We use US input–output data for the 1947–77 period to analyse the relations among research and development (R&D), technical change, and intersectoral linkages. Our most novel finding is that among manufacturing industries, an industry’s rate of technological progress is positively and significantly related to that of its supplying sectors. Another new finding is that among all sectors of the economy, a sector’s R&D intensity and rate of technological progress positively affect its degree of linkage with other sectors. We also find significant spillovers from R&D embodied in new investment.

I. INTRODUCTION

We investigate three issues in this paper. The first is the ‘spillover effect’ of research and development (R&D) performed in one industry on technical change in its customers (industries which buy its inputs). The second is whether technical progress in one industry directly affects the rate of technological progress in customers, independently of its level of R&D activity. The third is whether R&D or technical progress in an industry affects its linkage structure with other industries in the economy.


A third approach is to measure the ‘technological closeness’ between industries. For example, if two industries use similar processes (even though their products are very different or they are not directly connected by inter-industry flows), one industry may benefit from new discoveries by the other industry. Such an approach is found in Jaffe (1986) who uses patent data to measure technological closeness between industries.

1 New York University.
2 New York University and the National Bureau of Economic Research.
3 Griliches also identified a second, less common interpretation of spillovers, i.e. that inputs purchased from an industry engaging in R&D may embody quality improvements that are not fully appropriated by the supplier. It should be emphasized at the outset that while these two notions of spillovers are quite distinct, we cannot distinguish either analytically or statistically between them in our work.
industries. In our own work, we shall distinguish between two possible formulations of R&D spillover and provide corresponding econometric tests.4

The second issue is quite unexplored. As far as we are aware, there have been no previous econometric studies estimating direct technological spillovers. However, the previous literature is quite suggestive. For the German economy, Oppenlander and Schulz (1981) calculate that only about a third of new products are derived from new technology (i.e. process innovation). The remainder are ‘market innovations’, which are used to open up new markets for the products. Pavitt (1984) estimates that out of 2000 innovations introduced in the UK, only about 40% were developed in the sector using the innovation. The remaining innovations were borrowed from new technologies developed in other sectors.

The work of Nelson and Winters (1982) illustrates another approach. In their ‘evolutionary model’, spillovers in technology among firms may occur as firms search, or sample from, their environment to develop new production techniques. Moreover, Rosenberg (1982) and Rosenberg and Frischtak (1984) suggest the existence of clusters of innovations in industries that occupy a strategic position in the economy in terms of both forward and backward linkages. They speculate that there are certain intra-industry flows of new equipment and materials that have generated a vastly disproportionate level of technological change and productivity growth in the economy.5

The third issue also opens up a relatively new area of research. The linkage issue has a long history in development economics.6 The measurement of linkages has also received considerable treatment in the input–output literature.7 These indices essentially serve to assess the relative importance of one industry’s output as inputs in other industries (the so-called ‘forward linkage’).8

In our work, linkage structure is important in two ways. First, it provides another index of both R&D and technological spillovers. Gains from R&D and technological progress (which we will measure by the rate of total factor productivity growth) may take the form of an expansion in industry sales from the penetration of new markets (sectors). Indeed, R&D conducted by an industry may engender a whole new set of customers, if radically new technologies are developed, as the histories of the automobile and computer industries suggest. The expansion of linkages from technological progress may be a consequence of lowered product price or improved product quality. Though we cannot distinguish between these two possible effects with our data, we can measure their joint effect on linkage structure.9

4 For other treatments of R&D spillovers, see National Science Foundation (1977), Nadiri (1979), Griliches (1980a,b), Mansfield (1980), and Griliches and Lichtenberg (1981). Also, see Mohnen (1990) and Nadiri (1991) for recent reviews.
5 The aircraft industry is an example of a sector that has often worked closely with its major customer, the airlines, to develop new products. Pan American Airways, for example, had an historically close relationship with Boeing in the design of new aircraft. See Newhouse (1982) for details.
6 See, for example, Hirschman (1958) or Leontief (1966) for early treatments of these issues.
7 See, for example, Chenery and Watanabe (1958), Jones (1976), or Bulmer-Thomas (1982).
8 ‘Backward linkage’ refers to the importance of one sector as a market for the outputs of other sectors. Though this has also received attention in the input–output literature, we will not emphasize it here.
9 This argument is related to what is commonly referred to as Verdoorn’s law or Kaldor’s law, which asserts a positive feedback relation between output growth and productivity growth (see, e.g.
Second, increasing linkages may be socially beneficial in its own right, since it is tantamount to increasing specialization and division of labour in the economy and hence higher overall productivity. Indeed, Leontief (1966) found that more developed economies had greater linkages among producing sectors (fuller inter-industry tables) than less developed ones. This factor was also the basis of the Hirschman (1958) proposal for promoting inter-industry linkages as a development strategy.

We use an input–output framework to analyse the relations among R&D, technical change, and intersectoral linkages. Admittedly, though these three relations are necessarily dynamic and may occur with considerable lags, data limitations force us to analyse them contemporaneously. Despite this, we obtain several new and potentially important results. First, we find significant spillovers from R&D embodied in capital stock. Second, we find that a sector’s own rate of total factor productivity growth is significantly related to the total factor productivity growth of a sector’s supplying industries. Third, a sector’s degree of forward linkage with other sectors is found to be positively related to the sector’s R&D intensity and its rate of total factor productivity growth. Fourth, splitting R&D data into a privately-financed and government-financed component, we find stronger effects from private R&D embodied in inputs than from total embodied R&D.

The remainder of the paper is organized into four parts. Section 2 presents our basic model and the results on the spillover effects of R&D. Section 3 provides the results on spillover effects of sectoral technical change. Section 4 considers the relation between R&D, technical change, and linkage structure. Concluding remarks are presented in the last section.

