDV estimators. However if the random effects assumptions are incorrect then GLS estimators will be biased. Of course if we were to drop the classical criteria for choosing appropriate estimators then GLS estimators may be more desirable in mean squared error terms.

One view of the effect variables, in keeping with the discussion presented in section (2.2), is that they represent the influence of omitted variables. Nerlove (1971) and Maddala (1971) both observed that when fitting a time-series, cross-section model there are generally a large number of factors, which for one reason or another, are not explicitly included in the set of explanatory variables. These influences are appropriately summarized by a random disturbance term. But, as argued above, some of these omitted variables reflect factors peculiar to specific time periods but affecting individual units more or less equally, whilst others are peculiar to specific states and tend to affect the observations for a given state in more-or-less the same fashion over all periods of time. Finally there is thought to exist another set of omitted variables which are assumed to vary over both states and time periods. The three component model specified in equation (2.7) naturally follows from such arguments.

Mundlak (1978) however objected not only to the arbitrariness in deciding whether an effect is fixed or random, but also to the fact that the GLS approach ignored the consequences of the correlation which may exist between the effects and the explanatory variables. In particular, he argued that the μ_i are random variables which are correlated with the X's so that $E(\mu_i)$ will not be constant but rather some function of X_i. By explicitly incorporating this relationship into equations (2.6) and (2.7) via an auxiliary regression

$$\mu_i = X_{i.}\gamma + \mu_i^* \qquad (2.8)$$

and using the properties of a partitioned inverse he showed that the unconditional GLS and LSDV or within estimators of the β's were identical and that the GLS estimate of γ is given by the difference of the between and within estimators of the β's.

In the context of our model this is equivalent to assuming that differences in research efficiencies are correlated (on average) with interstate differences in research expenditures. Pakes and Griliches (1980a, pp.7-8) argue that in general, at the firm level, differences in $\tilde{\mu}_i$ are transmitted to differences in average research expenditures, $R_{i.}$, with more efficient research departments being allocated more research funds. This being the case we could then, following Mundlak

(1978), form the auxiliary regression

$$\tilde{\mu}_i = \sum_{s=0}^{S} \tilde{\phi}_s R_{i.,-s} + \tilde{\mu}_i^* \tag{2.9}$$

where

$$R_{i.,o} = T^{-1} \sum_{t=1}^{T} R_{i,t} \quad , \quad R_{i.,-1} = T^{-1} \sum_{t=0}^{T-1} R_{i,t-1} \qquad \text{etc.}$$

substituting (2.9) into (2.2), (2.3) and (2.4) we can rewrite (2.5) as

$$P_{it} = \theta + \sum_{s=0}^{S} \beta_s R_{i,t-s} + \sum_{s=0}^{S} \phi_s R_{i.,-s} + \mu_i + \lambda_t + w_{it} \tag{2.10}$$

$$i=1,2,\ldots.N \; ; \; t=1,2,\ldots.T$$

where $\tilde{\mu}_i = (\mu_i + \alpha\tilde{\mu}_i^*)$, $\tilde{\phi}_s = \alpha\phi_s$

and all other variables are defined as before.

In contrast to the private sector research process discussed by Pakes and Griliches (1980a) it is not clear, a priori, that the research efficiency-research expenditure relationship described by equation (2.9) holds in the case of public sector agricultural research. This ambiguity arises from the mechanisms whereby the benefits from public sector agricultural research are appropriated. In the Pakes-Griliches case, private firms directly capture the returns from research activity presumably via patents, new product (or process) developments or licensing agreements. Assuming profit maximizing behaviour, then Mundlak and Hoch (1965) have shown that the unobservable part of the K.P.F. is transmitted to a research input demand equation given by the first order profit maximizing conditions.

However, in the case of publicly funded agricultural research much of the benefit is not directly appropriated by those institutions and/or individuals undertaking the research but instead is filtered thru a political mechanism. Several authors (Guttman (1978), Rose-Ackerman and Evenson (1982) and Hadwiger (1982)) have suggested, that in the case of publicly funded agricultural research, political rather than just economic efficiency criteria influence the allocation of research resources. Within this context they identified a variety of factors correlated with increased appropriations to the SAES. Whether or not these factors are systematically related to the relative research efficiency of the SAES is not readily apparent so that the feedback mechanism described in the profit maximizing case above may not be operative here.

One approach which can 'resolve' the issue, for the purposes of estimation, is simply to proceed with the LSDV approach and make inferential statements concerning the estimated β's conditional on the realized values of μ_i and λ_t in the sample. These LSDV estimators are, conditional on the μ_i and λ_t in the sample, best linear and unbiased. Because this approach makes no specific assumptions about the distributions of μ_i and λ_t it can be used for a wider range of problems. Nevertheless if the restrictive distributional assumption of the variance component model is correct, then using this additional information will result in a more efficient estimator. As the superiority of the variance component over the covariance model is jeopardized in the presence of correlation between the effects and explanatory variables this issue will be explored empirically in chapter 4.

(iii) Fixed Effects Model:

Given the relatively short nature of the panel in this study we will find it convenient to rewrite equation (2.6) as

$$Y = Z\begin{pmatrix} \bar{\theta} \\ \mu \end{pmatrix} + X_{*}\beta_{*} + w \qquad (2.11)$$

where X_{*} represents a $1X(S+1)$ data matrix which includes a time variable[7] and s lagged research expenditure variables, and all other variables are defined as before.

A straightforward approach of estimating equation (2.11) is to incorporate the state effects directly into the estimated equation by the use of additive dummy variables and then apply OLS estimation techniques. Of course to avoid singularity in the overall data matrix we need to impose an appropriate restriction, such as eliminating the intercept term by setting $\bar{\theta} = 0$ or reparameterizing the μ vector. Suits (1957) shows how these restrictions are related algebraically whilst Ben-David and Tomek (1965) summarize the impact which the chosen restriction has on the interpretation of the estimated coefficients.

The more conventional approach is to impose the commonly used Q transformation which 'sweeps out' the effect variables, then estimate the remaining coefficient vector β by OLS. Indirect OLS estimates of the $\bar{\theta}$ and μ coefficients can then be obtained by substitution.

Letting $f_T = (1,1,1,....,1)$, two orthogonal projection operators can be defined as

$$Q_1 = I_{NT} - D_1 \quad , \quad D_1 = (I_N \otimes {}^1/_T\, f_T f_T')$$

which are idempotent matrices of rank N and TN-N respectively. Pre-multiplying a vector of ordered observations, D_1, transforms it into a vector of group means, i.e. $D_1 Y_1 = ({}^1/_T) \sum_{t=1}^{T} Y_{it} = Y_{i..}$ Likewise pre-multiplying by Q_1 gives a vector of deviations from group means, $Q_1 Y = \tilde{Y} = Y - Y_{i..}$ Finally we observe that Q_1 is orthogonal by construction to any time invariant vector of observations so that $Q_1 Z = Z - Z_{i.} = 0$

Transforming equation (2.11) by Q_1 gives

$$Q_1 Y_t = Q_1 Z_t \begin{pmatrix} \bar{\theta} \\ \mu_i \end{pmatrix} + Q_1 X_* \beta_* + Q_1 w_{it} \qquad (2.12)$$

which simplifies to

$$\tilde{Y} = \tilde{X}_* \beta_* + \tilde{w} \qquad (2.13)$$

Writing (2.13) in more extended notation we have

$$(Y_{it} - Y_{i.}) = \sum_{k=1}^{S} \beta_k (X_{kit} - \bar{X}_{ki.}) + w_{it} - {}^1/_T \sum_{t=1}^{T} w_{it} \qquad (2.13a)$$

$$i=1,2,\ldots N \; ; \; t=1,2,\ldots T$$

BLU estimates of β_* can be obtained by applying OLS to the transformed equation (2.13) where

$$\hat{\beta}_{w*} = (X_*' Q_1 X_*)^{-1} X' \; Q_1 Y \equiv (\tilde{X}_*' \tilde{X}_*)^{-1} \tilde{X}_*' \tilde{Y} \qquad (2.14)$$

From equation (2.13a) it is clear that this estimator utilizes only the variation of the variables within each state (i.e. the over time variation about state means) and is thus called the within estimator.

Indirect least squares estimates of the intercepts are obtained from

$$\widehat{(\bar{\theta} + \mu_i)} = \bar{Y}_{i.} - \sum_{k=1}^{S} \hat{\beta}_k \bar{X}_{ki.} \qquad (2.15)$$

(iv) Random Effects Model

With the μ_i taken to be random variables instead of fixed parameters and with $E(\mu_i|X) = 0$, $E(\mu_i) = \sigma_\mu^2$, $E(\mu_i \mu_j) = 0$ for $i \neq j$ and $w_{it} \sim IN(0, \sigma_w^2)$ we may rewrite equation (2.6) as

$$Y = X\beta + \mu \otimes f_T + w \qquad (2.16)$$

where $Y' = (Y_1', Y_2', \ldots\ldots Y_N')$, $X' = (X_1', X_2', \ldots\ldots X_N')$ such that the X_i' matrix now includes the constant term along with the time variable and current and lagged research expenditures, $\mu = (\mu_1, \mu_2, \ldots\ldots \mu_N)'$ and $w' = (w_1', w_2', \ldots\ldots w_N')$.

Notice that the λ_t effects have been incorporated into the X matrix. On the basis of a Monte Carlo study of the small sample properties of the σ_λ^2 estimator, Swamy and Arora (1972) do not recommend proceeding with the GLS approach (in the T dimension) if

T-K <10 as in the present study. Intuitively we can see that as T-K falls the number of degrees of freedom 'left over' to estimate σ_λ^2 declines as well.

Under the assumption that the μ_i and w_{it} are uncorrelated, the covariance matrix of the composite disturbance term is block diagonal and given by

$$\Omega = E\,[(\mu \otimes f_T + w)\;(\mu \otimes f_T + w)'] \qquad (2.17)$$

$$= I_N \otimes \Omega_1$$

where $\Omega_1 = \sigma_\mu^2 f_T f_T' + \sigma_w^2 f_T$ represents the covariance matrix for the ith state.

From (2.17) we observe that if σ_μ^2 and σ_w^2 were known then the problem is simply estimation of a linear regression model with non-scalar disturbance covariance matrix. The generalized least squares (GLS) estimator for β is Gauss-Markov and given by

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}Y \qquad (2.18)$$

where $\Omega^{-1} = I_N \otimes (f_T f_T' \;/\; T\sigma_1^2 + D_2/\sigma_w^2)$ (2.18a)

such that $\sigma_1^2 = T\sigma_\mu^2 + \sigma_w^2$ and $D_2 = I_T - f_T f_T'/T$.

However with σ_μ^2 and σ_w^2 unknown our first step in estimating β is to find consistent estimates of the respective variance components.

For this purpose it is useful to know that if we partition the estimator as $\hat{\beta}' = (\bar{\theta}_1, \hat{\beta}_*')$ then Maddala (1971) has shown that $\hat{\beta}_*$ can be written as the minimum variance matrix-weighted average of the within estimator $\hat{\beta}_{W*}$ and another estimator $\hat{\beta}_{B*}$ called the between estimator. Premultiplying (2.16) by D_1 gives

$$Y_{i.} = X_{i.}\beta + \mu_i \otimes f_T + w_{i.} \tag{2.19}$$

$$i=1,2,\ldots.N \ ; \ t=1,2,\ldots.T$$

with the between estimator, obtained by applying OLS to (2.19), given by

$$\hat{\beta}_B = (X'D_1X)^{-1}X'D_1Y \tag{2.20}$$

This is BLU given the earlier stochastic assumptions on μ_i and w_{it} and in particular the assumption that $E(\mu_i|X) = 0$. For the sake of computational convenience the between estimates in this study were obtained not from (2.19) but from applying OLS to

$$\bar{Y}_{i.} = \bar{X}_{i.}\beta + \mu_i + \bar{w}_{i.} \tag{2.21}$$

$$i = 1,2,\ldots\ldots N$$

where, for example, $\bar{Y}_{i.} = 1/T \sum_{t=1}^{T} Y_{it}$. This will not affect the between estimator, as equation (2.19) simply represents T repetitions of equation (2.21), but it will affect the size of the residual sum of squares[8].

The variance of the composite disturbance in equation (2.21) is

$$Var\ (\mu + \bar{w}.) = E\ [(\mu + \bar{w}.)\ (\mu + \bar{w}.)']$$

$$= I_N \otimes (\sigma_\mu^2 + \sigma_w^2 \,/\, T) \qquad (2.22)$$

$$= I_N \otimes \sigma_1^2 \,/\, T$$

To obtain GLS estimates of β from equation (2.16) a computationally convenient approach is to invoke Aitken's Lemma and find a suitable transformation matrix which allows OLS procedures to be applied to the transformed equation. Fuller and Battese (1969) suggest the transformation matrix

$$P = I_N \otimes P_i \qquad (2.23)$$

where $P_i = I_T - (1 - \sigma_w \,/\, \sigma_1)\, f_T f_T' \,/\, T$

such that $P'P = \sigma_w^2 \Omega^{-1}$

Pre-multiplying both sides of equation (2.16) by P gives

$$Y_{it} - \gamma \bar{Y}_{i.} = (1 - \gamma)\bar{\theta} + \sum^{K} \beta_k \,(X_{kit} - \gamma \bar{X}_{ki.}) + w_{it} - \gamma \bar{w}_{i.} \qquad (2.24)$$

where $\gamma = 1 - \sigma_w/\sigma_1$ and $v_{it} = w_{it} - \gamma w_{i.}$ is i.i.d.

Assuming γ is known then applying OLS to equation (2.24) will yield the GLS estimator $\hat{\beta}$. For this study we need to obtain consistent estimates of the variance components σ_1^2 and σ_w^2 to implement the transformation in equation (2.24).

Recall that for the between equation (2.21) it was assumed that $E[(\mu_i + \bar{w}_{i.})(\mu_j + \bar{w}_{j.})'] = 0$ for $i \neq j$ so that the standard least squares estimate of the composite error variance will be an unbiased estimate of σ_1^2/T. More formally then

$$\hat{\sigma}_1^2 \; / \; T = \hat{v}'\hat{v} \; / \; N-K$$

where $\hat{v}'\hat{v}$ is the sum of squared residuals from applying OLS to equation (2.21).

Likewise the estimated residuals $\hat{w}$, obtained from applying OLS to equation (2.13a), can be used to estimate σ_w^2 such that,

$$\hat{\sigma}_w^2 = \hat{w}'\hat{w} \; / \; N(T-1)-K'$$

where $K' = K-1$

Finally an estimator for σ_μ^2 can be obtained from equation (2.22) so that

$$\hat{\sigma}_\mu^2 = (\hat{\sigma}_1^2 - \hat{\sigma}_w^2) \; / \; T$$

Notice there is no guarantee that $\hat{\sigma}_\mu^2$ is positive. A negative value for this estimator may well be an indication that the model given by (2.16) is misspecified. For instance the maintained hypothesis of constant β over time and/or states may be in error or it could well be that the independence assumption $E\ (\mu_i | X) = 0$ is violated. These aspects will be considered in the empirical work to follow.

FOOTNOTES CHAPTER 2

1. For notational simplicity the gross superscript, g, will be suppressed unless needed for the sake of clarity.

2. See Mundlak (1961) and Hoch (1962).

3. See Price (1965).

4. Recent discussion on the economics of invention incentives (in the private sector) can be found in Wright (1983) and Pakes and Nitzan (1983).

5. All observations are ordered first by state and then by time. Consequently $Y' = (Y_1', Y_2', \ldots\ldots Y_N')$ where $Y_i = (Y_{i1}, Y_{i2}, \ldots\ldots\ldots Y_{iT})$.

6. These non-zero, off-diagonal elements persist even in panel data models in which the time effects are suppressed.

7. For the moment we assume the time effect is being proxied by a simple linear trend variable. This simplification will be examined empirically in the following chapter. Consequently, for estimation purposes, equation (2.7) can be treated as containing state effects only.

8. The residual sum of squares from equation (2.15) is T times as large as the residual sum of squares from equation (2.17).

Chapter 3

AGRICULTURAL KNOWLEDGE INPUTS AND OUTPUTS: VARIABLE CONSTRUCTION

Details concerning the knowledge input and output variables required to estimate the statistical model of the previous chapter will now be discussed. We will begin with a look at the publication-based proxy of SAES knowledge output and its associated quality adjusters. Given the paucity of previous work in this area some attention will be given to the conceptual issues involved along with the mechanics of variable construction. The chapter will close with a discussion of our efforts to obtain a reasonably accurate measure of the real resources used in the knowledge production process. This involves a substantial reconstruction of both the SAES expenditure series used by related studies as well as the deflators used to account for the effects of input price movements over time.

3.1 <u>The Quantity Dimension of Research Output</u>:

The object of this phase of the project is to obtain an estimate of the quantity of new agricultural knowledge produced by the 48 SAES[1] over the 6 year period 1970-1975. Here aggregate publication performance is used to directly proxy the quantity of agricultural knowledge produced by each of the experiment stations. Given the institutional and incentive structure under which SAES researchers operate it seems reasonable that publications more completely capture the knowledge output of the stations than alternative output proxies such as patents[2]. Publications afford researchers a means of establishing intellectual property rights over their work which will ultimately affect their salaries, promotion, professional standing and what-have-you[3].

A measure of the yearly publication output of each station can be obtained from the annual Cooperative State Research Service (CSRS) "Funds for Research at State Agricultural Experiment Stations" reports. They list popular and technical publications in four major categories - reports, bulletins and circulars; journal articles; periodicals; and pamphlets, leaflets and miscellaneous. Unfortunately articles were assigned to each category at the discretion of the reporting institution and there is no indication as to whether the reporting standards varied across institutions or time. For example, publications listed as technical articles by one institution may not be so listed by others. Furthermore, it was not possible to develop a quality index based on this information so it was discarded as a suitable data base for our purposes.

The procedure used here was to estimate the aggregate publication performance of each station on the basis of the average research performance of a random sub-sample of station researchers. First the researcher population of each experiment station, for the two fiscal years 1970/71 and 1974/75, was established by reference to the appropriate CSRS listings of "Professional Workers in State Agricultural Experiment Stations and Other Cooperating State Institutions". All individuals who could not reasonably be considered 'front-bench' scientists, charged with the responsibility of initiating and implementing research projects, were eliminated from the listing. This included individuals who, on the basis of their location (i.e. branch versus main station), degree, appointment and/or professorial status, could be reasonably classified as support or auxiliary staff.

This approach is preferred to obtaining a listing from USDA's Current Research Information System (CRIS), which is organized on a research work unit (or project) basis and lists only the primary investigator(s) from the SAES (and USDA institutions) currently involved in a research project[4]. It, therefore, biases the sample in favor of those researchers who are more likely to appear on some published work by virtue of the fact that they are the principal investigators in an active research program.

