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FUNDAMENTAL STOCKS OF KNOWLEDGE AND THE GROWTH OF INPUTS

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ABSTRACT

This paper studies induced factor growth and factor biases associated with measures of accumulated knowledge. These measures are indicators of stocks of academic science. We find strong evidence for biases of knowledge towards capital input, especially equipment, and also towards labor quality. The bias runs against labor quantity, particularly blue collar labor, consistent with the view that human capital is more valuable in a technically driven economy. Our results suggest a lag of 20 years in order for the peak effects of academic research on inputs to take place.

We argue that knowledge stimulates mainly capital formation at the aggregate level, estimating that annual growth in capital is 3% higher because of knowledge. This amounts to a 0.6% higher annual growth rate of output stemming from the induced growth of inputs. Combined with previous estimates of the effects on multifactor productivity in Adams (1990), our results suggest that academic science increased growth in aggregate output by about 1% per year. This is one third of total growth during the postwar era.

Useful comments on earlier versions were offered by John Bound, Lawrence Kenny, Paul Romer, and Sherwin Rosen. The paper also benefited from presentations at University of Chicago, University of Florida, and the 1989 Summer Meetings of the Econometric Society, University of Michigan. Brenda Brinton, Debasis Pal, and Nathan Wajsman helped process the data. Adams received support for this research from the ASA/NSF/BLS Senior Fellows program and from the Center For the Study of the Economy and the State, University of Chicago.

I. INTRODUCTION

This paper studies the relationship between changes in factor demands and changes in technology arising out of fundamental knowledge. A strong assumption underlying our thinking about this relationship is that technology and knowledge are treated as critically dependent on academic science, at least in a 20th century context. Our paper has two main concerns.

The first is with the connection between knowledge, growth in the demand for factors, and growth accounting. In a classic article Solow (1957) found that residuals imputed from production function estimates accounted for a large proportion of output growth. Despite early recognition that the residuals amount to ignorance concerning the black box of production, there has been a tendency to identify the residuals with technology. This tendency underlies recent efforts to improve measurement of factors. The most spectacular of these is Jorgenson, Gollop, and Fraumeni (1987), where the residual diminishes sharply after changes in factor quality are taken into account. Does this mean that knowledge or technology is less important as a source of growth? An answer of yes indicates neglect of technology's role in factor demand.

The identification of technology with the residual is inaccurate because factor demands are partly driven by technology, and because the residual consists of other causes of growth besides technology (Morrison 1986; Baltagi and Griffin 1988; Bernstein and Nadiri 1989).

In effect we can break up the impact of knowledge into direct effects on the residual and indirect effects on factor demands. This decomposition is a guiding principle of our paper.

Our second concern is with the biases generated by knowledge. Knowledge typically raises the demand for inputs since incomes rise over time. However its bias is probably in favor of higher quality inputs because these embody scarce knowledge (for an example see Horowitz and Sherman [1980]). Several studies have shown that input quality does rise over time. Schultz (1961) and Becker (1975) studied the rising stock of skills per worker from the perspective of human capital. Denison (1962) and Griliches and Jorgenson (1967) are landmark studies in growth accounting which demonstrated improved factor quality over time. Kendrick (1976) confirmed a pronounced deepening of human and physical capital per head. Jorgenson, Gollop, and Fraumeni (1987) showed that rising labor and physical capital quality accounted for much of U.S. growth since World War II.

Previewing the outcome of our investigation, we find that knowledge is biased in favor of capital, especially equipment. We find similar, very powerful effects on labor quality but on average knowledge is mildly labor saving. Factor saving is more pronounced for blue collar labor, which declines sharply with the growth of knowledge. The effects of knowledge on input growth are more expansive in high technology industries than elsewhere. Finally, at the aggregate level knowledge appears to stimulate growth at the rate of 0.5% per year holding multifactor productivity constant. Combined with the direct effects on productivity of 0.5% per year obtained in Adams

(1990), science appears to have been responsible for annual growth of 1%, or one third of postwar economic growth in the United States.

Until now formidable problems of measurement have made it impossible to study the link between knowledge and input growth despite the inherent interest of the topic. We overcome these difficulties by adopting estimates of the formation of academic science that first appeared in Adams (1988, 1990).

We employ two sets of production data. The first is that developed by Jorgenson, Gollop, and Fraumeni (1987). In our analysis of their data we study growth in the quantity and quality of labor, physical capital, and intermediate goods. Our second data set, from the Bureau of Labor Statistics, consists of distinct categories of labor and capital in two digit manufacturing industries. We study growth in two categories of physical capital, equipment and all other, and two categories of labor, white and blue collar workers.

Each set of data has its advantages and disadvantages. The data generated by Jorgenson and associates express growth in capital, labor, and intermediate goods in convenient summary form. But their summary nature conceals important details of technical change. The BLS data are able to capture these details since equipment, for example, probably embodies more technical change than other capital. Nevertheless, the discrete categories omit important dimensions relevant to factor productivity. To take just one case, the white and blue collar distinction misses the rise in skills within each group.

The rest of the paper explores the twin themes of factor growth and factor bias originating in knowledge. In Section II we present our

decomposition of the growth effects of knowledge. Section III discusses important new data on the accumulation of knowledge and describes the new variables. Estimates based on our two data sets are reported in Section IV. Section V draws implications for sectoral and aggregate growth. The final section is a summary and outline of additional research.

II. ANALYTICAL FRAMEWORK

A. Growth Accounting Considerations

Besides the direct effects of knowledge on productivity growth we have noted the indirect effects on factors. Indirect effects operate through growth equations for factors because to a first order approximation, factor growth rates predict the explained growth in output. Since knowledge influences growth in factors, the size of the indirect effects can be compared with the direct effects of knowledge on productivity (Adams 1990). Such comparisons are carried out in Sections V and VI.

The contrast between the direct and indirect effects of knowledge is sharpened by the following approximation to sectoral output growth

$$(1) \quad D\ell nq_t \cong \gamma + \sum_{k=1}^{M} \alpha_k D\ell nz_{kt} + \beta_N N_{t-L},$$

in which $D\ell nq_t$ is the percentage change in output, γ is disembodied growth, the α_i are cost shares, $D\ell nz_{it}$ is the percentage growth in input i, β_N is the effect of knowledge on multifactor productivity

growth, and N_{t-L} is knowledge. Notice that β_N and N_{t-L} can be specified as a vector when knowledge is heterogeneous, a feature that we exploit in Sections III and IV. Table 1 is a glossary of terms.

Now append linear equations in rates of growth of factor demand,

$$(2)\quad D\ell nz_{kt} \cong \eta_k N_{t-L} + \sum_{i=1}^{M} \mu_{ki} D\ell n(s_{it}/p_t) + \delta x_t, \qquad (k= 1...M)$$

in which η_k is the factor-specific effect of knowledge on growth in the kth input, μ_{ki} is the effect of the ith input price on growth in z_{kt}, $D\ell n(s_{it}/p_t)$ is the real rate of growth in the ith input price, and the x_t are shift factors. The factor growth equations (2) can be thought of as slopes of factor demand trajectories. Section II.B shows that (2) is based on several Taylor's Series expansions.

Substitute (2) in (1) and take the partial derivative with respect to knowledge. The result is

$$(3)\quad \frac{\partial D\ell nq_t}{\partial N_{t-L}} \cong \sum_{i=1}^{M} \alpha_k \eta_k + \beta_N.$$

The first term on the right of (3) is the indirect effect of knowledge on explained growth while the second is the direct effect of knowledge on productivity. Studies which link technology with the residual alone neglect the indirect effect of knowledge: a weighted average of the individual shift coefficients η_k, where the weights are cost shares. This paper is concerned only with the indirect effect.

