Spillovers, Linkages, and Productivity Growth in the US Economy, 1958 to 2007

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Abstract: I speculate that technological spillover effects may have become more important over time as information technology (IT) penetrated the US economy. The rationale is that IT may speed up the process of knowledge transfer and make these knowledge spillovers more effective. Using US input-output tables for years 1958 through 2007, I compare my new results with Wolff and Nadiri (1993) covering years 1947-1977 and Wolff (1997) covering 1958-1987. I estimate that the direct rate of return to R&D is now 22% and the indirect rate of return to R&D is 37%. The former is higher and the latter has a higher significance level than in the previous studies. Separate regressions on the 1958-1987 and 1987-2007 periods and the addition of successive periods to the sample also suggest a strengthening of R&D spillovers between the 1958-1987 and 1987-2007 periods. These results suggest a strengthening of the R&D spillover effect over time.

Keywords: Productivity, Technical Change, Input/Output, R&D, Spillovers

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This paper examines whether the contribution of inter-sectoral spillovers to industry productivity growth has increased over time in the US over the years from 1958 to 2007. There are two potential sources for this. First, the size of the inter-sectoral linkage may have grown over time – that is, linkages may have strengthened over time. Second, the coefficient on the inter-sectoral linkage may have risen over time. With the introduction of Information Technology (IT) and its widespread adoption beginning in the early 1970s, one would think that the speed of knowledge spillovers would have accelerated over time. Another contribution of the paper is that the results of the empirical analysis will make it possible to estimate the direct and indirect return (as well as the social rate of return) to R&D.

In this regard, this paper extends previous work (Wolff and Nadiri, 1993, and Wolff, 1997) on the measurement of R&D spillovers based on computing embodied R&D using US input-output tables from 1947 to 1987. Throughout the paper, I will compare the new results to the old ones to see whether the spillover effects found in the older papers still hold up for the more recent period (and whether new relations are found).

The paper is organized as follows. The first section provides a review of the pertinent literature on spillover effects across industries. Section 2 introduces the model to be used in the empirical analysis. Section 3 discusses the data sources and methods. Section 4 presents the results of the econometric analysis. Concluding remarks are provided in the last part, Section 5.

I. Review of Previous Literature

A. Domestic R&D Spillovers

R&D spillovers refer to the direct knowledge gains of customers from the R&D of the supplying industry (see Griliches, 1979).[1] There have been several approaches to measuring R&D spillovers. In, perhaps, the earliest work on this subject, Brown and Conrad (1967) based their measure of borrowed R&D on input-output trade flows

[1] Griliches also identifies a second interpretation of spillovers; namely, that inputs purchased from an R&D-performing industry may embody quality improvements that are not fully appropriated by the supplier. It should be emphasized at the outset that though these two spillover notions are quite distinct, they cannot be distinguished statistically in this work.

(purchases and sales) between industries. Terleckyj (1974, 1980) provided measures of the amount of R&D embodied in customer inputs on the basis of inter-industry material and capital purchases made by one industry from the supplying industries. Scherer (1982), using Federal Trade Commission line of business data, used product (as distinct from process) R&D, aimed at improving output quality, as the basis of his measure of R&D spillovers.

Another approach is to measure the degree of "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), then one industry may benefit from the new discoveries by the other industry. Such an approach is found in the work of Jaffe (1986), where patent data are used to measure technological closeness between industries.

Bernstein and Nadiri (1989) used total R&D at the two-digit Standard Industrial Classification (SIC) level as a measure of intra-industry R&D spillovers and applied this measure to individual firm data within industry. Mairesse and Mohnen (1990) used a similar schema by comparing R&D coefficients based on firm R&D with those based on industry R&D. If there exist intra-industry externality effects of firm R&D, then the coefficient of industry R&D should be higher than those of firm R&D. However, the results of Mairesse and Mohnen did not show that this was consistently the case.

There have been a large number of studies which have followed one or other of these approaches for estimating the spillover effects of R&D (see Mohnen, 1990 and 1992, Griliches, 1992, and Cameron, 1996, for reviews of some of the earlier literature). In contrast, the literature on direct productivity spillover is more limited. Some of the earlier literature on this subject was quite suggestive. For the German economy Oppenlander and Schulz (1981) calculated that only about one third of new products were derived from technology (that is, process innovation). The remainder are 'market innovations," which are used to open up new markets for the producers. Pavitt (1984) estimated that out of 2000 innovations introduced in the U.K, only about 40 percent were developed in the sector using the innovation. The remainder were borrowed from new technologies developed in other sectors.

The work of Nelson and Winters (1982) illustrated 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) suggested 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 speculated that there are certain intra-industry flows of new equipment and materials that have a disproportionate level of technological change in the economy.

A paper by Bartelsman et al. (1991) is also highly suggestive. Using regression analysis, they related the growth in an industry's output to a weighted average of the growth in the outputs of the supplying industries, where the weights are determined by the industry's input coefficients. They concluded that the linkage between an industry and its suppliers appeared to be the dominant factor in accounting for long-term growth externalities. However, they did no directly relate an industry's own productivity growth to the R&D of its suppliers or to its suppliers' rate of productivity advance.

Wolff and Nadiri (1993) provided one of the first investigations of direct productivity spillovers. They used as their measure of embodied technical change a weighted average of the TFP growth of the supplying industries, where the weights are determined by the industry's input-output coefficients. This formulation assumes that the knowledge gained from a supplying industry is in direct proportion to the value of that industry in a sector's input structure. Using U.S. input-output data from 1947 to 1977, they found a statistically significant effect of this index on an industry's own rate of technical change.

Wolff (1997) followed up this work using U.S. input-output data from 1958 to 1987 and found an even stronger effect of embodied TFP growth on an industry's own rate of technical advance, with an elasticity of almost 60 percent. The return to embodied R&S was estimated at 43 percent. Direct productivity spillovers from the technological progress made by supplying sectors appeared to be more important than spillovers from the R&D performed by the suppliers. Moreover, changes in the contribution made by direct productivity spillovers to TFP growth accounted for almost half of the slowdown in TFP growth in manufacturing from 1958-1967 to 1967-1977 and for 20 percent of the TFP recovery in this sector from 1967-1977 to 1977-1987.

Following up the work of Scherer (1982), Ornaghi (2006) considered a model where process innovations spillovers to other firms raise firms' relative efficiency and technological diffusion of product innovations enhances firms' demand. Using panel data of Spanish manufacturing firms over the period 1990 to 1999, he found technological externalities significantly affect firm-level productivity growth. He also found that technological diffusion of product innovations was larger than the one deriving from process innovations, both in magnitude and pervasiveness.

Several papers have looked at the importance of geographic proximity in explaining R&D spillovers. The usual argument is that firms that are located in the same or proximate locations have greater opportunities to communicate than those further away. Geographic proximity may lead to the formation of social networks that can facilitate learning. Adams and Jaffe (1996) used a panel of manufacturing establishments over time from the Census and Annual Survey of Manufactures, matched by firm and industry to the firm-level R&D survey conducted by the National Science Foundation. The sample period was from 1974 to 1988. They found that the effects of parent firm R&D on plant-level productivity are diminished by both the geographic and technological distance between the research lab and the plants.

Orlando (2004) looked at firms in SIC 35, Industrial, Commercial Machinery, and Computer Equipment. The primary data were from Standard & Poor's Compustat database from 1970 to 1998. These were supplemented with Bureau of labor Statistics price deflators for industry input and output, as well as county-level latitude and longitude data from the U.S. Geological Survey. He used a production- function framework to examine the role of geographic and technological proximity for inter-firm spillovers from R&D in SIC 35. He found that spillovers among firms within narrow, four-digit industrial classifications were generally stronger than those identified within the broader, three-digit class. Such spillovers, however, did not appear to be reduced by distance. Geographic distance did appear to attenuate spillovers that cross four-digit boundaries, suggesting that they may play a role in the formation of diverse (but not too diverse) industrial agglomerations.

Lychagin et. al. (2010) used U.S. Compustat data for manufacturing firms for the period 1980 to 2000. These were matched with patent data from the U.S. Patent and Trademark Office available from the NBER data archive. Inventor location was taken from the address of the lead inventor of the patent, which is recorded at the city level. Their purpose was to investigate the contributions to productivity of three sources of research and development spillovers: geographic, technology and product–market proximity. They found that technological proximity (as developed by Jaffe, 1986) was important in explaining R&D spillovers. Moreover, geographical distance also had an effect in accounting for R&D spillovers even after conditioning on horizontal and technological spillovers. However, product–market proximity was less important than these two factors in accounting for R&D spillovers.

