Is Embodied Technology the Result of Upstream R&D?

Industry-Level Evidence

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Abstract:

In this paper, I develop an industry-level index of capital-embodied R&D by capturing the extent of research and development directed at the capital goods in which a given industry invests. Compiling and adjusting data from the National Science Foundation and Commerce Department, I construct industry-level, time-series measures of this index and investigate its properties. The data allow me to identify the R&D directed at the development of specific types of capital rather than incorrectly assuming industry R&D spending is equivalent to R&D directed at the industry's product, an assumption typically made in the R&D literature.

It is first shown that R&D directed at a type of capital is a good measure of its technological change. The constructed index of an industry's capital-embodied R&D is then compared to rates of embodied technological change estimated using plant-level manufacturing data. The index of embodied R&D is found to be positively and significantly related to the estimated rates of embodied technological change. Likewise, embodied R&D is shown to have a positive and significant effect on conventionally-measured total factor productivity growth (i.e. the Solow Residual). This has two implications. First, the capital component of the Solow Residual is generally mismeasured as it does not adequately capture technological change. Second, the constructed index of embodied R&D is proportional to true embodied technological change. Rates of embodied technological change are thus imputed for non-manufacturing industries using the estimated relationship between embodied R&D and embodied technological change found in the manufacturing data.

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1. Introduction

To properly model long-run productivity growth, at least within the framework of Neoclassical production theory, one must accurately measure capital accumulation. To this end, one must understand the extent to which new capital is more productive (i.e. more technologically advanced) than old capital. This is the issue of capital-embodiment. Distinguishing between embodied (or investment-specific) and disembodied technological change has been a long sought after goal in economics, as has the dual problem of distinguishing between obsolescence and physical depreciation on the price/cost-side. The field of hedonic price measurement has provided a potential solution to this fundamental identification problem (see Hall (1968)).[2] However, hedonic methods require very specific time-series and cross-sectional data on prices and product characteristics -- data which is not available for many capital goods.

Sakellaris and Wilson (2001) developed an alternative, production-side approach to measuring embodied technological change that exploits time-series and cross-sectional variation in investment histories. This model was estimated using plant-level manufacturing data from the Longitudinal Research Database (LRD) available at the U.S. Census Bureau. I extend this study to allow the estimates of embodied technological change to vary by industry. Nonetheless, there remain two inherent limitations of these estimates: (1) they can only be obtained for manufacturing industries, and (2) there are no comparable results in the literature with which to evaluate the reasonableness of these estimates. That is, how does one know whether it is sensible for one industry to have a higher estimated rate of embodied technological change than another. An inspection of capital flows tables may be able to tell us which industries invest in goods that are considered “high-tech” (e.g., Stiroh (2001)) or “innovative”, but other than subjective priors, we have no way of quantifying the innovation embodied in an industry’s capital goods.

In order to evaluate the realism of estimated rates of embodied technological change in manufacturing industries and to extend these results to non-manufacturing industries, I propose an index that captures the amount of research and development ®&D) embodied in an industry’s capital. I then investigate the effectiveness of this index in explaining embodied technological change. The index is a weighted average of past and present R&D performed on the (upstream) capital goods purchased by a (downstream) industry. To construct this index, I create a data set containing R&D by product field from 1957 to 1997, using various releases of the National Science Foundation’s *Research and Development in Industry*. This data is then combined with Commerce Department data on industry investment by asset type. The *product field* R&D data allows me to avoid measurement problems associated with using R&D by *performing industry*.

The basic notion that technological change in any given product (capital goods in this case) is the result of past and present R&D directed at the invention and/or development of that product is the backbone of this paper and thus it is tested by comparing the R&D embodied in a capital good with another proxy of technological change: the decline in the good’s quality-adjusted price relative to the price of consumption. After discussing the ranking of industries

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[2]The decomposition between embodied and disembodied technological change can be inferred from the hedonic prices of investment and consumption given certain assumptions (see, e.g., Hornstein and Krusell (1996)).

according to their level of capital-embodied R&D, I search for some reduced-form relationships between embodied R&D and either the estimated rates of embodied technological change that I find at the plant-level or the Solow Residual. Embodied R&D turns out to be positively and significantly related to both the Solow Residual and the estimates of embodied technological change, implying that the R&D done "upstream" on capital goods *is* responsible for the measured productivity growth of "downstream" customer industries.[3]

2. Estimating Embodied Technological Change at the Plant-Level

In this section, I will briefly discuss the main empirical model used to estimate industry-specific rates of embodied technological change. The methodology, data, and motivation for the empirical model are discussed in detail in Sakellaris and Wilson (2001). The empirical model, which we estimated using establishment-level manufacturing data housed at the Center for Economic Studies, U.S. Census Bureau, can be summarized in four equations:

Capital Services

$$J^* = J \cdot \min\{U^J, (E/J)^{\frac{1}{\tau_J}}\} \tag{1}$$

where:

J = equipment capital stock in efficiency units

U^J = equipment capital utilization rate

E = Energy usage

τ_J = parameter representing the elasticity of energy with respect to equipment capital utilization.