A population of around 10,000 researchers was identified. It was clearly beyond the resources of this study to obtain the publication performance of all these researchers over a six year period. Consequently a stratified random sample consisting of around twenty percent of the population was chosen. The large variation in station size meant that some care was needed in stratifying the overall sample across each of the stations. With n_i and N_i representing the sample and population size respectively for stations i = 1,2, ... 48 we would ideally[5] have determined n_i by selecting a constant, k, defined as:

$$k = N_i^2 / n_i \ (1 - n_i / N_i) \qquad (3.1)$$

$$i = 1,2,\ldots\ldots 48$$

such that $\Sigma n_i / \Sigma N_i = 0.20$.

However, choice of k such that Σn_i approximately equals twenty percent of ΣN_i implied unrealistically small sample sizes ($n_i < 1$) for the smaller stations. A practical alternative[6] was to (iteratively) choose k^* such that

$$k^* = 1 / n_i (1 - n_i / N_i) \qquad (3.2)$$

$$i = 1,2,\ldots\ldots 48$$

If the underlying population variance was in fact constant across all stations, then this procedure would introduce heteroskedastic sampling error into a regression with total publications per station as the dependent variable. We will return to this issue in section (4.2) below. Randomizing the sample within each station was accomplished by reference to the Rand Corporation's random digits listing.

Details concerning the population and sample size of each SAES for both the 1970/71 and 1974/75 periods are listed in Table (1), Appendix (II). Tables (2), (3) and (4) in Appendix II give some background information on the nature of the researcher population in the SAES over the 1970-75 period. Around 86 percent hold Ph.D degrees. About 50 percent have joint college-station positions and approximately 13 and 15 percent hold college-only and station-only appointments respectively. About 90 percent of the researchers have professorial status with 40 percent at the full and 28 and 23 percent at the associate and assistant level respectively. Most of the remaining researchers are listed at the research associate level.

Table (3.1) indicates that overall the samples closely conform to the research disciplines represented in the SAES. Just over 50 percent of these researchers are associated with one of the plant science disciplines while 30 percent are spread amongst the animal sciences.

There is a constant turnover of research personnel at any particular SAES due to retirements, resignations and new appointments.

Table (3.1) Researcher Statistics - Number of Researchers per Discipline; Sample and Population Averages.[a]

	Average Number of Researchers			
	1970-73	1974-75	1970-75	
Discipline[b]	Sample I	Sample II	Sample	Popln.
Agronomy	539 (24.1)	533 (24.4)	546 (24.2)	2012 (20.2)
Entomology	172 (7.7)	195 (8.6)	184 (8.2)	880 (8.8)
Forestry	184 (8.2)	177 (7.8)	181 (8.0)	919 (9.2)
Horticulture	138 (6.2)	146 (6.4)	141 (6.3)	663 (6.7)
Plant Diseases	158 (7.1)	152 (6.7)	155 (6.9)	725 (7.3)
TOTAL PLANT SCI.	1191 (53.2)	1223 (53.9)	1207 (53.6)	5199 (52.3)
Animal Sci.	286 (12.8)	257 (11.3)	272 (12.1)	1019 (10.2)
Dairy	55 (2.5)	47 (2.1)	51 (2.3)	226 (2.3)
Fisheries	25 (1.1)	29 (1.3)	27 (1.2)	213 (2.1)
Poultry	43 (1.9)	42 (1.9)	43 (1.9)	197 (2.0)
Vet Medicine	260 (11.6)	236 (10.4)	248 (11.0)	1325 (13.3)
TOTAL ANIMAL SCI.	669 (29.9)	611 (27.0)	640 (28.4)	2980 (30.0)
Agric. and Envir. Sci.	44 (2.0)	64 (2.8)	54 (2.4)	219 (2.2)
Core Sciences and Statistics	225 (10.0)	250 (11.0)	238 (10.6)	896 (9.0)
Genetics and Plant Breeding	34 (1.5)	13 (0.6)	24 (1.1)	118 (1.2)
Nutrition and Food Science	73 (3.3)	102 (4.5)	88 (3.9)	524 (5.3)
Other	3 (0.2)	4 (0.2)	4 (0.2)	13 (0.1)
TOTAL	2239	2267	2253	9949[c]

(a) Figures in parentheses are percentages.

(b) Agronomy includes plant science, soil science and water and range science. Forestry includes wildlife. Horticulture includes pomology, vegetable crops, viticulture and oenology. Plant diseases includes nematology and plant pathology. Animal science includes animal husbandry. Fisheries includes aquaculture. Vet. Medicine includes animal diseases and microbiology. Environmental science includes landscape architecture. Core sciences includes biochemistry, biophysics, biology, botany, chemistry and zoology.

Scientists were generally allocated to research disciplines on the basis of the discipline classification reported in the listing of "Professional Workers in SAES and other Cooperating Institutions". Over time and between station inconsistencies were resolved by reference to the research specialization which was also recorded for each researcher. Multiple counts (i.e. where the same researcher is listed more than once per state, say, at the main as well as sub-station(s)) were eliminated by cross-matching the discipline listing with an alphabetical listing also recorded in the "Professional Workers" publication.

(c) This figure excludes 424 researchers who were also listed at various substations but could not be allocated to a specific discipline. These researchers are included in the state totals reported in Table (1), Appendix II. Also excluded are social science and agricultural engineering researchers. Adding all these researchers to this figure would increase the overall population size to 12270.

For this reason the 1970 to 1973 publication performance of each station was estimated using the 1970/71 sample of researchers (i.e. Sample I) whilst the 1974 and 1975 publication record used the 1974/75 researcher sample (i.e. Sample II). Both these samples represent independent draws from the population of SAES researchers and so add an additional degree of freedom to the data set. Sample I consists of 2239 researchers, or 23.2 percent of the 1970/71 population and sample II consists of 2267 researchers or 22.2 percent of the 1974/75 population.

The publication output of each sample researcher for the appropriate years was obtained from the Source Index of the Science Citation Index (SCI) compiled by the Institute for Scientific Information (ISI). The SCI data base is accessible through the Dialog Information Retrieval Service. However, attempts to obtain the necessary information from an on-line computer search were discarded in favor of a manual search using the listings published yearly by ISI[7].

The on-line approach was rejected because (a) for the large amount of data required for this study it was determined to be prohibitively expensive (b) contrary to Dialog's documentation the Source Indices prior to 1973 are not up on the system, and (c) perhaps most importantly there are a number of required error checks which could not be implemented using this approach.

The most serious obstacle to obtaining an accurate listing of an individual's publication output from the Source Index is the homograph problem. In some instances the publication output of two or more researchers with identical names is attributed to a single source author. The only means to correct for this problem through a computer search is by cross-matching an author's publication record, obtained from the Source Index, with the publication listings in the Corporate Index which classifies researchers according to their institutional affiliation. Unfortunately, for a variety of reasons, the Corporate Index listings are far from complete so that a large number of homograph cases go undetected.

Using a manual search procedure the homograph problem becomes somewhat more manageable. Errant articles can be identified through a variety of methods including cross-checking the subject matter (as determined from the journal name and/or article title) with the known discipline affiliation of the source author; cross checking the coauthor(s) (if any) with the known station colleagues of the source author and if all else fails attempting to determine the author's corporate affiliation by searching out the original journal article.

The Source Index is an ideal data base for our purposes. It provides the most consistent and comprehensive publication listing which is available in a readily accessible format. Its coverage includes mainly U.S. and overseas scientific publications (generally refereed journals) in all the major scientific disciplines and so acts as a screening device by excluding publications of a popular nature or those which have an extremely limited readership[8]. Its scope is quite staggering. In 1975 ISI tabulated information from 2,540 source journals yielding 411,617 authored source items (or references).

For each publication attributable to our source authors[9] we collected information on the publishing journal (name, volume, issue, etc.) publication length (if given), number and names of coauthors (up to a maximum of 10) and the publication type (article, note, correction, etc.). The over-all data set involved separate records for 16,050 publications. This data was then integrated with the biographical information concerning source authors (ie. station and discipline affiliation, degree, appointment and professorial status, etc.) which was discussed above.

Some summary publication statistics are presented in Tables (3.2) and (3.3). Nearly two-thirds of the publications are full-length articles. Most of the remaining publications are abstracts of papers presented at professional meetings or shorter notes. From Table (3.3) we observe that around 88 percent of the publications are jointly authored with the majority having one or two coauthors. Given this high percentage of coauthored articles we proceeded to calculate both the average number of articles and average number of prorated articles per sample researcher per year for each station. For the prorated measure a source author would be accredited with one-third of an article if it was published with two coauthors. The raw and prorated averages were scaled by the appropriate population number of researchers per station to yield estimates of the total publication output for each station for the 6 years 1970-1975[10].

Our attempts to correct for quality differences between stations in these raw publication counts will be developed in some detail in the following section.

3.2 The Quality Dimension of Research Output:

One of the most frequently encountered criticisms of direct indices of scientific output is that the unit of measurement does not

Table (3.2) Publication Statistics - Type of Publication, Period Averages.[a]

	Publications per Year		
Publication Type[b]	1970-73 average	1974-75 average	1970-75 average
Article	1807 (64.9)	1709 (66.6)	1758 (65.7)
Biographical	0	1	1
Correction	7 (0.3)	7 (0.3)	7 (0.3)
Discussion	3 (0.1)	2 (0.1)	3 (0.1)
Editorial	12 (0.4)	9 (0.4)	11 (0.4)
Letter	18 (0.6)	14 (0.5)	16 (0.6)
Meeting	679 (24.4)	600 (23.4)	640 (23.9)
Note	244 (8.8)	206 (8.0)	225 (8.4)
Review	14 (0.5)	21 (0.8)	18 (0.7)
Total	2783	2567	2675

(a) Figures in parentheses are percentages.

(b) The publication type categories are self explanatory. They are the same categories as used by ISI. (See ISI, 1982, p.14).

Table (3.3) Publication Statistics - Coauthor Frequency per Publication, Period Averages.[a]

	Publications per Year		
Number of Coauthors	1970-73 average	1974-75 average	1970-75 average
0	386 (13.9)	275 (10.7)	331 (12.4)
1	1036 (37.2)	910 (35.4)	973 (36.4)
2	759 (27.3)	749 (29.2)	754 (28.2)
3	400 (14.4)	393 (15.3)	397 (14.8)
4	140 (5.0)	156 (6.1)	148 (5.5)
5	44 (1.6)	52 (2.0)	48 (1.8)
>6	20 (0.7)	35 (1.4)	28 (1.0)

(a) Figures in parentheses are percentages.

adequately account for likely quality differences. This criticism is often leveled at patent-based measures of inventive output[11] although Comanor and Scherer (1969) found that raw patent counts were reasonably closely correlated with various other indicators of research activity.

A major problem is first to decide what is meant by quality in this context and then determine an appropriate means of quantifying it. In an economic context quality can be taken to mean the relationship between research benefits and the measured level of resources committed to that research. Hence, higher quality research generates a larger (present value) benefit stream for a given level of (measured) research inputs.

Scientific quality according to Evenson and Wright (1982) is measured by conformity to standards established by scientific work at the 'frontier' of the discipline. More generally the scientific quality of a researcher (or a body of research) is assessed with respect to the relative 'significance' of the individual's contribution (to their field). One method commonly used to establish 'significance' entails a peer group review procedure (see Shaw (1967)). This subjective evaluation technique is limited by the problems of standardization of evaluation criteria and the individual biases and knowledge base of the evaluators. Furthermore such exercises are essentially nonreplicable.

An alternative procedure is to measure the subsequent citation performance of a piece of research. The maintained hypothesis is that (on average) the cited work is a useful input in the production of current research. Thus citation performance is a quantifiable measure of the impact of published work on the future knowledge (publication) output of the profession[12]. This line of argument has been used in the recent economics literature by McDowell (1982) and Davis and Papanek (1984).

Citations have also been used extensively in the non-economic literature as a basis for establishing scientific quality (see Cole and Cole (1967) and Lawani (1977)) and/or mapping networks of scientific communication and interaction (see Price (1965)). As such they have not been free of criticism. Chubin and Moitra (1975) review many of the criticisms concerning the use of citation measures as a quality index[13].

They propose that a citation typology should encompass not simply the bibliographic references themselves but the context in which the references are made. To do so involves the notion of content analysis. They claim that an in-depth review of each citing publication allows citations to be 'classified' as either (essential, subsidiary or perfunctory) affirmative or (partial or total) negational citations. This approach has several drawbacks. First it reintroduces a subjective element into the assessment process. Secondly, because it is time consuming and requires a detailed knowledge of the subject matter under review it is inappropriate for broad based classification of a large number of publications. Finally, it is not at all clear that the affirmative versus negational nature of a citation is of significance if our quality yardstick is simply the impact which a particular piece of research has on subsequent research activity. As Cole and Cole (1971) observed, "It is unlikely that any work which is wrong without being a 'fruitful error' will ever accumulate very many citations ... these few pieces of research that stimulate wide criticism have, in fact, stimulated other research. Consequently, it must be considered mistaken but significant; it must be seen as work which has had an impact on future scientific work".

One of the major advantages of a citation based measure of scientific quality is its ability to capture not only the 'spatial' impact of a piece of research (ie. across disciplines) but also the temporal dimension of its influence. Price (1965) observed that although the citation performance of a particular article is somewhat capricious, the over time citation profile of a body of literature exhibits a fairly well defined pattern. In particular older publications are less frequently cited than more recent publications so that the rate of citation peaks for papers around 2-5 years old. These results are supported by Chubin and Moitra's (1975) study of a sample of high-energy physics articles. Their results show that the mean citation rate for full-length papers peaks at around 10 citations per year 3 to 4 years after publication whilst letters reach a maximum of 3-6 citations per year only 2 years after publication.

It seems reasonable to suggest that, ceteris paribus, articles which are cited more recently have a greater impact on the research process than those which are cited at a later point in time. The earlier an article is cited the greater its (indirect) impact on future research if the citing article is in turn cited by other researchers. Thus, in a present value context the citation profile and not simply the cumulative citation performance of a body of research is the important determinant of its overall impact on subsequent research.

As the present study involved observations on 16,050 publications it was well beyond our resources to map the citation performance of each article over a number of years. Rather than simply measure the cumulative citation rate of each article, and so miss the temporal dimension of its citation performance, it was decided to standardize the citation performance of each article on a particular year following its publication date. Clearly it makes sense to standardize on the year in which the citation 'frequency' is in some sense maximized. This was determined by examining the citation performance, over a six year period, of the primary articles published by a sub-sample of 150 researchers[14]. Results of this exercise are presented in Table (3.4).

The 150 researchers published a total of 340 primary articles over the four year period 1970 to 1973 giving an average publication rate of 0.57 primary articles per year. Around 42 percent of these articles were never cited in the six years following their publication. In any given year the percentage of articles not cited ranges from a low of 57.6 in year t-5 to a high of 71.5 in year t-4. These percentages for the agricultural science literature are certainly higher than Price's (1965) estimate that in any given year about 35 percent of the existing papers (from all scientific disciplines covered by SCI) are not cited. Table (3.4) also shows that the proportion of articles receiving higher citation rates tends to decline over time whilst the proportion of articles receiving either one or two citations peaks in year t-2. This year also has the second lowest proportion of noncited articles and the highest number of total citations.

Table (3.4) Frequency Distribution of Number of Citations per Primary Article for Various Years Following Publication Date.

Number of Total Citations per Article	Years Following Publication Date					
	1	2	3	4	5	6
0	240	218	232	243	196	235
1	48	58	58	41	44	61
2	19	35	25	26	17	18
3	9	12	15	12	12	13
4	11	10	3	10	7	6
5	4	3	2	1	4	3
6	4	2	3	3	1	2
≥ 7	5	2	2	2	2	2
Total Number of Citations	243	246	210	206	186	205

It is possible that self-citation by vainglorious publishers could distort the citation figures. However, it is plausible that researchers are more likely to publish in areas in which they have previously published. To the extent that self-citation reflects the influence of previous work on the citing publication it is an appropriate quality indicator in the present context. Results for total and net (total - self) mean citation rates are presented in Figure (3.1). The largest impact is on the two years immediately following publication where self-citation accounts for around 26 and 24 percent of total citations respectively. This drops dramatically to 8.5 percent in year t-3 and remains low for the remaining out years. Nevertheless the net, like the total, mean citation rate peaks two years following publication and was therefore chosen as the year on which to standardize the citation-based quality index.

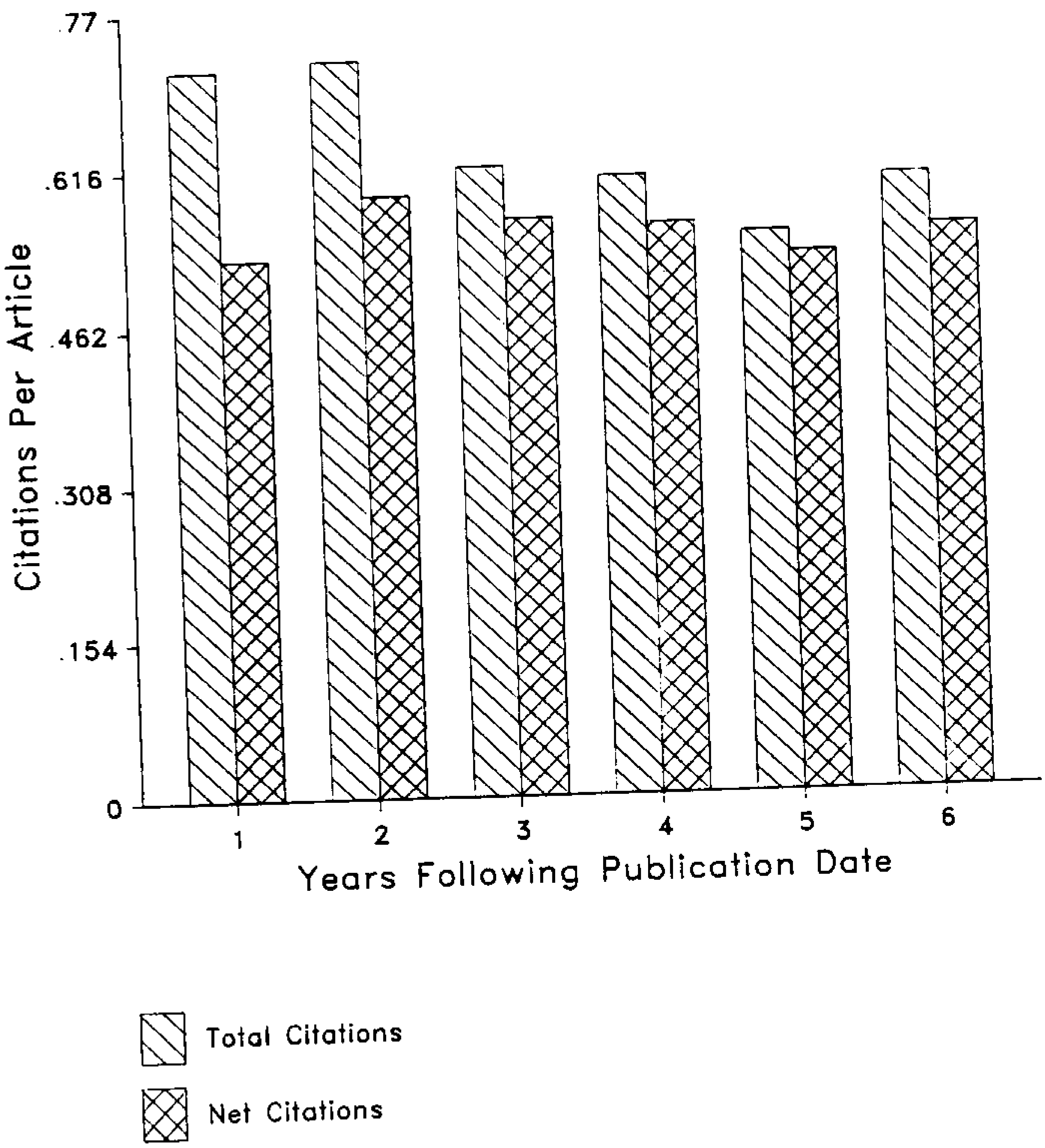
3.3 Research Inputs:

(i) Value Measures

To estimate equation (2.5) requires an accurate measure of the resources used by the SAES for research endeavors. Previous augmented production function studies have used a variety of research expenditure figures.