B. International R&D Spillovers

Over the last 15 years or so, much of the attention in this literature has been directed at international spillovers, and, as a result, there are also quite a few papers that have investigated the presence and importance of cross-national R&D and technological spillovers. Coe and Helpman (1995) were among the first to provide evidence on the importance of trade as a vehicle for the international diffusion of technology. They argued that if there is evidence (as seems to be the case) that innovation or R&D performed in one industry leads to technological gains in using industries, then is it possible that R&D performed in one country leads to technological gains in countries which import products from the first country? Coe and Helpman gathered data for 22 OECD countries covering the period from 1971 to 1990. They constructed measures of (domestic) R&D stock by country and estimated import flows between countries. Their major contribution was to construct a measure of "foreign R&D capital," which they defined as the import-share weighted average of the domestic R&D capital stocks of trade partners. Using bilateral import shares to weight foreign R&D expenditures, they calculated the variable S^f_i, which represented the foreign R&D stock of country i, as:

$$S^f_i = \sum_j m_{ik} RD_k$$

where m_{ik} is the share of imports coming from country k as a share of total imports into country i and RD_k is the stock of R&D in country k. Thus, the more R&D intensive the imports are from other countries, the higher is a country's stock of foreign R&D capital.

They then regressed a country's annual total factor productivity (TFP) growth on both its domestic and foreign R&D capital. They found like most studies that domestic R&D was a significant determinant of a country's TFP growth. However, their most important finding was that foreign capital was also a significant determinant of TFP growth within a country. They calculated a domestic R&D elasticity of 23 percent for the G-7 countries and about 8 percent for the 15 smaller OECD countries. However, their estimated elasticities for foreign R&D (that is, R&D embodied in imports into these countries) were 6 percent for the G-7 countries and 12 percent for the other OECD countries. They concluded that imported R&D was a more important factor in explaining domestic productivity growth in the smaller OECD countries but the converse was true for the larger OECD economies. They also found that the more open a country was, the higher the return to foreign R&D.

They then looked at two additional issues. First, they wanted to determine whether a country's productivity growth was greater to the extent that it imported goods and services from countries with a high (domestic) R&D intensity relative to imports from countries with low R&D expenditures. Second, after controlling for the composition of its imports, they were interested in whether a country's productivity growth would be higher the higher its overall import share. They found support for both predictions. In particular, they found that international R&D spillovers were related to both the composition of a country's imports as well as to its overall import intensity.

This paper stimulated a lot of additional work on the importance of foreign spillovers from trade and R&D. Park (1995), using aggregate data for 10 OECD countries (including the G-7 countries), had similar results. He estimated that foreign R&D accounted for about two thirds of the total effect of R&D on domestic productivity. He estimated a domestic R&D elasticity of 7 percent and a foreign R&D elasticity of 17 percent.

However, Verspagen (1997) challenged the findings of Coe and Helpman. Verspagen constructed a technology flow matrix based on European patent data which indicated not only in which sector the patent originated but also in which sectors the patent was used. This approach allowed the researcher to identify explicitly the pattern of inter-sectoral spillovers of knowledge. In contrast, Coe and Helpman based their spillover calculations on inter-sectoral trade (import) flows. Another difference was that Verspagen related TFP growth on the *sectoral* level to both direct and indirect R&D capital stocks.

Using a panel dataset of 22 sectors, 14 OECD countries, and 19 years (1974-1992, though there were missing data for some countries, sectors, and years), Verspagen was able to distinguish between R&D effects across sectors (the so-called "between" effect) and R&D effects over time (the so-called "within" effect). He found that foreign R&D spillovers were significant only in the "within" estimation (that is, the time-series effect). Foreign spillovers were positive in the "between" estimation (that is, between sectors) but not statistically significant. It thus appeared that the Coe and Helpman results overstated the contribution of foreign R&D to domestic productivity growth.

Eaton, and Kortum (1999) used a broader approach to calculating the relative importance of domestic and foreign R&D in domestic productivity growth. In their model, they included not only the direct effects on productivity growth but also a contribution from the transitional adjustment path to long-run equilibrium. They estimated that the portion of productivity growth attributable to domestic as opposed to imported R&D was about 13 percent in Germany, France, and the U.K; around 35 percent for Japan; and upwards to 60 percent in the U.S. Keller (2002) used a more general form of the R&D productivity function by allowing for multiple channels by which the diffusion of R&D can interact with domestic TFP growth. Using this method, he estimated that over the period from 1983 to 1995, the contribution of technology diffusion from France, Germany, Japan, the U.K., and the U.S. to nine other OECD countries amounted to about 90 percent of the total R&D effect on TFP growth.

Eaton and Kortum (1996), on the other hand, controlled for both distance and other effects. They found that once these other influences are controlled for, bilateral imports were not significant as a predictor of bilateral patenting activity, which they used as an indicator of international technology diffusion. Moreover, Keller (1998) replicated the set of regressions used by Coe and Helpman (1995) with what he termed “counterfactual import shares.” These were simulated import shares based on alternative assumptions rather than actual import shares that were used to create the imported R&D variable in the regression equations. Keller argued that for there to be strong evidence for trade induced international R&D spillovers, one should expect a strong positive effect from foreign R&D when actual bilateral import shares were used but a weaker and likely insignificant effect when the made-up “import” shares were used. Keller found high and significant coefficients when counterfactual import shares were used instead of actual import shares. The magnitude of the coefficients and the level of significance were similar in the two sets of regression. On the basis of these results, he disputed the claim of Coe and Helpman that the import composition of a country was an important factor in explaining the country’s productivity growth.

Xu and Wang (1999) showed that the import composition effect remained strong when trade in capital goods was used instead of trade in goods produced in total manufacturing. Xu and Wang obtained a R^2 statistic of 0.771 when the weights used in the construction of the imported R&D variable were based on imports of capital goods. In comparison, Keller obtained an R^2 statistic of 0.749 on the basis of his counterfactual import weights, and Coe and Helpman (1995) obtained a R^2 statistic of 0.709 in their original regressions.

Sjöholm (1996) took a different approach by analyzing citations in patent applications of Swedish firms to patents owned by inventors in other countries. Patent citations have been used in a number of studies now as an indicator for knowledge flows either between firms or between countries (see, for example, Jaffe, Trajtenberg, and Henderson, 1993). Sjöholm controlled for a number of other variables and found a positive and significant relation between Swedish patent citations and bilateral imports. He concluded that imports contributed to international knowledge spillovers.

Acharta and Keller (2008) looked at two channels by which imports affect productivity. The first is that import competition may lead to market share reallocation among domestic firms with different levels of production. This they called the “selection effect.” The second is that imports can also improve the productivity of domestic firms through learning externalities or spillovers. They used a sample of 17 industrialized countries covering the period 1973 to 2002. They reported two principal findings. First, increased imports lowered the productivity of domestic industries through selection. Second, if imports embodied advanced foreign technologies (as measured by their R&D intensity), increased imports could also generate technological learning through spillovers that on net raised the productivity of domestic industries.

Madsen (2007) took an even longer perspective on the relationship between trade and productivity growth. His data covered the period from 1870 to 2004. Using data for 16 OECD countries from Maddison (1982) and augmenting this with data on bilateral trade flows and patents for each of the countries, he constructed a measure of knowledge imports from foreign countries. Using a cointegration method, he estimated that as much as 93 percent of the TFP growth of the average OECD country could be attributed to the international transmission of knowledge through the channel of imports.

II. Accounting Framework and Input-Output Model

The input-output model can be introduced as follows, where all vectors and matrices are 45-order and in constant (2007) dollars, unless otherwise indicated:

$\mathbf{X_t}$ = column vector of gross output by sector at time t.

$\mathbf{Y_t}$ = column vector of final output by sector at time t.

$\mathbf{A_t}$ = square matrix of technical inter-industry input-output coefficients a_{ij} at time t.

It should be noted that we use the industry by industry matrix instead of the commodity by industry matrix because R&D data are available by industry of production, not by commodity.

$\mathbf{L_t}$ = row vector of labor coefficients ℓ_i, showing employment per unit of output at time t.

$\mathbf{K_t}$ = square matrix of capital stock coefficients k_{ij}, showing the capital stock of each type i per unit of output j at time t.

$\mathbf{N_t}$ = square matrix of investment coefficients n_{ij}, showing the new investment of each type i made by sector j at time t.

$\mathbf{P_t}$ = row vector of prices at time t, showing the price per unit of output of each industry.

In addition, let us define the following scalars:

w_t = annual wage rate at time t (assumed the same for all workers).

$\mathbf{i_t}$ = the rate of profit on capital stock at time t (assumed constant across industries and types of capital).

I will also make use of the so-called inter-industry value matrix A* defined as:

$\mathbf{A^*_t}$ = square matrix of value inter-industry input-output coefficients a^*_{ij} at time t, where $a^*_{ij} = p_i a_{ij} / p_j$.

Another concept that will be used is the sales coefficient matrix B, which shows the percentage of sector i's output that is sold to sector j and is given by:

$\mathbf{B_t}$ = square matrix of inter-industry sales coefficients b_{ij} at time t, where $b_{ij} \equiv a_{ij}x_j / x_i$.