An exactly analogous equation is specified for the structures capital services.

Equipment Capital Stock

$$J_t = \sum_{s=1}^{T} I_{t-s} D_{t,t-s} (1+\gamma)^{t-s-t_0} \tag{2}$$

where:

[3]There is a large literature seeking to measure the effects of R&D on productivity. However, the R&D variable that is generally used is R&D done *by* the firm, industry, or economy for which productivity is being measured. There is also a growing literature on the productivity effects of R&D spillovers -- that is, R&D done by other firms that are "close" to the firm/industry in question in terms of distance, industry, production process, input-output linkages, etc.. Though interesting in their own right, these types of R&D effects are likely to affect disembodied technological change and thus are separate from the embodied effects of R&D discussed in this paper.

I_{t-s} = Real investment in vintage t-s equipment (deflated using a non-hedonic deflator)
$D_{t,t-s}$ = the fraction of one dollar's worth of vintage t-s investment that is still used in production in year t
γ = parameter representing the rate of embodied technological change
t = current year (so t-s denotes vintage)
t_0 = numeraire year in which level of embodied technology is 1.

Production

$$\ln(Q_{it}) = [\text{Other Variables}]_{it} + \beta \cdot \ln(L_{it}) + \theta \cdot \ln(M_{it}) + \eta \cdot \ln(S^*_{it}) + \alpha \cdot \ln(J^*_{it}) \tag{3}$$

where:
Q = real gross output (i.e. plant shipments adjusted for inventory change)
L = labor hours
M = real materials
I denotes plant.

The services of structures capital, S*, is defined analogously to (1) and (2) except that γ is assumed to be zero in the construction of the structures stock. The "Other Variables" in equation (3) attempt to account for other factors that make plants with the same inputs more or less productive. They include year dummies, industry dummies, and a dummy variable indicating whether or not the plant is owned by a multi-plant firm. They also include dummy variables indicating whether or not the plant had a large investment episode (spike) in the previous year, two years ago, etc..., up to seven years ago. These latter variables are meant to capture the costs in terms of lost production due to the learning-by-doing accompanying a plant's use of large amounts of new equipment.

Substituting equations (1) and (2) into (3), assuming that $\tau_S = \tau_J$, and adding an error term yields a single regression equation that can be used to estimate α, β, γ, η, θ, τ, and the coefficients on the control variables using nonlinear least squares. A simple extension can be done to allow γ to vary by sector/industry while constraining the other coefficients to be the same across all plants in the sample. The constraint of other coefficients to be equal across industries is surely unrealistic; however, it was maintained in order to maximize the precision of the estimates of γ. This constraint should only affect the γ's if the other coefficients are somehow correlated with the intertemporal distribution of investment.

The estimates of γ by sector are shown in Table 1. The estimates seem sensible, though somewhat imprecise, for the most part with the exception of some slightly negative estimates and unrealistically high values in Computers (16) and Electronic components (19). The negative values are not too disturbing given their rather high standard errors. They also occur in sectors where one might expect low levels of embodied technology. The very high γ's in sectors 16 and 19 are most likely a result of the use of the BEA's 4-digit level shipments deflators. These deflators come from the BLS with two key exceptions: computers and semiconductors (semiconductors are a component of sector 19). I have also tried estimating the model using the Personal Consumption Expenditures (PCE) deflator (which has some theoretical justification as discussed in Sakellaris and Wilson (2001)). Yet, this results in strongly negative γ's for these two industries which is clearly unrealistic. Therefore, throughout the paper I use the γ's in Table 1, with the caveat that the relative rank of γ may be more informative than the actual levels.[4]

Overall, 15 industries have positive estimates (9 that are significant) of embodied technological change and 9 industries have negative estimates (5 significant). Aside from Computers and Electronic components, Communication equipment, Textiles, and Non-motor vehicle transportation equipment have the highest estimates. Paper, Motor vehicles, and Food and Tobacco have the lowest estimates.

Given the imprecision of the estimates and the finding of some unrealistically high and negative estimates, one would obviously like to know how realistic these estimates are. In particular, are the interindustry differences in the estimated rates of embodied technological change reasonable? There is little or no guidance from the embodiment literature on this question. To answer it, one needs to quantify the innovation embodied in industries' capital stocks. Related studies often associate innovation embodied in an industry's capital with how much the industry invests in "high-tech" capital using capital flows tables. Though such a technique is useful for determining the productivity impact of investment in a particular type of capital, it is far less useful for determining the productivity impact or innovation of investment in capital-embodied technology in general. Identifying embodied technology with high-tech investment shares requires a subjective determination of what capital types are high-tech vs. low-tech and discards any gradation in technology within the high-tech and low-tech classes. The index I propose below, on the other hand, uses objective data to capture the technology embodied in a capital good.

