WORKING PAPERS
RESEARCH DEPARTMENT

WORKING PAPER NO. 02-18
TECHNOLOGY FLOWS MATRIX ESTIMATION REVISITED

F.M. Scherer
Visiting Scholar, Federal Reserve Bank of Philadelphia

November 2002

FEDERAL RESERVE BANK OF PHILADELPHIA
Ten Independence Mall, Philadelphia, PA 19106-1574• (215) 574-6428• www.phil.frb.org

WORKING PAPER NO. 02-18
TECHNOLOGY FLOWS MATRIX ESTIMATION REVISITED

F.M. Scherer
Visiting Scholar, Federal Reserve Bank of Philadelphia

November 2002

TECHNOLOGY FLOWS MATRIX ESTIMATION REVISITED

F. M. Scherer*

November 2002 Revision

1. Introduction

During the early 1980s I estimated a highly disaggregated matrix of technology flows from U.S. industries that performed research and development (R&D) to industries expected to use the R&D outcomes. The results, extended to analyze how technology flows affected productivity growth in the 1960s and 1970s, are reported in Scherer (1982a, 1982b, and 1984). In this paper I return to the scene of the crime two decades later to see whether the desired matrix of technology flows could have been obtained using publicly available information, or information that could be gleaned as a by-product of existing surveys, without a costly effort extracting micro-data from a large sample of individual invention patents.

2. Significance of the Problem

It is well accepted among economists that the huge gains in consumers' material prosperity achieved in industrialized nations during the past two centuries are attributable in significant measure to technological change. See e.g. Schumpeter (1942), Solow (1957), Denison (1979), and Mokyr (1990).

---

*Professor emeritus, Harvard University; lecturer, Princeton University; and visiting scholar, Federal Reserve Bank of Philadelphia.

The original version of this paper was presented as a keynote address at the International Input-Output Association Conference in Montreal in October 2002.

Determining the precise contribution to those gains of new technology, as distinguished from augmented human capital, more intense collaboration of physical capital with labor inputs, shifts in demand from the goods and services of low-productivity to high-productivity industries, favorable governmental institutions and infrastructure, and the like, is more difficult. To solve the puzzle, one must understand how each of these factors is linked to productivity growth changes, usually measured over the span of a few years or decades. The received consensus is that technological change defined narrowly has been responsible for a substantial but minority fraction of observed productivity growth. See e.g. Griliches (1995).

On that inference there are of course dissenting views. Dale Jorgenson (1990) has tended in the past, even if less so recently, to assign relatively more weight to physical capital accumulation and less to technical change in the Solowian residual sense.[1] More recently, William J. Baumol (2002) has argued that the received consensus underestimates the role of technological change because, absent the scientific and technological advances that have occurred since the Industrial Revolution, it would have been difficult or even impossible to reach beyond immediate human subsistence needs, undertaking the education with which human capital has been augmented and accumulating complementary physical capital. On this broader interpretation, toward which I incline, my paper will have little to say. Rather, I focus on the problem of measuring more precisely the relatively short-run links between industrial R&D, as one source of technological change, and the growth of productivity.

This has typically been done by regressing estimates of industrial productivity growth on diverse indices of industrial technological advance, usually proxied by some estimate of research and development performed. The basic difficulty with this approach has been known at least since the publication of a brief paper by Gustafson (1962), who showed that the vast majority of industrial R&D, estimated from my own research (Scherer 1982a) to be on the order of 75 percent, was aimed at developing new and improved <u>products</u> sold to other firms and to end consumers. The technological advances from such product R&D would normally be <u>embodied</u> in the goods and services sold by the R&D performers and from which purchasers derive benefits, including enhanced productivity. Only about a fourth of industrial R&D was process-oriented, that is, aimed at improving the performing firms' internal production processes and hence arguably raising the performers' labor or total factor productivity. To illustrate, most of the R&D performed by the Pratt & Whitney Division of United Technologies leads to improved turbojet engines that increase the reliability, fuel economy, and range of the civilian and military aircraft in which they are embodied. The new drugs developed by Merck are sold to health maintenance organizations and end consumers, reducing the frequency and length of hospital stays and improving consumers' health and their productivity in work environments. Quite generally, significant benefits from product R&D are derived by those who purchase the goods and services in which the results of the R&D are embodied. For such product R&D, again, the majority of all industrial R&D, relating the productivity growth of industry i to the R&D performed in industry i, as all too many economists have done, could lead to seriously erroneous insights.

To move beyond this facile generalization requires an analysis at two levels of subtlety. At the first level, one focuses on what happens in an exact economic analysis of the changes wrought by product R&D. In Figure 1, we assume that a firm's R&D efforts lead to a new product for which the demand curve (taking into account the existence and prices of inferior substitute products) is represented by AD. If the firm has a monopoly in the new and superior product, it will equate marginal revenue with marginal cost (affected by process R&D, and assumed constant at OC per unit) and set price OP_M, realizing profits of P_MBFC. If previously the firm was in competitive equilibrium with revenues barely covering input costs, the profit represents an increase of revenues over input costs correctly attributable to the originating firm's benefit. But the firm's customers also gain a surplus measured by near-triangle ABP_M. Thus, in a correct accounting, part of the social surplus from the R&D is captured by the firm, part by its customers.[2] If however several firms come up with similar new products, they may compete on a price basis and force the subject firm's price down to OP_C. Now the lion's share of the benefits from the R&D is realized by consumers and only the smaller quantity P_CGHC is appropriated by firms performing the R&D. The more price competition there is, the smaller is the originating firm's share of the social benefits from its innovation.[3] Ignoring second-order general equilibrium effects on other monopolistically competitive firms' demand curves, which are sometimes substantial, this is the division a theoretically correct analysis of the benefits from industrial R&D would reveal.

However, the data with which economists must work in the real world of productivity analysis often fall short of theoretical ideals.

To measure productivity growth, we attempt to assess output changes in real, i.e., constant purchasing power, terms. Normally output changes are measured by comparing the value of a firm's (or more likely, industry's) sales (or value added) at an initial point in time with the value at a terminal point in time. But to perform the comparison correctly, nominal values must be deflated by price indices reflecting price level changes <u>and</u> changes in the product mix for a given industry. Product R&D leads to improved products which displace inferior products from market baskets. Obtaining price indices that correctly account for the change in product quality is difficult. Most analyses have concluded that the price indices compiled by government agencies such as the Bureau of Labor Statistics tend to underestimate the value-enhancing effects of product quality increases, and hence when used as deflators, to underestimate the gain in real output value from an initial period to a post-innovation period. See e.g. Griliches (1979). The more they underestimate the real value gain, all else equal, the lower is the productivity growth attributed to the industry selling improved products, and the lower is the imputed input cost to industries using the products, whose total factor productivity gains may be overestimated as a consequence.

The computer industry was for many years singled out as one in which official price deflators egregiously underestimated the rate at which technological improvements reduced the cost of computing operations -- estimated to be falling at roughly 28 percent per year during the 1960s and 1970s. See e.g. Flamm (1987, pp. 27-28). To correct the problem, the U.S. Bureau of Economic Analysis and then the Bureau of Labor Statistics began using essentially hedonic (i.e., function cost-based) price indices that implied a much more rapid rate of implicit computer services price decline and hence a much more rapid rate of real output value and productivity increase for the computer industry -- e.g., 26.8 percent per year for the 1973-1988 productivity growth data compiled by the National Bureau of Economic Research. See Young (1989) and Scherer (1993, p. 10).

The implications of these measurement conventions are illustrated in Figure 2. Suppose computer users base their purchasing decisions on the real cost, adjusted for general purchasing power changes, of computing services per gigaflop (billion floating point operations). In base period 1, the price is OP_1 and the quantity consumed, given the assumed demand relationship, OQ_1. Now suppose the price per gigaflop falls by period 2 to OP_2, leading to an increase in the quantity of computer services demanded to OQ_2. Ignoring changes in the economy-wide price level, one would conclude from contemporary Census reports that the value of computer industry output has increased slightly from P_1AQ_1O to P_2BQ_2O. But with hedonic methods, the price index in period 2 in terms of period 1 prices is P_2/P_1 and so the deflated real output of the industry increases to P_1HQ_2O. This is a very substantial increase. Indeed, the implied consumers' surplus gain P_1HBP_2 exceeds by the near-triangle AHB the actual increase P_1ABP_2. Given these assumptions, hedonic or function cost-based price indices tend to overestimate the real value gains from improved products, whereas traditional price indices tend to underestimate them.