Analogously, the matrix B_n shows the share of total investment of each type i that is sold to sector j:

$\mathbf{B_{nt}}$ = square matrix of investment coefficients b_{nij} at time t, where $b_{nij} \equiv n_{ij}x_j / x_i$.

Following Leontief (1953), I can now define a row vector $\boldsymbol{\pi}$, where the rate of TFP growth for sector j over period T is given by:

(1) $$TFPGRT_{jT} \equiv \pi_{jT} = -(\Sigma_i\ p_{jT}\Delta a_{ijT} + w_T \Delta \ell_{jT} + \Sigma_i\ \mathbf{i}_T \Delta k_{ijT}) / p_{jt0}$$

where Δ refers to the change over period T, p_{jT} is the average price of sector j over period T, w_T is the average wage over period T, $\mathbf{i}_T$ is the average rate of profit over period T, and p_{jt0} is sector j's price at the beginning of the period (t_0).

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

(2) $$RDX_{jT} \equiv r_{jT} = RD_{jT} / X_{jT}$$

which shows the amount of R&D expenditure (RD) in constant US dollars per constant dollar of gross output in sector j.

Forward spillovers from R&D are estimated on the basis of trade flows between sectors. I use 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 (that is, the magnitude of a_{ij}) and to sector i's R&D intensity:

$$(3) \qquad RDINDA_{jt} \equiv \Sigma_i \; a^0_{ijT} \, RD_{jt} / GDP_{jt}$$

where the matrix $\mathbf{A}^0$ is identical to the matrix $\mathbf{A}$, except that the diagonal of the matrix is set to zero in order to prevent double-counting of R&D expenditures. For period T, the average values of a^0_{ij} and the ratio RD_j / GDP_j are used.

The second approach assumes that the amount of R&D that spills over from sector i to sector j is proportional to the share of output that sector i sells to sector j. This approach was used by Terleckyj (1974, 1980). Then the alternative measure of indirect R&D, RDINDB, is given by:[2]

$$(4) \qquad RDINDB_{jt} \equiv \Sigma_i \; b^0_{ijT} \, RD_{it} / GDP_{jt}$$

A similar approach was used by Scherer (1982), except that his measure of indirect R&D is distributed proportionally to the number of patents issued by sector i which fall into sector j's industrial classification. In principle, Scherer's measure is identical to RDINDA except that indirect R&D is distributed proportionally to patents instead of sales.

The difference between the two measures, RDINDA and RDINDB, depends on different theories of knowledge transfers. According to RDINDA, if Sector A buys 15 percent of its total output from Sector B, then 15 percent of Sector B's R&D is carried forward to Sector A. In this case, knowledge transfer depends on how important B's inputs are in Sector A's input structure. On the other hand, according to RDINDB, if Sector B sells 15 percent of its output to Sector A, then 15 percent of Sector B's R&D is carried forward to Sector A.

Another source of borrowed R&D is new investment. In the first case, it is assumed that the information gain is proportional to the annual investment flow per unit of output:

[2] The matrix B^0 is used instead of B again to avoid double-counting of industry j's own R&D.

(5) $\quad RDKINDA_{jt} \equiv \Sigma_i \; n_{ijT} \, RD_{jt} / GDP_{jt}$

In the second case, it is assumed that the information gain from the R&D performed in the capital-producing sector i to sector j is proportional to the share of new investment that sector i sells to sector j:

(6) $\quad RDKINDB_{jt} \equiv \Sigma_i \; b_{nijT} \, RD_{it} / GDP_{jt}$

It is also possible to construct estimates of direct productivity spillovers, what I call "TFP spillovers," in analogous fashion to the approach for R&D spillovers. The rationale is that TFP growth is an indicator of "successful" R&D and therefore there may be a "contagion" effect between industries with a rapid rate of technological gain and those buying from these industries. TFP spillovers are measured by:

(7) $\quad TFPINDA_{jt} \equiv \Sigma_i \; a^0_{ijt} \, \pi_{it}$

which is a measure of sector j's indirect knowledge gain from technological change in its supplying sectors. In this case, it is assumed that the information gained from supplier i's TFP is proportional to its importance in sector j's input structure. An alternative measure is:

(8) $\quad TFPINDB_{jt} \equiv \Sigma_i \; b^0_{ijt} \, \pi_{it}$

where it is assumed that the knowledge gain from sector j's TFP growth is proportional to the percentage of sector i's output that is sold to sector j.

In sum, I have now introduced six different measures of possible inter-sectoral spillover effects. Are there ones that are preferable to others? With regard to RDINDA versus RDINDB (as well as RDKINDA versus RDKINDB), each has its own rationale. As discussed above, with regard to the two measures, RDINDA and RDINDB, each relies on a different theory of knowledge transfers. The selection of a preferred one will depend on the outcome of an empirical investigation of their relative importance and statistical significance in explaining industry level TFP growth ("the proof is in the pudding," as the old expression goes).

In contrast, both inter-industry spillovers (such as RDINDA) and spillovers from new investment (such as RDKINDA) may each contribute separately as factors in accounting for industry level TFP growth. Here, too, the choice of a preferred measure will depend on the results of an empirical investigation. With regard to the difference between R&D spillovers (such as RDINDA) and direct TFP spillovers (such as TFPINDA) each has its own rationale. If R&D is the medium through which knowledge is transferred between sectors, then the former is to be preferred but if direct technological change is the medium, the latter is to be preferred. Once, again, empirical investigation of the relative importance of each in explaining industry level TFP growth will lead to a preferred choice.

I also introduce several measures of inter-sectoral linkages. These have been developed in the input-output literature. The first is the average value of the input-output value coefficients, a^*_{ij}:

(9) $$LINK1_i = \Sigma_j\, a^*_{ij} \;/\; (\nu - 1),\ j \neq i$$

where ν is the number of sectors. The second index is the row sum of the value inverse matrix:

(10) $$LINK2_i = \Sigma_j\, [(I - A^*)^{-1}]_{ij}$$

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 an economy draws upon industry i in order to expand production. The third is given by:

(11) $$LINK3_i = \Sigma_j\, [(I - B')^{-1}]_{ij}$$

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,

III. Data Sources and Methods

The principal data are 85-sector input-output tables for the U.S. for years 1958, 1967, 1977, 1987, 1997, and 2007. Theses are produced by the Bureau of Economic analysis (and are available at: http://www.bea.gov/industry/.) I have decided to use 10-year intervals (or approximately 10 year periods) in order to avoid much of the cyclical variation in TFP growth over the business cycle. The last five of these years are near peaks of the business cycle in the U.S. However, unfortunately, 1958 is a recession year.[3] The first five of these tables are so-called benchmark tables. However, the 2007 table is one of the annual updates of the 2002 benchmark table. The 1958 table is available only in single-table format.[4] The 1967, 1977, 1987, 1997, and 2007 data are available in separate make and use tables.[5]

Two types of employment data were used. The first is Full-Time Equivalent Employees (FTEE) and the second is Persons Engaged in Production (PEIP). Both were obtained on the industry level from the U.S. Bureau of Economic Analysis, National Income and Product Accounts, Internet [http://www.bea.gov/national/nipaweb/], Tables 6.5 and 6.8. [[http://www.bea.gov/bea/dn2/home/annual_industry.htm].

Investment data refer to non-residential fixed investment in constant (2000) dollars. The source is: U.S. Bureau of Economic Analysis, National Income and Product Accounts, Internet [http://www.bea.gov/bea/dn2/home/annual_industry.htm].

Capital stock figures are based on chain-type quantity indexes for net stock of fixed capital in constant (2000) dollars, year-end estimates. Equipment and structures, including information technology equipment, are for the private (non-government) sector only. Source: U.S. Bureau of Economic Analysis, CD-ROM NCN-0229, "Fixed

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[3] There is also little that can be done to correct for the business cycle trough in 1958.

[4] The single-table format relies on the so-called BEA transfer method. See Kop Jansen and ten Raa (1990) for a discussion of this method and its associated methodological difficulties.

[5] Details on the construction of the input-output tables can be found in the following publications: 1967 -- U.S. Interindustry Economics Division (1974); 1977 -- U.S. Interindustry Economics Division (1984); and 1987 -- Lawson and Teske (1994).

Reproducible Tangible Wealth of the United States, 1925-97," and the Internet [http://www.bea.gov/bea/dn2/home/annual_industry.htm]. For technical details, see Katz and Herman, (1997).

Investment flows by industry and by type of equipment or structures are for the private (non-government) sector only. The source is: U.S. Bureau of Economic Analysis, CD-ROM NCN-0229, "Fixed Reproducible Tangible Wealth of the United States, 1925-97," and the Internet [http://www.bea.gov/bea/dn2/home/annual_industry.htm].