2. SPILLOVER EFFECTS OF R&D

Our model is based on an input–output accounting framework. Let:

\[ X_t = \text{(column) vector of gross output by sector at time } t. \]
\[ Y_t = \text{(column) vector of final demand by sector at time } t. \]
\[ A_t = \text{square matrix of inter-industry technical coefficients, } a_{ij}, \text{ at time } t. \]
\[ L_t = \text{(row) vector of labour coefficients at time } t, l_{it}, \text{ showing employment per unit of output.} \]
\[ K_t = \text{square matrix of capital stock coefficients, } k_{ij}, \text{ at time } t, \text{ showing the capital of each type required per unit of output.} \]
\[ P_t = \text{(row) vector of prices at time } t, p_{it}, \text{ showing the price per unit of output of each industry.} \]

Unless otherwise indicated, all variables are in real terms. In addition, let us define

Kaldor, 1967). Expanding markets are likely to lead to high productivity growth because of economies of scale and induced innovations in technology and the organization of production. The productivity increase, in turn, may further expand the industry’s market because of lowered relative price and/or better quality products. Our interest here is narrower and focuses on linkage effects of sectoral productivity growth.
the following scalars:

\[ w_t = \text{the annual wage rate.} \]
\[ i_t = \text{the rate of profit on the capital stock at time } t. \]

We can now define a row vector \( \pi_t \), where the rate of TFP growth for sector \( j \) is given by

\[ \text{TFPGRT}_j \equiv \pi_j = -\left( \sum_i p_i d a_{ij} + w d l_j + i d k_j \right)/p_j \]

(1)

where \( d \) refers to the differential.\(^{10} \) This measure is a continuous version of a measure of sectoral technical change proposed by Leontief (1953). Alternatively, since, for any variable \( z \), \( dz = z \cdot d \log z \), where \( \log \) is the natural logarithm, then sectoral TFP growth is given by

\[ \pi_j = -\left( \sum_i \alpha_{ij} (d \log a_{ij}) - v_{lj} (d \log l_j) - v_{kj} (d \log k_j) \right) \]

(2)

where \( \alpha_{ij} = p_i a_{ij}/p_j \), \( v_{lj} = w l_j/p_j \), and \( v_{kj} = i k_j/p_j \). These three terms give the current value shares of the respective inputs in the total value of output. Since productivity growth rates are measured over discrete time periods rather than instantaneously, we use the average value share of \( \alpha_{ij} \), \( v_{lj} \), and \( v_{kj} \) over the sample period to measure \( \pi \).

R&D is introduced into the model as follows. Let

\[ \text{RD}_j = \text{sector } j\text{'s expenditure on R&D (in constant dollars) in year } t. \]

Then, the R&D intensity of output, \( r_j \), is given by

\[ \text{RDGDO}_{jt} = r_{jt} = \text{RD}_j/x_{jt} \]

which shows the amount of R&D expenditure (in constant dollars) per unit of output. It should be noted that this differs from the usual treatment, where R&D intensity is defined as \( \text{RD}_j \) relative to GDP or value added rather than to gross output \( X \). We use this particular form of R&D intensity in order to be consistent with the other coefficients in an input-output framework and in order to construct measures of R&D embodied in material inputs. The correlation between \( \text{RDGDO} \) and the standard measure of R&D intensity, the ratio of R&D to GDP, is quite high, at 0.86, so that our results should not differ too much from previous ones on this account.

Following Mansfield (1980), Griliches (1980a,b), and others, we shall begin with the standard form for estimating the return to R&D:

\[ \text{TFPGRT}_{jt} = a_0 + b_0 \text{RDGDO}_{jt} + \Sigma c_i D_i + \epsilon_{jt} \]

(3)

where \( a_0 \) is a constant, \( b_0 \) the rate of return of R&D, \( D_i \) are time dummies and \( c_i \) the corresponding coefficients, and \( \epsilon_{jt} \) is a stochastic error term. Equation (3) is

\(^{10} \) The measurement of the rate of sectoral productivity growth is complicated by the fact that technical change often takes the form of the development of new products. In such cases, the proper procedure would be to use some sort of quality-adjusted or hedonic price index to measure the real output of a sector. In such a case, the change in sectoral coefficients used to measure \( \pi \) would be correctly captured. The Bureau of Labor Statistics price indices used for sectoral deflators do not, unfortunately, always do this, and therefore there may be some biases in the measured values of \( \pi \).
derived from the assumption that the (average) rate of return to R&D is equalized across sectors. Time dummies are introduced to allow for period-specific effects on productivity growth not attributable to R&D. We assume that the $\varepsilon_{it}$ are independently distributed but may not be identically distributed. For the regressions reported in Tables 3, 4, and 5 below, we also re-estimated them using the White procedure for a heteroscedasticity-consistent covariance matrix, with very similar results (results not shown).

We introduce forward spillovers from R&D on the basis of trade flows between sectors. However, we distinguish between two different formulations of R&D spillovers. The first assumes that the amount of information gained from supplier $i$’s R&D is proportional to its importance in sector $j$’s input structure (i.e. the magnitude of $a_{ij}$) and its R&D expenditure relative to the output of sector $j$ (i.e. the ratio of $R_D i$ to $x_j$). Then the amount of indirect R&D ($RDM_{IND}$) received by sector $j$ (from material inputs) is given by:

$$RDM_{IND} = \sum_i R_D i a_{ij} / x_j$$

where $A^0$ is identical to the $A$ matrix except that the diagonal is set to zero to prevent double-counting of R&D expenditures. The second assumes that the amount of R&D that spills over from sector $i$ to sector $j$ is proportional to the amount of output sector $i$ sells to $j$. This approach is used by Terleckyj (1974, 1977, 1980). Define the sales coefficient $b_{ij}$ as:

$$b_{ij} = a_{ij} x_j / x_i$$

which shows the percentage of sector $i$’s output that is sold to sector $j$. Then, the alternative measure of indirect R&D ($RDM_{INDA}$) is given by

$$RDM_{INDA} = (\sum_i b_{ij} R_D i) / x_j$$

A similar approach is used by Scherer (1981, 1982), except that his measure of indirect R&D is based on the number of patents issued by sector $i$ which falls in sector $j$’s industrial classification. In principle, his measure is identical to $RDM_{INDA}$, except that indirect R&D is distributed proportionally to patents instead of sales.