For purposes of tracing where and how much productivity growth occurs, the use of hedonic price indices tends to fix the locus of gains as the industry from which the improved products originate and indeed to overestimate those gains relative to the actual economic benefits. For industries purchasing the improved computers, which from Figure 1 can be assumed to derive substantial net benefits, the use of function cost-based price indices tends to exaggerate the value of the capital goods purchased and hence to reduce or perhaps eliminate the measured value of total factor productivity growth (even if not labor productivity growth without a capital intensity adjustment). Quite generally, the more price deflators underestimate the value of product improvements, the less productivity growth one is likely to attribute to industries originating the improvements. The more (as a result of hedonic methods) they overestimate the value of the improvements, the more productivity growth one is likely to attribute to industries originating the improvements. The shift to hedonic price deflators for computers has tended to show the total factor productivity gains from rapid technological progress to be concentrated in the computer producing sector even though, because of competitive pricing, virtually all sectors of the economy have benefitted substantially from that progress.[4]

These considerations have an important bearing on attempts to estimate econometrically the impact of R&D on productivity growth. If, as is often the case, price deflators do not fully account for the benefits of product improvement, it is necessary to trace the flow of product R&D out to using industries in order to estimate its full contribution. On the other hand, when hedonic price deflators are employed, most if not all of the impact will be found within the industry originating the product R&D. My experiments with alternative deflator assumptions for computers within a much larger sample of industries (Scherer 1993) support this generalization.

The focus here on benefits captured by either the innovator or purchasers of innovative products does not exclude the possibility of technology flowing through the economy in other ways. Zvi Griliches (1979) distinguishes between "rent" spillovers," which encompass the technology flows analyzed here, and "knowledge spillovers," which occur without embodiment in goods exchanged through market transactions. To the extent that "upstream" producers provide disembodied know-how to their customers along with the sale of hardware or software -- and there is reason to believe that such transfers are widespread[5] -- the two will indeed be correlated. But disembodied knowledge may also flow through the economy in ways unrelated to market transactions, e.g., through the third parties' examination of patent specifications and articles in technical journals. These flows are best analyzed not with the techniques analyzed here but through the tracking of citations data. See e.g. Jaffe and Trajtenberg (2002).

3. The Original Technology Flows Measurement Effort

Persuaded, rightly or wrongly, that existing measurement methods required an analysis of industries <u>using</u> innovative products to assess how R&D affected productivity growth, I embarked in the late 1970s upon a project seeking to trace the flows of embodied technology from originating to using industries. The conceptual basis for the effort was laid in Jacob Schmookler's pioneering (1966) book. Nestor Terleckyj (1974) had estimated a small-scale predecessor technology flows matrix and used it to evaluate the contributions of industrial R&D to productivity growth.

The event precipitating my research was the impending publication (U.S. Federal Trade Commission 1981) of data on industrial research and development expenditures for 1974 much more richly disaggregated (to 263 sectors) and with much less cross-industry contamination than any that had been available previously. Collection of the so-called Line of Business data, it should be noted, proceeded with valuable support from an affidavit submitted by Wassily Leontief in litigation that eventually reached the U.S. Supreme Court. Given these new data plus consternation over the decline of U.S. productivity growth rates, foreshadowed by an unprecedented drop in constant-dollar industrial R&D spending, it appeared worthwhile to develop a detailed matrix tracing technology flows from industries performing R&D to industries using the fruits of that R&D.

The link from R&D spending by individual firms in narrowly-defined (three or four-digit) industries was effected by analyzing 15,112 invention patents obtained by 443 typically large U.S. corporations filing Line of Business reports with the Federal Trade Commission. A team of four Northwestern University students -- an electrical engineer, a biology specialist, a chemical engineer, and a mechanically gifted farm boy -- devoted roughly three months each to extracting from each patent a battery of information, including the line of business in which the underlying R&D was done and the industrial fields, identified in patent specifications to justify the "utility" of claimed inventions, in which use of the inventions was likely. Each coding was reviewed by the author and in questionable cases rechecked, sometimes through direct contacts with companies. The coded patents were then linked to individual lines of business on which companies reported confidentially to the Federal Trade Commission. For each of 4,274 individual lines of business, an average R&D cost per assigned patent was computed. For each patent, its R&D cost, adjusted upward to reflect origin industry sampling ratios, was then flowed out to one or more of 286 using industries, including personal consumption, to estimate the technology flows matrix. For 66 percent of the patents, from one to three specific industries of use could be identified.[6] Their underlying R&D outlay averages were allocated among multiple industries according to the using industries' relative purchase volume, as determined from the 1972 input-output transactions matrix. The remaining third were categorized as inventions of general industrial use. The R&D costs of those inventions were allocated out to using industries in proportion to 1972 input-output transactions flows or (for inventions of ubiquitous use) economy-wide value added shares, with various modifications clarified later. Further methodological details are reported in Scherer (1984).

Figure 3 provides an aggregated schematic view of the resulting technology flows matrix. In 1974, 95 percent of all company-financed industrial R&D in the United States was performed within manufacturing industries. (Since then the contribution of nonmanufacturing industries, and especially the software and biotech industries, classified in services, has expanded to a reported 36 percent in 1999.) Roughly half of the technology originating in the manufacturing sector during 1974 flowed out to nonmanufacturing industries, arguably driving productivity growth in those industries. Only about seven percent of the R&D performed was directed solely toward creating new and improved consumer goods.

4. Reestimation Using Less Labor-Intensive Methods

When the technology flows matrix estimation methodology was articulated at a National Bureau of Economic Research conference in 1982, discussant Edwin Mansfield observed inter alia (Scherer 1984, p. 462), "I wonder whether it would be possible for Professor Scherer to compare his findings with what would have resulted if he had simply used an input-output matrix to allocate R&D expenditures." Certainly, if similar results could be obtained in the way Mansfield suggested, much less effort would have been required to do the job, and the effort could be replicated economically at regular intervals. At the time, I was exhausted both psychologically and financially by the work that had been accomplished and had plunged into a quite different project, so I did not follow up on Mansfield's suggestion. This, I gradually came to realize, was a serious mistake. I was induced to return to the question by a Bureau of Economic Analysis query as to whether it would be feasible to estimate technology flows matrices using input-output data for an extension to the Bureau's satellite accounts program. With help from Bureau staff, the requisite machine-readable transactions data for 1972 were retrieved and a reestimation effort could be attempted.[7] The remainder of this paper reports the results, compares them to estimates obtained using my original more labor-intensive approach, and speculates on future opportunities.

4.1 Which Input-Output Matrix?

Several conceptual questions had to be solved. Among them, perhaps the most fundamental is whether first-order input-output transaction matrices should be used to carry R&D from originating to using industries, or whether the total requirements (Leontief inverse) matrix, calculating inputs used both directly and indirectly to produce a given vector of outputs, was a better candidate. In his pioneering effort, Nestor Terleckyj used the first-order transactions matrix. More recently, an ambitious OECD effort (1996) opted for a modified total requirements matrix approach. My own approach was eclectic. For two-thirds of the patents, little or no resort to input-output data was required because the patents had been linked directly to using industries. For the other third, arguments in favor of each approach were recognized. The first-order "make and use" matrix was taken as a starting point, but for 22 technology-originating industries, transactions were carried farther from the first-order using industry to the industry purchasing the output of that industry or in one case (synthetic fibers) to the third-order user.[8] This choice can be criticized as arbitrary. Its principal defense is that it was based upon a detailed understanding, from reviewing 15,112 patents, of how the technology originated in diverse industries affected the activities of downstream industries.

The case for taking into account second and n^{th} order flows is best summarized by considering the computer industry. Our basic objective is to place technological innovations, wherever they originate, in the industrial sector where they are likely to yield measured productivity improvements. (A different objective might lead to alternative choices.) As we have seen earlier, improvements in computer technology have enormously reduced the costs of processing data. Many of those improvements have come from innovations in storage devices, which were in 1972 and are again under NAICS included as part of the four-digit computer industry, and, following Moore's Law, from innovations increasing the capacity and speed of microprocessors and memory chips. Since only the integrated circuits cross industry lines, we focus on them. The first-order transaction is from the semiconductor industry to the computer industry. But who derives the productivity benefits? Under the logic of Figure 1, the ultimate beneficiary, since cost reductions per semiconductor function tend to be passed on by computer makers to computer buyers, is the computer buyer, not the computer industry. However, by the logic of Figure 2, if hedonic price indices are used to deflate nominal computer industry output, the productivity effects are likely to show up in the computer industry (unless hedonic price indices are also used in deflating semiconductor industry output.) Thus, depending upon how the productivity data are compiled, an argument can be made for either a first-order flow (from semiconductors to computers) or for a second-order flow (from semiconductors to computer buyers). My choice in compiling my original technology flows matrix, recognizing that computer price deflators at the time understated true cost reductions per data processing operation, was to implement a second-order flow for semiconductors.