R&D expenditures performed by industry include company, federal, and other sources of funds. Company-financed R&D performed outside the company is excluded. "Private" refers to privately-funded R&D performed in company facilities including all sources except federally financed R&D. "Basic" refers to basic research performed in company facilities; "applied" refers to applied research performed in company facilities; and "development" refers to development R&D performed in company facilities. Series on the industry level run from 1957 to 2008. The sources are: National Science Foundation, *Research and Development in Industry*, (Arlington, VA: National Science Foundation), various years, and the Internet [http://www.nsf.gov/sbe/srs/nsf01305/htmstart.htm].

Data on full-time equivalent scientists and engineers engaged in R&D per 10,000 full-time equivalent employee, SCIENG, are also available. Series on the both the aggregate and industry level run from 1957 to 2008. The sources are: National Science Foundation, *Research and Development in Industry*, (Arlington, VA: National Science Foundation), various years, and the Internet [http://www.nsf.gov/sbe/srs/nsf01305/htmstart.htm].

These data were used to construct labor coefficients, capital coefficients, sectoral price deflators, and R&D coefficients. In addition, the deflator for transferred imports was calculated from the NIPA import deflator, that for the Rest of the World industry was calculated as the average of the NIPA import and export deflator, and the deflator for the inventory valuation adjustment was computed from the NIPA change in business inventory deflator. The source is U.S. Bureau of Economic Analysis, National Income and Product Accounts, available on the Internet (see above).

Altogether, five difference data sources are used in the empirical implementation of the work: (i) input-output tables, (ii) industry capital stock, (iii) industry employment, (iv) industry level price deflators, and (v) industry level R&D expenditures. In order to make the various data sources consistent, I aggregated the original input-output data to 45 sectors (see Appendix Table 1 for a listing of the sectors).

IV. Regression Models and Results

The basic regression model used in the empirical analysis is:

(12) $$TFPGRT_{jT} = \beta_0 + \beta_1 \, RDX_{jT} + \beta_2 \, IND_{jT} + \Sigma_k \, \zeta_k D_{kT} + \varepsilon_{jT}$$

where β_0, β_1, β_2, and ζ_k are coefficients, D_{kT} are time dummy variables, and ε_{jT} is a stochastic error term. IND refers to the various measures of indirect or embodied R&D and TFP (RDINDA, RDINDB, TFPINDA, TFPINDB, etc.). We assume that the terms ε_{jT} are independently distributed but may not be identically distributed. The regression results reported below use the White procedure of a heteroschedasticity-consistent covariance matrix. It is also assumed that $a_{.j}$ are independent – that is, the technology of each industry is independent of that of other industries. In both cases, the sample is a pooled cross-section time-series data set that consists of 45 industries in four time periods (1958-1967, 1967-1977, 1977-1987, and 1987-1997) and 33 sectors in 1997-2007.[6] Though ideally it would be useful to separate out a between sector effect from a within sector effect, as in Verspagen (1997), this is not possible in the present application because of the different sector scheme in the 1997-2007 period.

The coefficient b_1 is normally interpreted as the rate of return to R&D under the assumption that the (average) rate of return to R&D is equalized across sectors.[7] The

[6] The reason for the smaller number of industries in the last period is due to the adoption of the North American Industrial Classification System (NAICS) after 1997, as opposed to the Standard Industrial Classification (SIC) system in the preceding years. Moreover, as noted in the footnote to Table 3, since investment by kind is not available for public administration for the computation of RDKINDA and RDKINB, the number of sectors is reduced by one when these variables are used in the regression.

[7] See, for example, Mansfield (1980) or Griliches (1980).

coefficient b_2 is, correspondingly, usually interpreted as the indirect return to R&D and the sum of the two is considered to be the total or social rate of return to R&D.

Another set of regressions will look at the effects of industry level productivity growth and industry level R&D expenditures on linkage structure *per se* The regression specifications are of the form:

(13) $LINK1_{jT} = \gamma_0 + \gamma_1 \, RDX_{jT} + \gamma_2 \, TFPGRT_{jT} + \Sigma_k \, \xi_k D_{kT} + \varepsilon_{jT}$

The descriptive statistics, shown in Appendix Table 2, are, first, of interest. Average TFP growth across sectors shows the familiar pattern, with a marked slowdown between 1958-1967 and the next two periods and then an acceleration in the 1987-1997 and the 1997-2007 periods. R&D intensity remained relatively stable over the five time periods, averaging 0.012. The mean value of SCIENG, on the other hand, trended upward over the five time periods, particularly in the 1997-2007 period. RDINDA shows no clear time trend, though there is a sharp dip in the 1997-2007 period. RDINDB likewise shows no clear pattern of time, though in this case there is sharp increase in its value in the last period.

The time path for TFPINDA and TFPINDB generally follows the same trend as TFPGRT, with a fall off in value in the 1967-1977 and the 1977-1987 periods and then a pick up in the last two periods. In contrast, the mean value of RDKINDA and that of RDKINDB both tend to trend downward over time. The linkage measures, LINK1, LINK2, and LINK3, are generally stable over time, though LINK1 does show a rise in the 1997-2007 period while the other two linkage measures fall off in the last period.

I next present the results on embodied R&D from Wolff and Nadiri (1993) and Wolff (1997). In the first paper, we found a rate of return to R&D of about 10 percent among manufacturing industries alone and about 20 percent among all industries over the period from 1947 to 1977 (see Table 1). Fifty industries were used in the full sample. The coefficient of RDX was significant at the five percent level in all specifications. RDINDA did not prove statistically significant but had a positive coefficient in both specifications. RDKINDA was not statistically significant in the manufacturing sample (in fact, its coefficient was negative) but its coefficient was positive and significant at the five percent level among all sectors. The coefficient of TFPINDA was positive and significant at the five percent level among manufacturing industries but was positive though not significant among all industries. The variables RDINDB and RDKIND were not statistically significant.

[*Place Table 1 about here*]

Wolff (1997), using a sample of 68 industries over the period 1958 to 1987, estimated a rate of return to R&D of about 11 percent among all industries (see Table 2). The variable RDX was significant at the five percent level. RDINDA was significant at the 10 percent level and its coefficient, the indirect return to R&D, was estimated to be 0.43. The social rate of return was therefore estimated to be 53 percent. The alternative form of embodied R&D, RDINDB, was also significant at the ten percent level, with an estimated coefficient of 0.41. In these regressions, the dominant variable was TFPINDA, whose estimated coefficient was 1.30 and was significant at the one percent level. The size of the effect and the significance level of the coefficient of TFPINDA were found to be greater in Wolff (1997) than in Wolff and Nadiri (1993). In contrast, the estimated coefficient of TFPINDB was 0.15 but not significant. The R^2 statistic ranged from 0.060 to 0.096 (with TFPINDA) and the adjusted R^2 statistic from 0.045 to 0.078 (again with TFPINDA).

[*Place Table 2 about here*]

Regression results from the current study are shown in Table 3 based on pooled cross-section data covering the period from 1958 to 2007. The estimated coefficients of RDX range from 0.22 to 0.25, about twice the level of Wolff (1997), and are uniformly significant at the one percent level. The estimated coefficient of RDINDA is 0.366 and is significant at the one percent level (see Specification 2). As a result, the direct rate of return to R&D is 22 percent, the indirect rate of return to R&D is 37 percent, and the social rate of return to R&D is 59 percent in this specification. This compares to a 53 percent estimated social rate of return in Wolff (1997).

[*Place Table 3 about here*]

The coefficient of RDINDB is now only 0.022 and insignificant. This result contrasts to Wolff (1997), where the coefficient of RDINDB was 0.41 and statistically significant. It now appears that the input measure of embodied R&D, as reflected in

RDINDA, overwhelming dominates the sales-embodied R&D measure RDINDB, as originally proposed by Terleckyj. In other words, it appears that the knowledge transmitted by the R&D embodied in an industry's inputs depends on the importance of that input in the production structure of the industry rather than the share of the output of the supplying industry sold to that industry.

The estimated coefficient of TFPINDA is 0.713, smaller than its coefficient in Wolff (1997), and its significance level is 10 percent, compared to one percent in Wolff (1997). In contrast, the estimated coefficient of TFPINDB is only 0.064 and not statistically significant.

In contrast to Wolff and Nadiri (1993) and Wolff (1997), the coefficient of RDKINDA is 0.849 and is now statistically significant at the five percent level among all industries. In contrast, the coefficient of RDKINDB is not statistically significant. When both RDINDA and RDKINDA are included together, both remain statistically significant, the former at the one percent level and the latter at the ten percent level. The direct rate of return to R&D is now 25 percent, the indirect return is 35 percent, and the social rate of return is 60 percent. However, there is an added return to R&D from that embodied in investment goods. It is perhaps best to think of this added return as the productivity gain per dollar of investment. On the basis of the average investment over the period, this added return to R&D works out to be 0.23 per dollar of investment.