Latimer (1964) and Davis (1979) began with the total funds available to each SAES and deducted carry-over balances, funds derived from fees, sales & miscellaneous sources and land and building expenditures (from non-federal fund sources). Fees, sales & miscellaneous (FS & M) funds were deducted on the basis that they did not substantially contribute to the research function of the

Figure (3.1) Citations Per Article For Each Time Lag



experiment station. However, informal evidence suggests that around twenty percent of FS & M funds contribute to research endeavors. For certain stations in a given year revenues from FS & M sources approximately equal the funds made available to the experiment stations from state appropriations. To simply deduct such revenues from the research funds made available to the experiment stations could seriously underestimate the level of research expenditures for these particular stations.

Omitting land and building purchases from the expenditure figure also creates problems. To the extent that they are positively related to the remaining expenditures their omission acts to bias upward the estimated research expenditure coefficient and associated marginal internal rate of return to research.

Most of the remaining augmented production function studies have included equipment, land and buildings investments along with operating expenses in a total expenditure figure. However, this suffers from the 'apples and oranges' problem which results from summing stock and flow variables into the one measure. Although all labor and related operating expense items are appropriately expensed in the year of purchase this is not true of capital. The purchase of a unit of capital at the beginning of time period t results in a stream of service flows over a sequence of current and future time periods. Capital purchases or investments therefore represent gross additions to the capital stock at any point in time. The market valuation of this gross investment represents the current valuation of current and all future services expected from this addition to the capital stock (see Griliches (1960) and Yotopolous

(1967)). What is required is a measure of the current productive service flow of the capital assets which is viewed as an estimate of the capital resources used in the current period.

Parenthetically it should be stressed that the service flow issue arises simply from the durability of capital investments. A further complication arises from the nature of the (agricultural) research process in that the current service flow contributes not only to current output but also to future research output as do the other (non-durable) inputs into the research process. It is possible, however, that the lag structures for capital and non-capital inputs in the knowledge production function are not the same.

Given the (assumed) nature of the service flows, service life, salvage value and an appropriate discount rate, the value of the service flow in any future time period can be derived. Unfortunately as for most empirical studies, there is no direct evidence on the nature of the time path of current service flows available. For practical purposes we approximate the true time path by assuming a constant service flow equal to k_t and a zero salvage value - i.e. a one Hoss Shay assumption. With an average service life of T and a discount rate r we can write[15]

$$k_t = C_0 \left[r / (1 - (1/(1 + r)^T) \right] \qquad (3.3)$$

$$t = 0,1,\ldots\ldots,T-1$$

where C_0 is the gross (undepreciated) market value of a capital asset. Now considering a series of asset purchases (i.e. investments) measured in constant dollars

$$(C_{o,t'},\ C_{o,t'-1}, \ldots\ldots\ldots, C_{o,t'-\tau}) \qquad \text{where } \tau = T - 1$$

then

$$\bar{k}_{t'} = \sum_{t=t'}^{t'-T} k_t$$

$$= r \,/\, (1 - (1/(1 + r)^{T}) \sum_{t=t'}^{t'-\tau} C_{o,t} \qquad (3.4)$$

where $\bar{k}_{t'}$ is the total service flow of capital in period t', which under these assumptions is equal to the weighted sum of gross investments over the preceding T years.

For this study two categories of capital investments were identified. They were equipment purchases, which had an assumed average service life of 10 years, and land and buildings investments with an assumed average service life of 25 years. Both figures for the pre-1972 period were taken from the state and federal SAES appropriations reported in the CSRS annual "Funds for Research at State Agricultural Experiment Stations." Figures for the 1972-75 period were taken from unpublished CSRS2 financial reports of the agricultural experiment stations which were obtained directly from CSRS. After deflating[16], the total service flows derived from equipment and land and buildings investments were calculated using equation (3.4). These two series were then summed to get a measure of the total services flows arising from capital investments. Together with the deflated operating expense figures[17] they provide a reasonably accurate measure of the real resources used in the knowledge production process over the 1963 to 1975 period. Details of the deflators used in conjunction with these value aggregates are given in the following section.

(ii) A Digression on Research Expenditure Deflators:

Whilst the development of an appropriate Agricultural Research Deflator (ARD) using primary data sources is well beyond the resources of this study we can certainly improve upon the deflators commonly used to date. We will demonstrate that the correction of various mismeasurement and construction problems, implicit in previous measures, leads to a substantial revision in the index. This has serious implications for the validity of results obtained by a variety of earlier rates of return to agricultural research studies. Mansfield et.al. (1983) reached similar conclusions in a study of the deflators used in previous investigations in the non-agricultural sector.

The purpose in constructing an ARD series is to facilitate calculation of the real resources used or expended for public sector (or more particularly SAES) agricultural research in a particular year. More specifically the object of deflation is to convert a value aggregate for the t^{th} period, $\sum_i P_{ti}X_{ti}$, into $\sum_i P_{oi}X_{ti}$, which is the aggregate value of the level of inputs in the t^{th} period, X_{ti}, expressed in some reference or base year price, P_{oi}. This can be achieved by separately deflating the components of the value aggregate with the appropriate relative price indices such that

$$\sum_i ((P_{ti}X_{ti}) / (P_{ti}/P_{oi})) = \sum_i P_{oi}X_{ti} \qquad (3.5)$$

An identical result can be obtained by directly deflating the value aggregates using a current weighted (Paasche) price index so that

$$\frac{\sum_i P_{ti}X_{ti}}{(\sum_i P_{ti}X_{ti} \;/\; \sum_i P_{oi}X_{ti})} = \sum_i P_{oi}X_{ti} \qquad (3.6)$$

where the bracketed denominator is the appropriate Paasche price index.

A wide variety of R & D deflators have been constructed. Milton (1972) developed an index of average total cost per manyear. Unfortunately it does not represent a suitable research input price index as it varies with changes in both the salaries of scientists and the value of non-manpower inputs per scientist. Most of the other ARDs are developed within the conventional price index approach described by equation (3.6) but vary greatly in the number of expenditure categories, index weights and price trend proxies used to construct them. Some studies (see Peterson (1966) and Davis (1979)) use only one expenditure category and assume all of the appropriate price series move as one. They generally deflate total research expenditures by a salaries based price series.

Most of the other series use two expenditure categories, labor and non-labor, with either fixed or variable index weights. The fixed weight deflators (see for example Havlicek and Otto (1982)) generally use 0.7 to 0.3 labor to non-labor weights. Because of the lack of suitable input quantity data these weights reflect the approximate value share of the labor and non-labor components of total research expenditures. Deflating by a fixed weight (Laspayres) index is an acceptable approach only as long as there are no 'significant' shifts in the composition of the aggregate. The variable weight approaches (Cline (1975) and Evenson (1968) for instance) generally deflate the labor and non-labor components separately (see equation (3.5)).

Unfortunately specific index series representing price trends for (agricultural) research input categories are usually not available. This forces researchers to rely on appropriate trend data from secondary sources. Labor price series are often proxied by an index of the average salaries of college and university teachers (derived from American Association of University Professors' (AAUP) figures), and non-labor by the implicit price deflator for federal or state and local government purchases of goods and services.

In summary the most sophisticated deflation procedure used to date involves separate deflating of the labor and non-labor components of total agricultural research expenditure using the AAUP and implicit price deflator proxies respectively. The revisions undertaken in the present study involve,

(1) A major recalculation of the AAUP series taking care to remove the construction errors of previous compilations,

(2) A finer breakdown of gross expenditures to more accurately reflect shifts in the composition of the aggregate over time, and

(3) A restructuring of the (implicit) weights used to date, in recognition of the fact that not all capital investments are appropriately expensed in the year of purchase.

A recent salaries-based proxy for agricultural research labor price trends is found in Davis (1979). He reports an index of average salaries of College and University Teachers for the period 1927-74.

Data for the 1972-74 period comes from the AAUP Bulletin[18] and for the 1929-72 period from Cline. Cline's 1929-42 figures are in turn taken from Stigler (1950) who presents figures back to 1908[19]. A summary of the average annual research labor cost change implied by this Stigler-Cline-Davis (SCD) series is presented in Table (3.5).

Unfortunately the SCD series has several shortcomings. Cline's salary figures for the 1950-1958 period were calculated as a linear interpolation of the 1949 and 1959 figures. Applying the method Stigler used to construct the series for the earlier period, to salary data reported in the 1956 AAUP Bulletin (Vol. 42, No. 1, p. 37), we were able to calculate the 1950, 52, 54 and 56 average salary figures. We also corrected for the fact that the Cline-Davis figures for 1959 onwards were out of sequence by one year. For example, what they claim to be the salary figure for the academic year ending June 1960 is actually the figure for the academic year 1960-61. Finally the Cline-Davis figures for 1959 onwards represent the median salaries for associate professors only. The previous Stigler figures are a weighted average across all teacher ranks (Full, Associate and Assistant Professor plus Instructor) so to maintain consistency we also adopt a weighted average measure[20].

The quantitative impact of these adjustments is seen by comparing the SCD and corrected SCD research labor cost indices in Table (3.5). They imply over-time patterns of salary increases which are substantially different. The SCD series appears to seriously over estimate the research labor cost increases in both the 1950s and the 1960s and under estimate the average yearly increase for the first half of the 1970s. With labor costs accounting for a large share of

Table (3.5) Average Annual Rates of Price Change Derived from Various Agricultural Research Deflator (ARD) Series (Compound Percent Change).

Period	Stigler-Cline-Davis Series[a]	Corrected[b] Stigler-Cline-Davis Series	Gross Expenditure[c] Salary Based ARD Series	Gross Expenditure[c] Compensation Based ARD Series
1935-39	1.5	1.5	1.0	n.a.
1940-49	3.8	3.8	4.7	n.a.
1950-59	5.1	4.2	4.0	n.a
1960-69	5.0	4.5	4.2	4.4
1970-75	3.9	4.3	4.9	5.0

(a) The appropriate 1975 figure was added to the Davis series which ended in 1974.

(b) See discussion in text for details of the corrections undertaken.

(c) Gross Expenditures = Total Expenditures - .80 (Fees, Sales and Miscellaneous Revenues)

n.a - not available

total SAES research expenditures these revisions alone will have a significant effect on any attempt to deflate aggregate SAES research expenditures.

The (salary based) agricultural research deflator series presented in Table (3.5) was calculated as

$$ARD_t = V_{tL}P_{tL} + V_{tB}P_{TB} + V_{tO}P_{tO} \qquad (3.7)$$

where V_{tL}, V_{tB}, and V_{tO} are the current (t) value shares of gross expenditures (using total U.S. figures) attributed to labor, land and building and the other expenses categories respectively. The appropriate price trend indices are represented by P_{tL}, P_{tB} and P_{tO}.

Land and building cost increases were proxied by the Handy-Whitman public utility building cost index taken from the U.S. Bureau of the Census "Historical Statistics of the U.S." up to 1970 and the "Statistical Abstract of the U.S." thereafter. It was felt that investments in building and structures would dominate this input category. The 'other expenses' figure is a catch-all category. It includes equipment purchases along with all other operating expenses such as travel, supplies, communication and utility charges. The price trend proxy for this category was the implicit price deflator for state and local government purchases of goods and services, also taken from the U.S. Bureau of the Census "Historical Statistics of the U.S." up to 1970 and the "Statistical Abstract of the U.S." thereafter[21]. This index was chosen because most of the SAES expenditures in this category are at the state and local level. It also excludes specific defense related expenditures which are factored in to the federal goods and service index but are obviously not relevant for experiment station expenditures. The SAES expenditure data base developed for this study did allow equipment purchases to be isolated from the remaining items included in this category. However, the goods and service index was the most suitable price trend proxy available.

The pattern of research cost increases implied by this ARD series is also substantially different from both the corrected and uncorrected SCD series. The uncorrected SCD series appears to seriously underestimate the research cost increases for the 1940s due to a combination of war-time factors. During this decade the SAES became far less 'labor' intensive. In 1940 'labor' costs accounted for 70.6 percent of gross SAES expenditures. This declined steadily to bottom out at 62.7 percent of gross expenditures in 1948 (see Appendix II, Table (6) for more details on the 'labor'/capital ratios in research). Furthermore research salaries increased by 46.0 percent over the decade whilst the building and other expense items, now both with larger shares in the ARD, experienced price increases of 101.9 and 83.8 percent respectively.

The SCD series appears to be an equally poor indicator of research cost changes for all the remaining periods. It significantly over estimates the research price increases for the 1960s, 1950s and last half of the 1930s while under estimating the inflation rate experienced by the SAES during the first half of the 1970s.

The right-hand column in Table (3.5) presents an ARD series using a compensation rather than salaries based labor price proxy. Since 1959 the AAUP Bulletins report total compensation paid to college and university teachers. The compensation figure includes salaries plus fringe benefits which more accurately reflects the unit cost of researchers to the SAES.

Although the ARD series presented in table (3.5) are useful for comparative purposes a slightly different method of deflation was used for the present study. The index weights in equation (3.7) represent the current value share of gross expenditures for each expenditure category. However, in the previous section we discussed the notion that capital items, and in particular land, buildings and equipment investments, are not appropriately expensed in the year of purchase. Thus the weights for each input category should reflect the corresponding proportion of total resources used, rather than the proportion of total purchases in the current period, in any measure of the real resources devoted to research.

An estimate of the real resources used in the current period was obtained by separately deflating the appropriate components of the value aggregates as described by equation (3.5). Total SAES research expenditures were split into capital and non-capital categories. The capital figure consisted of two sub-categories - equipment and land and buildings. Prior to estimating the current service flow derived from equipment and land and buildings investments, they were deflated by their respective proxy price trends. They were then summed using the appropriate service flow weights (see previous section for details) to get an estimate of the real capital resources used in the current production period.

The non-capital purchases represent total expenditures net of equipment, land and buildings investments and 80 percent of revenues derived from fees, sales & miscellaneous. It includes expenditures made under the labor and other expense categories described earlier in this section. Approximately 77 percent of these expenses are labor related so a compensation based labor price index was used to deflate them. The resulting real capital flow and real operating expense categories can then be summed to get an estimate of the real resources used in the current production period.

Through all this discussion a state level subscript has been suppressed. If price indices and input mixes were reasonably invariant between states then a deflator derived from national level data is appropriate. Using detailed research expenditure by category data obtained directly from the SAES, Murphy and Kaldor (1980) did find that input mixes were similar across states. However, their findings relate only to data for the 1973-78 period and it is not clear that the input invariance feature across states is stable over longer time periods. There may also be some regional variation in the changes over time of agricultural research input prices. This is an area in which further refinement of the ARD index may prove fruitful.

FOOTNOTES CHAPTER 3

1. Sample excludes Alaska, Hawaii and Puerto Rico.

2. Evenson and Wright (1980) express similar sentiments.

3. Hansen, Weisbrod and Strauss (1978) show that research output as proxied by publications significantly enhances the earnings of academic economists. Shaw's (1967) results support this finding.

4. Publication data can be obtained directly from the CRIS files but was deemed too incomplete and unreliable for our purposes. The fixed length format of the CRIS records means that the CRIS files under-report the publication output of highly productive or large projects.

5. The goal is to estimate the total (ie. population) number of publications per station, $\tau_i = N_i p_i$. However the variance of τ_i is estimated by $V(\tau_i) = N_i^2 s_i^2 / (N_i - n_i)$ after applying the finite sample correction factor to the estimate of p_i. (Here $s_i^2 = \Sigma (Y_{ij} - Y_j)^2/n_i - 1$ and assumed to be relatively constant across different i's.) Thus in order to transmit homoskedastic sampling error to the error term in a regression of τ_i we need to choose sample sizes on the basis of (3.1).

6. This procedure would transmit a homoskedastic error term in a regression of p_i on R_i.

7. The task of undertaking a manual search was made somewhat less onerous by using the cumulative 1970-73 SCI rather than separate yearly indices.

8. Limiting the coverage to scientific publications also eliminates a potentially serious double counting problem which may result from using a broader class of publications. For example, many station bulletins etc. simply 'repackage' the knowledge produced by the station (and already reported in scientific articles) for a non-scientific audience.

9. Source Authors consist of the 2239 Sample I researchers for the 1970-73 period and the 2267 Sample II researchers for the 1974-75 period.

10. The pro-rated measure is empirically more appealing a priori because it removes the implicit double counting which is likely when scaling the unadjusted per researcher figure to a station level figure. The population figure used here for scaling was inclusive of social science and agricultural engineering researchers.

11. Kamien and Schwartz (1982) cite various drawbacks from using patent statistics as a means of identifying innovations. Patents are issued for minor as well as major innovations; many patented products and processes are never commercialized; and thirdly, many innovations are not patented.

12. As Stigler and Friedland (1975) observe, 'to some degree citations are influence, for they influence the reading by readers of the citing paper.' Note also, to the extent that citation measures are subject to replication they represent an objective measure of scientific quality.

13. See also the review article by Edge (1979).

14. They are the alphabetically first 150 researchers from Sample I. Primary articles consist of those articles in which the source author is listed first.

15. The continuous time version of this equation is derived by Yotopoulos (1967 p. 477).

16. Details of the deflating procedure employed are given in the next section.

17. Operating expenses were calculated as Total Expenses - .80 (Fees, Sales and Miscellaneous) - Equipment - (Land and Buildings).

18. Generally reported in the AAUP bulletin summer issue in articles on the "Economic Status of the Profession."

19. Stigler's figures prior to 1932 are based on Viva Boothe's <u>Salaries and the Cost of Living in Twenty-seven State Universities and Colleges 1913-32</u> (Ohio State University Press, 1932), and annual bulletins of the Office of Education.

20. The weights are the relative number of teachers in each of the teacher ranks. A corrected listing of average teachers salaries is presented in Table 5, Appendix II. Although not needed for the present study, figures from 1908 to 1982 are given for the sake of completeness.