TABLE 1

Glossary of Terms

Symbol	Meaning
Panel A. Variables	
EPV_t, EV_t	expected present value of the firm
q_t	output of the firm
p_t	price of output
z_{kt}	kth input of the firm
s_{kt}	kth input price
x_t	vector of shift factors
$E\lambda_{kt+1}$	expected marginal benefit of kth input in the future
ℓ_{jt}, ℓ_t	scientists in jth field, total scientists
KN_{t-L}	total own knowledge stock in an industry
N_{t-L}, N^*_{t-L}	weighted and unweighted own stocks of knowledge per scientist
I_{t-R}	spillover knowledge stock
Panel B. Parameters	
M	number of inputs
L, R	lags between absorption and application of own and spillover knowledge
$\cos \theta_{ij}$	correlation between scientific workforces in industries i and j; cosine of the angle between their scientific workforces

(continued next page)

TABLE 1
(Cont.)
Glossary of Terms

Panel B. Parameters(Cont.)	
α_k	share of kth input in cost
β	discount factor
β_N	effect of knowledge on productivity
γ	rate of disembodied growth
δ	vector of shift effects
η_k	effect of knowledge on growth in the kth input
μ_{ki}	elasticity of growth in the kth input with respect to the ith factor price

NOTE. all parameters are defined to be positive.

B. Behavior of Firms

Although the interpretation offered by (3) is convenient in its separation of the direct and indirect effects of knowledge on growth, it is (2) which makes this separation possible. We derive (2) below.

We make the following assumptions. Firms maximize expected present value of net cash flow over an infinite horizon. Optimization entails learning about science and technology, application of that learning to R&D, and production of goods and processes embodying the R&D. In this paper we avoid a separate R&D capital stock and enter indicators of science directly into the production function. A formulation of the firm's learning activities emphasizing basic science probably yields a more stable research function than an approach based on R&D alone. This follows from the replenishment of R&D payoffs by basic science in search-theoretic models of applied research (Evenson and Kislev 1976).

Expected present value is

$$(4) \quad EV_t = E_t \sum_{j=0}^{\infty} \beta^j \left[p_{t+j} q_{t+j} - \left(\sum_{k=0}^{M} s_{kt+j} z_{kt+j} \right) \right],$$

where E_t is the expectation at time t, $0<\beta<1$ is the discount factor, p_{t+j} is the price of output q_{t+j} in period t+j, and s_{kt+j} is the price of input z_{kt+j}. The firm maximizes (4) using discounted Dynamic Programming. Bellman's equation for this problem is

$$(5) \quad EV_t = \max_{z_{kt}} \left\{ \left[p_t q_t - \left(\sum_{i=1}^{M} s_{kt} z_{kt} \right) - c_t \right] + \beta EV_{t+1} \right\},$$

the maximized sum of current cash flow and the discounted expected Value Function in period t+1, EV_{t+1}. Assuming interior solutions for the controls z_{kt}, first order conditions required by (5) are:

$$(6) \quad p_t q_{kt} + \beta E\lambda_{t+1} = s_{kt}. \qquad (k = 1 \ldots M)$$

Here q_{kt} is the marginal product of z_{kt} and $E\lambda_{t+1} = E(\partial V_{t+1}/\partial z_{kt})$ is the effect of a current hire on the expected value of the firm next period. Naturally that effect exceeds zero when inputs build physical, human, and intellectual capital of the firm and hence future output.

The solution to (6) in terms of (2) is approximated as follows. Divide (6) by p_t, take logarithms, and first difference the result. These operations yield

$$(7) \quad \ell n\left[1 + \frac{\Delta q_{kt}}{q_{kt-1}}\right] = \ell n\left[1 + \frac{\Delta\left(\frac{s_{kt}}{p_t} - \beta\frac{E\lambda_{t+1}}{p_t}\right)}{\left(\frac{s_{kt-1}}{p_{t-1}} - \beta\frac{E\lambda_t}{p_{t-1}}\right)}\right].$$

Using the relation $\ell n(1+x) \cong x$ for small x, (7) is approximately

$$(8) \quad D\ell n q_{kt} \cong a_k D\ell n\left(\frac{s_{kt}}{p_t}\right) - b_k D\ell n\left(\frac{E\lambda_{t+1}}{p_t}\right),$$

where we employ the notation $D\ell n x_t \cong dx_t/x_{t-1}$, and a_k and b_k are assumed to be stable coefficients[1]. The growth rate of marginal product is on the left. We know this depends on inputs, knowledge, and shift factors. Expanding in Taylor's Series to the first order yields

$$(9)\quad D\ell nq_{kt} \cong \sum_{i=1}^{M} c_{ki} D\ell nz_{it} + d_k N_{t-L} + e_k x_{1t},$$

in which x_{1t} is a subset of x_t.

Growth of real future marginal benefit of z_{kt} is the second term on the right of (8). This too depends on inputs, knowledge, and shift factors. Thus an expansion similar to (9) gives

$$(10)\quad D\ell n\left[\frac{E\lambda_{t+1}}{p_t}\right] \cong \sum_{i=1}^{M} f_{ki} D\ell nz_{it} + h_k N_{t-L} + m_k x_{2t},$$

in which x_{2t} is another subset of x_t, and $x_{1t} \cup x_{2t} = x_t$. Equation (2) follows by direct substitution of (9)-(10) into (8):

$$(2)\quad D\ell nz_{kt} \cong \eta_k N_{t-L} + \sum_{i=1}^{M} \mu_{ki} D\ell ns_{it} + \delta X_t. \qquad (k= 1...M)$$

Equation (2) is readily applied to industry level data once it is interpreted as a system of factor demands by the average firm. For notice that

$$(11)\quad D\ell nZ_{kt} = D\ell nz_{kt} + D\ell nn_t, \qquad (k= 1...M)$$

where <u>industry</u> factor growth rates are on the left, the first term on the right is given by (2), and $D\ell nn_t$ is the percentage change in the number of firms n_t, taken to be linear in factor prices and knowledge

$$(12)\quad D\ell nn_t \cong \sum_{i=1}^{M} u_i D\ell ns_{it} + vN_{t-L}$$

Equations (2) and (12) in (11) yield the system estimated in Section IV[2]. But first we describe the empirical counterparts to the knowledge N_{t-L}.

III. INTERPRETATION AND DESCRIPTION OF THE KNOWLEDGE DATA

Data on factor quantities and prices used in this paper are documented elsewhere (Jorgenson et al. [1987]; U.S. Department of Labor [1983]). Thus we concentrate on the knowledge measures entering (2), (11), and (12). Consider the contents of the N_{t-L} vector. The foremost consideration is that the stock dimension of knowledge enter the growth equations. Why should the stock influence growth, rather than net investment, comprised here of new findings? In addition to the publicness of knowledge, which grants it a longer life than its creators (Romer 1990), we assert that older learning is useful to new research. In this view it is partly the longevity of mathematics which crowns it queen of the sciences and continually expands its domain.

Secondly we equate knowledge with academic science because of our belief that fundamental work has been essential to nearly all major technological advances in recent years (for a skeptical view see Rosenberg [1982], Ch. 7). This assumption, so affirmative of the importance of theory to practical concerns, is essential for the sequel.

We assume that academic science affects industry in two distinct ways. One way is through the own stock of knowledge acquired by an industry. The other is through spillovers of knowledge from other

industries. Spillovers entail the imitative behaviors stressed by Rosenberg (1976) and Schmitz (1989). Again we emphasize stocks because both old and new knowledge are useful for growth.

The own and spillover stocks of knowledge used in this paper are index numbers based on interactions by field of science between industry scientists and stocks of academic papers. A key assumption justifies the index numbers: that the scientific paper is a unit of theoretical innovation just as a patent is a unit of applied innovation. Although individual papers vary widely in value, the mean is reached with small error in large samples[3]. Advantages offered by stocks of scientific papers are that they represent basic science rather than development; that they cover a wide range of sciences; that they are available sooner than their main competitor, R&D expenditures, permitting tests of long lags in effect; and that they are more exogenous than R&D, given their world-wide scope.