The two approaches can be contrasted as follows. In the first, R&D performed by industry $i$ is treated as an industry-wide public good whose (indirect) benefit is the same for each sector which buys from industry $i$. The benefit industry $j$ receives is proportional to input $i$’s importance in $j$’s production structure (the coefficient $a_{ij}$). In the second, R&D is implicitly treated as a sector-specific product. Thus, a sector that engages in R&D and sells $p$ percent of its output to sector $j$ will, in a sense, indirectly devote $p$ percent of its R&D to improving sector $j$’s technology (either through product improvement or new knowledge). As with its own R&D, the productivity effect is proportional to borrowed R&D as a percentage of $j$’s output, $x_j$.

Another source of borrowed R&D is new investment. As far as we are aware, this source has not received attention in the spillover literature. In this case, we assume that the information gain is proportional to the annual investment flow (the time

\footnote{In this case, there is no need to zero out the diagonal and matrix $A$ can be used instead of $A^0$.}
derivative of the capital stock) per unit of output:
\[ \text{RDKIND}_j = \sum_i \text{RD}^{ij}_i / x_j \]
where a dot (\( \cdot \)) indicates the time derivative.\(^{12}\)

The new addition to sector \( j \)'s stock of knowledge is the sum of its own R&D and that borrowed from other sectors. The estimating model is then given by
\[ T\text{FPGR}_{jt} = a_0 + b_0 \text{RD} \text{GDO}_{jt} + b_1 \text{RDMIND}_{jt} + b_2 \text{RDKIND}_{jt} + \sum c_i D_i + e_{jt} \quad (4) \]
where \( D_i \) represents dummy variables for time periods. This specification is similar to that of Terleckyj (1974, 1977, 1980), except that no estimate of R&D embodied in capital stock was included in his work.\(^{13}\) Here, it should be stressed that we have not considered the ability of or the costs to the borrowing sector to absorb technical change.

2.1. Results on R&D Spillovers

Our basic data source consists of US input–output tables, which are available on an 87 sector level from official sources for years 1947, 1958, 1963, 1967, 1972, and 1977. All matrices were deflated to 1958 dollars using sectoral price deflators. In addition, data on employment and capital stock by sector were obtained for each of the 6 years.\(^{14}\) Because of limitation of R&D stock data, it was necessary to aggregate the 51 manufacturing sectors in the input–output tables to 19 sectors (see Table 1). Capital utilization rates were obtained on the 21 order level.\(^{15}\) Finally, estimates of average yearly R&D expenditure in constant dollars for each of the 19 aggregated manufacturing sectors in each of the five time periods were obtained from published National Science Foundation data. Most of the series ran from 1951 to 1978, and R&D data from 1951 to 1958 were used to estimate average R&D expenditure for the 1947–58 period.\(^{16}\)

\(^{12}\) There are some accounting difficulties with this approach. First, the sectoring of the capital matrix \( K \) is the same as that of the inter-industry flow matrix \( A \). As a result, it is not possible to segment the R&D expenditure performed by sector \( i \) into a portion dedicated to capital goods and a residual dedicated to material inputs. Second, in the Terleckyj approach, it is not possible to identify the sales of capital goods produced by sector \( i \) to each sector \( j \). Therefore, an alternative RDKIND measure cannot be devised corresponding to RDMINDA.

\(^{13}\) Moreover, because of the high correlation between RDMIND and RDKIND, of the order of 0.7, we usually used a separate specification for each.

\(^{14}\) The six total flow input–output tables are the standard 85 order Bureau of Economic Analysis version (see, e.g. US Interindustry Economics Division, 1984). Details on labour coefficients, capital coefficients, depreciation rates, sectoral price indices, and other data adjustments can be found in the Appendix to Wolff (1985). Data on hours worked by sector, though the preferable measure of labour input to employment, were not available by sector and year and therefore could not be incorporated. A refinement, suggested by Shankerman (1981), is to net out the inputs used in the R&D activity of each industry in order to avoid double-counting. Though possible for 1947 and 1958, this procedure was not possible for the other years because of insufficient data and was therefore not done.

\(^{15}\) Utilization rates for 1947 were obtained from the Brandeis Economic Research Center. Those for other years were obtained from the Wharton School of Finance and Commerce's 'Capacity Utilization Index' series. The variable \( K \) is then the utilized capital stock, measured as the net stock of fixed capital (plant and equipment) multiplied by the utilization rate.

\(^{16}\) The exceptions were SIC 20, 30, and 32, whose series began in 1956. For documentation on data sources and methods, see Nadiri (1980).
We begin with some descriptive statistics (see Table 2). Annual rates of TFP growth in manufacturing over the 1947–77 period range from a high of 1.9% in chemicals to a low of −0.2% in lumber and wood products. The unweighted average across all manufacturing industries is 0.65% per year. Average R&D intensity (R&D as a percent of GDO) among all industries over the 1947–77 period is 1.8%, ranging from a high of 9.6% in transport equipment to a low of 0.05% in textiles and apparel. The simple correlation coefficient between TFP growth (TFPGRT) and R&D intensity (RDGDO) is a positive 0.39. Moreover, dividing the 19 manufacturing industries into groups of five (four for the bottom group) according to their rate of TFP growth, we find that the group with the highest TFP growth also had the highest average R&D intensity (3.2%), followed, in turn, by the next group, the second lowest group, and the bottom group (bottom panel of Table 2).