Ignoring the price deflator problem, consider an improved synthetic resin originating in old S.I.C. industry 2821 used to make engineered plastic parts in automobile parts plants. If the utility of the innovation comes from faster or less waste-prone molding in the automobile parts plant, the productivity gains are likely to show up in the automobile parts industry. If however the benefit of the innovation is lighter weight or superior durability relative to parts previously produced, the productivity benefits are likely to be realized by industries and end consumers who buy the vehicles incorporating the parts.

Such ambiguities abound when one tries to trace the locus at which productivity gains are realized. Thus, the case for using first-order transaction as opposed to total requirements matrices is intrinsically equivocal. One way to resolve it is to make ad hoc choices depending upon the perceived dominant character of usage patterns, as I tried to do in constructing my original matrices. However, the goal of my revisited effort was to find simpler solutions, which meant an either-or carrier matrix choice. The first-order transactions matrix was initially given preference, in part because it was closer to my original approach.[9] A still better solution is to pursue both global alternatives and see which one yields results conforming more closely to my original matrix (in which, again, two-thirds of the allocations were based upon patent data) and which approach explains productivity growth more successfully. This dual assault on the problem is pursued here.

4.2 The Diagonal Problem

When published input-output matrices are used as the "carrier" to trace R&D from the industry where it is performed to the industry(ies) using it, there is inevitably a problem of mismatch between what the diagonal values measure and what one wishes them to measure. What _should_ be on the diagonal of an appropriate carrier matrix is the fraction of R&D performed by industry i and used by industry i, which consists preponderantly of process R&D. Industries vary widely in their orientation toward process as contrasted to product R&D -- in my original technology flows sample, from zero percent to 100 percent process, with a simple average value across industries of 29.9 percent process R&D and a median of 19 percent. For industries with a strong internal process orientation, the input-output transactions diagonal values are almost always much too low. For industries (typically the more research-intensive ones) with low process orientation, the diagonals are often too "fat," especially when there are extensive inter-plant shipments within an industry as defined. For 154 industries with positive process R&D values, the simple correlation between process R&D as a percent of total R&D, measured using R&D-weighted patents, and diagonal transaction matrix elements as a percentage of total intermediate industry shipments (excluding final demand vectors) was -0.03. Plainly, the use of input-output data to estimate the amount of own process R&D fails badly.

In my original application of input-output data to allocate general-purpose inventions (again, roughly one third of all inventions) to using industries, I tried to alleviate the intra-industry shipments problem by reducing diagonal elements to values not exceeding a fraction measuring the row industry's share of industry output. However, if input-output matrices were used in the future as the principal R&D allocator in constructing technology flows matrices, the results might be improved greatly through the incorporation of individual industry process R&D ratio estimates. Such estimates were collected in early U.S. R&D censuses and could be added to future questionnaires with little additional burden on respondents. Given this possibility, I constructed alternative carrier matrices in which the diagonal elements, expressed as fractions of total intermediate industry output (excluding personal consumption, gross private fixed investment, inventory changes, and other final demand items), were replaced by individual industry process R&D fractions derived from the data on 15,112 patents, with other elements renormalized so that all included row elements summed to unity. The technology flows carrier matrices derived in this way will be called "process-adjusted" matrices; those without diagonal adjustments will be called "naive" matrices.

4.3 <u>The Capital Goods Problem</u>

Under standard input-output conventions, the capital goods output of an industry is allocated in the transactions matrix to a gross domestic fixed investment category analogous to the personal consumption category, and not to individual using industries. If this convention were accepted at face value, flows of technology embodied in capital goods delivered to individual using industries would be lost or mismeasured. This would be most unfortunate, especially given the evidence from our analysis of individual patents that 44.8 percent of all the patents were associated with capital goods products sold to other industries, not including the 26.2 percent of patents covering process inventions, many of which would affect internally modified capital equipment.[10] In contrast, only 21.6 percent of the patents pertained to industrial materials. Thus, somewhat more than two-thirds of the technology flowing from an origin industry to other using industries and potentially affecting the productivity of the using industry was embodied in capital goods. To exclude capital goods transaction flows from the carrier matrix could lead to serious errors. Flows of spare parts and other non-capital items treated as inter-industry transactions originating in capital goods producing industries could be poor proxies for the flow of capital goods to users.

The U.S. Bureau of Economic Analysis (and apparently the input-output compilation agencies of other national governments) publishes separate matrices tracing capital goods flows from producing or origin industries to using industries. These are much more highly aggregated than the transactions matrices -- in the rows, because many industries sell no capital goods, but more importantly, in the columns, to only 80 using industries in the 1972 version.

In my original technology flows matrix estimation, I disaggregated the capital flow transactions in proportion to more narrowly-defined using industry new capital investment (or for some nonmanufacturing industries, value added) as a fraction of capital flows for the more aggregated industry category. The resulting capital flow estimates were added to the transactions estimates to arrive at the basic carrier matrix allocating R&D from origin to using industries.

A similar procedure was followed in reestimating carrier matrices to determine technology flows from input-output data alone, without recourse to the detailed patent use codings. The disaggregations were from 77 using industries out to 211 more narrowly defined industries. For 70 of the 192 technology-originating industries, capital flows were at least five percent of the sum of transactions plus capital flows. The mean capital flow value was 19.4 percent of combined transactions plus capital flows.

As with the transactions matrix lacking capital flow values, the combined transactions plus capital flows carrier matrix was computed in two ways -- one without correction of diagonal elements, and one with diagonals proportional to internal process R&D as a fraction of total originating industry R&D (and with other row elements renormalized to ensure unit row sums for all using (i.e., column) industries, excluding personal consumption and other final demand items). Capital goods supplying industries were on average much less process invention-intensive than industries with negligible capital goods flows. For capital goods suppliers, R&D devoted to process inventions was 8.6 percent of total R&D; for the latter (i.e., industries with at most trivial capital flows), process R&D averaged 42.1 percent of total R&D.

Ambiguity over whether one should base technology flows on the first-order transactions matrix or the total requirements matrix largely vanishes when capital flows are the focus. Except when the capital goods developer is the company that will utilize the new technology, in which case the R&D should be characterized as process R&D, the productivity benefits of new capital goods are normally realized by the first downstream purchasing industry.[11]

5. Reestimated vs. Original Values

Two criteria are applied to judge the superiority of alternative technology flows matrix estimation methods. For one, the technology flows matrix created during the early 1980s by classifying 15,112 patents can be viewed as a standard against which alternatives should be evaluated. To be sure, the original sample covered only the activities of 443 corporations conducting approximately 73 percent of all U.S. company-financed research and development in 1974. Excluded firms, which were for the most part smaller, could have had different usage patterns than those of included companies. And even for the included companies, one would expect usage patterns to undergo some statistical variation over time. Nevertheless, the classifications were made with extreme care, and because (with an exception to be noted later) alternative benchmarks do not exist, no better standard for assessing the revised matrices' accuracy is known. Second, the output of alternative matrix estimation methods can be used to predict productivity growth to see which contender yields the most satisfactory predictions. Both approaches are pursued here.

For purposes of predicting productivity growth in technology-using industries, the most relevant variables are the sums of the technology flows matrix columns -- that is, the sum of the various amounts of technology an industry imports from other industries along with the diagonal element measuring process technology originated by the industry in question. These were available for at most 205 industries, excluding inter alia personal consumption and gross private fixed investment, but including various government activities. Many of the non-manufacturing industries were highly aggregated -- e.g., finance, insurance, and real estate services -- and tended to dwarf the more highly disaggregated observations for manufacturing. Therefore, separate prediction error computations are also reported for manufacturing only.

The relatively disaggregated data were also aggregated back to a matrix with 42 technology-originating rows and 50 using industry sectors, including personal consumption, replicating as closely as possible the 41 x 53 matrix published (with various deletions owing to data element confidentiality) in Scherer (1982a, 1984). The new matrix resulting from these aggregations is presented here as Appendix Table 1. That matrix was constructed implementing the assumptions considered most suitable on a priori grounds -- i.e., with the first-order transactions and capital flows carrier matrices combined, and with corrections on the diagonal for the incidence of process technology.

Personal consumption column sums were excluded from most of the tests that follow because they posed special conceptual problems. Only 7.4 percent of the 15,112 patents pertained solely to consumer goods. Another 8.7 percent had joint consumer goods and producing sector applications. In the original matrix estimated two decades ago, R&D outlays linked to inventions identified as consumer goods only were allocated on the basis of the patent classifications to that use column. However, when there was joint use, personal consumption usage was treated as a public good ancillary to the industrial uses, and so input-output table weights summed to unity for the industrial uses, with double-counting of consumer goods usage. For the cruder input-output matrix-based approach here, normalizing row sum shares to unity excluding most final demand items -- the assumption most consistent with my original multi-use convention -- assigns too much weight and hence R&D cost to using industries other than personal consumption for the 7.4 percent of inventions (with slightly lower R&D per patent) actually used only in personal consumption.[12] Accepting this error was deemed the least of various alternative evils.