The constant term, which might be interpreted as the pure rate of technological progress, varies from 0.0049 to 0.0110. In my preferred regression, Specification (8), its value is 0.0049, about half a percentage point per year. The period dummy variables are generally not significant. In comparison to the period 1958-1967, the excluded period, the dummy variables generally increase over time. In Specification (8), they rise from -0.0075 for period 1967-1977 to 0.0052 for period 1997-2007. The R^2 statistic ranges from 0.056 to 0.121 and the adjusted R^2 statistic from 0.034 to 0.090. The best fit is provided by Specification (8).

In Table 4, the sample of industries is restricted to the 21 manufacturing industries in the data. Whereas in Wolff and Nadiri (1993), both RDX and TFPINDA were found to be statistically significant, in the present application neither RDX nor any of the spillover variables are statistically significant. However, the estimated direct return to R&D is about 11 percent, about the same as was found in Wolff and Nadiri (1993) within manufacturing.

[*Place Table 4 about here*]

I next look at whether there is any evidence that the indirect effects of embodied R&D or TFP have increased over time, as speculated in the introduction to the paper. I use five approaches to analyze this issue. In the first, I use single period data to estimate the effects of R&D on TFP growth. As shown in the first five columns of Table 5, no clear pattern emerges, with the estimated coefficient of RDINDA falling and then rising between subsequent periods. Likewise, the estimated coefficient of RDKINDA also falls and then rises between adjacent periods. In most cases, the coefficients of RDINDA and RDKINDA are insignificant in the single period estimations. These results, by the way, suggest that for the full pooled time-series cross-industry regressions, most of the explanatory power lies "within sector" as opposed to "between sector."

In the second method, I divide the sample into two periods: 1958-1987 and 1987-2007 (last two columns of Table 5). Here, the results are much clearer. Here the coefficients of both RDINDA and RDKINDA are both larger in the second period, as is the coefficient of RDX. The results suggest that spillover effects were stronger in the "IT period" of 1987-2007 in comparison to 1958-1987. The goodness of fit is also better for the second period, with the R^2 statistic and the adjusted-R^2 statistic considerably higher. However, a Chow test does not indicate that the econometric results of the two periods are statistically different, with a F-value of 1.33, significant at only the 0.26 level.

[*Place Table 5 about here*]

[*Place Table 6 about here*]

The third method consists of successively adding new periods to the 1958-1967 sample to reach the 1958-2007 sample. As shown in the first five columns of Table 6, the coefficient estimates as well as the significance levels of RDX, RDINDA, and RDKINDA generally increase with the addition of each new period. The R^2 statistic and the adjusted-R^2 statistic also tend to increase. These results also suggest a strengthening of the R&D spillover effect over time. The fourth method is to include interactive terms between RDINDA and period dummy variables. As shown in the last column of Table 6, the results are inconclusive as to whether the R&D spillover effect has risen over time.

In the fifth method, I decompose average TFP growth over both the 1958-1987 and the 1987-2007 periods using the coefficient estimates shown in the last two columns of Table 5 and the average values of each of the explanatory variables over their respective periods. There was a noticeable increase of average TFP growth between the two periods from 0.89 to 1.39 percent per year. However, there was a relatively small change in the average values of the explanatory variables between the two periods. The mean value of RDX rose slightly from 0.118 to 0.128, that of RDINDA fell slightly from 0.0093 to 0.0085, and that of RDKINDA also fell somewhat from 0.0039 to 0.0031. The main change were the sizeable increases in the coefficient values, as we saw above. As a result, whereas RDX accounted for 20.7 percent of TFP growth in the 1958-1987 period (computed by multiplying the mean value of RDX by its coefficient estimate and then dividing by the mean value of TFP growth), its contribution almost doubled to 40.3 percent in the 1987-2007 period. In contrast, the contribution of RDINDA rose much less, from 26.0 to 30.1 percent, and that of RDKINDA actually slipped a bit, from 28.4 to 27.5 percent. The total contribution of R&D spillovers (the sum of RDINDA and RDKINDA) increased somewhat, from 54.3 to 57.6 percent.

The first set of regressions as shown in Table 3 are now repeated with the variable SCIENG, the number of full-time equivalent scientists and engineers engaged in R&D per 10,000 full-time equivalent employees, substituted for RDX. The results are even stronger with SCIENG. The coefficients of SCIENG are all significant at the one percent level, with higher t-statistics than the corresponding RDX variable (see Table 7). The coefficient estimates and t-statistics of RDINDA and RDKINDA are higher than the corresponding ones in the first set of regressions. In Specification 8, in particular, the coefficient of RDKINDA is now significant at the five percent level, as opposed to the ten percent level in the original regression. The R^2 statistic and the adjusted-R^2 statistic are all substantially higher than the corresponding statistics in the original set of regressions. In the case of Specification 8, the R^2 is now 0.159 as opposed to 0.121. One reason for the better fit provided by SCIENG in comparison to RDX is that there are fewer missing values in the manufacturing industries.[8]

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[8] I repeated the same analysis to determine whether there is any evidence that R&D spillover effects had increased over time using SCIENG instead of RDX. The results were virtually the same. The individual

[*Place Table 7 about here*]

A. Linkage Measures

In the last piece of analysis, I consider the effects of TFP growth and R&D intensity on the size of forward linkages. The rationale is that more technologically active industries should acquire new customer industries and expand their ties with existing customer industries. This should show up as both increased values of input coefficients from the innovating industry and a greater number of positive input coefficients from this industry.

Results from Wolff and Nadiri (1993), covering the period from 1947 to 1997, are first shown in Table 8. Within the manufacturing sector itself, neither RDX nor TFPGRT showed any statistically significant effect on the size of their industry's LINK1 index. However, among all sectors of the economy, both RDX and TFPGRT were positively and significantly associated with higher values of both LINK1 and LINK2, and RDX (though not TFPGRT) was positively and significantly related to LINK3. The early results clearly indicated a positive relation between the degree of technological activity of a sector and its degree of forward linkage.

[*Place Table 8 about here*]

New results, for the 1958-2007 period, are shown in Table 9. Neither RDX nor TFPGRT have a significant relation to LINK1. Indeed, the estimated coefficient of RDX is negative. Results are quite similar for the linkage measure LINK2. In the case of LINK3, both RDX and TFPGRT are again statistically insignificant but in this case the estimated coefficient of RDX is positive and that of TFPGRT is negative. The apparent reason why neither RDX nor TFPGRT bear no significant relationship to forward linkages is that the forward linkages themselves remain almost unchanged over time (see Appendix Table 2).

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period regressions showed no clear pattern. A comparison of regression results from periods 1958-1987 with 1987-2007 showed much higher and more significant coefficients on RDINDA and RDKINDA for the later period. However, once again, the Chow test did not indicate that the two sets of regressions were statistically different. Adding data from successive periods to the 1958-1967 period to reach the full 1958-2007 sample generally showed successively greater and more significant coefficients on RDINDA and RDKINDA as the sample was expanded. Including interactive terms between RDINDA and period dummy variables revealed no clear pattern.

[*Place Table 9 about here*]

Conclusion

I speculated at the outset of the paper that technological spillover effects may have become more important over time as IT penetrated the U.S. economy. The rationale is that IT may speed up the process of knowledge transfer and make these knowledge spillovers more effective.

I estimated first of all that the direct rate of return to R&D is 22 percent and the indirect rate of return to R&D (RDINDA) is 37 percent. The rate of return to R&D estimates are higher than in my previous studies. The indirect rate of return to R&D is now significant at the one percent level, in comparison to insignificant coefficients in Wolff and Nadiri (1993) and a 10 percent significance level in Wolff (1997) (also see Table 10 for a comparison of results from the current study with those from the older two studies.) The newly estimated social rate of return to R&D is 59 percent, and this compares to a 53 percent social rate of return estimated in Wolff (1997).

[*Place Table 10 about here*]

In contrast to Wolff and Nadiri (1993) and Wolff (1997), the coefficients of R&D embodied in new investment (RDKINDA) are now statistically significant at the five percent level among all industries and the coefficient estimates are higher. When both RDINDA and RDKINDA are included together, both remain statistically significant, the former at the one percent level and the latter at the ten percent level. The direct rate of return to R&D is now 25 percent, the indirect return is 35 percent, and the social rate of return is 60 percent. There is also an added return to R&D from that embodied in investment goods, which I estimate to 0.23 per dollar of investment. All in all, the direct and indirect returns to R&D are at least as high in the later period as estimated here as in the earlier periods as estimated in Wolff and Nadiri (1993) and Wolff (1997).

Separate regressions on the 1958-87 and the 1987-2007 periods and the addition of successive periods to the sample also suggest a strengthening of the R&D spillover effect over time, particularly as between the 1958-1987 and the 1987-2007 periods. The coefficient estimates as well as the significance levels of RDX, RDINDA, and RDKINDA generally increase with the addition of each new period, as do the R^2 and the adjusted-R^2 statistics. A decomposition of TFP growth in the two periods also indicated a higher contribution from R&D spillovers in the later period than the earlier one. These results suggest a strengthening of the R&D spillover effect over time, as I speculated in the introduction to the paper.