R&D embodied in intermediate inputs (RDMIND) ranges from a high of 0.027 in transport equipment to a low of 0.001 in tobacco products. RDMIND is also positively correlated with TFP growth, 0.34. The average value of RDMIND is highest for the top five industries ranked by TFP group, followed, sequentially, by the next five, the next lower group, and the lowest group. In contrast, R&D embodied in capital investment (RDKIND) shows almost no correlation with TFP growth among manufacturing industries, and its average group value does not have the same rank order as TFP growth among the four groups.

Regressions were pooled over five time periods: 1947–58, 1958–63, 1963–67, 1967–72, and 1972–77. The use of synchronic time periods—in this case, five—is new in the literature, which typically presents estimates of the return to R&D based on
Table 2. Mean Values and Correlation Coefficients of Key Variables for Manufacturing Industries, 1947–77

<table>
<thead>
<tr>
<th>SIC code</th>
<th>Name</th>
<th>TFPGRT TFP growth (% per year)</th>
<th>RDGDO R&amp;D/GDO (%)</th>
<th>Embodied R&amp;D</th>
<th>RDMIND</th>
<th>RDKIND</th>
<th>TFPIND</th>
<th>LINK2</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>Processed foods</td>
<td>0.78</td>
<td>0.181</td>
<td>0.0013</td>
<td>0.0300</td>
<td>0.0045</td>
<td>2.350</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>Tobacco products</td>
<td>0.88</td>
<td>0.264</td>
<td>0.0011</td>
<td>0.0002</td>
<td>0.0048</td>
<td>1.337</td>
<td></td>
</tr>
<tr>
<td>22, 23</td>
<td>Textiles and apparel</td>
<td>1.31</td>
<td>0.054</td>
<td>0.0029</td>
<td>0.0051</td>
<td>0.0082</td>
<td>2.916</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>Lumber and wood products</td>
<td>−0.17</td>
<td>0.130</td>
<td>0.0021</td>
<td>0.0014</td>
<td>0.0021</td>
<td>2.275</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>Furniture</td>
<td>0.23</td>
<td>0.115</td>
<td>0.0032</td>
<td>0.0009</td>
<td>0.0035</td>
<td>1.078</td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>Paper and paper products</td>
<td>0.30</td>
<td>0.498</td>
<td>0.0039</td>
<td>0.0067</td>
<td>0.0030</td>
<td>3.035</td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>Printing and publishing</td>
<td>0.01</td>
<td>0.279</td>
<td>0.0027</td>
<td>0.0046</td>
<td>0.0032</td>
<td>2.140</td>
<td></td>
</tr>
<tr>
<td>28</td>
<td>Chemicals</td>
<td>1.86</td>
<td>2.493</td>
<td>0.0098</td>
<td>0.0129</td>
<td>0.0057</td>
<td>4.269</td>
<td></td>
</tr>
<tr>
<td>29</td>
<td>Petroleum refining</td>
<td>0.61</td>
<td>1.272</td>
<td>0.0027</td>
<td>0.0028</td>
<td>−0.0031</td>
<td>2.305</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>Rubber products</td>
<td>1.47</td>
<td>1.107</td>
<td>0.0074</td>
<td>0.0035</td>
<td>0.0057</td>
<td>2.020</td>
<td></td>
</tr>
<tr>
<td>31</td>
<td>Leather and footwear</td>
<td>0.51</td>
<td>0.260</td>
<td>0.0033</td>
<td>0.0003</td>
<td>0.0047</td>
<td>1.345</td>
<td></td>
</tr>
<tr>
<td>32</td>
<td>Glass, stone, and clay products</td>
<td>−0.09</td>
<td>0.877</td>
<td>0.0035</td>
<td>0.0032</td>
<td>0.0024</td>
<td>1.770</td>
<td></td>
</tr>
<tr>
<td>33</td>
<td>Primary metals</td>
<td>−0.04</td>
<td>0.527</td>
<td>0.0052</td>
<td>0.0205</td>
<td>−0.0011</td>
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<tr>
<td>34</td>
<td>Metal products</td>
<td>0.13</td>
<td>0.588</td>
<td>0.0059</td>
<td>0.0050</td>
<td>0.0016</td>
<td>2.657</td>
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<tr>
<td>35</td>
<td>Machinery and industrial equipment</td>
<td>0.46</td>
<td>2.782</td>
<td>0.0124</td>
<td>0.0088</td>
<td>0.0033</td>
<td>2.793</td>
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<tr>
<td>36</td>
<td>Electrical machinery</td>
<td>1.59</td>
<td>7.658</td>
<td>0.0168</td>
<td>0.0096</td>
<td>0.0047</td>
<td>2.381</td>
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<tr>
<td>37</td>
<td>Transport equipment</td>
<td>0.62</td>
<td>9.574</td>
<td>0.0273</td>
<td>0.0096</td>
<td>0.0039</td>
<td>2.441</td>
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<tr>
<td>38</td>
<td>Scientific equipment</td>
<td>1.29</td>
<td>4.607</td>
<td>0.0126</td>
<td>0.0018</td>
<td>0.0046</td>
<td>1.357</td>
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<tr>
<td>39</td>
<td>Miscellaneous manufacturing</td>
<td>0.61</td>
<td>0.223</td>
<td>0.0020</td>
<td>0.0011</td>
<td>0.0036</td>
<td>1.330</td>
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<tr>
<td></td>
<td>Unweighted average</td>
<td>0.65</td>
<td>1.770</td>
<td>0.0068</td>
<td>0.0053</td>
<td>0.0034</td>
<td>2.345</td>
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<tr>
<td></td>
<td>Weighted average†</td>
<td>0.72</td>
<td>2.413</td>
<td>0.0050</td>
<td>0.0074</td>
<td>0.0036</td>
<td>2.739</td>
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<td></td>
<td>Correlation with TFP growth</td>
<td></td>
<td>0.39</td>
<td>0.34</td>
<td>0.08</td>
<td>0.60</td>
<td>0.07</td>
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<tr>
<td></td>
<td>Averages of groups ranked by TFPGRT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>top 5</td>
<td>1.50</td>
<td>3.224</td>
<td>0.0099</td>
<td>0.0066</td>
<td>0.0038</td>
<td>2.589</td>
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<tr>
<td></td>
<td>next 5</td>
<td>0.70</td>
<td>2.291</td>
<td>0.0075</td>
<td>0.0033</td>
<td>0.0027</td>
<td>1.953</td>
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<td>next 5</td>
<td>0.33</td>
<td>0.849</td>
<td>0.0057</td>
<td>0.0043</td>
<td>0.0032</td>
<td>2.182</td>
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<tr>
<td></td>
<td>bottom 4</td>
<td>−0.07</td>
<td>0.453</td>
<td>0.0034</td>
<td>0.0074</td>
<td>0.0017</td>
<td>2.733</td>
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</tbody>
</table>