21. Both the Handy-Whitman and Implicit Price deflator were reported on a calendar year basis while research expenditure data is reported on a fiscal year basis. To match up these series we took a two year moving average of both price deflators.

Chapter 4

QUANTIFYING THE RESEARCH EXPENDITURE-RESEARCH OUTPUT RELATIONSHIP FOR AGRICULTURE

4.1 Data and Major Variables:

With details concerning the construction of all variables given in Chapter (3) we will preface this discussion of the empirical results with a brief overview of the data. Table (4.1) provides some summary statistics of the various research output measures constructed for this study.

Average station size, as measured by the number of researchers (i.e. excluding administrative, support and extension-only staff), is around 255 - ranging from a low of 44 at Nevada to 727 at California. There are eight stations, Delaware, Nevada, New Hampshire, New Mexico, Rhode Island, Vermont, West Virginia and Wyoming with less than 100 researchers. Five stations, namely California, Colorado, Michigan, New York, and Texas have greater than 500 with California and New York topping this group with around 700 researchers each.

The average publication performance per researcher (per station) per year is given by the PUB and PROPUB variables. Averaging across all disciplines and SAES gives a yearly publication output measure (PUB) of around 1.2 which is approximately halved to 0.53 if publications are pro-rated (PROPUB) according to the number of coauthors per publication[1]. Given the relatively small proportion of sole authored publications, as shown in Table (3.3), this is to be expected.

The two research quality weights used in this study are the TOTCIT and NETCIT variables respectively. Both measure the average yearly

Table (4.1) Descriptive Statistics for Selected Publication Based Agricultural Research Output Measures.[a]

Variable	Mean	Standard Deviation	Minimum	Maximum
Population	255.4	162.96	44.0	727.0
Per Researcher				
Pub	1.159	0.471	0.160	3.019
Propub	0.527	0.211	0.093	1.242
Totcit	0.960	0.570	0	3.835
Netcit	0.790	0.580	0	3.288
Per Station[b]				
Pub	330.08	238.37	8.80	1501.7
Propub	151.24	134.25	5.132	698.4
Pub x Net[c]	321.24	452.31	0.0009	3004.4
Pro x Net[c]	145.96	204.29	0.0005	1244.1

(a) These figures are derived from a panel data set consisting of observations on 48 states (Alaska and Hawaii omitted) for the period 1970-75 inclusive.

(b) Per station figures are simply the per researcher figures weighted by the appropriate population figure.

(c) When used as a quality weight, the zero net citation count was arbitrarily set at 0.0001. This allowed logarithmic values to be calculated.

citation performance of publications two years following their publication date. The TOTCIT variable captures the total number of citations for this period and the NETCIT variable nets out self-citations by both source and coauthors. Despite the large range in both these figures their relatively low coefficient of variation suggests that the average citation performance of quite a few stations is at the lower end of the data range. Both measures show that for at least one of the sample years, 1970-75, none of the publications from Delaware were cited whilst Wisconsin achieved the highest total and net citation rate of 3.84 and 3.29 respectively.

The final four rows of Table (4.1) present summary statistics for various estimates of the citation weighted and unweighted total publication performance of the SAES. The general pattern revealed by the per researcher data is preserved in these per station statistics, although the relative magnitude of the mean and standard deviation for the citation weighted figures suggests that these measures are somewhat positively skewed.

It was argued in section (3.2) that pro-rated publication output, weighted by net citations, is an appropriate indicator of the overall performance of the SAES. Nevertheless an analysis of the relationship between these various measures, afforded by the correlation matrix in Table (4.2), is instructive. A $\rho = 0.947$ indicates a strong positive relationship between the two quantity measures PUB and PROPUB with an even stronger relationship ($\rho = 0.984$) holding between the quality measures TOTCIT and NETCIT. In contrast, the relationship between the various quantity and quality measures is far less definitive. These results show that the systematic variance ratio from a regression of

Table (4.2) Simple Correlation Matrix for Various Agricultural Research Output and Quality Indicators[a]

1 Pub	1.000							
2 Propub	0.947	1.000						
3 Totcit	0.370	0.349	1.000					
4 Netcit	0.374	0.355	0.984	1.000				
5 Pub x Tot	0.705	0.662	0.849	0.846	1.000			
6 Pub x Net	0.689	0.647	0.847	0.860	0.994	1.000		
7 Pro x Tot	0.697	0.696	0.854	0.853	0.989	0.985	1.000	
8 Pro x Net	0.679	0.678	0.851	0.867	0.982	0.989	0.994	1.000
	1	2	3	4	5	6	7	8

(a) All variables are measured on an average researcher per state basis.

either quantity measure on either quality measure ranges from 0.126 to 0.140. Thus, at the station level, there is a positive but reasonably loose association between research quality and quantity.

The simple correlation coefficients in Table (4.2) also suggest the results from estimating equation (2.5) will be sensitive to the form of the dependent variable. Accepting citation measures as appropriate quality adjusters, then regressions using citation adjusted publication output should form the benchmark for assessing the relationship between research inputs and research outputs. Nevertheless, a comparison with results obtained from using quality unadjusted output variables will add to our understanding of the research process and will be presented below.

Finally the correlation coefficients presented in the right hand tail of Table (4.2) show, that on statistical grounds, the four quality adjusted research output indicators are good proxies for each other. However, on conceptual grounds, the PRONET variable is the most appealing and will be used extensively in the regression analysis to follow.

4.2 Specification Search:

Prior information concerning the appropriate form of the relationship between publication output and research expenditure described by equation (2.5) is sparse. We open our investigation by addressing this question. To keep the search within manageable proportions, we restricted our choice to linear, log linear, semi log and double log forms. However, even this limited portfolio of possible functional forms gives rise to selection problems. No direct choice between the two models with linear P and log P is possible. As they stand the models are not nested in the sense that no linear or non-linear restriction on the parameters in either model will yield the remaining model. In fact the models in general are internally inconsistent since negative P's are admissible under the linear P specification but the logarithmic model will be undefined for such values.

The approach taken was to artificially nest these models by use of the (Box-Cox) power transformation (where all variables, z, are transformed by $(z^{\lambda} - 1)/\lambda)$, and then attempt to statistically discriminate between the four alternatives (now considered restricted forms of the more general model) by application of the Likelihood Ratio test and a series of standard Fisher F-tests.

The regressors were log and linear current expenditures on labor and estimated capital service flow, additive time and state dummies and multiplicative size dummies[2]. Taking medium sized stations as the reference group, the size dummies allowed the expenditure coefficients potentially to vary for small(< 100 researchers), medium and large (> 500 researchers) stations[3].

The results of this exercise were mixed. Neither a linear or log form for the dependent variable was preferred by the data. The model which maximized the value of the likelihood function implied a $\lambda = 0.270$. As we have no rationale for accepting this value other than its statistical difference from the $\lambda = 1$ (linear P) or $\lambda = 0$ (log P) alternatives it was decided to continue the specification search with linear and log P as two admissible maintained hypotheses.

Under the maintained hypothesis of log P the data failed to reject the null hypothesis of no (additive) size effect ($\hat{F}_{8,223}$ = 1.135) so that size dummies were excluded from further specifications of this particular model[4]. The data gave reasonable support for the log over the linear form of the regressors. An F-test that the linear coefficients were jointly equal to zero could not be rejected ($\hat{F}_{2,231}$ = 0.950) but a similar test on the log form of these variables gave a fairly respectable $\hat{F}$ value of 2.950. The data could not reject a test that a trend line represents an adequate approximation of the time dummies in this model. Finally we strongly reject the null hypothesis that the state dummies jointly equal zero ($\hat{F}_{47,233}$= 6.486) thereby supporting the notion that significant differences in state level research efficiencies exist.

Under the maintained hypothesis of a linear P there is evidence that a statistically significant large state effect exists, with the appropriate $\hat{F}_{4,227}$ = 2.53 exceeding the test statistic (2.37) at the five percent level. Further testing indicated that the slope coefficients on the small and medium size stations were statistically indistinguishable. The data failed to discriminate between a linear and semi log model. Both the linear and log form of the expenditure regressors generated coefficients which were jointly different from zero. Once again a trend variable adequately approximates the time dummies and the state level effects strongly differ from zero ($\hat{F}_{47,227}$ = 8.258).

In summary the specification with log P appears less 'volatile' than the linear P model. The data suggests that a double log model is preferred over a log linear specification, size effects (at least as they impact the slope coefficients) are degenerate and significant trend and state effects are present. The linear P specification also endorsed these trend and state effect results but suggested results for the size and slope parameters which were at odds with the log P specification.

The 'unsatisfactory' performance of the linear P model may be 'resolved' by a closer inspection of the statistical properties of the w error vector from equation (2.11). If we recall the discussion in section (3.1), the sampling procedure used to estimate the total publication output of the SAES had the potential for transferring measurement error induced heteroskedasticity to the error term w in equation (2.11). A simple linear regression of the absolute value of the w_{it}'s from a linear form of equation (2.11) on the square of station size (i.e.POPLN^2) gave

$$\widehat{|w_{it}|}_{linear} = \underset{(3.506)}{14.583} + \underset{(14.333)}{0.0004POPLN_{it}^2} \qquad R^2 = 0.418$$

$\hat{F} = 205.4$

( ) = t value

This is a strong indication of the existence of a heteroskedastic error term[5] of the form $\sigma_{wi} \simeq POPLN_i \sigma_w$. This procedure was repeated for equation (2.11) in which all variables were entered in log form to give

$$\widehat{|w_{it}|}_{log} = \underset{(11.410)}{0.478} - \underset{(1.971)}{0.0000006POPLN_{it}^2} \qquad R^2 = 0.013$$

$\hat{F} = 3.885$

( ) = t value

Both the coefficient on the POPLN^2 variable and the overall F value decline to insignificance in this case so the assumption of a homoskedastic error term for the double log model appears reasonable.

4.3 Some Preliminary Results:

One of the stated goals of this study is to inquire into the strength of the systematic relationship between SAES research expenditures and publication based indices of research output. Various measures of research input and output were presented earlier and given the panel nature of the data set it is possible to partition their variance into several dimensions. This is done in Table (4.3).

In all cases the between (states) dominates the within (states) variance with the various output measures showing relatively more variation in the within, or over time dimension, than the expenditure figures. Given the relatively large spread of station sizes and the short nature of the panel (6 years) this is not unexpected. Weighting the raw publication count measures (PUB and PROPUB) by the net citation count increases the variation proportionately more in the within than the between dimension.

The combined labor plus capital variable behaves similarly to the labor variable itself. Again this is not surprising given agricultural research in the SAES is quite 'labor' intensive. With capital measured in service flow terms, the 'labor'-capital ratio averaged across all stations for 1963 was 7.64. It declined for the rest of this decade to 6.32 in 1970 to finish at 7.06 in 1975, the last year in our sample[6].

The proportionately small amount of variation in the within

Table (4.3) Partitioning of Sample Moments for Various Agricultural Research Output and Expenditure Measures (N = 48, T = 6).[a]

	Between Variance[b]	Within Variance[c]	Ratio of Within to 'Total' Variance
Pub	5.479	0.050	0.009
Propub	5.465	0.061	0.011
Pubnet	11.097	0.650	0.055
Pronet	11.100	0.630	0.054
Labor	3.102	0.007	0.002
Capital	3.594	0.017	0.005
Labor + Capital	3.342	0.006	0.002

(a) All (state-level) research output and expenditure variables are measured in their natural log form.

(b) Given by $\frac{T \sum (X_{i.} - X_{..})}{N-1}$

(c) Given by $\frac{T \sum (X_{it} - X_{i.})}{N(T-1)}$

dimension has a bearing on the regression estimates. Mairesse (1978) observed that by discarding all the information contained in the variability between firms and relying on the comparatively smaller variation within firms over time, the within estimates are more sensitive to any measurement errors. Moreover, focusing only on the within estimates gives credence to the information contained in the annual changes of the variables to the exclusion of the more permanent differences in these variables. He also argues that omitted variables and errors in included variables may exhibit large variations within firms as well as between firms whereby the independence assumption for the usual error, w_{it}, is potentially as dubious as it is for the state specific error term, μ_i. If in fact the w_{it}'s are correlated (over time) with the explanatory variables then we may be prepared to put somewhat more faith in the between estimates.

Thus the within and between estimates have an all or nothing character in that the former uses only within state variation over time and the latter only the between state variation. Another option is to form estimates of the slope parameters on the basis of an approximate GLS procedure. This method, described in detail in chapter 2, uses both the within and between variation. From equation (2.22) we observe that the GLS and within estimates are close when the number of years, T, is large (becoming identical asymptotically). Such large sample equivalence is not anticipated for the present rather truncated panel. However, with the variation in the state dimension dominating the time dimension we would expect the between and total (or OLS) estimates to be quite close.

In chapter (2) we asserted that the error term, $\tilde{w}_{it}$, in the knowledge production function (equation 2.2) is orthogonal to $\approx{w}_{it}$, the error term from the indicator function (equation 2.3). With

$$R^2_{P.\dot{K}} = 1 - \mathrm{var}(\approx{w}) \;/\; \mathrm{var}(P)$$

then given this orthogonality assumption

$$R^2_{P.\Sigma R} = 1 - (\alpha^2\,\mathrm{var}(\tilde{w}) + \mathrm{var}(\approx{w})) \;/\; \mathrm{var}(P)$$

It follows that the coefficient of determination from a regression of P on current and lagged R gives the lower bound of the systematic to total variance ratio of P as a measure of knowledge increments $\dot{K}$. In this sense the $R^2_{P.\Sigma R}$ statistic gives the 'proxy error' which follows from using (weighted) publications as an indicator of gross additions to the stock of knowledge.

From the results presented in Table (4.4) we observe that, in the total or OLS relationship of quality adjusted publication counts on summed research capital and labor expenditures, no more than 47 percent of the variation in P can be attributed to its 'error' as a measure of knowledge stock increments. Of course the actual 'proxy error' may be far less than this figure if the noise in the knowledge production function were known to dominate the overall error term w_{it} in equation (2.5).

Partitioning the total relationship into its between and within components we observe, using the complete sample, that the 'proxy error' drops to a maximum of 25 percent in the between dimension.

Table (4.4) Regression of Citation Adjusted Publication Output (PRONET) on Agricultural Research Expenditure[a]

Variable	OLS	WITHIN	BETWEEN	EGLS[b]
R_0	-0.5994 (1.0050)[c]	0.0252 (0.8050)	-5.4798 (10.735)	0.0204 (0.8473)
R_{-1}	-0.0075 (1.2889)	0.0789 (0.8986)	-5.4824 (21.584)	0.3080 (0.9920)
R_{-2}	-0.1180 (1.2709)	-0.9056 (0.8992)	8.3317 (16.079)	-0.3187 (0.9835)
R_{-3}	1.0557 (1.2559)	-0.1406 (0.8817)	24.977 (14.755)	0.6920 (0.9640)
R_{-4}	0.2871 (1.2745)	-0.4862 (0.8931)	-28.982 (19.648)	0.3462 (0.9754)
R_{-5}	-0.0557 (1.2994)	-0.3574 (0.8868)	20.689 (18.662)	-0.0226 (0.9938)
R_{-6}	-0.0823 (1.3153)	-0.1552 (0.9166)	-33.306 (17.776)	0.3767 (1.0132)
R_{-7}	0.9123 (1.0260)	-1.5631 (0.8741)	20.828 (9.4215)	0.0902 (0.8635)
Trend	0.0377 (0.0384)	177.37 (43.095)	—	0.0473 (0.0301)
ΣR_{-i}	1.5567 (0.0896)	-3.5041 (1.3761)	1.5740 (0.2005)	1.4922 (0.1546)
R^2	.5315	.0660	.7521	.2737
NT	288	288	48	288
'Mean' Lag	3.76	4.83	4.47	3.41
χ^2				16.395

(a) All variables measured in natural logs.

(b) All variables, z_{it}, transformed as $z_{it} - \hat{\gamma} z_{i.}$ where $\hat{\gamma} = 1 - \hat{\sigma}_w/\hat{\sigma}_1$. Here $\hat{\sigma}_1^2 = 3.3162$, $\hat{\sigma}_w^2 = 0.6110$ and $\hat{\sigma}_\mu^2 = 0.4509$.

(c) Standard errors in parentheses.

Thus, the 'on average' knowledge increment-lagged expenditure pattern for each experiment station appears to be captured fairly completely using quality adjusted publications as a proxy for knowledge increments.

However, for the publication-expenditure relationship in the within dimension R^2's of the order of 0.07 were recorded. From the data available to us we cannot identify the source of this large random component in yearly deviations of each SAES from its average level of operations. It would arise if the publication process were subject to a great deal of instability over time. Alternatively it may be that the knowledge production process is such that (within the range of our data at least) small fluctuations over time in the research expenditures of a particular station are not systematically translated to changes in research output ($\dot{K}$) for particular years.

Qualitatively these results are surprisingly similar to those obtained by Pakes and Griliches in their 1980 study of the firm level patent-R&D expenditure relationship. Using raw patent data over an eight year period from 1968-1975, and research expenditure data over the 1963-75 period for 121 medium and large U.S. corporations, they estimated the double log relationship between patents and current and (five years) lagged R&D expenditures. They obtained R^2's for the total regressions ranging from 0.74 to 0.95, for the between dimension ranging from 0.77 to 0.97, and for the within dimension ranging from 0.11 to 0.49[7].

In all dimensions their R^2's were somewhat higher than those obtained for this study. This may simply result from the bigger data set used in their investigation. However, it may also arise in part from the use of raw patent counts to proxy research output. In our study using the raw publication count (PROPUB) rather than the citation adjusted measure (PRONET) in general causes the R^2's to increase (cf. Table (4.4) and Table (4.5)). It may also be that the biologically orientated research of the SAES is inherently more noisy than the research and development projects undertaken by the corporations in the Pakes-Griliches sample[8] (i.e. the var ($\tilde{w}$) term is relatively larger for biological as opposed to industrial research). Alternatively the patenting process, being the outcome of a corporate decision making process, may be less sporadic in nature (particularly in the over time or within dimension) than the publishing process which, as discussed earlier, represents in part the aggregate publishing propensities of individual researchers within each of the SAES.

4.4 Nature of the Research Lag:

A second objective of the empirical work was to gain some insights into the nature of the lagged relationship between research inputs and outputs. As we already observed in Chapter (1) surprisingly little work has been directed toward this end. Most of the extended production function studies proceeded by imposing, a priori, a 'suitable' lag structure on the research expenditure-agricultural output relationship. Suitability in such cases is often determined on the basis of data availability, empirical convenience or some combination of the two.