The definition of the total own stock of knowledge acquired by an industry is

$$(13) \quad KN_{t-L} = \sum_{j=1}^{F} \ell_{jt} N_{jt-L},$$

in which ℓ_{jt} is the employment of scientists in field j and the N_{jt} are article count stocks in field j, both at time t. According to (13) the size of the science labor force in a given field captures the relevance of that science to an industry. The test of relevance is a telling one in economics: the willingness to pay for a resource.

The definition requires the distributions of both industrial

scientists and stocks of scientific papers. The industrial distribution of scientists by field and industry is taken from U.S. Department of Labor (1973), National Science Foundation (various years), and unpublished National Science Foundation tabulations[4]. An appendix explaining collection procedures is available on request.

The article count stocks are obtained as follows. Raw data on scientific papers are drawn from major abstracting journals in the nine science fields in Table 2. These provide world-wide flows of publications over the periods listed in the table. Flows are accumulated into stocks at social rates of obsolescence ranging from 1 through 25 percent in 2 percent intervals. Stocks of depreciated scientific papers in fields from agriculture through physics are the result. Weighting the stocks with the industrial distribution of scientists yields (13). Further details of the realized stocks are gathered for convenience in Table 3. Note the short lag on the scientist weights: this is consistent with findings on brief developmental lags in Griliches, ed. (1984). Much longer lags on scientific papers are preferred by the data, consistent with sizable gestation periods for the peak influence of fundamental research on industry.

Unfortunately the employment of scientists in (13) is endogenous, so we prefer the <u>per scientist</u> own stock of knowledge instead:

$$(14)\quad N_{t-L} = \left(\sum_{j=1}^{F} \ell_{jt} N_{jt-L}\right)/\ell_t,$$

or (13) divided by the total number of scientists in an industry.

TABLE 2

Bibliographic Sources of the Article Count Data

Field of Science	Time Period	Source Index
Agriculture	1930-1983	Series is the Sum of article counts derived from 10 British Abstracting Journals: Review of Applied Entomology Plant Breeding Abstracts Herbiage Abstracts Helminthological Abstracts Animal Breeding Abstracts Nutrition Abstracts Review of Applied Mycology Forestry Abstracts Horticultural Abstracts Soils and Fertilizers
Biology	1918-1926	Series is the sum of article counts taken from 2 American Journals: Abstracts of Bacteriology Botanical Abstracts
	1927-1983	Biological Abstracts
Chemistry*	1907-1983	Chemical Abstracts
Computer Science	1957-1965	Science Abstracts, Sections 27-30
	1966-1968	Control Abstracts
	1969-1983*	Computer and Control Abstracts
Engineering, Combined*	1928-1983	Engineering Index
Geology	1933-1983	GeoRef

(continued next page)

TABLE 2
(cont.)
Bibliographic Sources of the Article Count Data

Field of Science	Time Period	Source Index
Mathematics and Statistics	1868-1942	Jahrbuch Uber Die Fortschritte der Mathematik (Berlin)
	1943-1983	Mathematical Reviews
Medicine	1879-1898 (1899)	Index Medicus, 1st Series (interpolated)
	1900-1902	Bibliographia Medica (Paris)
	1903-1920	Index Medicus, 2nd Series
	1921-1926	Index Medicus, 3rd Series
	1927-1940	Quarterly Cumulative Index Medicus
	1941-1950	Current List of Medical Literature
	1951-1983*	Index Medicus, 4th Series
Physics*	1896-1983	Physics Abstracts

Notes. Annual counts are estimates obtained by random sampling, except when marked by an asterisk. * Indicates exact counts supplied by the index or abstracting journal over the time period.

TABLE 3

Definitions of Knowledge First Differences

Concept	Formula	Preferred Lags	Industry Coverage
Total Own Knowledge	see (13) in text	1 year on scientist weights; 0-20 years on scientific papers	18-19 2-Digit Industries in Manufacturing[a]
Own Knowledge Per Scientist	see (14) in text	1 year on scientist share weights; 0-20 years on scientific papers	18-19 2-digit Industries in Manufacturing[a]
Weighted Own Knowledge Per Scientist	see (15) in text	1 year on scientist share weights; 0-20 years on scientific papers; 1950 total industry employment weights	18-19 2-digit Industries in Manufacturing[a]
Spillover Knowledge	see (16) and (17) in text	1 year on scientist weights; 0-30 years on scientific papers	18-19 2-digit Industries in Manufacturing[a], 9 sectors outside Manufacturing[b]

NOTES. Preferred lags are best fitting in the regressions below. Share weights for own knowledge are the fraction of scientists in an industry in each of the following nine fields: agriculture, biology, chemistry, computer science, engineering, geology, mathematics and statistics, medicine, and physics. Scientific papers are similarly classified, as in Table 2. Note that the spillover omits engineering. [a] The manufacturing industries are food and kindred, textiles, apparel, lumber, furniture, paper, printing, chemicals, petroleum, rubber and plastics, stone, clay, and glass; primary metals, fabricated metals, machinery, except electrical; electrical equipment, automobiles, other transportation equipment, instruments, and miscellaneous. [b] The nine sectors outside manufacturing are mining, construction, transportation, communications, public utilites, finance and services, federal government, state and local government, and colleges and universities. Note that coverage of own knowledge is limited by the regression sample and is less than coverage of the spillover.

The weights applied to the article count stocks N_{jt-L} in (14) are <u>shares</u> in the science labor force of an industry. This improves on (13) since the share weights are more exogenous than employment.

Our final and favored definition of own knowledge multiplies (14) by the 1950 employment of scientists in each industry ℓ_0 in order to capture the technological intensiveness of an industry:

$$(15)\quad N^*_{t-L} = \ell_0 N_{t-L}.$$

Notice that the 1950 employment weights used in this third definition of own knowledge are initial conditions since they precede the 1951-1979 period of our study. We prefer (14) and (15) to (13) given the exogeneity of knowledge per scientist.

Our definition of spillovers follows Jaffe (1986):

$$(16)\quad I_{it-R} = \sum_{j\neq i, j=1}^{N} \mathrm{Cos}\theta_{ij} KN_{jt-R},$$

where KN_{jt-R} is given by (13) and $\mathrm{Cos}\theta_{ij}$ is the cosine of the angle between the scientific employment vectors in industries i and j,

$$(17)\quad \mathrm{Cos}\theta_{ij} = \frac{\sum_{k=1}^{F} \ell_{ik}\ell_{jk}}{[(\sum_{k=1}^{F} \ell_{ik}^2)(\sum_{k=1}^{F} \ell_{jk}^2)]^{1/2}}.$$

$\mathrm{Cos}\theta_{ij}$ measures the similarity of the science employment vectors for industries i and j. As any two vectors become more similar, (17), which is bounded between 0 and 1, approaches 1. Equation (16) gives

the spillover stock as the weighted sum of the knowledge stocks of other industries, where each is computed according to (13). Note lag R in (16): we expect that R>L, since interindustry spillovers must first be absorbed as own knowledge, with lag L, and then acquired by other industries, with lag R-L>0. Note that the spillover purposefully omits engineering in order to increase the sensitivity of the cosine weights to differences in industry employment. This concludes our discussion of data sources and data construction.

Figures 1 to 3 graph the raw data on scientific papers and the derived knowledge stocks. To convey an idea of the article count data before weighting according to (14)-(17), Figure 1 presents yearly averages of stocks and flows of articles across the nine fields of Table 2. Stocks and flows are contemporaneous in this graph. Not surprisingly flows of scientific papers fall sharply during both World Wars, and the rise in stocks temporarily ceases.