† The figure shown for TFPGRT is the average annual rate of TFP growth over the 1947–77 period. For RDGDO, RDMIND, RDKIND, and LINK2, the figure shown is the unweighted average value of the variable in 1947, 1958, 1963, 1967, 1972, and 1977. For TFPIND, the figure shown is the unweighted average value of the variable in five periods: 1947–58, 1958–63, 1963–67, 1967–72, and 1972–77.

‡ Weighted by gross output shares.
single-period regressions. These estimates may be period-dependent. Our approach allows us to capture long-term effects of R&D on productivity. Moreover, since R&D data were available only for manufacturing sectors, most regressions were performed only on manufacturing sectors. Other specifications, when appropriate, were performed across all sectors (50 in all).

Regression results on R&D spillovers are shown in Table 3. R&D intensity is significantly related to sectoral TFP growth at the 5% significance level. The estimated direct return to R&D was about 11% among exclusively manufacturing sectors but 20% among all sectors. These estimates fall in the low part of the range of previous estimates of the direct rate of return to R&D, which range from about 3% (Griliches and Lichtenberg, 1984a) to 76% (Griliches and Lichtenberg, 1984b). (Also see table 1 of Nadiri, 1991, and the paper for an extensive review of the literature.) Our estimates are likely on the low side because we use TFP growth based on gross output (including intermediate inputs), instead of value added (excluding intermediate inputs), so that our estimates of sectoral TFP growth are about half those based on value added.17

The estimated indirect return to R&D based on RDMIND is found to be 14% among manufacturing sectors and 8% among all sectors. These estimates also fall within the range of previous estimates, which vary from 11% (Bernstein and Nadiri, 1988) to 183% (Terleckyj, 1980), though are, again, on the low side (also see table 2 of Nadiri, 1991). Moreover, the coefficient estimates are not statistically significant. This has been the case in several other studies (see, e.g. Odagiri, 1985).18

We also find that R&D embodied in capital stock (RDKIND) is significant at the 10% level among all sectors, with an estimated rate of return of 9%.19 This, as far as we are aware, is a new finding. Moreover, by adding together RDGDO, RDMIND, and RDKIND, we obtain estimates of the total or social rate of return to R&D of 27% within manufacturing and 42% among all sectors, both significant at the 1% level. These again fall within the range of previous estimates.

The time dummy variables fall into a consistent pattern (results not shown). They indicate that the general rate of TFP growth, not attributable to R&D, was highest in the 1958–63 period, followed by the 1963–67 period, the 1947–58 period, the 1967–72 period, and, lastly, the 1972–77 period. These results correspond directly to the general pattern of productivity growth over the postwar period, particularly the post-1967 productivity slowdown. The F-statistics for the time dummy variables as a group are significant at the 1% level.

We also include direct measures of forward industry linkage (see Section 3 below) as explanatory variables in equation (4). The argument here is that the existence

\footnote{Terleckyj's 1980 paper supports this conjecture. With a two-factor TFP index, the coefficient on direct (private) R&D is 0.27, significant at the 1% level; with a three-factor TFP index, the coefficient is 0.20 but is not statistically significant (table 6.6, p. 375).}

\footnote{Results for RDMINDA are similar.}

\footnote{It is likely that the spillover effects from R&D embodied in the new capital stock are understated. The reason is that RDKIND is measured according to net investment flows (i.e. the change in net capital stock). It is probable that borrowed R&D is more strongly related to gross investment, since replacement investment may also embody new technology. Data limitations prevent us from using the gross investment measure.}
Table 3. The Effect of R&D Intensity, Borrowed R&D, and Borrowed TFP on the Sectoral Rate of TFP Growth