5.1 Goodness-of-Fit Analysis

Table 1 summarizes the tests conducted. Used to assess goodness of fit is the simple Pearsonian correlation coefficient $\underline{r}$ and four summary measures -- mean, median, and values computed at the first and fourth quartile distribution boundaries -- of the percentage deviations between newly estimated and original column sum technology usage, in millions of 1974 dollars.

Among the computations using first-order transactions, the naive transactions matrix performs least well as an R&D carrier by nearly all measures. When technology flows are based on either the transactions matrix or the sum of transactions plus capital flows, unambiguously better fits result when diagonal elements are corrected for the observed incidence of own-process usage.

The principal surprise relative to a priori expectations is the superior performance, at least for percentage errors, of the estimation using only the transactions matrix rather than the theoretically preferred combination of transactions and capital flows matrices. However, the preferred combination performs better in terms of simple correlation coefficients. Evidently, the latter had smaller prediction errors for relatively extreme values, which tend disproportionately to influence correlation coefficients, while using industries with intermediate used R&D values in the original study had somewhat larger prediction errors when capital flows were added to transaction values in computing the relevant carrier matrices.

Figure 4 is a scatter diagram arraying the observations for all 205 using industries according to R&D usage (in millions of dollars) predicted with full use of the data on 15,112 patents (horizontal axis) and R&D usage predicted with the process diagonal-corrected matrix combining transactions and capital flows. The most extreme positive errors are general government,[13] which was also an error outlier in the process-corrected transactions-only analysis, and construction, which was not an outlier in the transactions-based analysis. The reason why construction is an error outlier when predictions include capital flows is straightforward. The capital flows matrix allocates to construction large volumes of kitchen and bathroom appliances, heating and air conditioning apparatus, office partitions, and the like which probably do little to improve productivity on the construction building site, but whose benefits flow largely to those who buy and use the structures constructed. In other words, it is important to implement second-order technology flows, which was done in formulating the original flows matrices but not in the new estimations reported here. The largest negative outlier is air transport, whose estimate in the new matrix undoubtedly understates the dual-use technology contributions of engine and electronic communications and navigation systems producers shared between the defense and air transport sectors.

Among the subset of relatively disaggregated manufacturing industries, the largest positive error outlier is passenger automobiles, whose value in the new estimate includes such innovations as improved disk brakes and electronic ignition controls and more efficient air conditioners whose benefits accrue mainly to vehicle purchasers, but which, without the second-order technology flow adjustments made in the original compilation, are perceived to remain within the vehicle-producing sector. Other large residuals were found for organic fibers and aircraft assembly, both of which were appreciably affected by second-order flows in the original matrix estimation but not in the new estimates described here. These problems suggest that if input-output data were used as the basis of technology flows estimates in the future, <u>selective</u> use of second-order flow adjustments could lead to substantially improved accuracy.

The fifth and sixth entries in Table 1 assess goodness-of-fit when a Leontief inverse total requirements matrix is used as the carrier for technology flows.[14] For reasons stated earlier, no attempt was made to combine capital flows with conventional transactions; the inverse matrix was derived solely from an appropriately aggregated first-order transactions matrix. To avoid excessively "fat" diagonal values overestimating the importance of what should be process technology, the unit value reflecting deliveries to final demand is subtracted from each diagonal element.[15] The matrix derived in this way is called the "naive" Leontief matrix. An alternative in which process elements were replaced by actual industry process usage ratios and all elements were renormalized to sum to unity is called the "process-adjusted Leontief matrix." By all measures, the fit is much worse than with any of the first-order matrices. The process-adjusted row sums conform slightly more closely than unadjusted values. Since the differences did not appear to be attributable to matrix inversion errors,[16] it seems clear that the total requirements approach characterizes rather different phenomena than those measured in my original effort two decades ago or in my reconstruction emphasizing first-order flows only. The implications of this difference will be addressed subsequently.

The final entries in Table 1 reveal that some of the large mean and quartile estimation errors observed using disaggregated first-order data for some 205 industries are more or less random, cancelling out when the process adjusted-estimates including capital flows are aggregated down to 49 broader sectors.

5.2 Predicting Productivity

An alternative perspective for assessing the success of the new technology flows estimates is to use the column sums as an explanatory variable in regression analyses "explaining" productivity growth, taking into account also other relevant variables. This was a principal purpose of the original estimation effort two decades ago. At the time, productivity growth data disaggregated by industry were scarcer than they are now. The principal results, reported in Scherer (1982b), emphasized what was at that time a new Bureau of Labor Statistics series using input-output industry definitions and including 87 industries -- 81 of them from the manufacturing sector along with agriculture, crude oil and gas production, railroads, air transport, communications, and the combined electric-gas-sanitary utilities sector. These data are used also in my new analysis, although because of gaps attributable mainly to the confidentiality of certain Federal Trade Commission Line of Business data, only 80 (or with the Leontief inverse data, 79) industries can be covered here. The dependent variable is the percentage growth of labor productivity LP, i.e., (estimated) real output per unit of labor input, between 1973 and 1978, both cyclical peak years. An additional variable from the original productivity growth data set was the percentage growth of capital intensity (K/L) over the same period. Two variables were emphasized in the original paper and are employed again here to measure the contributions of technology: UsedRD, which is the appropriately aggregated column sum estimating industry i's R&D usage, either as process R&D or R&D imported from other industries, and ProdRD, or the amount of non-process R&D performed by industry i, virtually all of which was assumed to be exported in embodied form to other using industries. Both are measured as a percentage of relevant industry output values. Ignoring measurement difficulties, ProdRD should characterize the benefits appropriated internally by the innovating firm, e.g., area P_MBEP_C in Figure 1, and UsedRD the external or exported benefits ABP_M in Figure 1. Our main concern is the contribution of UsedRD computed in various alternative ways. Following a proof attributable to Terleckyj (1974), the regression coefficients on the

R&D variables can be interpreted, subject to some qualifications, as rates of return on research and development investment.

Table 2 reports the regression results. Regression (1) is drawn from Scherer (1982b) using my original technology flows data. All three variables made statistically significant contributions to the explanation of productivity growth during the (relatively stagnant) middle 1970s (and also, it was shown, with some limitations, in the more dynamic 1964-1969 period). The R^2 value is modest, however, indicating that considerable unexplained noise remains. Regression (2) reports results using the original technology flow estimates for the new sample from which seven industries were removed because of data gaps. It will be taken as the benchmark against which regressions using the new estimates will be compared. In all new regressions (3)-(10), the (K/L) and <u>ProdRD</u> variables are identical to those used in the second, N = 80, entry.

There are several surprises. First, regressions (3) and (5), with and without capital goods flows added, but without process diagonal adjustments, outperform their counterparts. Second, the greatest explanatory power (R^2) using first-order carrier matrices is achieved with regression (5), which is based on summed transactions and capital flows, but without process diagonal adjustments. That regression, however, reveals a surprising and indeed implausible constellation of technological impact coefficients. The coefficient on <u>UsedRD</u> implies rates of return of 225 percent on process plus imported R&D -- much higher than any estimated with the original data set. At the same time, this strong used R&D effect destroys the impact of internal product R&D, which is also implausible. The reason for this second result is that the regression equation suffers from severe multicollinearity. The simple correlation between the two output-deflated R&D variables is 0.760, and the used R&D variant (without process diagonal adjustment) overwhelms its correlated own-product R&D analogue. Given these anomalies, one is inclined to reject regression (5) and favor regression (6), with the strongest a priori support and the second-highest explanatory power of the new contenders. Indeed, the explanatory power R^2 of regression (6) is identical to that of regression (2) incorporating used R&D data from the original technology flows matrix derived through inspection of 15,112 patents, and the regression coefficients differ only trivially.

Additional surprises materialize when column sums from the Leontief total requirements carrier matrices are substituted to obtain the key used R&D variable. With Leontief inverse estimates both unadjusted for process diagonal values (regression (7)) and process-adjusted (regression (8)), R^2 is less than that of the best two regressions using new first-order technology flow vectors. Neither total requirements-based used R&D variable achieves statistical significance by conventional standards, exceeding the 1.67 t-ratio value delineating 95 percent confidence in a one-tailed test. As with the first-order estimates, explanatory power is greater without process diagonal adjustments, but at the cost of degrading the product R&D variable's role. A reason for the product R&D impact is that the Leontief estimates without process diagonal adjustments are fairly strongly correlated with the product R&D variable, and this collinearity degrades the product R&D coefficients.[17] See Table 3, which presents a matrix of correlation coefficients for alternative R&D flow measures defined as a percentage of the value of industry output.