Figure 2 graphs own stocks of knowledge per scientist in an industry weighted by ℓ_0 as in (15). Here the count data are lagged 20 years and depreciated at 13 percent since these parameter values fit best in the regressions. Recall that own knowledge is an average of stocks of scientific papers; then its path is determined by the past behavior of stocks of academic research and by assumptions concerning lags in effect. To show that lags matter we present three variants of own knowledge in Figure 2. The slowest growing assumes a uniform 20 year lag in effect of science. The fastest growing assumes a 10 year lag for technology and a 20 year lag for basic science. Actual declines occur in Figure 2. This follows from the assumed lags, the 13

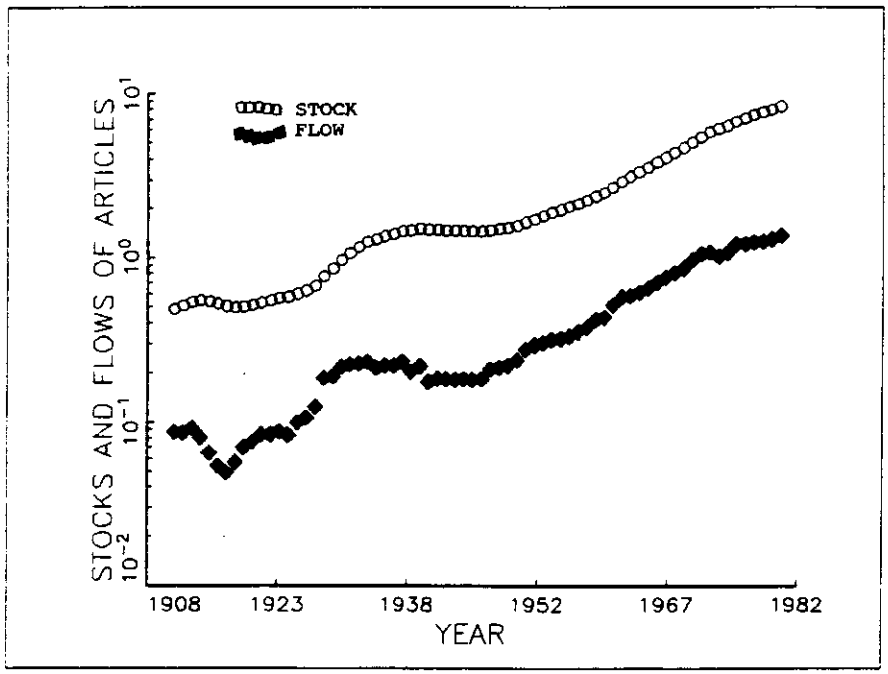

Fig. 1 - Stocks and Flows of Scientific Papers, in 100 Thousands, 1911-1980: Yearly Averages Across 9 Fields of Science. Obsolescence Rate is 13 Percent. Source: See Text.

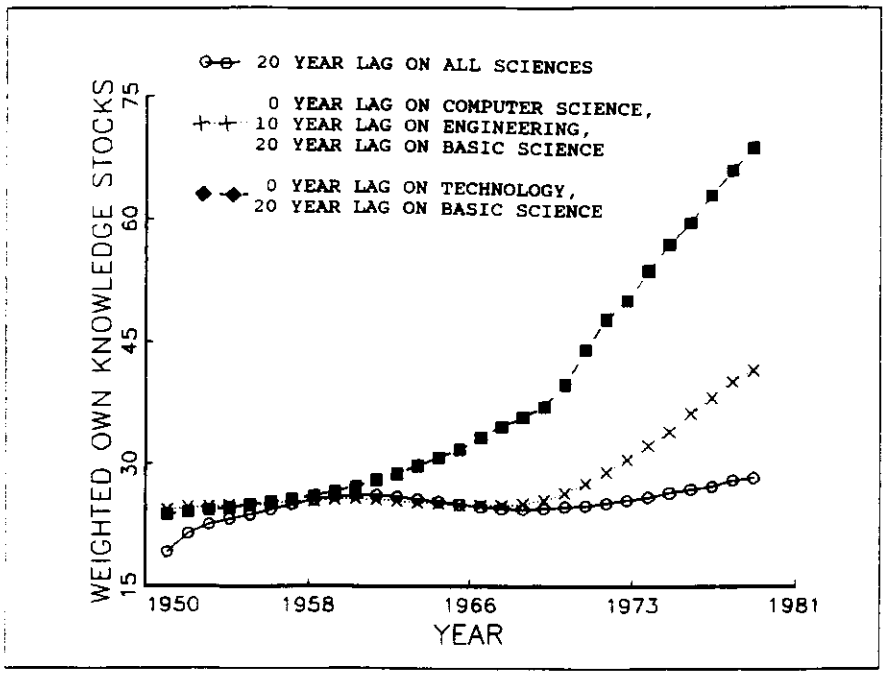

Fig. 2 - Weighted Own Stocks of Knowledge, 1951-1979: Yearly Averages Across 19 Manufacturing Industries. Obsolescence Rate is 13 Percent. Source: See eq. (14) and the text.

per cent depreciation rate, and the decline in academic science during World War II.

Interindustry spillovers defined according to (16) are depicted in Figure 3. Again three variants are shown. The pattern is one of rapid growth until 1971, decline until 1976, and recovery thereafter[5]. In assessing the decline of spillovers during the 1970s one should be aware of an additional factor which was absent in Figure 2. Since spillovers are partly determined by the size of science workforce in other industries, their path is determined by industrial scientific employment as well as lags, obsolescence, and past science. In fact employment of scientists seems to have declined sharply during most of the 1970s (National Science Foundation [1981]) and this is the main reason for the spillover's decline through 1976. Given the long lags noted above, the slowdown in science employment during the 1970s may follow from the slowdown in basic science during World War II. This concludes the presentation of the new data.

IV. EMPIRICAL RESULTS

A. Findings from the Jorgenson, Gollop, and Fraumeni Data

Descriptive statistics are shown in Table 4. According to rows 1-3, quantities of capital and intermediate goods grow more rapidly than labor's. The reverse holds for prices in rows 4-6 since wages appreciate more rapidly than other input prices. The story told by the standard deviations and the extremes of input quantity and price growth agrees with previous research on relative factor adjustment

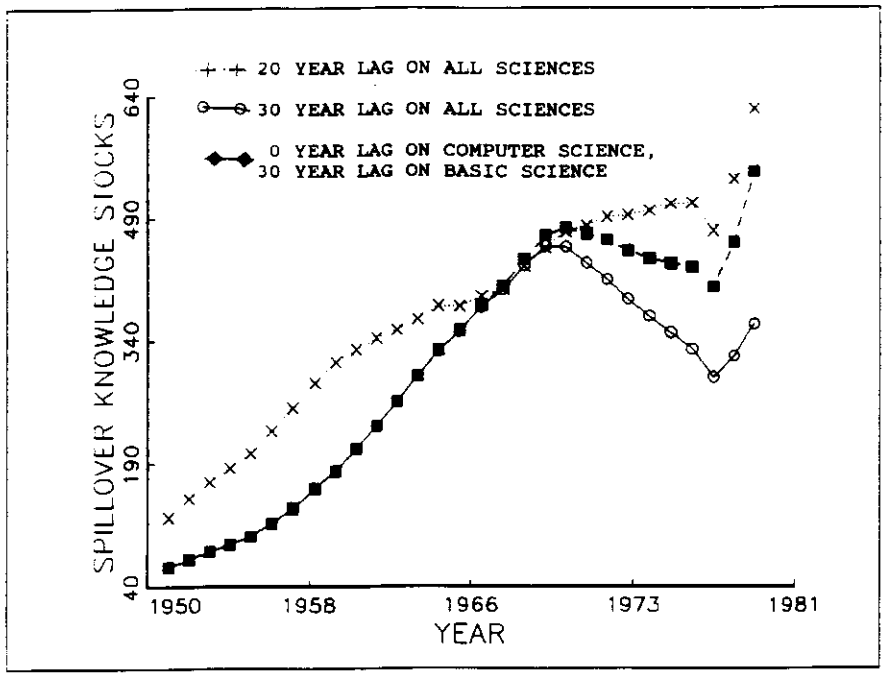

Fig. 3 - Spillover Stocks of Knowledge, 1951-1979:
Yearly Averages Across 19 Manufacturing Industries.
Obsolescence Rate is 13 Percent.
Source: See eq. (15), (16), and the text.