Following the procedure suggested by Wallace (1975) and Hatanaka and Wallace (1980) we estimated the distributed lag relationship between research inputs and research outputs in a form-free manner. They suggest this is an appropriate approach to take if we are

Table (4.5) Regression of Raw Publication Output (PROPUB) on Agricultural Research Expenditure[a]

Variable	OLS	WITHIN	BETWEEN	EGLS[b]
R_0	-0.1718 (0.4682)[c]	-0.1103 (0.2527)	-2.8121 (6.4844)	0.0345 (0.2770)
R_{-1}	0.4966 (0.6004)	0.3850 (0.2821)	1.1064 (13.038)	0.5597 (0.3143)
R_{-2}	-0.1319 (0.5921)	-0.4261 (0.2823)	-1.3339 (9.7122)	-0.1623 (0.3115)
R_{-3}	0.5089 (0.5851)	-0.1050 (0.2768)	15.544 (8.9129)	0.2178 (0.3039)
R_{-4}	0.2160 (0.5937)	0.0125 (0.2804)	-15.974 (11.868)	0.3183 (0.3079)
R_{-5}	0.0058 (0.6053)	-0.0784 (0.2784)	8.5244 (11.273)	0.0429 (0.3131)
R_{-6}	-0.1290 (0.6127)	-0.2141 (0.2878)	-10.703 (10.738)	-0.0321 (0.3211)
R_{-7}	0.3713 (0.4779)	-0.3965 (0.2745)	6.8120 (5.6910)	0.1114 (0.2829)
Trend	-0.0432	10.066 (13.531)	—	-0.0397 (0.0098)
ΣR_{-i}	1.1659	-0.9329 (0.4321)	1.1638	1.0900
R^2	.7480	.0466	.8163	.3529
NT	288	288	48	288
'Mean' Lag	3.23	3.50	4.28	2.69
χ^2				16.621

(a) All variables measured in natural logs.

(b) See note (b) Table (4.4). Here $\hat{\sigma}_1^2 = 1.2102$, $\hat{\sigma}_w^2 = 0.0602$ and $\hat{\sigma}_\mu^2 = 0.1917$.

(c) Standard errors in parentheses.

interested in capturing certain features of a lag distribution, such as the long run lag response (ie. the sum of the lag coefficients), the mean lag, and the variance of the lag, with few ad hoc constraints being imposed on the lag distribution.

Many previous studies have treated research labor and capital purchases as perfect substitutes, while some (for example Latimer (1964) and Davis (1979)) have simply deducted capital purchases (or part thereof) from the total expenses incurred by the stations[9]. As we described in Chapter (3) it is appropriate to expense all of the labor component in the year of its purchase but not so for capital. An estimate of capital service flows for a given year was constructed from a weighted accumulation of the previous 25 years land and building purchases plus the previous 10 years equipment purchases. Unfortunately, we were frustrated in our attempts to obtain separate estimates of the lag coefficients on the labor (or more precisely operating expenses) and capital expenses of the SAES. A service flow measure of capital, by construction, is less volatile than a capital investment figure, and given the slowly changing nature of deflated operating expenses causes these two input measures to be highly collinear. A larger panel may well inject enough independent variation into the sample to allow for separate estimates of capital and non-capital lag coefficients. For this study the lag structure for summed capital and non-capital research expenditures is investigated with both figures measured in equivalent flow terms.

The results in Tables (4.4) and (4.5) indicate that the individual lag coefficients are estimated with a low degree of precision. However, the sum of the lag coefficients, measuring the long run expenditure response of (quality adjusted) publication output, is estimated quite precisely. As expected the OLS and between estimates are very close. They show that a 1 percent (once and for all) increase in real research expenditures leads to around a 1.6 percent increase in constant quality research output. The output response for unadjusted research output is somewhat lower at around 1.2. Thus the use of quality unadjusted publication counts underestimates the research output response resulting from increased research expenditures by approximately 25 percent. This result holds across most of the specifications reported here.

The EGLS long run elasticity estimate appears to be dominated by the between variation and is at odds with the within estimate. Given the truncated nature of the panel this is not surprising but the magnitude of the difference (plus the negative sign on the within estimate) is unexpected.

Several reasons could account for this discrepancy. The first concerns misspecification of the random effects model. Recalling the discussion from chapter (2), we noted that a violation of the orthogonality assumption concerning the state effects variable μ_i and the X_{it}'s (i.e. $E(\mu_i|X_{it}) \neq 0$) causes the random effects estimator to be biased and inconsistent, while having no effect on the fixed effect estimator.

Hausman (1978) suggests a natural test of the null hypothesis of independent μ_i's is to consider the difference between the two estimators, $\hat{q} = \hat{\beta}_{FE} - \hat{\beta}_{RE}$. If no misspecification is present then $\hat{q}$ should statistically be near zero. From results presented in Hausman, we can write $V(\hat{q}) = V(\hat{\beta}_{FE}) - V(\hat{\beta}_{RE})$ and form the specification test statistic

$$m = \hat{q}'\hat{M}(\hat{q})^{-1}\hat{q} \overset{A}{\sim} \chi^2_K$$

where

$$\hat{M}(\hat{q}) = (X'Q_1X)^{-1} - (X'\hat{\Omega}^{-1}X)^{-1}$$

and

K = the number of unknown parameters in β when no misspecification is present[10].

The equivalent test in a regression format is to perform OLS on the augmented equation

$$y_{GLS} = X_{GLS}\beta + X_{FE}\alpha + v$$

where y_{GLS}, X_{GLS} and X_{FE} are the appropriately transformed variables and test whether $\alpha=0$ by comparing the estimated variance from the random effects specification to the estimated variance from the augmented specification.

The critical value for a χ^2_8 distribution is 20.090 at the one percent level. The relevant χ^2 statistics presented in Tables (4.4) and (4.5) suggest there is no significant misspecification in the random effects model for either the PRONET or PROPUB case. The maintained hypothesis that the X_{it}'s and the μ_i variable are orthogonal is not rejected.

This contrasts with the Pakes-Griliches study of the private sector patent production process where firm specific effects were correlated with research expenditures. As we discussed in chapter (2) the funding mechanism regarding public sector agricultural research is such that the direct or indirect link between these state specific effects and the level of research expenditures is more tenuous than in the case of private sector funding.

The discrepancy between the within and GLS estimates of the expenditure coefficients does not appear to lie in a failure of the state effects to uphold the orthogonality assumption. Comparing the figures in Table (4.4) with Table (1), Appendix (3) suggests some alternative explanations. The within estimate of the expenditure coefficients for the PRONET model is extremely sensitive to the inclusion or omission of a trend variable. The deviation of (slowly changing) research expenditures around an over-time mean is not only small but appears to be highly collinear with a simple trend variable. The spread between the within and EGLS estimates drops sharply when the trend variable is omitted[11]. In contrast, the OLS and EGLS estimates of the long run response of research output are relatively insensitive to changes in the trend variable specification.

Table (4.6) shows the difference between the EGLS and within result for the PRONET model is further reduced by the omission of four outlier states - Delaware, Maine, Nevada and New Mexico. Outliers are properly treated as 'foreign' to the data set if they were not generated in the same manner as the rest of the observations.

In a 1964 study of the relationship between SAES research expenditures and final agricultural output, Griliches formed four

Table (4.6) Regression of Citation Adjusted Publication Output (PRONET) on Agricultural Research Expenditures[a]

Variable	OLS	WITHIN	BETWEEN	EGLS[b]
R_0	0.3367 (0.8707)[c]	0.4875 (0.5724)	-6.9013 (10.961)	0.3042 (0.6123)
R_{-1}	-0.7926 (1.1479)	-0.6302 (0.6566)	-1.8776 (23.569)	-0.6316 (0.7096)
R_{-2}	0.2694 (1.1465)	-0.1402 (0.6558)	15.791 (19.031)	-0.0894 (0.7124)
R_{-3}	0.9849 (1.1819)	1.0121 (0.6733)	1.9235 (16.713)	1.0693 (0.7330)
R_{-4}	0.5729 (1.1248)	0.5282 (0.6249)	11.091 (21.374)	0.5689 (0.6929)
R_{-5}	-0.6560 (1.140)	-0.8193 (0.6388)	13.839 (18.441)	-0.7484 (0.7044)
R_{-6}	0.0359 (1.170)	0.5086 (0.6562)	-29.706 (17.344)	0.5151 (0.7263)
R_{-7}	1.2883 (0.8727)	0.1079 (0.5453)	19.401 (9.4456)	0.3270 (0.5913)
ΣR_{-i}	1.3623 (0.0809)	1.0548 (0.5923)	1.3784 (0.0474)	1.315 (0.1498)
R^2	.5320	.0352	.6877	.2421
NT	264	264	44	264
'Mean' Lag	3.87	3.30	4.64	3.62

(a) Four outlier states (Delaware, Maine, Nevada and New Mexico) and trend variable omitted. All variables measured in natural logs.

(b) See note (b) Table (4.4). Here $\hat{\sigma}_1^2 = 3.0410$, $\hat{\sigma}_w^2 = 0.2640$ and $\hat{\sigma}_\mu^2 = 0.4628$.

(c) Standard errors in parentheses.

groupings from the six New England states, Delaware and Maryland, New Mexico and Arizona and Wyoming, Utah and Nevada. In the recent augmented production function study by Davis (1979) the six New England states plus Delaware and Maryland were eliminated from his observation set[12]. Davis omitted them, in part, on the basis that the research agenda of "most of these states" had become more concerned with the environmental and consumer aspects of agriculture rather than emphasizing agricultural production. Very little evidence was presented to substantiate this claim.

For the four outlier states in our study (three of which were also omitted from the Davis study) this does not appear to be the case (See Table 2, Appendix 3). The proportion of total researchers in the non-production oriented disciplines shows no systematic deviation from the all-states level of around 15 percent. Likewise, neither the proportion of total researchers in the plant and animal sciences, or the plant-animal science ratio for these four states, indicates any clear pattern of deviation from the all-states averages.

Nevertheless, for at least one of the six years in the sample, these states exhibit a calculated error $|Y_{it} - \hat{Y}_{it}|$ greater than twice the standard deviation of the estimate. Omitting them from the sample causes the sum of squares residuals to drop by approximately 62 percent. The precise cause of this 'deviant' research performance is not clear but could be related to the relatively small size of these stations. In particular, there may exist an aggregation effect whereby the summed research output of a small number of researchers is more 'volatile' than for a somewhat larger research organization. Unfortunately corroborative evidence on such a size effect is difficult to come by. For instance, Pakes and Griliches in their 1980 study of the patent-R&D relationship eliminated 16 percent of the original 144 firms in their sample whose R&D programs were less than a minimal size (R&D expenditure < $0.5 million).

By comparing the results in Table (4.5) and Table (3) Appendix (3) we observe that the within estimates are sensitive to the inclusion or omission of a trend variable for the PROPUB model as well. However, in this case the point estimate of the long run elasticity of research remains negative. In table (4.3) we observed that only one percent of the 'total' variance in the PROPUB variable was in the within dimension. Indeed the within variation for this variable is less than the PRONET variable by a factor of 10. Thus, even though the long run response estimate appears to be statistically different from zero, the lack of variability in the data, combined with the observation by Griliches and Hausman (1984) that within estimates are likely to be (extremely) sensitive to any errors of measurement - whose relative importance gets magnified in the within dimension - causes us to place relatively little weight on this estimate.

Using the absolute value of the estimated lag coefficients we can construct point estimates of the mean of the normalized lag distributions, m_i, such that,

$$\hat{m}_i = \hat{\mu}_i \ / \ \hat{\mu}_0$$

where $\hat{\mu}_i = \sum_{s=0}^{K} s^i |\hat{\beta}_s|$ $\qquad i = 0, 1, \ldots, k.$

Various estimates of the mean lag were given in the preceding tables and are averaged in Table (4.7) along with comparative figures from some other studies. The gestation lag represents the average lag between project inception and completion while the time from project completion to commercial application is given by the application lag.

Averaging the Rapoport (1971) and Wagner (1968) figures gives a mean gestation lag of around 1.34 years which is close to the Pakes-Griliches (1980) estimate of 1.6 years. The quality unadjusted estimate from this study, which is closest to the output measures used by these comparative studies, suggests that the mean gestation lag for public sector, biologically orientated research is around 0.7 to 1.0 years longer than the private sector, manufacturing orientated research. The different nature of both the research problems and the institutional environment could account for this difference.

Moreover, the mean gestation lag between research expenditures and quality adjusted research output is consistently longer than the quality unadjusted output measures. The summary figures in Table (4.7) show that for the case of public sector agricultural research, the quality adjusted lag is approximately six months (19 percent) longer than the quality unadjusted figure. These results suggest that in failing to standardize the units by which research output has been quantified, previous studies (such as the Pakes-Griliches (1980) study which simply used raw patent counts) have significantly underestimated the mean lag between project inception and project completion[13].

Finally we recall that all the models discussed to date were estimated subject to the maintained hypothesis of an inter-temporally

Table (4.7) Estimates of the 'Mean' R&D Lag (in years).

	R&D Gestation Lag	Application Lag	Total Lag
Rapoport[a]			
Chemicals	1.48	0.24	1.72
Machinery	2.09	0.31	2.40
Electronics	0.82	0.35	1.17
Wagner[a]			
Durables	1.15	1.47	2.62
Nondurables	1.14	1.03	2.17
Pakes-Griliches[a]			
All Manufacturing	1.16	n.a.	n.a.
Pardey[b]			
Agriculture			
(i)Quality Adjusted	3.36	n.a.	n.a.
(ii)Quality Unadjusted	2.83	n.a.	n.a.

(a) From Pakes and Schankerman (1978) calculated from data contained in Rapoport (1971) and Wagner (1968).

(b) Represents an average of the 'mean' lags from the specifications presented in Table (4.6) and Table(3), Appendix III, minus 6 months, an approximation of the average publication lag from project completion to publication.

stable lag distribution. To examine briefly the possibility that the lag structure was unstable over time we ran independent OLS regressions on the six cross-sections corresponding to each of the separate years of the study period. The results of this exercise for both the PRONET and PROPUB dependent variables are presented in Table (4.8).

For the quality unadjusted (PROPUB) case the long run expenditure elasticity is virtually invariant over time. The mean lag estimate does decline to a minimum in 1973 and then shows a quite rapid increase for the last two years in the sample. Using the conceptually more appealing PRONET dependent variable, both the elasticity and mean lag figures exhibit no systematic trend. Only the 1971 elasticity estimate indicates any marked divergence from the remaining figures but its relatively high standard error suggests this divergence is of little practical significance.

Taken as a whole, it would seem from the evidence presented in Table (4.8) that the research expenditure lag was reasonably stable over the six years 1970-75[14]. Of course temporal instability of this lag relationship may well be an issue for longer panel data sets.

4.5 Summary:

These initial results on the agricultural research expenditure-research output relationship are quite encouraging. Although they convey relatively little information about the precise shape of the lag distribution we have been able to obtain a significant, and apparently intertemporally stable, relationship between lagged research expenditures and weighted publication output, even after

Table (4.8) OLS Estimates of Quality Adjusted and Unadjusted Knowledge Production Function for Various Years.[a]

	Years						
	1970	1971	1972	1973	1974	1975	1970-1975[b]
Dependent Variable: PRONET							
ΣR_i	1.3379 (0.0535)	2.0447 (0.3611)	1.6489 (0.2387)	1.4416 (0.1986)	1.4177 (0.1787)	1.6223 (0.1935)	1.5567 (0.0896)
'Mean' Lag	3.99	4.34	3.80	4.14	4.23	4.14	3.76
R^2	.6812	.4940	.6185	.6339	.6660	.6453	.5315
Dependent Variable: PROPUB							
ΣR_i	1.1644 (0.0359)	1.2527 (0.1261)	1.1909 (0.1108)	1.1390 (0.1175)	1.1241 (0.0988)	1.1428 (0.0311)	1.1659
'Mean' Lag	4.94	4.03	3.69	3.12	3.91	4.08	3.23
R^2	.7547	.7592	.7622	.7763	.7849	.7754	.7480

(a) Figures in parentheses are the standard errors of the sum.

(b) Trend variable included.

controlling for unspecified state specific effects. Summary measures such as the 'mean' gestation lag and long run expenditure response were used to characterize this relationship. These measures were informative and plausible in the light of comparative studies in the private, non-agricultural research sector. The empirical implications of using raw versus quality adjusted publication output variables were also explored and found to be of significance.

The relationship between research expenditures and research output within states over time appeared quite tenuous, whereby short term fluctuations in research expenditures showed little systematic influence on research output. The on-average or longer run differences in research expenditures between the states does appear to influence research performance in a fairly systematic manner.

The summary measures do suggest that a significant lag between research inputs and outputs exist although Hall et. al (1984), summarizing extensive empirical work on the patent-R&D relationship for the private sector, highlight the substantial difficulties which exist in trying to pin down this relationship. Key issues involve possible simultaneity between patent output and R&D expenditures, lag truncation biases due to the relationship between pre and in-sample R&D expenditures, and a lack of independence between unspecified state-specific effects and in-sample R&D expenditures.

In the present study we tested formally for the failure of this independence assumption and got results which suggest that unspecified state effects were not correlated with in-sample research expenditures. Nevertheless in both the PROPUB and PRONET models these unspecified state effects appeared to account for significant differences in the research performance of the SAES, even after controlling for differences in research spending. The next chapter explores the nature of these differences in relative research efficiencies in some depth.

FOOTNOTES CHAPTER 4

1. These averages are in line with those obtained for other studies. Shaw (1967) recorded a mean publication per year count of 1.68 based on the complete publication records of approximately 3,000 scientists in ARS-USDA through to January 1965. Limiting the count to peer reviewed articles (as does this study) Salisbury (1980, Table 9) obtained an annual publication output, averaged across all Illinois SAES scientists for the 1948-78 period, of 1.08.

2. The specification search used only current capital and labor figures to conserve degrees of freedom. Including current plus seven year lagged expenditures with multiplicative dummies etc. would have involved a total of 149 regressors.

3. Experimentation with other size groupings did not change the results in any substantive manner.

4. It is still possible that a size effect may be captured in the state specific effects.

5. This procedure is similar to Glejser's (1969) test for heteroskedasticity.

6. See Table (6) Appendix II for more complete statistics on the research 'labor'-capital ratio of the SAES grouped according to station size.

7. These figures dropped even further to range from 0.06 to 0.47 after partialling out time.

8. Their sample included 38 firms in the chemical drugs and medicine industry, 13 in machinery, 10 in office computing and accounting machinery, 8 in electronics components and communication, 11 in professional and scientific instruments and 41 in other manufacturing.

9. To the extent that capital purchases (or service flows) are positively correlated with labor expenses, their omission acts to bias upward the estimated production elasticity on research labor.

10. In fact $\hat{M}(\hat{q}) = 1/T \; V(\hat{q})$

11. In an extended discussion on the veracity of within estimates Mairesse (1978) cites this collinearity problem, along with the fact that within deviations are not generally large and may be severely affected by measurement error, as good reasons for resorting to the between estimates.

12. The coefficient on the (Griliches-type) research and extension variable in Davis' study was very sensitive to the size of the observation set employed. For instance, using a 1974 cross section, the research and extension coefficient switched from 0.0013 using all 48 states to -0.02 using the 39 states in his reduced data set.

13. Pakes and Schankerman (1978) show that increases in the mean gestation lag lowers the (private) internal rate of return to research, although the rates of return seem more sensitive to variations in the rate of decay of appropriable revenues than variations in the mean gestation lag.