From regressions (7) and (8) in Table 2, the generally similar Pearsonian correlations between 1973-78 productivity growth and alternative R&D flow measures in Table 3, and the Leontief variables' typically low correlations with first-order R&D usage variables, it would appear that the R&D usage variables derived from total requirements matrices are characterizing a different dimension of technology flows, but one that has at least some utility in explaining productivity growth. To pursue this insight further, regressions (9) and (10) in Table 2 introduce together two distinct technology usage variables, one derived with emphasis on first-order transactions and one based on the total requirements matrix without process diagonal adjustment. Higher R^2 values are achieved than in any but regression (5), rejected as implausible on a priori grounds. The first-order and total requirements technology usage coefficients exceed 95 percent statistical significance thresholds in three out of four cases, although, as in equation (7), the power of the product R&D variable is degraded. We observe too that the implied returns on R&D investment are in the range of 70 to 80 percent with first-order flow measures but only 23 to 37 percent with n^{th} order measures. It would appear that the more diffuse usage traced using the Leontief inverse approach yields lower returns than the direct usage in first-order technology embodiments. We conclude more generally that both the first-order and total requirements approaches help explain the links between research and development and productivity growth, with the first-order measures holding a modest edge over those based upon the Leontief inverse.

6. An Alternative Technology Flows Measurement Approach

A promising alternative approach to measuring the inter-industry flow of technology has been pioneered by Robert Evenson and associates at Yale University, using unique data developed in the Canadian Patent Office (CPO). See Evenson and Johnson (1997a, 1997b) and Kortum and Putnam (1997). Beginning in the late 1970s, the CPO began having its staff classify most of the patents it grants (roughly half of which originate from U.S. inventors) according to industry of manufacture, which corresponds to my industry of origin concept, and sector of use, which corresponds to my industry of use concept. See Ellis (1981). The classifications, discontinued during the 1990s, were typically made at the four-digit industry level in the then-prevailing Canadian Standard Industrial Classification System. Evenson and colleagues have arrayed the Canadian data into technology flow matrices like mine. The comparison made here is from Evenson and Johnson (1997b), whose Table 2 reports flow matrix column sums for counts of issued patents analogous to those analyzed in the previous section. My original technology flows matrix was based upon U.S. patents issued to U.S. corporations in 1976 and 1977, to which the patent usage sums reported by Evenson and Johnson for 1978-1981 correspond most closely in time.

The Evenson et al. data are relatively highly aggregated to the level of 33 sectors. By aggregating my original matrix column sums, combining six of the Evenson sectors into three, and omitting three incompatibly defined sectors, an acceptable match was achieved for 27 sectors, including 19 manufacturing and eight nonmanufacturing sectors. Figure 5 arrays their issued patent counts (vertical axis) against my original technology flow matrix column sums (horizontal axis), measured in millions of dollars. Inspection reveals substantial departures from what ought, if the same phenomenon is being measured, to be a linear array of data points. The correlation between the two data sets is 0.560. Especially large discrepancies are observed for the combination of their electrical equipment and electrical machinery groups, which in my analysis had a relatively high incidence of second-order product technology flows; the various transportation services industries (which in my analysis were recipients of substantial first- and second-order technology flows); and the wholesale and retail trade sectors, which in my matrix received many general-use inventions apparently not coded by the Canadian Patent Office.[18] It is also possible that the patterns of patenting in Canada, mostly by foreigners, were different than in the United States, in which during 1977 foreign residents were a distinct minority among patent recipients.

Whatever the reasons, it seems clear that the Canadian patent classifiers and my late 1970s effort measured somewhat different phenomena. Further research on the reasons for discrepancies using more disaggregated column sums and information on second-order technology flows seems in order.

7. Conclusions

From the tolerably good results I have achieved attempting to emulate my original labor-intensive technology flows matrix using mainly input-output data as the carrier matrix, it seems clear that future iterations might be feasible. If the effort is undertaken, combining the transactions and capital flows matrices is essential, since much of the technology flowing between industries is embodied in capital goods. Ideally, capital flows should be capitalized over a larger number of years and depreciated. There is also a persuasive argument for replacing the standard input-output matrix diagonals with information on the share of each industry's R&D effort devoted to internal process improvement. On this, more in a moment. From the results reported here, taking into account second and n^{th}-order technology flows is also important. Doing so selectively, as I did two decades ago, yields productivity explanations different from (and somewhat stronger than) those using n^{th} order Leontief total requirements matrices as the technology flow carrier. That the two alternative methods yield superior predictions when used in tandem suggests that both approaches warrant support in future work.

There are several possible ways to obtain the data needed to estimate process diagonals correctly. Ideally, respondents in the joint National Science Foundation - Census Bureau industrial R&D surveys could be asked to provide an estimate for their operations. They may not know the correct fraction precisely, but a knowledgeable approximation is much better than ignorance and manifest error. In diversified corporations, however, a company-wide estimate may conceal wide inter-industry variations. Alternatively, the process breakdowns (averaging 22 percent for 1996) elicited through a smaller survey conducted periodically by the private-sector Industrial Research Institute could be tapped. See Bean et al. (1998). Or at higher cost but greater potential precision, patent applicants might be asked whether their inventions pertain mainly to potential products, internal process improvements, or some mixed or "other" category.

In my opinion, understanding how technology flows through the economy and enables economic growth is one of the most important matters to which economic analysis can contribute, and therefore it warrants a richer allocation of information-gathering resources. I therefore propose that the U.S. Patent Office emulate its Canadian cousins, but go farther. It would ask each applicant to disclose the NAICS industry category in which the invention originated (with a catch-all for inventions from broad-mandate basic research laboratories and an "unaffiliated" option for unaffiliated inventors), along with the principal industries in which use of the invention is contemplated, with "industries to which the originating industry sells products" and "throughout the economy" as alternatives for general-use inventions. Once patent attorneys became accustomed to asking inventors for such information, the incremental compliance burden would be minute, and valuable information on the structure of the economy would be obtained.

Developing this information as a by-product of invention patenting would go a long way toward solving what was with my research two decades ago a minor problem but has now taken on major proportions -- the measurement of imported technology flows. My research was focused on patents issued in 1976 and 1977, when the United States was the world's clear leader in most areas of industrial technology and 34.4 percent of all U.S. invention patents went to foreign residents. At the time the role of foreign inventors was rising rapidly. From 1966 to 1970, the average share of foreign inventors in total U.S. patenting was only 22 percent; it rose to 47 percent in the late 1980s before receding to 44 percent during the mid-1990s. At the time my original study was conducted, high-technology imports were penetrating the U.S. economy at an accelerating rate. See Scherer (1992). When my research was carried out, one could defend ignoring foreign technology sources, but that is no longer possible. Assuming that imports disseminate technology or its underlying R&D results with the same usage patterns as domestic technology sources, as the OECD staff (1996, pp. 26-27 and 143) has been compelled by data limitations to assume, provides at best a crude approximation to the contribution of imported technology. A much better estimate could be obtained if foreign inventors, like U.S. inventors, were required to disclose the industry from which their inventions originated (which could then be linked to national R&D statistics) and the industries likely to utilize their inventions.[19]

I have saved for last the most difficult problem to be solved in future technology flows matrix development efforts -- obtaining accurate, reliable origin industry research and development data. I began my project during the late 1970s because for the first time ever, reliable R&D data for highly disaggregated industries became available through the Federal Trade Commission's Line of Business program. Complete reports for four years -- 1974 through 1977 -- were obtained before the program was terminated as a result of political pressure orchestrated by U.S. industry.

The closest analogue to the FTC R&D reports covering some 263 industries has been the collection in NSF-Census surveys of applied R&D expenses for some 37 "product fields." That data collection effort was discontinued following the 1997 survey because of poor response rates.[20] As a result, the only industrial R&D expenditure disaggregations from the NSF-Census surveys are reported for roughly 50 industry groups (expanded through disaggregation of many nonmanufacturing groups from the 26 reported in 1997) by the "principal industry" method. That is, the principal industry in which a company operates is ascertained, and <u>all</u> of the company's R&D is thereupon assigned to that industry. For large diversified companies, this method leads to large allocation errors. To illustrate, among the companies included in my study two decades ago, General Electric obtained 706 patents. It is uncertain to which of the many fields in which GE operated at the time, ranging from synthetic resins to aircraft engines, the Census Bureau staff would classify its R&D activities. It was probably "other electrical equipment," in which case 57 percent of GE's patents would be misclassified. If GE were located in the broader (old S.I.C.) two-digit "electrical equipment" group, the error rate would be 42 percent. Or to take a less diversified company, 47 percent of du Pont's 391 patents would be misclassified if its principal industry were deemed to be "industrial chemicals." Even at the two-digit S.I.C. level of detail, 24 percent of du Pont's patents originated outside the broad "chemicals and allied products" sector. Basing a technology flows matrix on such "contaminated" R&D data would impart considerable inaccuracy.