(Nadiri and Rosen [1973]), since capital growth varies less than other input growth but capital price growth varies more. The BLS data tell a very similar story in the next five rows.

Turning to the final three rows we see that weighted own knowledge is larger and more variable than its unweighted counterpart. That pattern reflects multiplication of knowledge per scientist by 1950 industrial scientific employment in the weighted case. By either definition the spillover is considerably larger, 10 times larger even than the weighted definition of own knowledge. This follows from the wider coverage of the spillover, average values of the cosine weights of about 0.5, and its definition in terms of current scientific employment rather than the 1950 weights applied to own knowledge (see Table 3). Current employment is considerably larger given the rapid growth of scientific personnel during this time.

Tables 5-6 present regression findings on the pooled Jorgenson data. These consist of triplets of input growth rates for 19 industries over the period 1951-1979. Table 5 reports results for unweighted and weighted own stocks of knowledge defined according to (14) and (15). A very specific lag structure is employed in this Table. Lags in effect of own knowledge are assumed to be 0 years for computer science, 10 years for engineering, and 20 years for basic science. Corresponding spillover lags are 0 years for computer science and 30 years on basic science[6]. Later on in Table 6 we experiment with other lags. T-statistics in all the regession tables are corrected for heteroskedasticity using the method of Halbert White (1980).

TABLE 4

Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Jorgenson, Gollop, and Fraumeni Data:				
Percentage Growth in Input Quantities				
Physical Capital	0.040	0.05	-0.14	0.33
Labor	0.016	0.07	-0.24	0.49
Intermediate Goods	0.039	0.11	-0.54	0.57
Percentage Growth in Deflated Input Prices				
Physical Capital	-0.023	0.20	-0.97	1.23
Labor	0.015	0.02	-0.05	0.07
Intermediate Goods	-0.006	0.02	-0.12	0.06
BLS Data:				
Percentage Growth in Input Quantities				
Equipment	0.040	0.03	-0.04	0.17
All other capital	0.038	0.04	-0.19	0.27
White Collar Labor	0.026	0.04	-0.11	0.25
Blue Collar Labor	0.007	0.07	-0.23	0.23
Materials	0.037	0.08	-0.31	0.30

TABLE 4
(cont.)
Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Knowledge Stock Data:				
Own Knowledge Stock Per Scientist[a]				
Weighted	28.1	30.6	2.0	150.1
Unweighted	1.8	0.7	0.4	3.9
Spillover Knowledge Stock[b]	308.6	160.9	50.3	665.7

NOTES. Number of observations is 551 in the Jorgenson data, 522 in the BLS data. Statistics are drawn from the sample of 18-19 industries defined in Table 2 over the period 1951-1979. See text for sources of the knowledge data. [a] Weighted own knowledge per scientist is defined by (15) of the text; unweighted own knowledge per scientist is defined by (14). Assumed lag on the underlying article counts is 20 years on basic science, 10 years on engineering, and 0 years on computer science. [b] Definition of the spillover is given by (16) and (17). Note that engineering is omitted from the spillover. Lag assumed on the underlying article counts is 30 years for basic science, 0 years for computer science.on the inputs.

Turning to the results in Table 5, notice that we include the log of each input lagged once as a check for adjustment costs. Lagged capital stock is significant but other lagged inputs usually are not, consistent with greater adjustment costs for capital. For the purpose of later calculations we report the knowledge coefficients to a higher degree of accuracy in 5.1-5.3 than elsewhere. Weighted own knowledge has a nearly identical effect across 5.1-5.3. Unweighted own knowledge favors labor and intermediate goods in 5.4-5.6, but differences are insignificant in a test for equality of the coefficients across equations ($F= 0.56$, $F_{.95}= 3.00$)[7]. Weighted own knowledge enters more significantly than unweighted knowledge.

Cross-equation differences are greater for interindustry spillovers. In both sets of equations the spillover is capital-using, but saving in labor and intermediate goods. This difference is significant at the 1% level in 5.1-5.3 ($F=8.63$) and 5.4-5.6 ($F=9.26$)[8]. The input growth equations in Table 5 include growth in real factor prices[9]. Own price effects, with the exception of labor, are usually negative as one would expect from a demand curve. Later we discuss attempts to take the many errors and biases associated with factor prices into account, but few of them made much difference to the findings reported here.

We introduce several shift variables for macroeconomic events. Controls for the composition of product and factor demand are the trade surplus, the surplus of the federal government, and

TABLE 5

Input Growth Equations, 1951-1979
Jorgenson, Gollop, and Fraumeni Data
(Asymptotic T-statistics in Parentheses)*

Variable or Statistic	Equation					
	Capital	Labor	Int. Goods	Capital	Labor	Int. Goods
	5.1	5.2	5.3	5.4	5.5	5.6
Constant	0.015	0.060	0.132	-0.002	0.016	0.082
	(0.9)	(1.9)	(2.4)	(-0.1)	(0.5)	(1.4)
$Log(z_{kt-1})$	-0.012	-0.012	-0.014	-0.009	-0.001	-0.007
	(-4.8)	(-2.1)	(-1.6)	(-3.4)	(-0.3)	(-1.0)
Own Knowledge Per Scientist[a]:						
Weighted	0.336E-3	0.319E-3	0.295E-3			
	(5.1)	(3.1)	(1.7)			
Unweighted				0.9E-2	1.2E-2	1.5E-2
				(3.1)	(3.5)	(2.6)
Spillover Knowledge Stock[b]	0.715E-4	-0.675E-4	-0.690E-4	0.5E-4	-0.9E-4	-0.9E-4
	(3.9)	(-2.1)	(-1.2)	(3.0)	(-2.9)	(-1.6)
% Growth in Factor Price:						
Capital	-0.07	0.11	0.17	-0.07	0.11	0.17
	(-6.4)	(6.5)	(6.0)	(-6.4)	(6.6)	(6.0)
Labor	-0.03	0.04	0.54	-0.03	0.02	0.52
	(-0.3)	(0.2)	(1.8)	(-0.3)	(0.1)	(1.8)
Int.Goods	0.09	0.11	-0.42	0.08	0.08	-0.44
	(1.2)	(1.2)	(-2.3)	(1.1)	(0.9)	(-2.5)

(continued next page)

TABLE 5
(cont.)
Input Growth Equations, 1951-1979
(Asymptotic T-statistics in Parentheses)*

Variable or Statistic	Equation					
	Capital	Labor	Int. Goods	Capital	Labor	Int. Goods
	5.1	5.2	5.3	5.4	5.5	5.6
Shift Factors:						
Trade Surplus	1.02 (3.0)	-0.94 (-1.9)	-2.02 (-2.3)	0.88 (2.5)	-1.14 (-2.4)	-2.25 (-2.6)
Federal Budget Surplus	0.39 (2.6)	0.31 (1.2)	0.82 (2.0)	0.41 (2.6)	0.35 (1.3)	0.90 (2.1)
Defense Share	0.28 (2.1)	-0.51 (-2.4)	-1.02 (-3.9)	0.25 (1.9)	-0.52 (-2.4)	-0.99 (-2.8)
Capacity Utilization	0.01 (2.2)	0.05 (4.7)	0.05 (2.2)	0.02 (4.4)	0.07 (4.7)	0.08 (3.5)
Real Energy Price:						
Growth Rate	0.63 (1.9)	-0.72 (-1.1)	-2.46 (-2.3)	0.68 (2.0)	-0.63 (-1.1)	-2.36 (-2.2)
Growth Rate xCapacity Utilization	-0.78 (-2.0)	0.83 (1.1)	3.08 (2.5)	-0.85 (-2.1)	0.72 (1.1)	2.96 (2.4)
Adjusted R^2	0.254	0.185	0.160	0.231	0.188	0.164
F	16.6	11.4	9.8	14.8	11.6	10.0

NOTES. Number of observations is N=551. * T-statistics are computed using White's (1980) heteroskedasticity-consistent standard errors for the coefficients. [a] Assumed lags are 0 years on computer science, 10 years on engineering, and 20 years on basic science. [b] Assumed lags are 0 years on computer science and 30 years on basic science. Engineering is omitted from the spillover.

defense expenditures. All are expressed as shares of Gross National Product. Secondly we include a set of business cycle controls: the Federal Reserve index of manufacturing capital utilization, growth in real energy price, and the interaction between real energy price and capacity utilization.