14. It is possible to formally test the assumption of intertemporally stable β's in a fairly straightforward manner by including multiplicative time dummies into the regression. However to do so in this particular case would involve a prohibitively large number of regressors.

Chapter 5

ACCOUNTING FOR DIFFERENCES IN SAES RESEARCH EFFICIENCIES

5.1 Introduction:

From the evidence presented in the previous chapter it is clear that systematic cross-sectional differences in research productivity exist. State effects were consistently significant across a range of raw and quality adjusted research output indicators. In this chapter we begin with a discussion of the likely causes of these differences. Our attempts to construct various empirical proxies of the 'conceptual' variables thereby identified will also be presented. The chapter will conclude with a presentation of some empirical results.

5.2 Sources of Research Efficiency:

Some of the likely explanators follow naturally from the characterization of the research process as a production activity. Others arise from the nature of the production unit under study, namely the SAES, and in particular the relationship between the research and teaching functions of these institutions. A final set arises from the nature of the research activity itself - that is mission-orientated public sector agricultural research.

The existing evidence on this topic is fragmentary, impressionistic and generally not subjected to empirical testing. An early study by Scherer (1965), using raw patent counts per firm as a measure of inventive output, found that output increases (less than proportionately) with firm sales and does not appear to be systematically related to variations in market power, prior profitability, liquidity or degree of product-line diversification. Using a pooled data set he also observed that interindustry differences account for almost the same amount of variance in overall patenting levels as interfirm variations in sales volume. He did no more than to speculate that these interindustry factors reflect 'dynamic supply conditions' dependent in turn upon the broad advance of scientific and technological knowledge.

In a 1968 study Evenson used variables other than state level research expenditures to account for productivity differences between experiment stations. Here productivity referred to the induced change in agriculture output per dollar's worth of research and extension effort. His results supported hypotheses that 'station productivity' was positively related to university or college graduate program size, number of researchers, and researcher salary levels. He found no support for the hypothesis that productivity is related to the ratio of faculty holding Ph.D to total faculty[1].

Unfortunately the issues discussed in Chapter (1) concerning the augmented production function model limits the accuracy of Evenson's inferences. Simultaneity problems between final agricultural output and this set of regressors may well exist. Moreover, given the reduced form nature of the augmented production function, it is not possible using these results to infer anything about the research process per se. While the Scherer study comes closer to achieving this objective it focuses on non-agricultural research in the private sector.

(i) Economies of Scale and Scope:

There has been a good deal of discussion, but little hard evidence on the existence of scale economies in the research process. Summarizing the empirical literature on the innovation production function Kamien and Schwartz (1982, p.66) state "the scant evidence that exists indicates no economies of scale in the innovation process. Indeed, constant or even diminishing returns appear to be the more likely characteristic of the innovation production function." The usual approach to investigate (static) scale economies in a direct production function is to formally test its homogeneity properties. A less rigorous method of testing for 'size effects' is to assume the impact multipliers (between research expenditures and research output) remain unchanged over various size categories and include additive (i.e. intercept) size dummies in the estimated equation. This will be the approach used here.

Another structural characteristic of the SAES which may affect measured differences in research efficiency relates to costs savings (or output enhancements) from the scope rather than scale of the SAES. The recent economics literature[2] asserts that positive economies of scope exist when a single firm can produce a given level of output of each product line more cheaply than a combination of separate, single product firms. Economies of scope arise from inputs which are shared either in part or completely. Examples include imperfectly divisible inputs whose excess capacity in the production of one or more outputs can be committed to additional product lines, inputs which have some properties of a public good so that their purchase for one production process makes them freely available to others or intangible assets which can be shared across various production lines.

It seems reasonable to suggest that the knowledge output of a

SAES varies (in a more-or-less continuous manner) with respect to certain attributes or qualities. For instance, if two stations had the same aggregate publication count over the course of a year their effective output and costs could be quite different if one station concentrated on agronomic and the other on animal science pursuits. By viewing the stations as essentially 'multi-product firms' it is clear that a large category of inputs contribute jointly or are shared across various 'product lines' or research disciplines within a station. For example, imperfectly divisible inputs such as central administration, computing facilities, and station land, buildings and equipment contribute jointly to the research effort across various disciplines. There is also the possibility of significant human capital spillovers between the various disciplines within a station. It is possible that the spillover effect is more significant between some disciplines than others. For instance, human capital resources may be more readily shared within the animal and plant science disciplines than across researchers working in these separate fields.

Several empirical measures will attempt to capture the effect of scope economies on the relative research efficiencies of the SAES. If economies of scope extend more-or-less equally across research disciplines then, ceteris paribus, a station which limits its research endeavors will appear less efficient than one which spreads its resources amongst a larger set of disciplines. A measure of concentration similar to a Herfindahl Index will be used to capture this effect. We would anticipate the more concentrated stations to exhibit lower levels of research efficiency. However the degree of scope economies may not extend equally across all the research disciplines. If spillovers within the plant and animal science disciplines dominate the between effect then a measure of the proportion of plant or animal scientists per total number of researchers is likely to be positively related to research efficiency.

The degree to which states fragment their research systems by the operation of numerous sub-stations is likely to decrease the discipline specific scale effects. It will also limit the extent to which research resources (both physical and human) can be shared amongst different research lines. Thus both scale and scope considerations are likely to diminish the research efficiency of a fragmented state system[3]. The proportion of state research centers per total number of researchers will be used to measure this effect.

(ii) Research Externalities:

Numerous production function studies have determined the extent by which out-of-state (or region) research expenditures have influenced in-state agricultural output. The results of these exercises have been mixed[4] but were meant to capture the spillover effects resulting from public sector agricultural research. Analogous spillovers are assumed to occur between different industries in the non-agricultural sector (see Griliches (1979) and Jaffe (1984)). However, in contrast to industrial sector research, applied agricultural research exhibits a degree of geo-climatic specificity. This limits the extent to which the results of agricultural research in one region are applicable or freely available to other geo-climatic regions. One perspective which follows from this is that the knowledge output of the SAES takes on the characteristics of a local public good[5].

However, the notion that this knowledge is freely available to agents within a particular geo-climatic boundary and excludable from agents outside this region is somewhat extreme. A more appropriate view is that agricultural research output is generally transferred between (and within) geo-climatic regions at some non-zero cost with the cost of transfer increasing as the 'geo-climatic distance' between the knowledge source and its recipient increases (See Englander (1980)). These costs are incurred not only by private firms and experiment stations in the recipient region undertaking screening and adaptive research, but by potential adopters who incur search and evaluation costs which are also a positive function of their 'geo-climatic distance' from the research source (See Lindner, Pardey and Jarrett (1982))[6].

Clearly then, interstate or interregional effects estimated using augmented production functions reflect in part the unmeasured influence of this search and screening activity in the recipient locale. Moreover, to the extent that true (i.e. unpriced) externalities are also captured, it is impossible to disentangle the producer to producer and producer to consumer effects. Here producer to producer externalities are the unpriced effect of one station's research output on another whilst producer to consumer effects reflect the unpriced impact of knowledge generated by one state system on other out-of-state agents who directly use this information in their own production activities.

The advantage of this study is our ability to zero in on producer to producer (i.e. station to station) externalities. A convenient measure of the degree to which one station borrows the research output of others is the rate at which source publications from recipient stations cite out-of-state articles. Unfortunately it was beyond our resources to construct such an index. Our alternative was to develop a metric of the 'technological distance' between stations. The measure is based on the notion that the degree of overlap and hence potential spillovers between the SAES is reflected in the congruence of the discipline mix of the research personnel employed at the various stations. Thus a particular SAES system is technologically closer (i.e. has a more closely aligned research interest) to another SAES system which employs a similar mix of plant and animal scientists than it is to a station which employs (say) only plant scientists.

Two distance measures were constructed. The proportion of researchers in each of sixteen disciplines[7] was first used to calculate the Euclidian distance between each station and a representative or average national station. This proxies the degree to which each station can borrow from the national pool of publicly produced agricultural knowledge. It should be negatively related to the research efficiencies of the stations.

A second measure is the Euclidian distance between each station and a representative or average regional station. Although it is reasonable to expect some geo-climatic specificity to much agricultural research it seems likely that the boundaries of common research interests are more diffuse than a simple geo-climatic measure implies. The passage in 1946 of the Research and Marketing Act provided an institutional mechanism for cooperative interstate research. The four regional associations (north east, north central, south and west) formed by this act use allocations from the Regional Research Fund to perform joint research in areas of common interest to every state in the region. It represents an appropriate basis on which to group state systems and measure possible intra-regional spillovers at the research level. Once again we anticipate the regional distance metric to be inversely related to state level research efficiencies.

(iii) Research-Teaching Interactions:

Over the 1965-75 period the proportion of SAES researchers with teaching commitments has averaged around 66 percent; ranging across stations from a low of 34 to a high of 92 percent. With such a high level of researchers involved directly in the teaching programs of the Land Grant College System it is natural to expect that the relative research efficiency of the stations is affected by these teaching commitments.

We attempt to capture several dimensions of these research-teaching interactions in this study. We hypothesize that increased undergraduate teaching loads are detrimental to current research activity. The academic rigor of undergraduate courses is generally too far removed from the cutting edge of research to effectively contribute to a scientist's research endeavors. Higher undergraduate teaching loads also entail increased administrative duties which further distract from research undertakings. For the period under study (1963-75) an average four-fold increase in undergraduate teaching loads probably means that the scientific resources of the SAES are to some degree subsidizing the teaching mission of the land grant colleges[8].

In contrast we hypothesize, like Evenson (1968), that research efficiency is positively related to graduate (Ph.D and Masters) teaching commitments. The fact that around 88 percent of the publications canvassed in this study were coauthored indicates that an overwhelming amount of SAES research is carried out on a joint or group basis. Casual empiricism suggests that graduate student participation in these joint investigations is high.

(iv) Other Structural Characteristics:

There is a miscellaneous set of other variables likely to influence the research efficiency of the SAES. Lucas (1967) and more recently Prescott and Visscher (1980) have argued that the unit cost of adjustment for a firm is an increasing function of the rate of adjustment. In the context of the SAES, higher adjustment costs may result from the additional costs of organization required to integrate incoming research personnel into an existing (longer run) research program. It generally takes some time for new personnel to 'learn the ropes'. This learning process is costly to the extent that existing research resources are 'withdrawn' from production and committed to intergrating entry level personnel into the research activities of the SAES. Furthermore, newly installed buildings and equipment usually require a shakedown period before they reach their productive potential. With this in mind we included a variable measuring the arithmetic growth in scientific personnel from 1965 to 1975. Across all experiment stations this figure averaged 14.8 percent but varied markedly from station to station. Texas for instance recorded an overall growth for this period of 73.0 percent. The adjustment cost argument suggests that research efficiency would be negatively related to the growth rate of scientific personnel.

However, other effects are also captured by this growth rate variable. To the extent that the expansion of the SAES scientific workforce occurred through an influx of younger, pretenured faculty we would anticipate the average productivity of station research personnel to increase. The incentive structure in SAES with respect to salary levels and attainment of tenure is likely to induce a higher than average level of research productivity (at least as indexed by publication rates) from such faculty. These influences would suggest a positive correlation between the growth rate of scientific personnel and research efficiency. Thus the observed relationship is left as an open empirical question.

5.3 Data Sources and Variable Construction:

SAES size dummies were calculated on the basis of the 1970/71-1974/75 average number of station personnel engaged full or part-time in research presented in Table (1), Appendix (2). Three size categories, small, medium and large, were identified and the two included dummy variables were normalized on the medium category. Small stations, those with less than 100 researchers, include Delaware, Nevada, New Hampshire, New Mexico, Rhode Island, Vermont, West Virginia and Wyoming. Large stations, those with greater than 500 researchers, are California, Colorado, Michigan, New York and Texas.

The index of concentration used to capture scope effects is defined as

$$CONC_j = \sum_{j=1}^{N} S_{ij}^2$$

where S_i is the proportion of researchers in the ith discipline[9] and N is the total number of disciplines in the jth state. It attains a maximum value of one when the station has a single discipline. The value declines with increases in the number of disciplines and with falling inequality among any given number of disciplines. For our data it averages .166 and ranges from a low of .092 to a high of .328.

The scale and scope effects of fragmenting state systems are captured by PCEN, the number of research centers per total number of researchers. The number of research centers (including main station) per state was taken from the 1972/73 USDA "Professional Workers in State Agricultural Experiment Stations and Other Cooperating State Institutions." It averaged 7.8 centers per state and ranged from 1 to 36. The number of researchers per state was the 1965-70-75 average number of workers engaged full or part-time in research taken from the appropriate issues of USDA "Funds for Research at State Agricultural Experiment Stations and Other State Institutions".

Regional and National technological distance indices were defined as

$$(R \text{ or } N)DIS_j = \left(\sum_{i=1}^{17} (p_{ij} - \bar{P}_i)^2\right)^{1/2}$$

where p_{ij} is the (1970/71-1974/75 average) proportion of researchers from station j in the ith discipline and $\ddot{P}_i$ is either the regional (R) or National (N) average proportion of researchers in the ith discipline[10]. To give a quantitative dimension to this measure the figures in Table (5.1) show the technological distance between representative regional stations and a national average station. As we would suspect the north central region lies closest to the national average whilst the north eastern region, including the six New England states plus West Virginia, Pennsylvania, New York, Massachusetts, New Jersey and Maryland, is technologically distant from the national research agenda of the SAES. The southern and western regions are bounded by these two polar cases.

Table (5.1) Average Technological Distance of Regions from a National Mean

Region	Average RDIS
North-Central	5.270
North-East	7.022
Southern	6.882
Western	6.216

Graduate program size is proxied by the average proportion of agricultural graduate degrees earned per total number of researchers (PAG). Graduate (Ph.D and Masters) degrees earned in agricultural and forestry disciplines associated with the experiment station were taken from various issues of U.S. Dept. of H.E.W. "Earned Degrees

Conferred". The figure used here is a three year (1964/65, 1969/70 and 1973/74) average. A similar figure was constructed measuring agricultural bachelors degrees earned per total number of researchers (PAB). The summary statistics presented in Table (5.2) show there were 0.44 and 1.32 graduate and undergraduate degrees conferred per researcher per year. These same figures were used to calculate the arithmetic growth rate in total graduate (GTLGR) and undergraduate (BTLGR) teaching loads over the 1965-74 period.

From unpublished information obtained from USDA's Current Research Information System (CRIS) data base we were able to divide total person years per station for the fiscal years 1967, 1970 and 1975 into four categories; scientific (assistant professor and above), professional support, technical support and clerical labor and other. These figures were used to construct various scientific support ratios (PTS, PPS).

The CRIS data base was also used to obtain estimates of SAES expenditures on administrative services for the fiscal years 1967, 1970 and 1975. We had planned to construct a ratio of administrative to total SAES expenditures to proxy the degree of administrative support (or burden!) per station. Unfortunately the administrative expenditure data suffered from too many omissions and inconsistencies to allow a reliable estimate of this proxy to be calculated.

Descriptive statistics for all these variables are presented for convenience in Table (5.2).

Table (5.2) Descriptive Statistics for Explanators of Interstate Variation in Relative Research Efficiency[a]

Variables	Symbol	Unit	Mean	St. Dev.	Minimum Maximum
Dummy variable coefficients from pronet ANCOVA estimates	DPN	—	0.8110	0.7546	-0.9635 2.5519
Dummy variable coefficients from propub ANCOVA estimates	DPP	—	0.0965	1.4086	-3.0052 3.1977
Number of agricultural graduate degrees earned per total number of researchers	PAG	Ph.D. and masters degrees per researcher	0.4350	0.1674	0.2011 1.1221
Number of non-agricultural graduate degrees earned per total number of researchers	PNAG	—	5.023	3.71	1.312 21.79
Number of agricultural bachelors degrees earned per total number of researchers	PAB	Bachelors degrees per researcher	1.3178	0.5561	0.5173 2.9731
Technological distance from a regional representative station	RDIS	—	211.92	78.611	88.0 408.0
Technological distance from a national representative station	NDIS	—	216.71	76.863	112.0 425.0
Number of research centers per total number of researchers	PCEN	Centers per researcher	0.0397	0.0277	0.0033 0.1094
Total (graduate and undergraduate) teaching load growth rate	TLGR	x 100	356.68	334.78	-1.125 1673.8
Bachelors teaching load growth rate	BTLGR	x 100	407.95	339.03	6.807 2110.9
Graduate teaching load growth rate	GTLGR	x 100	284.53	248.01	-18.510 1444.7
Index of concentration of researchers by discipline	CONC	x 1000	166.0	52.18	93.0 328.0
Proportion of researchers in the plant sciences	PPLA	x 100	51.77	12.003	20.10 78.00
Proportion of researchers in the animal sciences	PAN	x 100	29.896	8.60	11.90 49.20
Proportion of SMY's to total support staff man years	PTS	—	0.530	0.322	0.250 2.116
Proportion of SMY's to professional support staff man years	PPS	—	0.820	0.373	0.337 2.236
Growth rate of scientific personnel	SGR	x 100	14.82	24.32	-24.07 73.01

(a) Data sources are described in text. Figures include all 48 states.

5.4 Empirical Results:

To investigate the structural or institutional sources of interstate differences in relative research efficiency we regressed the set of variables described above on the state intercept coefficients obtained from the analysis of covariance estimates. Final form equations using state intercepts from both the PRONET and PROPUB models are given by

$$\text{State Intercept}_{PRONET} = \underset{(0.3437)^{*}}{1.0486} + \underset{(0.4582)^{*}}{1.7248}\ PAG - \underset{(0.0011)^{*}}{0.0032}\ RDIS$$

$$-\underset{(2.8862)^{*}}{8.5248}\ PCEN + \underset{(0.0033)^{**}}{0.0061}\ SGR - \underset{(0.1831)^{*}}{0.4853}\ DPL1 + \underset{(0.2610)^{+}}{0.4211}\ DPL2 \qquad (5.1)$$

$$\bar{R}^2 = .5469 \qquad \hat{F} = 10.456$$

$$\text{State Intercept}_{PROPUB} = \underset{(0.5717)^{*}}{2.2428} + \underset{(0.7702)}{1.7341}\ PAG - \underset{(0.0019)^{*}}{0.0145}\ RDIS$$

$$-\ \underset{(4.8513)}{3.5106}\ PCEN + \underset{(0.0056)}{0.0049}\ SGR + \underset{(0.3077)^{+}}{0.5108}\ DPL1 + \underset{(0.4387)^{**}}{0.8815}\ DPL2 \qquad (5.2)$$

$$\bar{R}^2 = .6326 \qquad \hat{F} = 14.490$$

(Standard errors given in brackets. * significant at the 1 percent level; ** significant at the 5 percent level; + significant at the 10 percent level; Both regressions include all 48 states)

All the variables in equation (5.1) achieved reasonable levels of statistical significance and jointly differ from nullity at the 1 percent level of significance. Around 55 percent of the variation in relative research efficiency is accounted for by the model. As expected the PAG variable, measuring the size of the agricultural graduate program, is positively related to interstate differences in research efficiencies. Both technological distance at the regional level (RDIS) and the degree of institutional fragmentation captured by the PCEN variable are, as predicted, negatively related to research efficiencies. The scientific growth rate variable (SGR) is positively related to research efficiency and suggests that age, tenure, and human capital effects dominate the adjustment cost influences which are jointly captured by the variable.