Direct TFP spillovers (TFPINDA) now appear to be less important than in Wolff and Nadiri (1993) and Wolff (1997). The coefficient estimates and significance levels are smaller than in the prior work. Moreover, in contrast to the earlier work, R&D spillovers now appear to be more important than direct TFP spillovers (as gauged by the significance level of the respective coefficients).

In contrast to the Wolff and Nadiri (1993), no statistically significant relation now appears between forward linkages and either RDX or TFPGRT. The apparent reason is that in this application, measures of forward linkages are relatively unchanged over time.

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[*Place Appendix Table 1 about here*]

[*Place Appendix Table 2 about here*]

Table 1. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth On R&D Intensity, Embodied R&D, and Embodied TFP Growth, 1947-1977

Independent Variables	Specification (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.0041	0.0084 *	0.0047	0.0029	0.0000	-0.0030	-0.0010	- 0.0003
	(1.33)	(2.07)	(1.42)	(0.99)	(0.01)	(0.07)	(0.27)	(0.07)
RDX	0.106 *	0.103 *	0.111 *	0.106 *	0.188 *	0.173 *	0.208 *	0.189 *
	(2.21)	(2.39)	(2.26)	(2.28)	(2.31)	(2.13)	(2.53)	(2.31)
RDINDA		0.143				0.076		
		(1.59)				(1.23)		
RDKINDA			-0.008				0.092 #	
			(0.51)				(1.73)	
TFPINDA				0.889 *				0.114
				(2.48)				(0.25)
R^2	0.222	0.244	0.224	0.273	0.062	0.070	0.075	0.063
Adjusted R^2	0.179	0.193	0.172	0.224	0.041	0.049	0.049	0.037
Standard Error	0.0125	0.0124	0.0126	0.0122	0.0243	0.0243	0.0242	0.0244
Sample	Manuf.	Manuf.	Manuf.	Manuf.	All	All	All	All
Sample Size	95	95	95	95	250	250	250	250

Source: Wolff and Nadiri (1993).

Note: The sample consists of pooled cross-section time-series data, with observations on each of 19 (or 50) industries in 1947-1958, 1958-63, 1963-67, 1967-72, and 1972-77. Time dummy variables for the last four periods are included but the coefficient estiamtes are not shown.
The estimation uses the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 2. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth On R&D Intensity, Embodied R&D, and Embodied TFP Growth, 1958-1987

Independent Variables	Specification (1)		(2)		(3)		(4)		(5)	
Constant	0.004	#	0.002		-0.001		0.002		0.004	
	(1.84)		(0.62)		(0.37)		(0.67)		(1.62)	
RDX	0.126	**	0.101	**	0.112	**	0.102	**	0.124	**
	(3.32)		(2.50)		(3.00)		(2.51)		(3.28)	
RDINDA			0.429	#						
			(1.76)							
TFPINDA					1.300	**				
					(2.80)					
RDINDB							0.408	#		
							(1.66)			
TFPINDB									0.146	
									(0.91)	
DUM6777	-0.003		-0.003		0.002		-0.003		-0.003	
	(1.10)		(0.89)		(0.48)		(0.91)		(0.99)	
DUM7787	0.000		0.001		0.004		0.001		0.000	
	(0.06)		(0.32)		(1.19)		(0.29)		(0.07)	
R^2	0.060		0.074		0.096		0.073		0.064	
Adjusted R^2	0.046		0.056		0.078		0.054		0.045	
Standard Error	0.0168		0.0167		0.0166		0.0168		0.0168	
Sample Size	204		204		204		204		204	

Source: Wolff (1997).

Note: The sample consists of pooled cross-section time-series data, with observations on each of 68

industries in 1958-67, 1967-77 and 1977-87.
The estimation uses the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 3. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth On R&D Intensity, Embodied R&D, and Embodied TFP Growth, 1958-2007

Independent	Specification															
Variables	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Constant	0.0111	**	0.0096	*	0.0110	*	0.0066		0.0107	*	0.0059		0.0092	#	0.0049	
	(2.64)		(2.33)		(2.25)		(1.37)		(2.45)		(1.14)		(1.96)		(0.98)	
RDX	0.227	**	0.222	**	0.227	**	0.202	*	0.227	**	0.254	**	0.235	**	0.248	**
	(2.91)		(2.93)		(2.85)		(2.56)		(2.90)		(3.17)		(2.96)		(3.17)	
RDINDA			0.366	**											0.350	**
			(3.42)												(3.24)	
RDINDB					0.022											
					(0.04)											
TFPINDA							0.713	#								
							(1.84)									
TFPINDB									0.064							
									(0.42)							
RDKINDA											0.849	*			0.768	#
											(2.01)				(1.86)	
RDKINDB													0.222			
													(1.26)			
	-		-		-		-				-		-		-	
DUM6777	0.0079		0.0196	#	0.0078		0.0044		0.0076		0.0045		0.0063		0.0075	
	(1.35)		(1.85)		(1.34)		(0.73)		(1.29)		(0.73)		(1.04)		(1.24)	
	-		-		-		-		-		-		-		-	
DUM7787	0.0068		0.0095	#	0.0067		0.0047		0.0067		0.0045		0.0053		0.0075	

	(1.16)	**(1.66)**	**(1.10)**	**(0.80)**	**(1.15)**	**(0.75)**	**(0.88)**	**(1.26)**
	-	**-**	**-**	**-**				**-**
DUM8797	**0.0015**	**0.0047**	**0.0014**	**0.0011**	**0.0016**	**0.0003**	**0.0000**	**0.0035**
	(0.26)	**(0.82)**	**(0.23)**	**(0.19)**	**(0.03)**	**(0.04)**	**0.00**	**(0.60)**
DUM9707	**0.0011**	**0.0012**	**0.0011**	**0.0008**	**0.0013**	**0.0067**	**0.0019**	**0.0052**
	(0.18)	**(0.20)**	**(0.18)**	**(0.13)**	**(0.20)**	**(0.81)**	**(0.29)**	**(0.79)**
R^2	**0.0564**	**0.1070**	**0.0564**	**0.0717**	**0.0573**	**0.0743**	**0.0631**	**0.1205**
Adjusted R^2	**0.0336**	**0.0810**	**0.0290**	**0.0446**	**0.0298**	**0.0466**	**0.0351**	**0.0897**
Standard Error	**0.0276**	**0.0269**	**0.0276**	**0.0274**	**0.0276**	**0.0276**	**0.0278**	**0.0270**
Sample Size	**213**	**213**	**213**	**213**	**213**	**208**	**208**	**208**

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. Investment by type is not available for the public administration sector. As a result, the number of sectors is reduced by one when RDKINDA and RDKINDB are used in the regression.
The estimation uses the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 4. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth on R&D Intensity, Embodied R&D, and Embodied TFP Growth, Manufacturing Industries, 1958-2007

Independent Variables	Specification (1)		(2)		(3)		(4)		(5)		(6)		(7)	
Constant	0.0190	**	0.0181	*	0.0121		0.0172	*	0.0167	*	0.0191	#	0.0145	#
	(2.77)		(2.59)		(1.42)		(2.09)		(2.37)		(1.80)		(1.76)	
RDX	0.110		0.111		0.066		0.112		0.113		0.110		0.103	
	(1.15)		(1.15)		(0.65)		(1.16)		(1.18)		(1.13)		(1.07)	
RDINDA			0.141											
			(0.60)											
RDINDB					1.469									
					(1.33)									
TFPINDA							0.191							
							(0.38)							
TFPINDB									0.267					
									(1.28)					
RDKINDA											-0.047			
											(0.02)			
RDKINDB													1.744	
													(0.97)	
DUM6777	-0.0052		-0.0062		-0.0046		-0.0042		-0.0033		-0.0054		-0.0027	
	(0.58)		(0.67)		(0.51)		(0.45)		(0.36)		(0.52)		(0.29)	
DUM7787	0.0063		-0.0072		-0.0019		-0.0057		-0.0064		-0.0064		-0.0042	
	(0.70)		(0.79)		(0.20)		(0.63)		(0.71)		(0.66)		(0.46)	

DUM8797	**-0.0088**	**-0.0100**	**-0.0030**	**-0.0088**	**-0.0098**	**-0.0088**	**-0.0068**
	(0.98)	**(1.80)**	**(0.31)**	**(0.97)**	**(1.09)**	**(0.94)**	**(0.73)**
DUM9707	**0.0049**	**0.0040**	**0.0064**	**0.0038**	**0.0052**	**0.0037**	**0.0058**
	(0.41)	**(0.42)**	**(0.67)**	**(0.40)**	**(0.56)**	**(0.34)**	**(0.61)**
R^2	**0.0363**	**0.0399**	**0.0539**	**0.0378**	**0.0528**	**0.0363**	**0.0458**
Adjusted R^2	**-0.0139**	**-0.0207**	**-0.0059**	**-0.0229**	**-0.0070**	**-0.0245**	**-0.0144**
Standard Error	**0.0291**	**0.0292**	**0.0290**	**0.0292**	**0.0290**	**0.2925**	**0.0291**
Sample Size	**102**	**102**	**102**	**102**	**102**	**102**	**102**