<table>
<thead>
<tr>
<th>Independent variables</th>
<th></th>
<th>Dependent variable: TFPGR</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0041</td>
<td>0.0029</td>
<td>0.0047**</td>
<td>0.0188**</td>
<td>0.0173**</td>
<td>0.0001</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(1.15)</td>
<td>(0.99)</td>
<td>(1.42)</td>
<td>(2.26)</td>
<td>(2.28)</td>
<td>(0.01)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>RDGDO</td>
<td>0.106**</td>
<td>0.016**</td>
<td>0.111**</td>
<td>0.106**</td>
<td>0.076</td>
<td>0.008</td>
<td>0.092*</td>
</tr>
<tr>
<td></td>
<td>(2.21)</td>
<td>(2.39)</td>
<td>(1.59)</td>
<td>(1.23)</td>
<td>(1.23)</td>
<td>(0.51)</td>
<td>(1.73)</td>
</tr>
<tr>
<td>RUMIND</td>
<td>0.0143</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.59)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDKIND</td>
<td>-0.008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFPIND</td>
<td>0.224</td>
<td>0.224</td>
<td>0.224</td>
<td>0.041</td>
<td>0.0243</td>
<td>0.0243</td>
<td>0.114</td>
</tr>
<tr>
<td></td>
<td>(0.244)</td>
<td>(0.273)</td>
<td>(0.224)</td>
<td>(0.043)</td>
<td>(0.243)</td>
<td>(0.243)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Standard error σ</td>
<td>0.0125</td>
<td>0.0124</td>
<td>0.0126</td>
<td>0.0243</td>
<td>0.0243</td>
<td>0.0243</td>
<td>0.0244</td>
</tr>
<tr>
<td>Sample</td>
<td>manufacturing</td>
<td>manufacturing</td>
<td>manufacturing</td>
<td>manufacturing</td>
<td>all</td>
<td>all</td>
<td>all</td>
</tr>
</tbody>
</table>

1 Estimated coefficients are shown next to the respective independent variables and the absolute value of the t-statistic is shown in parentheses. Time dummy variables for four time periods are included: 1938-63, 1963-67, 1967-72, and 1972-77. Coefficient estimates of the dummy variables are not shown.

2 Sample size for the manufacturing sample is 95 (19 industries in five time periods). Sample size for all sectors is 250 (50 sectors in five time periods).

* Significant at the 0.10 level (two-tailed test).

** Significant at the 0.05 level (two-tailed test).

*** Significant at the 0.01 level (two-tailed test).
of a large array of customer industries may stimulate the development of new technology in the supplying industry because of knowledge flows from customer to supplier. However, the forward linkage variables are not found to be statistically significant. But, as we shall see below, the converse is not the case.20

2.2. Spillover Effects of Private and Government-Financed R&D

Using National Science Foundation data, we split R&D expenditures in each period into one part that was financed by private sources ('private' R&D) and a second part that was government-financed. Company-financed R&D comprised more than 90% of total R&D spending in all industries except rubber products (SIC 30); engines, machinery, and industrial equipment (SIC 35); electrical machinery and appliances (SIC 36); motor vehicles and transportation equipment (SIC 37); and scientific equipment and supplies (SIC 38). Indeed, in electrical machinery and transportation equipment, government-financed R&D accounted for about two-thirds of total R&D.

We first estimate the return to privately-financed R&D, RP, and government-financed R&D, RG, by dividing RDGDO into these two components:

\[ \text{RDGDO} = \text{RDPGDO} + \text{RDGGDO}. \]

As found in other studies,21 the return to private R&D is much higher and more significant than that to total R&D. In manufacturing, the estimated rate of return is about 40% and among all sectors about 60% (see Table 4). The return to government-financed R&D is statistically insignificant. It is possible that the effect of government-financed R&D is indirect via an inducement to increase company-financed R&D. However, recent results by Lichtenberg (1984) suggest the opposite. Also government R&D is concentrated in a few industries and probably is undertaken for objectives other than promotion of overall productivity growth. Moreover, as Griliches (1986) has suggested, most of the direct output of federally funded research is 'sold' back to the government as a 'cost-plus' basis and is thus not likely to be reflected in the firm's productivity.

It is also possible to develop measures of borrowed privately-financed and government-financed R&D, and assess their effect on productivity growth. Results for private R&D embodied in intermediate inputs (RDPMIND) is statistically significant, at the 10% level, among manufacturing industries. The estimated indirect rate of return is 17%. However, RDPMIND is insignificant across all sectors of the

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20 We also investigated two other sources of borrowed R&D. The first is 'second-round' borrowings of R&D by sector j from sector i. This is estimated by \( \Sigma_i \Sigma_k a_{ik} a_{ij} \text{RD}_i / x_i \). This term would thus, for example, capture the computer sector's (i) R&D which, through sales of computers to telecommunications (k) and of telecommunications to the sales sector (j), is indirectly embodied in sales output. Second-round R&D transfers are likely to be extremely weak and, indeed, are found to be statistically insignificant in our regression analysis. The second are 'backward' spillovers from R&D. The argument for this is that technology developed by industry j may create new technological knowledge and opportunities for supplying industries. In particular, it may induce the development of new technology or products in the supplying industries. We developed several measures of backward spillovers, but none are found to be statistically significant.

Table 4. Spillover and Linkage Effects of Private R&D

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>TRPGRT</th>
<th>TFPGRGRT</th>
<th>TFPGRRT</th>
<th>TFPGRGRT</th>
<th>LINK1</th>
<th>LINK2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0026</td>
<td>0.0028</td>
<td>-0.0006</td>
<td>-0.0013</td>
<td>0.0099***</td>
<td>2.004***</td>
</tr>
<tr>
<td></td>
<td>(0.85)</td>
<td>(0.98)</td>
<td>(0.17)</td>
<td>(0.36)</td>
<td>(15.56)</td>
<td>(29.83)</td>
</tr>
<tr>
<td>RDPGDO</td>
<td>0.430***</td>
<td>0.378***</td>
<td>0.612**</td>
<td>0.589**</td>
<td>0.243***</td>
<td>17.52**</td>
</tr>
<tr>
<td></td>
<td>(2.95)</td>
<td>(3.21)</td>
<td>(2.46)</td>
<td>(3.21)</td>
<td>(3.62)</td>
<td>(2.53)</td>
</tr>
<tr>
<td>RDGGDO</td>
<td>-0.072</td>
<td>-0.087</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.81)</td>
<td>(0.50)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDPMIND</td>
<td>0.171*</td>
<td>0.105**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.72)</td>
<td>(1.98)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDPKIND</td>
<td>0.268</td>
<td>0.281</td>
<td>0.076</td>
<td>0.090</td>
<td>0.048</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>(0.218)</td>
<td>(0.234)</td>
<td>(0.051)</td>
<td>(0.065)</td>
<td>(0.041)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Standard error x</td>
<td>0.0122</td>
<td>0.0120</td>
<td>0.0242</td>
<td>0.0240</td>
<td>0.0082</td>
<td>0.919</td>
</tr>
<tr>
<td>Sample</td>
<td>manufacturing</td>
<td>manufacturing</td>
<td>all</td>
<td>all</td>
<td>all</td>
<td>all</td>
</tr>
</tbody>
</table>