How should the controls be interpreted? Consider compositional shift variables first. National income accounting implies that the trade surplus equals domestic saving minus investment when the government surplus is held constant[10]. State and local governments operate in approximate budget balance so the overall government surplus is held constant along with the federal surplus. Since the trade surplus captures abundance of domestic saving in these circumstances, we expect it to promote capital formation. Support for this view is offered by 5.1 and 5.4. Another interpretation is that trade surpluses are associated with more capital intensive manufacturing. This is consistent with declines in labor and intermediate goods as the trade surplus rises. Partly reflecting its cyclical component, the sign of the federal budget surplus is positive and significant in Table 5. Turning to the defense share we observe a bias towards capital much like the trade surplus. This suggests that defense promotes capital intensive methods and industries.

Next consider the cyclical controls. Capacity utilization captures upturns, so we expect the more rapid growth of factors in Table 5 as utilization rises. Growth of real energy price is a shock effect (Griliches 1988), yet regressions 5.1 and 5.4 show that it promotes capital growth. Increased replacement demand for capital

caused by changes in energy price may produce this finding. On this interpretation, capital replacement conceals the disruptive effects noticeable for labor and intermediate goods. Finally, turn to the interaction of capacity utilization and energy price growth. The effect on capital is significantly negative in 5.1 and 5.4 but positive elsewhere. Cyclical peaks seem to attenuate capital replacement due to energy shocks. Conversely, cyclical peaks dissipate real energy price disruptions to labor and intermediate goods.

Table 6 reports sensitivity tests. Since the controls behave very similarly in the two tables, only knowledge coefficients are reported. We use the weighted definition of own knowledge given by (15). Panel A shortens lags in the effect of basic science. We reduce the lag on basic science to 10 and 20 years in the definition of own and spillover knowledge. As in Table 5 lags on academic technology (computer science and engineering) remain at 0 and 10 years. While the results are similar, own knowledge is generally weaker in these equations. This suggests a lag in the peak effect of basic science of 20-30 years. The lag structure agrees closely with the analogous structure for productivity (Adams [1990]).

Panel B of Table 6 extends the 20-30 year lags on basic science to academic technology. Longer lags on technology fit capital growth about as well as shorter ones: compare 6.1 of Panel B with 5.1. Longer lags also make little difference in the labor and intermediate goods equations. Therefore, the peak lag in effect of technology is probably on the order of 10 or more rather than 0 years.

Shift variables matter strongly to the results we have reported.

Panel C drops all controls except lagged inputs and price growth. The lag structure in Table 5 is retained: 0-10 years on technology, 20-30 years on basic science. Findings are quite different though knowledge generally stimulates growth. Surprisingly, its bias turns in favor of intermediate goods. In our opinion the results without shift factors are less meaningful than the others. The amplitude of the business cycle rises, international competitiveness erodes, and defense spending declines during an expansion of knowledge in the 1970s. None of this implies diminishing returns to science, but much of it seems to bear on capital formation and other growth.

Panel D studies growth in factor quality: the difference between price-weighted and unweighted growth in inputs[11]. We observe significant positive effects on labor quality of own and spillover knowledge but insignificant effects elsewhere. The findings on labor quality are consistent with evidence that new technology increases the demand for highly educated labor (Bartel and Lichtenberg [1987]). The findings on capital and intermediate goods quality are inconsistent with this view. The negative evidence may reflect more accurate measurement of labor quality.

One somewhat troubling implication of Tables 5 and 6 relates to labor input. The negative effect of the spillover dominates the positive effect of own knowledge at sample means: on average knowledge reduces labor (see Table 8 below). This is consistent with observations of successful plant retoolings made by the MIT Commission on Industrial Productivity (Dertouzos, Lester, and Solow [1989]). Still, knowledge may be saving in the type of labor prevalent in the

1970s, but not saving of the more skilled labor force about to enter during this period. This second view is consistent with the positive effect of knowledge on labor quality. Since the decline in the science work force during the 1970s represents an aberration from the norm, perhaps even data error, those years are dropped from panel E. The negative sign of the spillover essentially disappears. In all candor however, this negative sign reappears if lags in effect of knowledge are shortened, so the experiment is not an unqualified success.

We carried out many other checking procedures. We implemented the collinearity diagnostics of Belsley, Kuh, and Welsch (1980), but found only slight evidence for collinearity, largely confined to energy price and its interaction with capacity utilization. We checked for division error bias between input quantity and price growth by regressing current input growth on 3 year moving averages of input prices. Since results were unchanged, division error bias was not the source of the negative own price coefficients in Table 5. Also we corrected for endogeneity of factor price growth by estimating a six equation system consisting of all three inputs and all three input prices. Our method was Three Stage Least Squares[12]. However these results failed to reverse the positive sign of wage growth in the labor equations. For the same reason we added growth of the civilian labor force to the labor equations in order to control for supply changes, but that too had little effect on the estimates.

This concludes our discussion of the Jorgenson data.

TABLE 6

Input Growth Equations, 1951-1979:
Specification Experiments
(Asymptotic T-Statistics in Parentheses)*

Variable or Statistic	Equation		
	Capital	Labor	Intermediate Goods
	6.1	6.2	6.3
Panel A. Experiments with shorter lags on basic science: lag=10 on basic science in own knowledge, lag=20 on basic science in spillover knowledge.			
Weighted Own Knowledge Per Scientist	0.2E-3 (4.7)	0.2E-3 (3.0)	0.2E-3 (1.8)
Spillover Knowledge Stock	0.2E-4 (1.2)	-0.6E-4 (-2.0)	-0.8E-4 (-1.3)
Panel B. Experiments with uniform lags on all sciences and technology: lag=20 on own knowledge, lag=30 on the spillover.			
Weighted Own Knowledge Per Scientist	0.4E-3 (5.2)	0.3E-3 (2.8)	0.3E-3 (1.6)
Spillover Knowledge Stock	0.7E-4 (3.8)	-0.8E-4 (-2.7)	-0.8E-4 (-1.3)
Panel C. Experiments without shift variables. Specification of lags is exactly as in Table 5.			
Weighted Own Knowledge Per Scientist	0.3E-3 (4.7)	0.5E-3 (4.5)	0.4E-3 (2.8)
Spillover Knowledge Stock	-0.2E-5 (-0.2)	-0.8E-5 (-0.5)	7.1E-5 (2.1)

(continued next page)

TABLE 6
(Cont.)
Input Growth Equations, 1951-1979:
Specification Experiments
(Asymptotic T-statistics in Parentheses)*

Variable or Statistic	Equation		
	Capital	Labor	Intermediate Goods
	6.1	6.2	6.3
Panel D. Experiments with pure factor quality: lags are exactly as in Table 5.			
Weighted Own Knowledge Per Scientist	0.1E-4 (0.3)	0.4E-4 (3.9)	-0.0E-4 (-0.5)
Spillover Knowledge Stock	-0.1E-5 (-0.1)	0.9E-5 (2.4)	0.1E-5 (1.1)
Panel E. Experiments with sample period: years 1971-1976 are omitted. Lags are exactly as in Table 5.			
Weighted Own Knowledge Per Scientist	0.4E-3 (5.1)	0.4E-3 (3.5)	0.4E-3 (2.1)
Spillover Knowledge Stock	8.5E-5 (3.9)	-0.9E-5 (-0.3)	-0.0E-5 (-0.0)

NOTES. Number of observations is N=551 except for Panel E, where N=437.