The piecewise linear representation of the plant to total scientist ratio is negatively related to research efficiency for the DPL1 (> 60.0 percent) category. This suggests that diseconomies of 'scale' and scope become a factor in the higher plant to total scientist ratio range. However, we should caution that this variable may also be acting as a control type variable to the extent that it captures possible differences in the publishing traditions of the plant versus animal science disciplines.

Other variables were tried but omitted from the reported results due to a lack of statistical significance. In particular, coefficients on both the small (< 100 researchers) and large (> 500 researchers) size dummies were statistically indistinguishable from zero. This suggests that the SAES are scale neutral with respect to their relative research efficiency. A multiplicative interaction variable between the size dummies and the RDIS variable showed there was no statistically significant enhancement of the spillin effect as station size increased.

The size of the undergraduate agricultural program (PAB) was, as expected, negatively related to research efficiency but failed to achieve statistical significance. Both the undergraduate and graduate teaching load growth rate variables as well as a variable (PNAG) proxying, inter alia, the intra-university borrowing of knowledge by SAES researchers were statistically insignificant. Both researcher support variables (PTS and PPS) were positively related to research efficiency but at lower than acceptable levels of significance.

Finally the variable measuring technological distance from a national representative station (NDIS) was negatively related to research efficiency, as hypothesized, but statistically insignificant. It appears that the site specificity characteristics of agricultural research, in conjunction with the formal inter-station research linkages which are implicitly captured by the RDIS but not the NDIS variable, are important determinants of SAES research efficiency.

For comparative purposes the results using state intercepts from the PROPUB model are presented in equation (5.2). All variables other than DPL1 retain their signs but the PCEN and SGR coefficients are no longer statistically significant. Parenthetically it is worth noting that if small and large size dummies are also included as regressors they both achieve high levels of significance with smallness acting to reduce research efficiency and largeness acting to enhance it. It seems that this result stems principally from a failure to adjust for interstate quality differences in the research output proxy given the insignificance of size variables in the PRONET model. It throws some doubt on the results of previous research which indicates significant 'size effects' when using raw patent counts as a proxy for research output.

To investigate the source of research efficiency in the variance components framework we included the set of regressors identified in equation (5.1) directly into the GLS estimation procedure used in Table (4.6) and Table (3), Appendix III. The results of this exercise are reported in Table (5.3).

The coefficients on the state specific characteristics match the variance components estimates of both the PROPUB and PRONET models. When comparing the $\hat{\sigma}^2_\mu$ estimates from the GLS and augmented GLS regressions we observe a 55.8 and a 70.8 percent decline for the PRONET and PROPUB models respectively. This set of regressors clearly contributes to a substantial decline in the variance of the permanent state specific component.

The results in Table (5.4) help quantify the impact of institutional specific characteristics on research efficiency. The states were grouped into quartiles on the basis of these institutional characteristics and the upper and lower quartiles were compared. For this (44 state) sample the average ratio of graduate degrees conferred per full or part-time researcher (PAAS) was 0.44, which almost halved to 0.27 for the states in the smaller quartiles and increased to 0.66 for those in the largest quartile. Holding all other characteristics at their sample means we would expect a representative state with a low graduate to scientist ratio to produce only 80.6 percent the research output of a state with a large graduate program. Allowing the other characteristics to vary reduces the relative research efficiency of those states with small graduate programs to 78.8 percent.

The relative research efficiencies of quartiles grouped by the regional technological distance metric and the scientific growth rate

Table (5.3) Auxillary Regressions on Citation Adjusted Publication Counts Including Institutional Regressors

	Dependent Variable			
	PRONET[a]		PROPUB[b]	
Variable	OLS	EGLS	OLS	EGLS
Intercept	-3.9611* (1.4988)	-3.6556+ (2.6133)	-0.4952 (0.7588)	1.3059 (1.3759)
ΣB_r	1.1595	1.1365	0.9564	0.8436
PAG	1.5330* (0.2655)	1.5992* (0.4701)	0.9089* (0.1370)	0.9998* (0.2519)
RDIS	-0.0020* (0.0010)	-0.0021 (0.0017)	-0.0022* (0.0005)	-0.0030* (0.0009)
PCEN	-8.5360* (1.7161)	-8.7316* (3.0762)	-5.8379* (0.8323)	-5.8962* (1.5585)
SGR	0.0085* (0.0021)	0.0077** (0.0036)	0.0067* (0.0011)	0.0059* (0.0019)
DPL1	-0.5720* (0.1010)	-0.5750* (0.1989)	-0.1648* (0.0552)	-0.1264 (0.1041)
DPL2	0.2724** (0.1579)	0.2850 (0.2853)	0.5073* (0.0747)	0.5343* (0.1412)
$\bar{R}^2$	.6996	.4085	.8690	.6384
$\hat{\sigma}_t^2$	—	1.4901	—	0.3952
$\hat{\sigma}_\mu^2$	—	0.2044	—	0.0559

(a) Regression omits 4 'outlier' states - Delaware, Maine, Nevada, New Mexico - and a trend variable.

(b) Includes all 48 SAES.

Standard errors in paretheses.
* Significant at the 1 percent level.
** Significant at the 5 percent level.
+ Significant at the 10 percent level.

Table (5.4) SAES Characteristics and Research Efficiency Differences

Variable		Mean value of group characteristics					
		PAG	RDIS	SGR	PCEN	I	II
PAG	highest quartile	0.660	210.18	4.626	0.027		
	lowest quartile	0.271	196.36	25.50	0.035	80.6%	78.8%
RDIS	closest quartile	0.438	119.82	13.42	0.036		
	farthest quartile	0.418	297.00	8.926	0.036	82.4%	80.9%
SGR	highest quartile	0.445	192.82	47.68	0.038		
	smallest quartile	0.485	225.73	-13.69	0.037	81.9%	83.1%
PCEN	lowest quartile	0.465	198.28	11.07	0.010		
	highest quartile	0.376	213.46	19.83	0.074	74.1%	68.3%
EFFIC[a]	most efficient quartile	0.558	172.80	24.80	0.028		
	least efficient quartile	0.360	236.18	9.823	0.054		44.5%[b]
Average		0.443	202.16	14.41	0.037		

Column I is the 'predicted' output of the less efficient quartile relative to the more efficient quartile due only to the distinguishing characteristic. Column II is relative output levels allowing all the characteristics to vary. I and II figures based on EGLS estimates from PRONET model Table (5.3).

(a) Efficiency as determined by analysis of covariance.

(b) Total efficiency, not just difference attributable to state specific characteristics.

variable are of similar orders of magnitude. For stations grouped according to PCEN, the number of research centers per total number of researchers, a representative state in the lower quartile is expected to produce 74.1 percent of the output of an otherwise identical state in the higher quartile. This drops to 68.3 percent if all other characteristics are allowed to vary. Finally, states with the least efficient configuration of institutional characteristics produce only 44.5 percent of the research output of those in the most efficient quartile.

5.5 Some Concluding Comments:

These results represent a systematic attempt to empirically identify some key institutional variables which account for differences in the relative research efficiency of the SAES. Using quality adjusted publication counts as a metric of research output minimizes the simultaneity and identification problems which are implicit in the few prior efforts in this area. From the discussion in chapter (3) we recall that the state effects variable captures cross-sectional differences in both research efficiency and the propensity to publish. It is the maintained hypothesis of the present discussion that researchers effectively operate in a national market so that state level differences in publication incentives have little measurable influence on the propensity to publish. On this basis we argue that the significant institutional variables identified in this chapter account for interstate differences in research efficiency, undistorted by cross-sectional differences in the propensity to publish.

Of course the notion of research efficiency used here relates to the relative technical efficiency with which SAES produce new agricultural knowledge. We have not necessarily assumed any form of cost minimizing behavior on the part of station directors and/or researchers although this has been assumed in other studies of SAES activity[11]. The issue of 'economic' efficiency has not been confronted here. Economic efficiency in this context involves maximizing the economic benefits derived from a given level of research expenditures. Conceivably we could expand the model to link final agriculture output to conventional input variables and a research output variable as proxied by quality adjusted publication counts. To successfully estimate such a model would require a much longer publication output series than was available from this study. Nevertheless the production efficiency with which knowledge increments are translated into final agricultural output could be isolated from the research efficiency component identified here.

The relationship between production and research efficiency is not immediately obvious. Conceptually, technical efficiency is determined by structural variables essentially internal to the SAES. Relative production efficiency on the other hand is a function of variables related to the diffusion and obsolesence of knowledge. At an empirical level the use of quality adjusted publication counts to measure knowledge output can introduce 'proxy bias' into the measured efficiency levels. For example, the notion of quality used in this study relates more directly to the scientific rather than 'economic quality' of research output. Thus if citation counts systematically overstate the 'economic quality' of research output, then measured levels of technical efficiency would be biased upward, whilst production efficiency would be biased downward.

Finally we simply note that in this exploratory study research efficiency is measured by deviations around an average research production relation. An alternative approach would be to estimate a frontier production relation using a one-sided distributed state specific error component. These non-positive deviations measuring state specific technical inefficiencies would reflect the notion that research output must lie on or below its frontier.

FOOTNOTES CHAPTER 5

1. Evenson also reported these results in Fishel (1971) in a chapter titled, "Economic Aspects of the Organization of Agricultural Research."

2. See for example Panzar and Willig (1977), Spady and Friedlaender (1978), and Bailey and Friedlaender (1982).

3. It should be stressed that this statement relates only to the efficiency with which research expenditures are transformed into research output. It is conceivable that a state system may become 'over-centralized' with respect to its impact on final agricultural output. Strategically located sub-stations may lower search and evaluation costs on the part of potential adopters and so stimulate the diffusion of new knowledge produced by the SAES. It may also lower the costs of transmitting information back to researchers concerning actual and potential production problems and so enhance the ability of state systems to select an optimal portfolio of research topics.

4. See for example Evenson (1978), Davis (1979), Norton (1981), and White and Havlicek (1981).

5. In fact this knowledge output is more appropriately characterized as a public input rather than output. A discussion of this issue can be found in Sandmo (1972) and Hillman (1978).

6. This point underscores a major deficiency in the existing production function literature. They assume a separability between in-state and out-of-state research expenditures which may not be applicable.

7. Includes the 14 disciplines listed in Table (3.1) plus social scientists and agricultural engineers.

8. It is also interesting to note that the proportion of full-time to total researchers in the SAES system has declined from around 50 percent in 1938, to 41 percent in 1960 and then sharply down to 27 percent in 1975.

9. Measured as the 1970/71-1974/75 state-level average. National totals by discipline for these years are given in Table (3.1).

10. The regional groupings were determined from the state associations formed through the Regional Research Fund program. See the 1982 OTA study, Part B, Commissioned Paper I for details.

11. See for example Huffman and Miranowski (1981).

Chapter 6

SUMMARY

Economic analysis of the process of technical change generally involves 'macro-level' studies of its causes and consequences. Little attention has been given to the more fundamental knowledge generation process itself. This stems in large part from the real difficulties of obtaining appropriate indicators of research output.

The first objective of this study was to construct measures of the new knowledge produced by agricultural researchers in the public sector. Both raw and quality adjusted indices were developed for the contiguous 48 State Agricultural Experiment Stations (SAES) for the 6 years, 1970-75. Scientific publication counts (16,050 in all) measured the total knowledge increment per SAES per year. This was the most complete measure of knowledge output available given the incentive mechanisms and institutional structure of the SAES. The subsequent citation performance of these publications was used to adjust for variations in scientific quality.

To obtain a reasonably accurate measure of the real resources committed annually to SAES research, it was necessary to reconstruct both the research spending series and their associated deflators. Expenditures were split into capital (land, buildings and equipment) and 'labor' categories. Improving on previous work, they were measured in equivalent service flow terms for the period 1963-75. The quantitative impact of these revisions is quite substantial.

The attempt to estimate something like a knowledge production function for agricultural research was most encouraging. Raw and quality adjusted publication counts were significantly related to a series of current and (7 year) lagged research expenditures. For our data at least, the research input-output relationship within states over time appears quite tenuous. This suggests that short term increases or decreases in research spending have little systematic influence on measurable research output. The on-average or longer run differences in research expenditures between the states does appear to influence research performance in a fairly systematic manner.

Although the lag relationship between research inputs and outputs appears stable for the period covered here, the precise nature of the research lag is difficult to determine. Nevertheless, relatively accurate summary measures were obtained and suggest a 'mean' gestation lag of around 3.36 years using quality adjusted publication output and 2.83 years for the unadjusted measure. The long run elasticity of quality adjusted publication output to research spending is around 1.6 and about 25 percent lower for the raw publication indices.

Contrary to results for the private sector, the relative efficiency with which SAES produce new agricultural knowledge does not appear to be significantly related to the level of research spending. A set of institutional variables was found to account for about 55 percent of the variation in research efficiency, after controlling for interstate differences in research spending. Agricultural research efficiency was positively related to the size of the graduate program and the growth rate in scientific personnel, but negatively related to the 'technological distance' of each station from a representative regional station and the degree of fragmentation (through substations) of each state system.

Going beyond these qualitative results, we measured the quantitative impact of these institutional characteristics. Ceteris paribus, states with the least efficient configuration of institutional characteristics produce only 44.5 percent of the research output of those with the most efficient configuration. Although research efficiency is not a sufficient condition for economic efficiency, these results do suggest that when allocating research resources, social planners should consider the institutional structure within which these resources are spent.

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Appendix I

In chapter 1 we describe how the total lag between research spending and growth in agricultural output represents the convolution of various sub-processes or sub-lags. The purpose of this note is to illustrate the sensitivity of the total lag to changes in these underlying processes. With no loss of generality assume the total lag can be characterized by two sub-processes; a net diffusion lag (which subsumes the obsolescence and depreciation lags described in chapter 1) linking $\dot{K}$ to Y, and a gestation lag linking R to $\dot{K}$.

To tighten the exposition somewhat we follow Feller (1968, pp.266f.) and consider X and Y, two non-negative, independently distributed random variables with probability distributions $P_j = P(X=j) = a_j$ and $P_k = P(Y=k) = b_k$. The event $(X=j, Y=k)$ then has the probability $a_j b_k$. Let the sum $S = X + Y$ be a new random variable where the event $S = s$ is the union of the mutually exclusive events

$$(X=0,\ Y=s),\ (X=1,\ Y=s-1), \ldots\ldots\ldots\ldots\ldots (X=s,\ Y=0).$$

Therefore the distribution $c_s = P(S=s)$ is given by

$$c_s = \sum_{j=0}^{s} a_j b_{s-j} \qquad \text{(I.1)}$$

and represents the convolution of the series a_j and b_k.

For our purposes it will be useful to consider the case, discussed in some detail by Solow (1960), where X and Y are both described by a Pascal distribution. The Pascal is a two parameter ($\lambda \subset (0,1)$, and $r \subset (o,\infty)$) distribution which can be written as

$$P_i(\lambda,r) = \binom{r+i-1}{i}(1-\lambda)^r\lambda^i \qquad (i = 0,\ 1,\ 2,\ldots\ldots)$$

Its mean is $r\lambda/(1-\lambda)$, variance $r\lambda/(1-\lambda)^2$ and mode the integral part of $(r\lambda-1)/(1-\lambda)$. The distribution is skewed to the right (the mode is always less than the mean) with larger λ and smaller r leading to greater skewness. For $r = 1$ the Pascal is simply a Geometric distribution and approaches a Poisson (of mean m) as $\lambda \to 0$ and $\lambda r \to m$. In addition if m is large the limiting form is a Gaussian.

We will exploit this flexibility, and the 'equivalence' between polynomials in the lag operators used in chapter 1 and the probability generating functions described by Griliches (1968), to illustrate how relatively minor changes in the two sub-lags (represented as changes in the parameters r and λ) result in substantial changes in the total or convoluted lag process.

The weights on the two (not necessarily identically distributed) independent random variables X and Y are given by

$$a_{i_a} = \binom{r_a+i_a-1}{i_a}(1-\lambda_a)^{r_a}\lambda_a^{i_a} \qquad (I.2a)$$

$$b_{i_b} = \binom{r_b+i_b-1}{i_b}(1-\lambda_b)^{r_b}\lambda_b^{i_b} \qquad (I.2b)$$

where $P(X=i_a) = a_{i_a}$ and $P(Y=i_b) = b_{i_b}$. Now let $S = X+Y$ such that $c_s = P(S=s)$ then,

$$c_s = \sum_{j=0}^{s} a_j b_{s-j}$$

$$= \sum_{j=0}^{s} \binom{r_a+j-1}{j} (1-\lambda_a)^{r_a} \lambda_a^{j} \binom{r_b+s-j-1}{s-j} (1-\lambda_b)^{r_b} \lambda_b^{s-j}$$

and letting $\lambda_a = \lambda_b = \lambda$ this simplifies, after some manipulation, to

$$= \lambda^{s} (1-\lambda)^{r_a+r_b} \binom{r_a+r_b+s-1}{s} \qquad (I.3)$$

which is Pascal $(\lambda,\ r_a+r_b)$.

Taking selected values of λ and r we can generate a variety of primary lag distributions, whose weights are given by (I.2 a and b), and some associated convolutions of these distibution, whose weights are given by (I.3). For values of λ = .6 and .8 and r = 1 and 2 we have sketched the resulting primary and convoluted distributions in Figures Ia and b. (Some Pascal distributions with other parametric values are presented in Solow (1960, p.395)).

Clearly the primary distributions are sensitive to the parametric values chosen, particularly when comparing distributions with r = 1 (a Geometric) and r ≠ 1 - although Solow shows that Geometric-like distributions are not limited to r = 1 specifications. Moreover, the convoluted distributions are most sensitive to relatively small changes in the underlying primary distributions. For instance, holding $\lambda_a = \lambda_b = .6$, $r_a = 1$ and changing the value of r_b from 1 to 2 causes the convoluted distribution to shift from K to L. A further change in r_a from 1 to 2 causes a shift in the convoluted distribution to M with its modal value again increasing. With $\lambda = .8$, the convoluted Pascal for $r_a = r_b = 2$ is given by distribution N.

Clearly these dramatic shifts in the convoluted distribution would yield substantial changes in the implied MIRR. It follows therfore that relatively loose priors concerning the primary distributions (in this case modelled as a spread in the parameters which define the underlying Pascal distributions) do not enable us to readily discriminate between competing, admiscible convoluted distributions.