3. Embodied R&D as a Proxy for Embodied Technology

A natural choice for a variable that is likely to be related to the true rate of embodied technological change, γ, would be the amount of research and development (R&D) that went into developing the technology that is embodied in an industry's capital. As Hulten (1996) puts it: "Most advances in knowledge are the result of systematic investments in research and development." In fact, Scherer (1999) finds that a firm's R&D spending has a roughly one-to-one correspondence with its own valuation of the resulting patent(s), implying that a doubling of R&D results in a doubling of technological change as measured by the value of new patents.[5] Earlier studies such as Jaffe (1986) have also found that technological change as measured by counts of new patents is proportional to R&D. So if R&D is how technology is produced (I provide further evidence of this in Section 5), then R&D directed towards the equipment assets used by an industry is the main input into the "production" of its capital-embodied technology. To capture this notion of "capital-embodied R&D," I create a weighted average of past and present R&D done on an industry's equipment capital. As opposed to inferring embodied technology from an

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[4]Correspondingly, rank (Spearman's) correlations will be provided in addition to the ordinary (Pearson's) correlations.

[5]See p.62 and Figure 5-3. Scherer's finding is derived from results in Harloff, Scherer, and Vopel (1998).

industry's asset composition, embodied R&D has the advantage of being a single, continuous, and objective metric which reflects both the changing asset mix of an industry's capital *and* the technological advances (to the extent they are due to R&D) that have taken place in the underlying capital goods. The hope is that this index of embodied R&D will be a useful predictors of embodied technological change.

The theoretical basis for a relationship between R&D expenditures directed at capital goods upstream and productivity benefits in the downstream customer industries rests on spillovers from product-oriented R&D – spillovers that are both real and figments of measurement error. Clearly, *process*-oriented R&D should exclusively benefit the industry(ies) who utilize the R&D-induced process innovations and should have no effect on either the measured or real productivity of those industries who purchase the R&D performer's product.

However, the effects of *product*-oriented R&D (which is the majority of R&D) are more complex. As pointed out by Scherer (1982) and Griliches (1979), much of measured downstream benefits of R&D may be due to measurement error in the price of capital goods. If prices adjusted fully for quality change, real output for capital producers and real investment for downstream industries would be augmented to reflect the increased quality embodied in the capital being produced. One would then expect to observe the majority of (total factor) productivity gains, if there were any, in the capital-supplying industry and smaller TFP gains in the downstream industries.[6] These smaller downstream gains that do occur, known as *pure* rent spillovers (pure in the sense that they are not due to mismeasurement), are the result of price competition in the upstream industry which prevent the nominal price of newly-invented capital from increasing in proportion to the increase in quality. On the other hand, if prices do not adjust for quality, then real output of the supplying industry and real investment of purchasing industries will be understated. In this case, increases in measured TFP should show up primarily in the downstream industries. Whether the downstream measured productivity gains are due to mismeasured capital prices or to pure rent spillovers, either way these gains reflect investment-specific technological change since they would cease to appear if the downstream industry did not invest.[7]

The index I construct in this paper are related yet very different from the usual measures of embodied or "indirect" R&D in capital that are used in the literature on R&D spillovers. For the purposes of comparison and to avoid confusion with other measures of indirect R&D, it will be helpful to see the measure of indirect R&D in capital generally used in the R&D spillover literature:

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[6]Of course, both the supplying and the purchasing industries would have substantial measured and real average *labor* productivity gains: the supplying industry due to the increase in output and the purchasing industry due to capital deepening in terms of quality units.

[7]Yet another avenue through which upstream R&D could cause downstream investment-specific technological change is knowledge spillovers, i.e. technological diffusion from supplier to customer facilitated by their business interactions.

$$IRD_i(t) = \sum_j B_{ji}(t) \cdot \frac{RD_j(t)}{Y_j} \tag{4}$$

where B_{ji} is industry j's sales of capital to industry i, RD_j is the R&D stock for industry j, and Y_j is industry j's output. The R&D stock is generally measured using a perpetual inventory accumulation of past and present R&D expenditures assuming some rate of depreciation. RD/Y is referred to as "R&D intensity." Thus, investment in each upstream industry is multiplied by the R&D intensity of that industry and then summed across industries. This measure was developed by Terleckyj (1974) and has been used in numerous studies.[8]