B. Findings from the Bureau of Labor Statistics Data

Table 7 records results from the BLS data. Again we restrict reported coefficients to the knowledge stocks since the controls behave similarly to Table 5. In these data own knowledge is biased towards capital rather than labor and intermediate goods. To interpret this, recall that labor growth equals unweighted growth in hours of work in the BLS data. Thus quality as defined in Tables 5 and 6 is omitted from these results. Since labor quality increases strongly with own knowledge, this may explain the weaker relationships between knowledge and labor growth in Table 7.

The spillover is the second point of comparison between Tables 5 and 7. Spillover knowledge has a more negative effect on the two forms of labor in Table 7 than before, again consistent with an omitted quality story. Note that the spillover increases capital growth but decreases labor growth just as before. There is little effect of knowledge on intermediate goods.

The contribution of Table 7 lies in comparisons between categories of inputs. In 7.1 we observe powerful effects of knowledge on capital equipment coming especially from the spillover. At sample means the combined effects are sufficient to dwarf those for any of the other inputs (see Table 8, Panel B)[13]. This is a hint that equipment embodies many of the technical advances in other industries.

Spillover knowledge is also less biased against white collar labor than blue collar. On average knowledge shifts the composition of the labor force towards white collar workers, as one would expect[14].

TABLE 7

Input Growth Equations, 1951-1979
Bureau of Labor Statistics Data
(Asymptotic T-statistics in Parentheses)*

Variable or Statistic	Equation				
	Equipment Capital	Other Capital	Wh. Collar Labor	Bl. Collar Labor	Int. Goods
	7.1	7.2	7.3	7.4	7.5
Weighted Own Knowledge Stock per Scientist	0.27E-3 (7.3)	0.34E-3 (5.6)	0.18E-3 (3.0)	0.18E-2 (2.5)	0.14E-2 (1.6)
Spillover Knowledge Stock	0.7E-4 (5.6)	0.1E-4 (0.8)	-0.7E-4 (-4.3)	-1.3E-4 (-5.0)	-0.8E-4 (-2.3)
Adjusted R^2	0.258	0.301	0.438	0.510	0.411
F	14.0	17.0	30.0	39.8	27.0

NOTES. Number of observations is N=522. The sample covers 18 industries and 29 years. Motor vehicles and other transport equipment are combined in these data. * T-statistics are computed using White's (1980) heteroskedasticity-consistent standard errors for the coefficients.

V. INTERPRETATION OF THE FINDINGS

Table 8 collects the major findings of this paper. It reports imputed effects at means in which imputations are products of means and regression coefficients. Panel A records imputed effects from the Jorgenson data, where the source is regressions 5.1-5.3. Panel B records imputations from the BLS data, regressions 7.1-7.5. Throughout our verbal discussion emphasizes the combined effect of own and spillover knowledge. Table 8 provides added details.

Panel A reveals that input growth proceeds most rapidly in high technology industries. This relationship is monotonic across subpanels 1-3, reflecting the relative size of own knowledge in high technology and other industries[15]. Consider Subpanel 2, which records imputations for the full sample. Combined effects of knowledge on capital, labor, and intermediate goods growth are 3.1%, -1.1%, and -1.3%, though negative effects are rarely significant[16]. Therefore knowledge is capital using rather than labor or intermediate goods saving.

Panel B summarizes imputations from the BLS data. Again these rise monotonically from low to high technology samples. The key difference between Panels A and B lies in the statistical significance of the negative effects of knowledge on labor input. Blue collar labor is hardest hit, undergoing significant decline due to knowledge in each of subpanels 1-3. White collar labor declines also, yet its rate of decline is just half that of blue collar labor in the full sample, -1.8% compared with -3.6%. Since labor quality is omitted these results are downward biased. But the great decline in blue collar

TABLE 8

Estimated Contributions of Knowledge to Input Growth, 1951-1979
(T-Statistics in Parentheses)*

Sample, Factor of Production	Estimated Contribution of: Own Knowledge	Spillover Knowledge	Combined Knowledge
Panel A. Jorgenson, Gollop, and Fraumeni Data[a]			
1. Low Technology Subsample[b]			
Capital	0.0021	0.0209	0.0230
	(5.1)	(3.9)	(4.2)
Labor	0.0023	-0.0197	-0.0174
	(3.1)	(-2.1)	(-1.8)
Intermediate Goods	0.0020	-0.0202	-0.0182
	(1.7)	(-1.2)	(-1.0)
2. Full Sample[c]			
Capital	0.0090	0.0221	0.0311
	(5.1)	(3.9)	(4.8)
Labor	0.0094	-0.0208	-0.0114
	(3.1)	(-2.1)	(-1.0)
Intermediate Goods	0.0083	-0.0213	-0.0130
	(1.7)	(-1.2)	(-0.6)
3. High Technology Subsample[d]			
Capital	0.0168	0.0218	0.0386
	(5.1)	(3.9)	(5.2)
Labor	0.0177	-0.0206	-0.0029
	(3.1)	(-2.1)	(-0.2)
Intermediate Goods	0.0156	-0.0210	-0.0054
	(1.7)	(-1.2)	(-0.2)

(continued next page)

TABLE 8
(cont.)
Estimated Contributions of Knowledge to Input Growth
at Means, 1951-1979
(T-Statistics in Parentheses)*

Sample, Factor of Production	Estimated Contribution of: Own Knowledge	Spillover Knowledge	Combined Knowledge
Panel B. BLS Data[e]			
1. Low Technology Subsample[b]			
Equipment	0.0018	0.0208	0.0226
	(7.3)	(5.6)	(5.9)
Other Capital	0.0023	0.0042	0.0066
	(5.6)	(0.8)	(1.2)
White Collar Labor	0.0012	-0.0218	-0.0206
	(3.0)	(-4.3)	(-4.0)
Blue Collar Labor	0.0012	-0.0393	-0.0381
	(2.5)	(-5.0)	(-4.8)
Intermediate Goods	0.0009	-0.0243	0.0233
	(1.6)	(2.3)	(-2.2)
2. Full Sample[c]			
Equipment	0.0079	0.0220	0.0299
	(7.3)	(5.6)	(7.0)
Other Capital	0.0102	0.0045	0.0147
	(5.6)	(0.8)	(2.4)
White Collar Labor	0.0052	-0.0230	-0.0178
	(3.0)	(-4.3)	(-3.1)
Blue Collar Labor	0.0052	-0.0415	-0.0363
	(2.5)	(-5.0)	(-4.1)
Intermediate Goods	0.0041	-0.0256	-0.0216
	(1.6)	(-2.3)	(-1.9)

(continued next page)

TABLE 8
(cont.)
Estimated Contributions of Knowledge to Input Growth
at Means, 1951-1979
(T-Statistics in Parentheses)*

Sample, Factor of Production	Estimated Contribution of: Own Knowledge	Spillover Knowledge	Combined Knowledge
Panel B. BLS Data(cont.)[e]			
3. High Technology Subsample[d]			
Equipment	0.0195	0.0218	0.0413
	(7.3)	(5.6)	(8.1)
Other Capital	0.0252	0.0044	0.0296
	(5.6)	(0.8)	(4.0)
White Collar Labor	0.0128	-0.0227	-0.0099
	(3.0)	(-4.3)	(-1.4)
Blue Collar Labor	0.0128	-0.0410	-0.0282
	(2.5)	(-5.0)	(-2.8)
Intermediate Goods	0.0101	-0.0254	-0.0153
	(1.6)	(-2.3)	(-1.2)