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. Investment by type is not available for the public administration sector. As a result, the number of sectors is reduced by one when RDKINDA and RDKINDB are used in the regression. The estimation uses the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 5. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth On R&D Intensity and Embodied R&D by Selected Period, 1958-2007

Independent	Period										
Variables	1958-67	1967-77	1977-87		1987-97		1997-07		1958-87		1987-07	
Constant	0.0071	0.0059	-0.0077		0.0027		-0.0004		0.0072		-0.0051	
	(1.35)	(1.05)	(1.14)		(0.35)		(0.03)		(1.57)		(0.65)	
RDX	0.120	0.117	0.276		0.073		1.151	**	0.157	#	0.436	**
	(1.15)	(0.73)	(1.49)		(0.39)		(4.14)		(1.89)		(2.69)	
RDINDA	0.523	-0.182	0.553	**	0.490	*	-1.771		0.251	*	0.489	*
	(0.54)	(0.91)	(2.93)		(2.69)		(0.82)		(2.03)		(2.47)	
RDKINDA	0.548	0.448	1.444		0.591		5.409		0.657		1.222	
	(1.59)	(0.28)	(1.18)		(0.61)		(1.19)		(1.61)		(1.19)	
DUM6777									-0.0073			
									(1.37)			
DUM7787									-0.0071			
									(1.36)			
DUM9707											0.0115	
											(1.38)	
R^2	0.1000	0.0314	0.2398		0.1621		0.3829		0.0953		0.1642	
Adjusted R^2	0.0325	-0.0412	0.1828		0.0992		0.3168		0.0594		0.1171	
Standard Error	0.0173	0.0239	0.0267		0.0296		0.0320		0.0234		0.0323	
Sample Size	44	44	44		44		32		93		76	

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. Investment by type is not available for the public administration sector. As a result, the number of sectors is reduced by one when RDKINDA and RDKINDB are used in the regression.
The estimation uses the White procedure for a heteroschedasticity-consistent

covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 6. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth On R&D Intensity and Embodied R&D by Selected Period and with Interactive Term, 1958-2007

Independent	Period											
Variables	1958-67		1958-77		1958-87		1958-97		1958-07		1958-07	
Constant	0.0071		0.0102	*	0.0072		0.0071		0.0049		0.0062	
	(1.35)		(2.42)		(1.57)		(1.53)		(0.98)		(0.80)	
RDX	0.120		0.139		0.157	#	0.134	#	0.248	**	0.257	**
	(1.15)		(1.63)		(1.89)		(1.74)		(3.17)		(3.21)	
RDINDA	0.523		-0.168		0.251	*	0.353	**	0.350	**	0.022	
	(0.54)		(1.01)		(2.03)		(3.54)		(3.24)		(0.02)	
RDKINDA	0.548		0.505		0.657		0.637	#	0.768	#	0.776	#
	(1.59)		(1.30)		(1.61)		(1.66)		(1.86)		(1.89)	
RDINDA x											-0.215	
DUM6777											(0.16)	
RDINDA x											0.549	
DUM7787											(0.40)	
RDINDA x											0.472	
DUM8797											(0.35)	
RDINDA x											0.291	
DUM9707											(0.14)	
DUM6777			-0.0048		-0.0073		-0.0082		-0.0075		-0.0024	
			(0.99)		(1.37)		(1.46)		(1.24)		(0.27)	
DUM7787					0.0071		-0.0079		-0.0075		-0.0115	
					(1.36)		(1.45)		(1.26)		(1.33)	

DUM8797				**-0.0037**	**-0.0035**	**-0.0069**
				(0.68)	**(0.60)**	**(0.80)**
DUM9707					**0.0052**	**0.0039**
					(0.79)	**(0.35)**
R^2	**0.1000**	**0.0890**	**0.0953**	**0.1140**	**0.1205**	**0.1568**
Adjusted R^2	**0.0325**	**0.0451**	**0.0594**	**0.0825**	**0.0897**	**0.1095**
Standard Error	**0.0173**	**0.0205**	**0.0234**	**0.0249**	**0.0270**	**0.0267**
Sample Size	**44**	**88**	**132**	**176**	**208**	**208**

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. Investment by type is not available for the public administration sector. As a result, the number of sectors is reduced by one when RDKINDA and RDKINDB are used in the regression.
The estimation uses the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 7. Pooled time-Series Cross-Industry Regressions of Industry TFP Growth On SCIENG, Embodied R&D, and Embodied TFP Growth, 1958-2007

Independent Variables	Specification (1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Constant	0.0080	*	0.0095	*	0.0111	*	0.0069		0.0109	*	0.0054		0.0092	*	0.0043	
	(2.27)		(2.36)		(2.22)		(1.45)		(2.58)		(1.10)		(2.03)		(0.89)	
SCIENG	0.0332	**	0.0394	**	0.0389	**	0.0361	**	0.0388	**	0.0423	**	0.0394	**	0.0427	**
	(3.77)		(4.23)		(4.00)		(3.74)		(4.02)		(4.28)		(4.00)		(4.43)	
RDINDA			0.378	**											0.364	**
			(3.61)												(3.44)	
RDINDB					0.007											
					(0.01)											
TFPINDA							0.654	#								
							(1.72)									
TFPINDB									0.029							
									(0.19)							
RDKINDA											0.925	*			0.850	*
											(2.23)				(2.10)	
RDKINDB													0.223			
													(1.29)			
DUM6777	-0.0047		-0.0110	#	-0.0082		-0.0050		-0.0081		-0.0046		-0.0067		-0.0077	
	(0.90)		(1.97)		(1.43)		(0.84)		(1.40)		(0.76)		(1.12)		(1.29)	
DUM7787	-0.0042		-0.0107	#	-0.0079		-0.0059		-0.0078		-0.0056		-0.0065		-0.0086	

	(0.81)	(1.91)	(1.32)	(1.02)	(1.37)	(0.94)	(1.09)	(1.48)
	-	-	-	-	-	-	-	-
DUM8797	0.0047	0.0073	0.0040	0.0034	0.0040	0.0029	0.0025	0.0063
	(0.81)	(1.29)	(0.65)	(0.59)	(0.70)	(0.49)	(0.42)	(1.09)
	-	-	-	-	-	-	-	-
DUM9707	0.0090	0.0100	0.0100	0.0095	0.0099	0.0067	0.0098	0.0071
	(1.52)	(1.52)	(1.47)	(1.40)	(1.45)	(0.96)	(1.40)	(1.03)
R^2	0.0805	0.1441	0.0900	0.1029	0.0902	0.1090	0.0944	0.1588
Adjusted R^2	0.0628	0.1192	0.0635	0.0768	0.0637	0.0824	0.0674	0.1294
Standard Error	0.0272	0.0263	0.0271	0.0269	0.0271	0.0271	0.0273	0.0263
Sample Size	213	213	213	213	213	208	208	208

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. Investment by type is not available for the public administration sector. As a result, the number of sectors is reduced by one when RDKINDA and RDKINDB are used in the regression. The estimation uses the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient. Key:

SCIENG: Full-time equivalent scientists and engineers engaged in R&D per 10,000 full-time equivalent employees.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 8. The Effect of R&D Intensity and Productivity Growth on Forward Linkage Structure, 1947-1977

Independent	Dependent Variable													
Variables	LINK1		LINK1		LINK1		LINK1		LINK2		LINK2		LINK3	
Constant	0.0122	*	0.0123	**	0.0093	**	0.0094	**	1.957	**	1.986	**	2.437	**
	(13.01)		(6.78)		(16.17)		(7.76)		(31.52)		(15.14)		(32.43)	
RDX	0.031				0.081	*			6.594	*			6.835	#
	(1.09)				(2.86)				(2.15)				(1.84)	
TFPGRRT			-0.011				0.042	*			3.961	**		
			(0.02)				(2.59)				(2.24)			
R^2	0.013		0.007		0.032		0.028		0.018		0.021		0.013	
Adjusted R^2	0.002		0.000		0.028		0.008		0.014		0.017		0.010	
Standard Error	0.0075		0.0077		0.0085		0.0086		0.921		0.927		1.114	
Sample	Manuf.		Manuf.		All		All		All		All		All	
Sample Size	95		95		250		250		250		250		250	

Source: Wolff and Nadiri (1993).
Note: The sample consists of pooled cross-section time-series data, with observations on each of 19 (or 50) industries in 1947-1958, 1958-63, 1963-67, 1967-72, and 1972-77.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 9. The Effect of R&D Intensity and Productivity Growth on Forward Linkage Structure, 1958-2007

Independent Variables	Dependent Variable: LINK1		LINK1		LINK2		LINK2		LINK3		LINK3	
Constant	0.0105	**	0.0097	**	1.608	**	1.574	**	2.137	**	2.180	**
	(13.41)		(12.86)		(36.72)		(36.89)		(26.11)		(27.51)	
RDX	-0.033				-0.022				0.017			
	(1.19)				(1.43)				(0.59)			
TFPGRT			0.025				0.430				-1.698	
			(1.00)				(0.31)				(0.65)	
R^2	0.007		0.005		0.010		0.001		0.002		0.002	
Adjusted R^2	0.002		0.000		0.005		-0.005		-0.003		-0.003	
Standard Error	0.0097		0.0968		0.5437		0.5464		1.016		1.015	
Sample Size	213		213		213		213		213		213	

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. See text for definitions of LINK1, LINK2, and LINK3.