Figure (I.1) Pascal Distributions

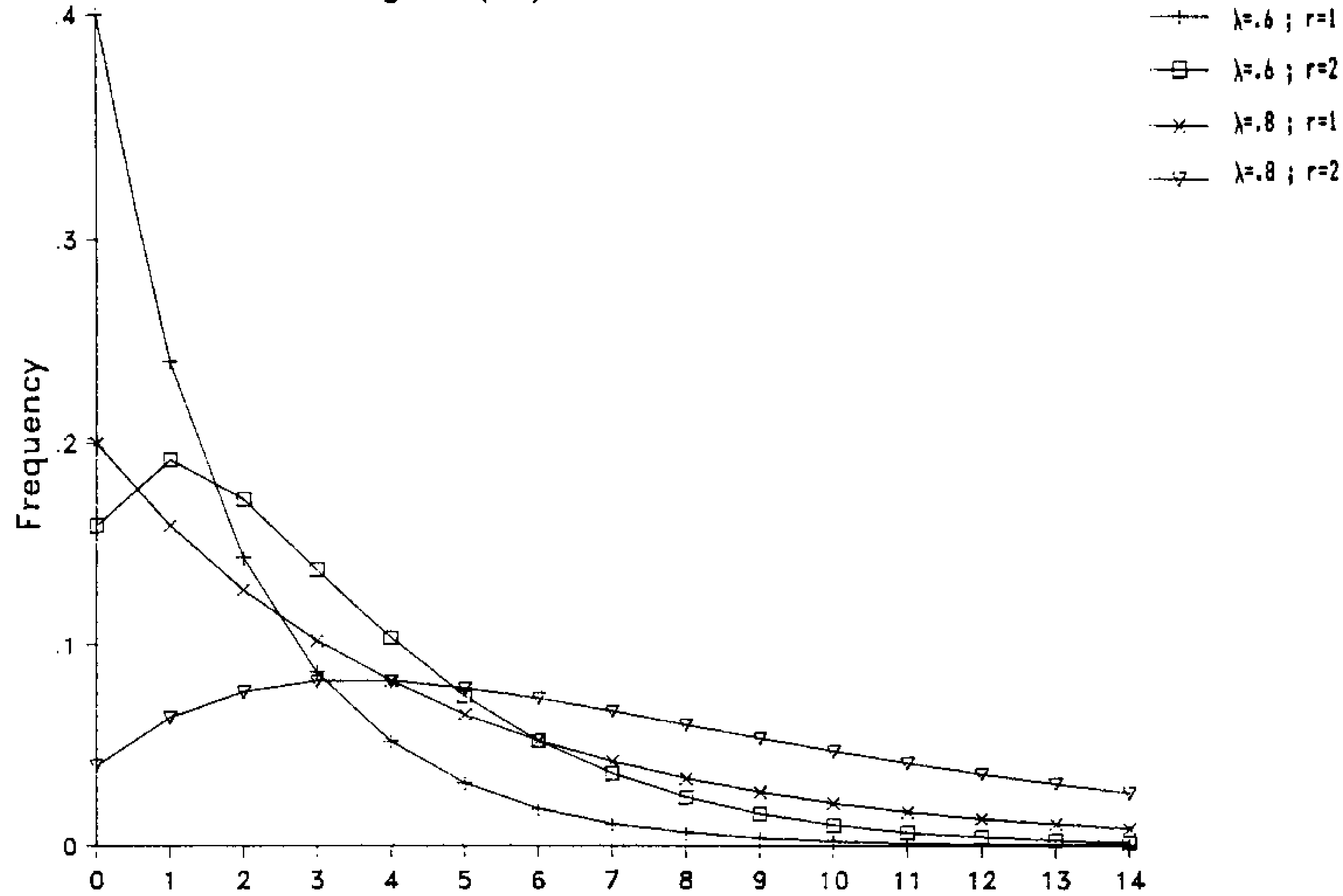
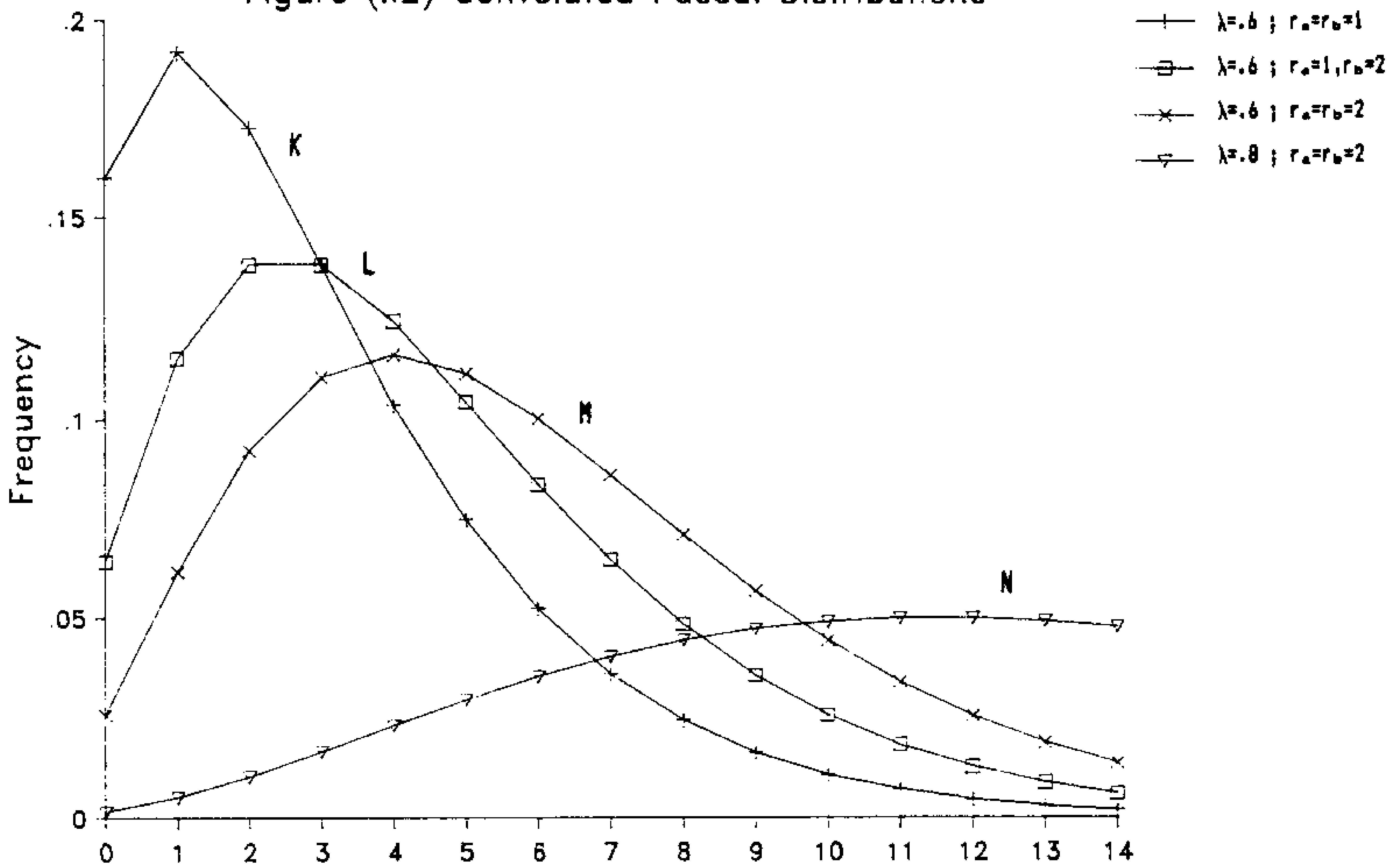


Figure (I.2) Convoluted Pascal Distributions



For the sake of clarity these discrete distributions have been plotted in continuous form.

Appendix II

Table (1) Population and Sample Researchers by State[a]

States	1970-71 Sample I	1970-71 Popln.	1974-75 Sample II	1974-75 Popln.
Alabama	52	232	55	314
Arizona	49	187	50	201
Arkansas	37	85	39	95
California	60	616	61	656
Colorado	56	352	58	436
Connecticut	40	99	39	93
Delaware	25	41	28	48
Florida	56	368	58	445
Georgia	56	359	56	353
Idaho	42	115	45	139
Illinois	53	267	53	256
Indiana	54	288	55	317
Iowa	51	221	51	217
Kansas	53	255	52	239
Kentucky	45	141	45	142
Louisiana	49	192	49	190
Maine	40	98	41	104
Maryland	41	105	42	111
Massachusetts	44	129	45	136
Michigan	58	438	58	458
Minnesota	55	319	55	311
Mississippi	47	158	50	206
Missouri	52	233	52	228
Montana	44	128	45	138
Nebraska	47	160	48	174
Nevada	27	44	23	35
New Hampshire	34	71	34	69
New Jersey	46	147	47	155
New Mexico	32	61	31	59
New York	60	568	60	596
North Carolina	57	389	57	404
North Dakota	44	126	44	126
Ohio	55	300	55	327
Oklahoma	46	146	45	143
Oregon	55	316	55	327
Pennsylvania	53	268	54	275
Rhode Island	32	60	32	63
South Carolina	45	134	44	132
South Dakota	42	117	44	127
Tennessee	45	143	44	132
Texas	59	488	59	545
Utah	49	182	49	187
Vermont	29	50	30	56
Virginia	51	225	52	242
Washington	51	211	52	236
West Virginia	36	79	39	92
Wisconsin	54	283	54	295
Wyoming	31	59	33	64
TOTAL	2239	10053	2267	10694

(a) Calculated from researcher listings in the USDA's, "Professional Workers in State Agricultural Experiment Stations and other Cooperating Institutions".

Table (2) Researcher Statistics - Degree Status of Sample Researchers, Period Averages[a]

Degree Status	1970-73	1974-75	1970-75 average
Ph.D	1912 (85.4)	1967 (86.6)	1940 (86.1)
MS	306 (13.7)	272 (12.0)	289 (12.8)
BS	15 (.7)	21 (.9)	18 (.8)
Other	6 (.3)	10 (.4)	9 (.4)
Total	2239	2267	2253

(a) Figures in parentheses are percentages.

Table (3) Researcher Statistics - Appointment Status of Sample Researchers, Period Averages.[a]

Appointment Status	1970-73	1974-75	1970-75 average
College Staff	304 (13.6)	270 (11.9)	287 (12.7)
Station Staff	329 (14.7)	338 (14.9)	334 (14.8)
Coop USDA	114 (5.1)	115 (5.1)	115 (5.1)
College and Station Staff	1142 (51.0)	1135 (50.1)	1139 (50.6)
College, Station And Extension Staff	105 (4.7)	121 (5.3)	113 (5.0)
Other	245 (10.9)	288 (12.7)	269 (11.9)
Total	2239	2267	2253

(a) Figures in parentheses are percentages.

Table (4) Researcher Statistics - Professorial Status of Sample Researchers, Period Averages.[a]

Professorial Status	1970-73	1974-75	1970-75 average
Full Prof.	870 (38.9)	921 (40.6)	896 (39.8)
Associate Prof.	638 (28.5)	637 (28.1)	638 (28.3)
Assistant Prof.	543 (24.3)	476 (21.0)	510 (22.6)
Research Associate	121 (5.4)	169 (7.5)	145 (6.4)
Collaborator	20 (0.9)	14 (0.6)	17 (0.8)
Other	47 (2.1)	50 (2.2)	49 (2.2)

(a) Figures in parentheses are percentages.

Table (5) Average Salaries of College and University Teachers at Large Public Institutions for the Academic Years 1908-1982. (1967 = 100)[a]

Academic Year	Salary in Current Dollars	Index Value	Academic Year	Salary Current Dollars	Index Value
1908	1656	15.94	1946	3429	33.01
1909	1728	16.64	1947	3705	35.67
1910	1746	16.81	1948	4098	39.45
1911	1763	16.97	1949	4217	40.06
1912	1748	16.83	1950[c]	4521	43.53
1913	1785	17.18	1951[b]	4840	46.60
1914	1821	17.53	1952[c]	5159	49.67
1915	1861	17.92	1953[b]	5418	52.16
1916	1860	17.91	1954[c]	5676	54.65
1917	1923	18.51	1955	5824	56.07
1918	1943	18.71	1956[c]	5971	57.49
1919	2068	19.91	1957[b]	6281	60.47
1920	2410	23.20	1958[b]	6591	63.45
1921	2661	25.62	1959[d]	6901	66.44
1922	2834	27.28	1960[d]	7492	72.13
1923	2886	27.78	1961	7750	74.61
1924	2919	28.10	1962	8094	77.92
1925[b]	2939	28.29	1963	8513	81.96
1926	2958	28.48	1964	8906	85.74
1927	2991	28.80	1965	9341	89.93
1928	3045	29.32	1966	9816	94.50
1929	3056	29.42	1967	10387	100.00
1930	3065	29.51	1968	11033	106.22
1931	3134	30.17	1969	11760	113.22
1932	3111	29.95	1970	12637	121.66
1933[b]	2963	28.53	1971	13284	127.89
1934[b]	2815	27.10	1972	13823	133.08
1935	2666	25.67	1973	14552	140.10
1936	2732	26.30	1974	15459	148.83
1937	2843	27.37	1975	16403	157.92
1938	2861	27.54	1976	17450	168.00
1939[b]	2874	27.67	1977	17930	172.62
1940	2886	27.78	1978	18897	181.93
1941[b]	2889	27.81	1979	20120	193.70
1942	2892	27.84	1980	21620	208.14
1943	2988	28.77	1981	23650	227.69
1944	3282	31.60	1982	25750	247.91
1945	3236	31.15			

(a) For sources and other details see section (3.3) part (ii). All salary figures are on a 9-10 month academic year basis.

(b) Obtained by linear interpolation.

(c) Calculated from salary data reported in the 1956 AAUP bulletin Vol. 42, No.1, p. 37.

(d) Calculated as total compensation minus fringe benefits, which were estimated at 6.0 percent of total compensation, based on the compensation and salary figures for 1961.

Table (6) Research 'Labor'-Capital Ratios for the SAES.

		L[b]/K[c] Ratios				Percent Change in L/K Ratios	
Station Size[a]	Number of Stations	1963	1965	1970	1975	1965-70	1970-75
Small	8	8.39	8.01	6.32	7.10	-0.21	0.12
Medium	35	7.16	7.04	6.04	6.60	-0.14	0.09
Large	5	9.78	9.52	8.26	10.25	-0.13	0.24
Very Large	3	10.31	10.08	8.31	9.97	-0.18	0.20
Total	48	7.64	7.46	6.32	7.06	-0.15	0.12

(a) Small is ≤ 100 researchers ; Medium is 100 < researchers < 500 ;
Large is ≥ 500 researchers ; Very Large is ≥ 550.

(b) L includes all recurrent or non-capital expenses. For 1963-1975 the labor only component of non-capital expenses averaged around 77 percent.

(c) K is a service flow measure constructed from land, buildings and equipment expenditure. See section (3.3) for details.

Appendix III

Table (i) Regression of Citation Adjusted Publication Output (PRONET) on Agricultural Research Expenditures[a]

Variable	OLS	WITHIN	BETWEEN	EGLS[b]
R_0	-0.4868 (0.9984)[c]	0.3767 (0.8229)	-5.4798 (10.735)	0.0747 (0.8503)
R_{-1}	-0.1336 (1.2824)	0.1022 (0.9238)	-5.4824 (21.584)	0.0927 (0.9898)
R_{-2}	-0.2361 (1.2652)	-0.6715 (0.9226)	8.3317 (16.079)	-0.5121 (0.9824)
R_{-3}	1.0167 (1.2552)	0.4289 (0.8952)	24.977 (14.755)	0.6387 (0.9701)
R_{-4}	0.3952 (1.2696)	0.4331 (0.8889)	-28.982 (19.648)	0.4996 (0.9775)
R_{-5}	-0.1574 (1.2952)	-0.2443 (0.9113)	20.689 (18.662)	-0.1356 (0.9982)
R_{-6}	0.0903 (1.3152)	0.3988 (0.9321)	-33.306 (17.776)	0.4409 (1.0194)
R_{-7}	1.0763 (1.0123)	0.0951 (0.7975)	20.828 (9.4215)	0.4342 (0.8420)
ΣR_{-i}	1.5647	0.9190 (1.1765)	1.5740	1.5332 (0.1495)
R^2	.5299	.0092	.7521	.2760
NT	288	288	48	288
'Mean' Lag	3.93	3.18	4.47	4.03

(a) Excludes trend variable. All variables measured in natural logs.

(b) See note (b) Table (4.4). Here $\hat{\sigma}^2_1 = 3.3162$, $\hat{\sigma}^2_w = 0.6453$ and $\hat{\sigma}^2_\mu = 0.4452$.

(c) Standard errors in parentheses.

Table (2) Researcher Portfolio of Selected SAES.[a]

	Percent 'Social Science' Researchers[b]	Percent of Total No. Researchers in		Plant Scientist Animal Scientist Ratio
		Plant Science	Animal Science	
Delaware	.26	.38	.25	1.5
Maine	.13	.53	.21	2.5
Nevada	.17	.26	.14	1.8
New Mexico	.22	.37	.28	1.3
All States	.15	.42	.24	1.7

(a) All figures are 1970-1975 averages.

(b) Measures the (no.'social science' researchers)/(total no. researchers). 'Social science' researchers includes agricultural economics, home economics and engineering.

Table (3) Regression of Raw Publication Output (PROPUB) on Agricultural Research Expenditures.[a]

Variable	OLS	WITHIN	BETWEEN	EGLS[b]
R_0	-0.3007 (0.4692)[c]	-0.0904 (0.2511)	-2.8121 (6.4844)	0.0169 (0.2846)
R_{-1}	0.6409 (0.6026)	0.3864 (0.2819)	1.1064 (13.038)	0.7462 (0.3195)
R_{-2}	0.0032 (0.5945)	-0.4128 (0.2815)	-1.3339 (9.7122)	0.0060 (0.3171)
R_{-3}	0.5535 (0.5898)	-0.0727 (0.2732)	15.544 (8.9129)	0.2585 (0.3121)
R_{-4}	0.0923 (0.5966)	0.0647 (0.2713)	-15.974 (11.868)	0.1759 (0.3143)
R_{-5}	0.1223 (0.6086)	-0.0720 (0.2781)	8.5244 (11.273)	0.1232 (0.3210)
R_{-6}	-0.1382 (0.6180)	-0.1826 (0.2844)	-10.703 (10.738)	-0.1151 (0.3292)
R_{-7}	0.1837 (0.4757)	-0.3024 (0.2434)	6.8120 (5.6910)	-0.2154 (0.2786)
ΣR_{-i}	1.1568	-0.6818 (0.2697)	1.1638	0.9961 (0.0909)
R^2	.7427	.0447	.8163	.3153
NT	288	288	48	288
'Mean' Lag	2.66	3.32	4.28	3.05

(a) Trend variable excluded. All variables measured in natural logs.

(b) See note (b), Table (4.4). Here $\hat{\sigma}^2_1 = 1.2102$, $\hat{\sigma}^2_w = 0.0601$ and $\hat{\sigma}^2_\mu = 0.1917$.

(c) Standard errors in parentheses.