NOTES. Number of observations is N=551 in Panel A, N=522 in Panel B.
* Contributions are the products of the mean knowledge stocks and the regression coefficients. T-statistics are the mean contributions divided by their standard errors. See the text for definitions of the standard errors. [a] Source is the regression triplet 5.1-5.3 of Table 5. [b] Low technology subsample consists of food, textiles, apparel, lumber, and furniture. [c] Full sample consists of all manufacturing industries in the data that could be matched to our science data. Note that tobacco and leather products are omitted, and that, in the Jorgenson data, transportation is broken into motor vehicles and other transportation equipment. Thus there are 19 2 digit industries in the Jorgenson data, and 18 industries in the BLS data. [d] High technology sample consists of instruments, transportation equipment, chemicals, and electrical equipment. [e] Source is the set of regressions 7.1-7.5 of Table 7.

labor is no artifact. Rather it confirms a growing sense that education is essential in a technically driven economy.

Remaining patterns are by now familiar: the induced growth of equipment is the largest of any input, followed by other capital. Intermediate goods are saved by knowledge, but this effect is often insignificant.

VI. SUMMARY AND CONCLUSIONS

A number of conclusions can be drawn from these findings. Knowledge seems to be biased towards capital input, especially equipment. It is biased towards labor quality and against labor quantity, particularly blue collar employment. Knowledge shifts the economy towards high technology industries and inputs. It is a powerful mover of the entire structure of production.

At the aggregate level the indirect effect of knowledge on output, attributable to induced input growth, seems to be comparable to the direct effect on productivity. This can be seen as follows.

Evaluation of the indirect effect depends on the elasticity of aggregate factor supplies. Let aggregate labor supply be perfectly inelastic, so that knowledge effects the real wage rather than output. Then the effects of knowledge on output due to labor growth are approximately zero. Also, changes in intermediate goods cancel out at the level of the whole economy.

Then to a first approximation, only the effects of knowledge on capital remain to be considered in assessing the indirect effects on

aggregate output. Let the aggregate supply of capital be perfectly elastic. Evaluated at means for the full sample of manufacturing industries, Table 8 implies that capital grows 3% faster as a result of knowledge[17]. Now, the average share of capital in cost is approximately 0.2 in manufacturing. It follows that the indirect contribution of knowledge to output is about 0.6% per year. This estimate is conservative since wages probably rise and capital goods prices probably fall due to knowledge. In Adams (1990) the estimated effects of knowledge on productivity cluster around 0.5%. Thus, if manufacturing is at all representative, then the effects of knowledge on capital are comparable with the direct effect on productivity, and the combined effect on annual growth in output is roughly 1%. This is a sizable contribution, about a third of postwar economic growth in the United States.

In the next stage of our research we shall study the complex linkages between academic science and industrial R&D. It is just possible that the deep problem of the connections between the many facets of research-- academic, governmental, and industrial-- and the still deeper question, of the connection between research in all its forms and the growth that we have experienced, will eventually be illuminated by this approach.

FOOTNOTES

[1] It is readily seen that the coefficients a_k and b_k are

$$a_k = \frac{\frac{s_{kt-1}}{p_{t-1}}}{\frac{s_{kt-1}}{p_{t-1}} + bE\frac{dV_t}{dz_{kt-1}}} \qquad b_k = \frac{bE\frac{dV_t}{dz_{kt-1}}}{\frac{s_{kt-1}}{p_{t-1}} + bE\frac{dV_t}{dz_{kt-1}}}$$

Thus, in the text we are taking a_k and b_k to be independent of time.

[2] This is a dynamic approach to factor demand based on different approximations than Nickell (1986). Note the difference in emphasis from the production function approach in static modelling of factor demand (Hamermesh [1986], Jorgenson[1986]): most are intractable in a dynamic context.

[3] A failing of the count data is that citation weights measuring cross-field differences in influence do not presently exist. Adams (1990) discusses many other details of measurement.

[4] We are indebted to Michael Crowley and Keith Wilkinson of NSF for advice concerning the data on scientists.

[5] Figure 3 shows two series that are virtually identical until 1970: the spillover with a uniform lag of 30 years applied to basic and computer science, and the spillover with the same 30 year lag except for a lag of 0 on computer science. The two series are identical until 1970 because of the insignificant employment in industry of computer scientists until later in the 1970s.

[6] The spillover deliberately excludes engineering in order to increase sensitivity of the cosine weights to industry differences in fields of science. See Section III.

[7] The 95 percent F value reported in the text has degrees of freedom (f1,f2)= (2,1614) and is approximated by $F_{2,\infty}$.

[8] When the own knowledge coefficients are restricted to be equal across the three equations and the spillover coefficients are forced to be separately equal, then the F statistics for 5.1-5.3 and 5.4-5.6 are 4.52 and 4.86, both significant at the 1% level.

[9] Real input price growth equals growth in the nominal input price less growth in the GNP deflator.

[10] Since aggregate expenditure is C+I+G+X and aggregate income is C+S+T+M, then I+G+X= S+T+M, and X-M= S-I-(T-G). Here C is consumption; I, G, and X are investment, government spending, and exports; and S, T, M are saving, taxes, and imports. When the budget surplus T-G is held constant, the trade surplus X-M equals S-I, or domestic saving minus investment.

[11] Growth in factor quality amounts to relative growth of higher valued classes of inputs within the three input categories. Mean growth of labor, capital, and intermediate goods quality in the sample is 0.45%, 0.56%, and 0.02% respectively.

[12] The 3SLS system satisfied both rank and order conditions for identification. In the case of the factor growth equations, the system was the same as Table 5. In the case of the factor price growth equations, the specification included industry dummies, productivity

growth, industry input growth (endogenous), and other industry input growth of the factor whose price growth is at issue. Besides these variables, growth in the labor force affected growth of wages, and the change in the savings rate affected growth of capital and intermediate goods prices.

[13] Own knowledge coefficients on the two forms of capital are not significantly different. The Chi-square statistic for the difference in the log likelihoods is 1.26, so one cannot reject equality. Corresponding statistics for equality of spillover coefficients and for equality of the two sets of coefficients separately are 7.66 and 11.08. Cross-equation equality is rejected at the 1% level.

[14] Differences in own knowledge coefficients in the two labor equations are again insignificant, Chi-square=0.42. Differences in the spillover coefficients are again significant, yielding corresponding statistics of 8.78 and 8.80.

In additional runs we tested the influence of knowledge on indexes of white and blue collar education over the period 1959-1979. We found a positive effect of own knowledge on white collar education (t= 2.4), but an insignificant effect on blue collar education (t=0.8). The spillover had no discernable effect on either index.

[15] In the Jorgenson data own and spillover means for the high technology, full, and low technology samples are 52.7 and 305.2; 28.1 and 308.6 ; and 6.7 and 292.3. Magnitudes are similar in the BLS data.

[16] Formulas for the T-statistics reported in Table 8 are unchanged from the source tables with the exception of the combined effects listed in the third column. Their standard deviations are given by

$$\sqrt{\bar{N}^2 \mathrm{Var}(\beta_N) + 2\mathrm{Cov}(\beta_N, \beta_I) + \bar{I}^2 \mathrm{Var}(\beta_I)}$$

Reported T-statistics are ratios of combined effects to the standard deviations.

[17] The indirect effects of knowledge on output at the sectoral level are much smaller, approximately zero, since knowledge decelerates labor and intermediate goods growth. But it is the aggregate level which is relevant to a whole economy calculation.

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