The simplest solution to this problem would be to restore line of business reporting in the National Science Foundation - Census Bureau surveys, disaggregating the reporting lines more finely than they have been disaggregated in the past, and exerting strenuous efforts to convince industry participants that the data shed important light on the dynamics of the American economy. Failing that, the principal alternative basis for measuring inter-industry technology flows could be requiring patent applicants to disclose industries of origin and use in their applications. In this case, an average R&D cost per company patent could be estimated using publicly-available annual reports on company-financed R&D expenditures. Or for companies that do not report their R&D figures, the data could be obtained on a confidential basis from NSF-Census filings.

I conclude that it is indeed feasible to construct meaningful technology flow matrices using approaches less labor-intensive than those accepted for my effort two decades ago. But substantial progress requires improvements in the data obtained from industry in annual R&D surveys or patent filings.

END NOTES

1. Compare Jorgenson and Stiroh (2000) and the comment by Gordon (2000, p. 215).

2. With cost-saving process innovations, it is possible but not necessary that all of the benefits are appropriated by the innovator. See Arrow (1964). If the innovations induce price reductions, the benefits are shared.

3. Mansfield et al. (1977) estimate that at the median in a sample of 17 innovations, innovators appropriated roughly 44 percent of the discounted economic benefits from their innovations.

4. Because in deriving gross national product estimates "real" industry outputs are weighted by industry price indices, changes in the price index base year can lead to surprisingly large reductions in estimated GNP. This was a special problem in the early 1990s, until GNP weights were chain-linked annually instead of every five years.

5. See Harhoff (1996).

6. Sixty-four percent of these involved a single using industry.

7. The author is grateful in particular to Peter Kubach and Jiemin Guo of BEA.

8. The industries from which second-order flows were computed were weaving mills, fabric knitting mills, organic fibers, tires and tubes, rubber hose and belting, flat glass, pressed and blown glass, internal combustion engines, pumps, anti-friction bearings, compressors, speed changers and industrial drives, mechanical power transmission equipment, automotive carburetors etc., vehicular lighting equipment, electron tubes, cathode-ray tubes, semiconductors, other electronic components, starter and traction batteries, aircraft engines, and buttons, zippers, etc. Not all transactions, but only those that were preponderantly of a "component sale to further assemblers" nature, were treated in this way.

9. But see Scherer (1982b), p. 631, in which matrices with second-order flows were emphasized on a priori grounds even though slightly higher Pearsonian correlations with productivity growth were obtained when only first-order flows were measured.

10. On this, see Carter (1970), p. 21, who correctly observes that "New types of capital goods are at the core of technological

change."

11. An important exception, the construction industry, will be discussed subsequently.

Purchasers farther downstream benefit when competition forces cost reductions at the first using stage to be passed on in the form of lower prices. But the change in productivity occurs at the stage using the capital good.

12. The average 1974 R&D cost per consumer good invention patent was $533,000, as compared to $594,000 for industrial use inventions. Patents on inventions whose use was considered to be of general use, without any specific industry assignment, had the highest average R&D cost at $743,000. Patents covering complex system inventions had the highest average R&D cost of $707,000 among several technological categories; the lowest average was for production processes, at $450,000.

13. On both dimensions the most extreme observation is defense and space operations. The R&D values include only company-financed R&D (although some so-called "independent" R&D reported as company-financed was ultimately reimbursed by the Department of Defense). In addition to the $1.2 billion of company-financed R&D allocated to defense and space, the original study identified $4.8 billion of government-financed R&D.

14. The author is indebted to Aubhik Khan and Robert Hunt of the Federal Reserve Bank of Philadelphia for inverting the 207 x 207 transactions matrix, which was too large for the author's ancient computer.

Two using industries -- guided missile production and the government's defense and space operations -- had to be omitted.

15. A somewhat different procedure to avoid overestimation of diagonal effects was adopted by the OECD group (1996, pp. 142-143).

16. Some sectors of the 207 square matrix were at the same level of disaggregation as the 487 x 487 matrix published in U.S. Department of Commerce (1979, volume II), so a comparison to verify the accuracy of our inversion effort was possible. All diagonal elements had unadjusted values of unity or greater, as is required. Most of the compared cells differed by no more than 10 percent. A few larger deviations were expected (and found) in inverting matrices of such disparate aggregation.

17. That the Leontief inverse measures without process diagonal adjustment are associated with advanced product technology is suggested also by an examination of the three most extreme values, all taken as a percentage of industry output value: computers, 10.04 percent; optical and ophthalmic instruments, 9.36 percent; and other office machinery, 6.15 percent. The median value for all industries was 1.36 percent. With my original used R&D indices, the largest three values occurred in electronic components (3.39 percent), air transportation (3.02 percent), and synthetic fibers (2.56 percent). Two of the three are high process technology users; the third (air transport) a major importer of embodied technology.

18. See Kortum and Putnam (1997), p 174, note 13. For those who might wish to replicate the comparison, it should be noted that in Scherer (1984), p. 451, which presents disaggregated used R&D matrix column sums, the value for coal mining should be 72.4 rather than 35.1.

19. For a pioneering effort using Canadian patent data, see Hanel (2000). Several studies have found that patents sought outside one's home market tend to be of greater economic value on average than patents received at home.

20. Communication from Raymond Wolfe of the National Science Foundation May 23, 2002. From a mini-conference April 23, 1998, on "R&D and Innovation Statistics" under the auspices of the Census Bureau's Advisory Committee of Professional Associations, one of the strongest recommendations to emerge was that more effort be devoted to obtaining industrial R&D expenditure data broken down by disaggregated originating lines of business.

REFERENCES

Arrow, Kenneth J. (1962). "Economic Welfare and the Allocation of Resources for Invention," in the National Bureau of Economic Research conference report, The Rate and Direction of Inventive Activity (Princeton: Princeton University Press).

Baumol, William J. (2002). The Free-Market Innovation Machine: Analyzing the Growth Miracle of Capitalism (Princeton: Princeton University Press).

Bean, Alden S, M. Jean Russo, and Roger L. Whiteley (1998). "Benchmarking Your R&D: Results from IRI/CIMS Annual R&D Survey for FY '96," Research " Technology Management (January-February), pp. 21-30.

Carter, Anne P. (1970). Structural Change in the American Economy (Cambridge: Harvard University Press).

Denison, Edward F. (1979). Accounting for Slower Economic Growth (Washington: Brookings Institution).

Evenson, Robert E., and Daniel Johnson (1997a). "Introduction: Invention Input-Output Analysis," Economic Systems Research, vol. 9, pp. 149-160.

Evenson, Robert E., and Daniel Johnson (1997b). "Innovation and Invention in Canada," Economic Systems Research. vol. 9, pp. 177-192.

Flamm, Kenneth (1987). Targeting the Computer: Government Support and International Competition (Washington: Brookings Institution), p. 24.

Gordon, Robert J. (2000). "Comment," Brookings Papers on Economic Activity 2001:1, pp. 212-222.

Griliches, Zvi (1979). "Issues in Assessing the Contribution of Research and Development to Productivity Growth," Bell Journal of Economics, vol. 10: pp. 91-116.

Griliches, Zvi (1995). "R&D and Productivity." In Paul Stoneman, ed., Handbook of the Economics of Innovation and Technological Change (Oxford, Basil Blackwell).

Gustafson, W. Eric (1972). "Research and Development, New Products, and Productivity Change," American Economic Review, vol. 52, pp. 177-185.

Hanel, Petr (2000). "R&D, Interindustry and International Technology Spillovers and the Total Factor Productivity Growth of Manufacturing Industries in Canada," Economic Systems Research, vol. 12, pp. 345-361.

Harhoff, Dietmar (1996). "Strategic Spillovers and Incentives for Research and Development," Management Science, vol. 42, pp. 907-925.

Jaffe, Adam B., and Manuel Trajtenberg (2002). Patents, Citations & Innovations: A Window on the Knowledge Economy (Cambridge, MIT Press).

Jorgenson, Dale W. (1990). "Productivity and Economic Growth," in Ernst R. Berndt and Jack Triplett, eds., Fifty Years of Economic Measurement (Chicago: University of Chicago Press), pp. 19-118.

Jorgenson, Dale W., and Kevin Stiroh (2000), "Raising the Speed Limit: U.S. Economic Growth in the Information Age," Brookings Papers on Economic Activity 2000:1, pp. 125-211.

Kortum, Samuel, and Jonathan Putnam (1997). "Assigning Patents to Industries: Tests of the Yale Technology Concordance," Economic Systems Research, vol. 9, pp. 161-175.

Mansfield, Edwin, et al. (1977). "Social and Private Rates of Return from Industrial Innovations," Quarterly Journal of Economics, vol. 91, pp. 221-240.

Mokyr, Joel (1990). The Lever of Riches (Oxford, Oxford University Press).