Significance levels: # - 10% level; * - 5% level; ** - 1% level.

Table 10. Summary of Findings from Earlier Studies and Current Study On R&D Intensity, Embodied R&D, and Embodied TFP Growth, 1947-1977

Independent Variables	Wolff and Nadiri (1993)[a]	Wolff and Nadiri (1993)[a]	Wolff (1997)[b]	Current Study[c]	Current Study[d]
RDX	Signif. at 5% level	Signif. at 5% level	Signif. at 1% level	Signif. at 1% or 5% level	Not Signif.
SCIENG			Signif. at 1% level	Signif. at 1% level	
RDINDA	Not Signif.	Not Signif.	Signif. at 10% level	Signif. at 1% level	Not Signif.
RDKINDA	Not Signif.	Signif. at 10% level		Signif. at 5% or 10% level	Not Signif.
TFPINDA	Signif. at 5% level	Not Signif.	Signif. at 1% level	Signif. at 10% level	Not Signif.
RDINDB			Signif. at 10% level	Not Signif.	Not Signif.
TFPINDB			Not Signif.	Not Signif.	Not Signif.
RDKINDB				Not Signif.	Not Signif.
Sample	Manufacturing	All Industries	All Industries	All Industries	Manufacturing
Sample Size	95	95	204	213	102

a. The sample consists of pooled cross-section time-series data, with observations on each of 19

(or 50) industries in 1947-1958, 1958-63, 1963-67, 1967-72, and 1972-77.
b. The sample consists of pooled cross-section time-series data, with observations on each of 68 industries in 1958-67, 1967-77 and 1977-87.
c. The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007.
d. The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007.

Appendix Table 1. Classification of 45-Sector Schema and Concordance with the BEA 85-Order Input-Output Sectors

45- Sector Classification		BEA 85-Order	1987 SIC
Number	Name	Codes[a]	Codes
1	Agriculture, forestry, and fishing	1-4	01-09
2	Metal mining	5-6	10
3	Coal mining	7	11,12
4	Oil and gas extraction	8	13
5	Mining of nonmetallic minerals, except fuels	9-10	14
6	Construction	11,12	15-17
7	Food and kindred products	14	20
8	Tobacco products	15	21
9	Textile mill products	16-17	22
10	Apparel and other textile products	18-19	23
11	Lumber and wood products	20-21	24
12	Furniture and fixtures	22-23	25
13	Paper and allied products	24-25	26
14	Printing and publishing	26	27
15	Chemicals and allied products	27-30	28
16	Petroleum and coal products	31	29
17	Rubber and miscellaneous plastic products	32	30
18	Leather and leather products	33-34	31
19	Stone, clay, and glass products	35-36	32
20	Primary metal products	37-38	33
21	Fabricated metal products, including ordnance	13,39-42	34
22	Industrial machinery and equipment, exc. electrical	43-52	35

23	Electric and electronic equipment	53-58	36
24	Motor vehicles and equipment	59	371
25	Other transportation equipment	60-61	37
26	Instruments and related products	62-63	38
27	Miscellaneous manufactures	64	39
28	Transportation	65	40-42,44-47
29	Telephone and telegraph	66	481,482,489
30	Radio and TV broadcasting	67	483,484
31	Electric, gas, and sanitary services	68	49
32	Wholesale trade	69A	50-51
33	Retail trade	69B,74	52-59
34	Banking; credit and investment companies	70A	60-62,67
35	Insurance	70B	63-64
36	Real estate	71B	65-66
37	Hotels, motels, and lodging places	72A	70
38	Personal services	72[part]	72
39	Business and repair services except auto	73C, 72[part]	73,76
40	Auto services and repair	75	75
41	Amusement and recreation services	76	78-79
42	Health services, including hospitals	77A	80
43	Educational services	77B[part]	82
44	Legal and other professional services and non-profit organizations	73A,73B, 77B[part]	81,83,84,86 87,89
45	Public Administration	78,79,84	43[b]

a. Bureau of Economic Analysis 85-sector industrial classification system for input-output data (1987 version).
b. U.S. postal service only.

Appendix Table 2. Mean Values and Standard Deviations of Variables by Time Period

	Time Period					
Variables	**1958-2007**	**1958-1967**	**1967-1977**	**1977-1987**	**1987-1997**	**1997-2007**
TFPGRT						
1. Mean	0.0107	0.0140	0.0058	0.0071	0.0126	0.0151
2. Std. Dev.	0.0280	0.0175	0.0232	0.0292	0.0309	0.0383
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
RDX						
1. Mean	0.0122	0.0124	0.0111	0.0119	0.0131	0.0125
2. Std. Dev.	0.0243	0.0287	0.0232	0.0225	0.0249	0.0221
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
SCIENG						
1. Mean	13.8	7.3	7.5	9.9	14.0	36.0
2. Std. Dev.	21.8	11.4	11.5	15.5	22.5	33.3
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
RDINDA						
1. Mean	0.0092	0.0043	0.0117	0.0118	0.0131	0.0040
2. Std. Dev.	0.0177	0.0032	0.0186	0.0217	0.0245	0.0028
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
RDINDB						
1. Mean	0.0033	0.0049	0.0037	0.0017	0.0011	0.0056
2. Std. Dev.	0.0040	0.0053	0.0025	0.0012	0.0008	0.0060
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
TFPINDA						
1. Mean	0.0051	0.0068	0.0019	0.0039	0.0062	0.0072
2. Std. Dev.	0.0053	0.0048	0.0045	0.0047	0.0047	0.0064
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
TFPINDB						
1. Mean	0.0060	0.0071	0.0023	0.0062	0.0090	0.0054
2. Std. Dev.	0.0128	0.0104	0.0108	0.0146	0.0148	0.0121
3. (Sample Size)	(213)	(45)	(45)	(45)	(45)	(33)
RDKINDA						
1. Mean	0.0037	0.0062	0.0021	0.0034	0.0047	0.0016
2. Std. Dev.	0.0049	0.0078	0.0024	0.0035	0.0048	0.0013

3. (Sample Size)	**(208)**	**(44)**	**(44)**	**(44)**	**(44)**	**(32)**
RDKINDB						
1. Mean	**0.0048**	**0.0096**	**0.0021**	**0.0025**	**0.0027**	**0.0080**
2. Std. Dev.	**0.0115**	**0.0213**	**0.0024**	**0.0023**	**0.0023**	**0.0128**
3. (Sample Size)	**(208)**	**(44)**	**(44)**	**(44)**	**(44)**	**(32)**
LINK1						
1. Mean	**0.0100**	**0.0095**	**0.0095**	**0.0096**	**0.0095**	**0.0128**
2. Std. Dev.	**0.0097**	**0.0084**	**0.0084**	**0.0086**	**0.0090**	**0.0141**
3. (Sample Size)	**(196)**	**(41)**	**(41)**	**(41)**	**(41)**	**(32)**
LINK2						
1. Mean	**1.557**	**1.573**	**1.578**	**1.576**	**1.562**	**1.493**
2. Std. Dev.	**0.546**	**0.499**	**0.507**	**0.523**	**0.535**	**0.671**
3. (Sample Size)	**(205)**	**(41)**	**(41)**	**(41)**	**(41)**	**(41)**
LINK3						
1. Mean	**2.114**	**2.244**	**2.185**	**2.126**	**2.105**	**1.910**
2. Std. Dev.	**1.019**	**1.152**	**1.075**	**1.016**	**0.990**	**0.856**
3. (Sample Size)	**(205)**	**(41)**	**(41)**	**(41)**	**(41)**	**(41)**

Note: The sample consists of pooled cross-section time-series data, with observations on each of 45 industries in 1958-1967, 1967-1977, 1977-1987, and 1987-1997 and on each of 33 industries in 1997-2007. Investment by type is not available for the public administration sector. As a result, the number of sectors is reduced by one when RDKINDA and RDKINDB are used in the regression.