1 Estimated coefficients are shown next to the respective independent variables and the absolute value of the t-statistic is shown in parentheses.

2 Sample size for the manufacturing sample is 95 (19 industries in five time periods). Sample size for all sectors is 250 (50 sectors in five time periods).

* Significant at the 0.10 level (two-tailed test).

** Significant at the 0.05 level (two-tailed test).

*** Significant at the 0.01 level (two-tailed test).

ECONOMY (results not shown). Private R&D embodied in new investment (RDPKIND) is statistically significant at the 5% level among all sectors of the economy, with an estimated indirect rate of return of 11%. However, the variable is insignificant among manufacturing sectors (results not shown). Borrowed government-financed R&D is uniformly insignificant (results not shown).

3. SPILLOVER EFFECTS OF TECHNICAL CHANGE

We next construct estimates of direct technological spillovers in analogous fashion to that of R&D spillovers. Thus

\[ TFPIND_j = \Sigma_i \pi_{ij} a_{ij} \]

is a measure of sector \( j \)'s indirect knowledge gain from technological progress in its supplying sectors. According to the descriptive statistics, shown in Table 2, the average value of TFPIND over the first periods 1947–58, 1958–63, 1963–67, 1967–72, and 1972–77 ranges from a low of -0.003 in petroleum refining to a high of 0.008 in textiles and apparel. TFPIND is strongly correlated with industry TFP growth, with a correlation coefficient of 0.60. The average value of TFPIND is over three times as great in the group of industries with the highest (direct) TFP growth than in the group with the lowest TFP growth, and about twice as great as in the middle two groups of industries.
Results are shown in Table 3. The principal finding is that among manufacturing sectors, an industry's TFP growth is positively and significantly related to the TFP growth of its supplying sectors. Since

$$\text{TFPIND}_i = \left[ \frac{\Sigma_i a_{ij}^P \pi_j / \Sigma_i a_{ij}^P}{\Sigma_i a_{ij}^P / 1} \right]$$

TFPIND can be interpreted as a weighted average of the TFP growth of supplying sectors multiplied by the ratio of the value of intermediate inputs to the total value of inputs. Since the latter ratio averages about 0.6, this indicates that a 1% increase in the TFP growth of a sector's suppliers would be associated with a half percentage point 'productivity pass through' in the sector's own productivity growth.

As with other specifications for the manufacturing sample, the R&D intensity variable is significant at the 5% level, and its estimated coefficient is 0.11. By the usual criteria ($R^2$, adjusted $R^2$, and standard error of the regression), this form provides the best fit of the four shown in Table 3 for the manufacturing sample. However, indirect TFP proved to be insignificant in regressions run across all sectors. The likely reason is that while within manufacturing there is sufficient technological closeness to promote direct borrowing among industries, this is not the case among the major sectors of the economy (between manufacturing and various services, for example).

4. LINKAGE STRUCTURE

To measure linkages, we use three indices developed in the input–output literature. The first is the average value of the value coefficients, $a_{ij}^P$ (defined as $p_i a_{ij} / p_j$):

$$\text{LINK}_1 = \Sigma a_{ij}^P / (N - 1)$$

where $N$ is the number of sectors (50 in our case). The second index is the row sum of the value inverse matrix:

$$\text{LINK}_2 = \Sigma_j [(I - A^*)^{-1}]_{ij}$$

This measure shows the total increase in output in sector $i$ that would be forthcoming to meet a dollar increase in the demand for the output of each sector of the economy. This index expresses the extent to which the system of industries in the economy draws upon industry $i$ in order to expand production. The third is given by

$$\text{LINK}_3 = \Sigma_j [(I - B^*)^{-1}]_{ij}$$

The column sum of the $(I - B^*)$ inverse matrix shows the total output of user industries needed to absorb an additional dollar of sector $i$'s output.

Descriptive statistics for LINK2, shown in Table 2, indicate a range of values from 1.08, in the furniture sector (primarily sells household consumption goods), to 4.76, in primary metals (sells almost exclusively to other industries). Among manufacturing industries, there is almost no correlation between LINK2 and industry TFP growth.