OECD (Organization for Economic Cooperation and Development)(1996). Technology and Industrial Performance. Paris.

Scherer, F. M. (1982a). "Industrial Technology Flows in the United States," Research Policy, August 1982, pp. 227-245.

Scherer, F. M. (1982b). "Inter-Industry Technology Flows and Productivity Growth," Review of Economics and Statistics, vol. 64: pp. 627-634.

Scherer, F. M. (1984). "Using Linked Patent and R&D Data To Measure Inter-Industry Technology Flows," in Zvi Griliches, ed., R&D,

Patents, and Productivity (Chicago: University of Chicago Press), pp. 417-461.

Scherer, F. M. (1992). International High-Technology Competition (Cambridge: Harvard University Press).

Scherer, F. M. (1993). "Lagging Productivity Growth: Measurement, Technology, and Shock Effects," Empirica, vol. 20:, pp. 5-24.

Schmookler, Jacob (1966). Invention and Economic Growth (Cambridge: Harvard University Press).

Schumpeter, Joseph A. (1942). Capitalism, Socialism, and Democracy (New York: Harper).

Solow, Robert A. (1957). "Technical Change and the Aggregate Production Function," Review of Economics and Statistics, vol. 39, pp. 312-320.

Terleckyj, Nestor E. (1974). Effects of R&D on the Productivity Growth of Industries: An Exploratory Study. Washington: National Planning Association.

U.S. Department of Commerce, Bureau of Economic Analysis, The Detailed Input-Output Structure of the U.S. Economy: 1972 (2 volumes, Washington: USGPO, 1979).

U.S. Federal Trade Commission (1981). Statistical Report: Annual Line of Business Report: 1974. Washington.

Young, Allen H. (1989). "BEA's Measurement of Computer Output," Survey of Current Business, July: pp. 109-115.

Table 1

Goodness-of-Fit Measures: 1982 Estimates as Basis

	N	Corr.	Percentage Errors* Mean	Median	1st Quart.	3rd Quart.
Naive Transactions						
All industries	205	.701	78.60	18.41	-37.31	116.82
Manufacturing	181	.528	90.04	22.01	-30.20	126.25
Process-Adjusted						
All industries	205	.716	33.85	8.78	-15.23	63.50
Manufacturing	181	.878	37.53	12.24	-11.23	63.50
Transactions plus Capital Flows Combined						
All industries	205	.859	62.73	25.30	-20.37	111.22
Manufacturing	181	.715	68.14	36.22	-14.48	122.18
Combined, Process-Adjusted						
All industries	205	.899	41.52	19.64	-3.91	68.78
Manufacturing	181	.921	43.62	24.12	-2.30	68.86
Naive Leontief Matrix						
All industries	203	.113	669.60	229.44	6.85	718.68
Manufacturing	180	.218	754.45	280.00	55.37	859.44
Process-Adjusted Leontief Matrix						
All industries	203	.246	574.26	162.84	27.86	629.91
Manufacturing	180	.381	645.85	242.43	46.83	703.45
Aggregated Appendix Matrix (Process-Adjusted, with Capital Flows)						
All industries	49	.843	25.25	10.77	-1.49	37.98

* 100 [(New Estimate - Original Estimate) / Original Estimate)

Table 2

Regressions Explaining 1973-1978 Labor Productivity Growth

	UsedRD		ProductRD	(K/L)	R^2	N
(1) Original data	0.742 (1.89)		0.289 (2.01)	0.347 (3.30)	.193	87
(2) Original data, matching sample	0.698 (1.74)		0.357 (2.27)	0.332 (3.03)	.192	80
(3) New naive transactions	0.565 (1.19)		0.194 (0.81)	0.314 (2.85)	.175	80
(4) New transactions, process-adjusted	0.352 (0.66)		0.359 (2.07)	0.312 (2.81)	.164	80
(5) New transactions plus capital flows	2.25 (2.68)		-0.073 (0.31)	0.268 (2.48)	.232	80
(6) New transactions plus capital flows, process-adjusted	0.751 (1.73)		0.320 (1.96)	0.299 (2.72)	.192	80
(7) New Leontief inverse	0.302 (1.41)		0.198 (0.92)	0.322 (2.91)	.183	79
(8) New Leontief, process-adjusted	0.232 (0.88)		0.321 (1.72)	0.316 (2.84)	.169	79
	1st Order	Inverse				
(9) UsedRD from (6) and (7)	0.815 (1.88)	0.336 (1.60)	0.079 (0.36)	0.302 (2.76)	.220	79
(10) UsedRD from (2) and (7)	0.817 (2.02)	0.374 (1.77)	0.088 (0.40)	0.339 (3.12)	.225	79

Subscripted parentheses report t-ratios.

Table 3

Correlation Matrix for Variables used in the Regression Analysis

	(Q/L)	ProductRD	$UsedRD_{orig}$	$UsedRD_{k,p}$	$UsedRD_{L}$	$UsedRD_{L,p}$
(Q/L)	1.000	.264	.204	.279	.259	.227
ProductRD		1.000	.186	.308	.689	.532
$UsedRD_{orig}$			1.000	.805	.009	.236
$UsedRD_{k,p}$				1.000	.151	.419
$UsedRD_{L}$					1.000	.844
$UsedRD_{L,p}$						1.000

Notation

(Q/L)	Percent annual labor productivity growth, 1973-78
ProductRD	Product R&D (percent of industry output value)
$UsedRD_{orig}$	Used R&D (original measures) (percent of industry output value)
$UsedRD_{k,p}$	Used R&D, new estimates, with capital flows and process diagonal adjustments (percent)
$UsedRD_{L}$	Used R&D, Leontief inverse (percent)
$UsedRD_{L,p}$	Used R&D, Leontief inverse, with process diagonal adjustments (percent)

Figure 1
Theoretical Distribution of Benefits from Product Innovation

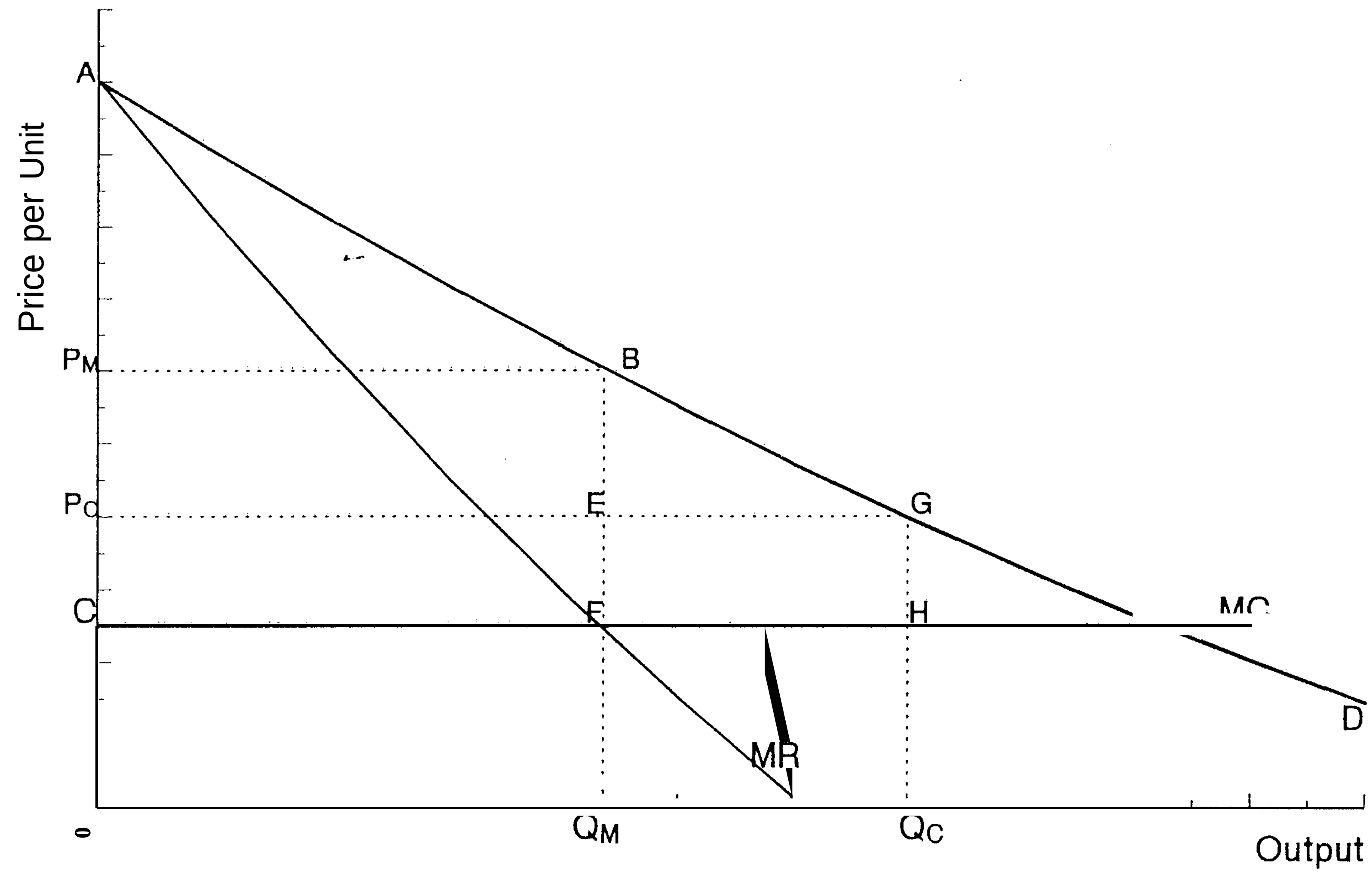

Figure 2

Prices and Quantities with Hedonic Price Changes

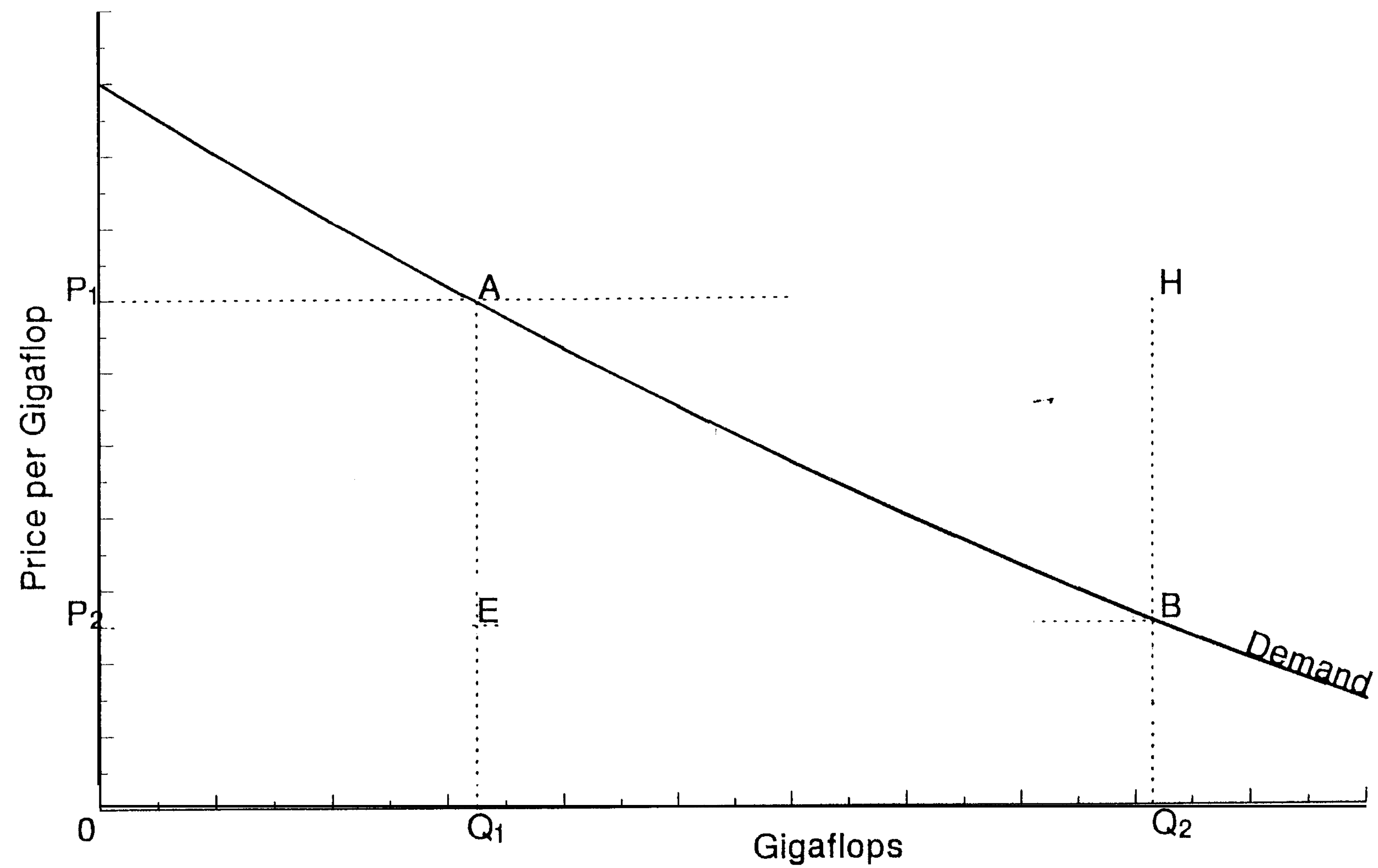

Figure 3
Industrial Technology Flows in the U.S. Economy: 1974

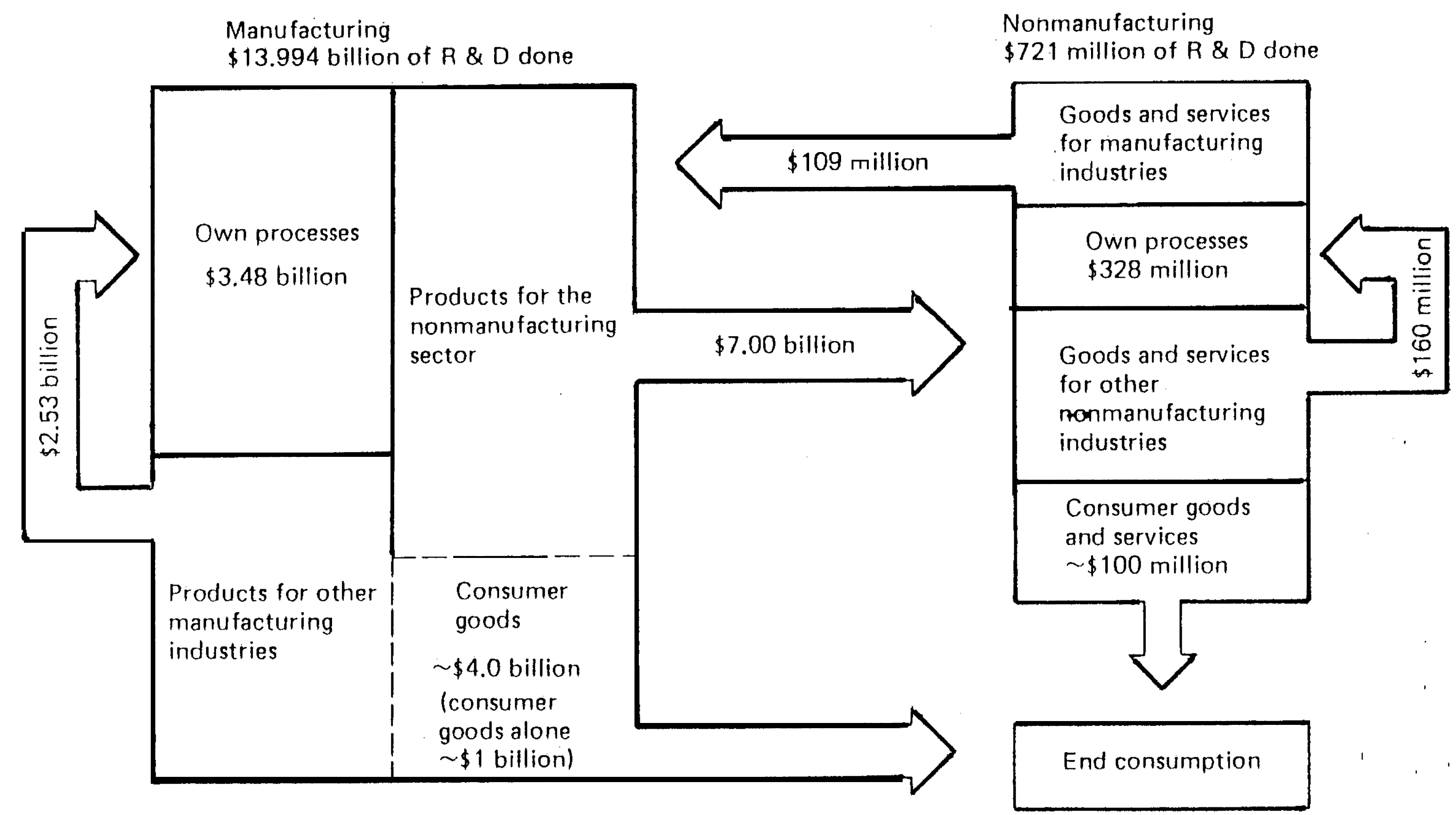

Figure 4

Scatter Diagram of Combined and Process-Corrected User Data