A variant uses the coefficients $a_{ij}^P / \Sigma_i a_{ij}^P$, which shows the importance of input $i$ exclusively among other intermediate inputs. Results are similar to those of LINK1.
TABLE 5. The Effect of R&D Intensity and Productivity Growth on Forward Linkage Structure

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>LINK1</th>
<th>LINK1</th>
<th>LINK1</th>
<th>LINK1</th>
<th>LINK2</th>
<th>LINK2</th>
<th>LINK3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0122***</td>
<td>0.0123***</td>
<td>0.0093***</td>
<td>0.0094***</td>
<td>1.957***</td>
<td>1.986***</td>
<td>2.437***</td>
</tr>
<tr>
<td>(13.01)</td>
<td>(6.78)</td>
<td>(16.17)</td>
<td>(7.76)</td>
<td>(31.52)</td>
<td>(15.14)</td>
<td>(32.43)</td>
<td></td>
</tr>
<tr>
<td>RDGDO</td>
<td>0.031</td>
<td>0.081***</td>
<td>6.594**</td>
<td>6.835</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.09)</td>
<td>(2.86)</td>
<td>(2.15)</td>
<td>(1.54)$^*$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFPGRT</td>
<td>-0.011</td>
<td>0.042***</td>
<td>3.961***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.18)</td>
<td>(2.59)</td>
<td>(2.24)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.013</td>
<td>0.007</td>
<td>0.028</td>
<td>0.008</td>
<td>0.014</td>
<td>0.017</td>
<td>0.10</td>
</tr>
<tr>
<td>$R_s^2$</td>
<td>0.002</td>
<td>0.0077</td>
<td>0.0085</td>
<td>0.0066</td>
<td>0.921</td>
<td>0.927</td>
<td>1.114</td>
</tr>
<tr>
<td>Standard error $\sigma$</td>
<td>0.0075</td>
<td>manufacturing</td>
<td>manufacturing</td>
<td>all</td>
<td>all</td>
<td>all</td>
<td>all</td>
</tr>
</tbody>
</table>

Sample: manufacturing manufacturing all all all all

1 Estimated coefficients are shown next to the respective independent variables and the absolute value of the t-statistic is shown in parentheses.
2 Sample size for the manufacturing sample is 95 (19 industries in five time periods). Sample size for all sectors is 250 (50 sectors in five time periods).
* Significant at the 0.10 level (two-tailed test).
** Significant at the 0.05 level (two-tailed test).
*** Significant at the 0.01 level (two-tailed test).

The correlation coefficient is 0.07. Moreover, groupings by industries ranked by TFP growth indicate that the average value of LINK2 is highest for the bottom group, second highest for the top group, third highest for the next to bottom group, and lowest for the second group.

Regression results are shown in Table 5. The various linkage indices are regressed alternately on sectoral TFP growth and R&D intensity. Among all sectors, R&D intensity and TFP growth are generally positive and statistically significant. This result must be interpreted with some caution, since it may simply reflect the greater forward linkage of manufacturing (high R&D and relatively high productivity growth sectors) with non-manufacturing sectors due to the position of manufacturing in the normal flow between primary and final output. On the other hand, among exclusively manufacturing industries, no statistically significant relations are found. However, it is possible that this negative finding is due to the high level of aggregation within the manufacturing sector (to 19 industries) and that further disaggregation might produce significant results.

Finally, we can assess the effect of both private and government-financed R&D on linkage structure. As shown in Table 4, we find very significant positive effects of private R&D intensity on the degree of forward linkages among all sectors. Both the estimated coefficients and the significance levels are greater than for corresponding forms using total R&D intensity. Government-financed R&D, on the other hand, is uniformly insignificant as a determinant of linkage strength.

23 No time dummy variables are included in this case, since there are no clear period-specific effects in this mode.
5. CONCLUSIONS

As in most previous studies, we find a statistically significant relation between the R&D intensity of a sector and its rate of productivity growth. We also find, as in other studies, spillover effects of R&D embodied in intermediate inputs within manufacturing. The results are statistically significant for private R&D embodied in intermediate inputs, but not for total embodied R&D. However, a new finding here is that R&D embodied in capital stock, and even more strongly private R&D embodied in capital stock, is found to have statistically significant, spillover effects on sectoral TFP growth among all sectors. However, within manufacturing, spillover effects of R&D embodied in capital stock are not significant.

Our most novel finding is that within manufacturing the TFP growth of supplying sectors is significantly related to a sector's own productivity growth. However, among all sectors this relation is not statistically significant. The likely reason is that among manufacturing firms, the technologies of different industries are sufficiently close to permit direct borrowings of new processes, whereas among all sectors, technologies of the various industries differ too much. Thus, it appears that within manufacturing, new technical knowledge is borrowed by observing the new technology of suppliers, whereas among non-manufacturing industries the borrowing of knowledge takes place through the acquisition of new capital stock.

Another new finding is that the degree of forward linkage of a sector is positively and significantly related to both its R&D intensity (particularly company-financed R&D) and its rate of TFP growth. The results lend support to our argument that R&D and technological progress, through quality improvement, lowered price, and the development of new products, expands an industry's market and leads to a greater number of new customers.

Our results are admittedly crude and only suggestive because of the high level of aggregation of the data, particularly in manufacturing. However, they do point the way toward the importance of technological spillovers among closely connected industries. Such 'agglomeration' effects have been discussed by others (see, e.g. Rosenberg, 1982), but this is apparently the first direct evidence of technological change in one sector affecting TFP growth in purchasing sectors and affecting the degree of forward linkage. Hopefully, greater disaggregation will lend greater support to our conclusions. It would also be interesting to consider in greater detail the role of different inputs as carriers of new technology, particularly different components of capital investment.

Moreover, though, unfortunately, our analysis ends in 1977 (limited by available input–output data), we suspect that the results on inter-sectoral spillovers may be heightened during the 1980s because of the paradigmatic shift from electrochemical automation to information technologies (see, e.g. David, 1991). Indeed, this study has not been able to adequately capture the role of computerization in the spread of new technologies, a process that was likely to have been particularly important during the 1980s.

Another potential area of future research is the role of imported technology. This issue can be addressed in similar fashion by, for example, breaking out imported...
intermediate inputs and capital goods from domestically produced ones, where the data permit. Such an analysis could consider the effects of R&D embodied in such inputs, as well as the effects of technological progress in the (foreign) industries producing these goods. Correspondingly, one could consider the role of R&D embodied in exports and the technological progress of industries producing exports on productivity growth in export destination countries.

ACKNOWLEDGEMENTS

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REFERENCES