A problem with the Terleckyj approach is that R&D spending (and therefore R&D stock) by an industry is not necessarily equal to the total R&D done on that industry's products. The use of own-R&D is inappropriate if there are non-zero off-diagonal elements in the interindustry R&D flows matrix -- i.e., if industries perform R&D on products other than their own. There are two reasons to expect this to be a problem. As Griliches and Lichtenberg (1984) put it:

> (1) Many of the major R&D performers are conglomerates or reasonably widely diversified firms. Thus, the R&D reported by them is not necessarily "done" in the industry they are attributed to. (2) Many firms perform R&D directed at processes and products used in other industries. There is a significant difference between the industrial locus of a particular R&D activity, its "origin," and the ultimate place of use of the results of such activity, the locus of its productivity effects. (p.466)

Evidence of this can be seen in the NSF's annual tables on applied R&D by industry and by product field which show numerous large off-diagonal elements in any given year. Thus, a key innovation of this paper is the use of product-field R&D rather than industry own-R&D when measuring embodied R&D.

Surprisingly, though the data is readily available, the NSF data on R&D by product field has rarely been used in economic studies. When it has been used, for example in Griliches & Lichtenberg's study, the productivity effects of product field R&D are sought within the industry which produces that product rather than in downstream industries.

Aside from this misidentification, for the purposes of predicting γ, the Terleckyj measure is inappropriate because it uses investment flows (B_{ji}) rather than investment shares (i.e. B_{ji} divided by total investment of industry i). That is, embodied technological change should be independent of the scale of an industry's investment. Thus, in the index described below, I use investment shares rather than investment flows.

The index I construct is based on the premise that an industry's γ in a given year is simply a weighted average of the embodied technological change in each of the capital goods the industry purchases:

[8]See, e.g., Goto & Suzuki (1989), Sveikauskas (2000), Scherer (1982, 1984), and Sakurai, et al. (1997).

$$\gamma_{it} = \sum_p x_{pit} \cdot \gamma_{pt} \tag{5}$$

where x_{pi} is the share of industry i's equipment investment spent on capital good p, and γ_p is the rate of embodied technological change in capital type (product field) p. I hypothesize that γ_{pt} is proportional to the stock of R&D directed at capital type p, R_{pt}:

$$\gamma_{pt} = A \cdot R_{pt} \tag{6}$$

where A is a factor of proportionality. I measure this stock of R&D as a perpetual inventory of past and present R&D:

$$R_{pt} = (1-d)R_{p,t-1} + r_{pt} \tag{7}$$

where d is the assumed rate of depreciation and r_p is the R&D spending on product field p, deflated by the PCE deflator. Thus, let us define an index of capital-embodied R&D in industry i as:

$$g_{it} = \sum_p x_{pit} R_{pt} \ , \tag{8}$$

which implies:

$$\gamma_{it} = A \cdot g_{it} \tag{9}$$

Equations (6) and (9) are tested in section 5.

4. Data

The principal source for industrial R&D data in the U.S. is the firm-level Survey of Industrial Research and Development done by the Census Bureau and financed by the NSF. This survey has been conducted since 1957. However, to reduce the burden on respondents, certain data items such as R&D by product field have generally only been requested in odd years. The exceptions to this are that product field detail was not collected for 1965 and 1969 and was collected for even years in the intervals 1958-64 and 1968-76. The vast majority of these product fields correspond to categories of equipment (e.g. farm machinery). The industry aggregates of the survey data are published in the NSF's *Funds for Research and Development in Industry*.[9]

Unfortunately, there are many holes in the aggregate data due to non-disclosure of certain values and changes in the product field classification over time. Holes were due to one of several factors. First, R&D was collected for the "Professional and scientific instruments" field but not separately for its subfields "Scientific and mechanical measuring instruments" and "Optical, surgical, photographic, and other instruments" until 1987. I used the average split between these two subfields between 1987 and 1997 and applied it to the pre-87 totals for the two fields. Second, in 8 of the 28 years in which the survey was conducted, the value for R&D in motor vehicles could not be disclosed for reasons of confidentiality. In these cases, values were imputed using the share of motor vehicle R&D to total transportation equipment R&D in the nearest adjacent year. Third, in 1957 R&D data was collected for the broad field of "Machinery" but not separately for the 6 product fields within machinery. The value of R&D for each product field was imputed using the machinery total and the 1958 share of the product field's R&D in total machinery R&D. Finally, product field R&D for years in which the survey was not done were interpolated using values from the closest adjacent years. These interpolations and imputations may lower the informational content from intertemporal movements in the data but should have little or no affect on the cross-product field relationships.

Another discontinuity in the data comes from the fact that in 1985, R&D by product field was no longer imputed for non-respondents of the survey. Fortunately, the NSF does supply the coverage ratios so that total R&D by product field can be approximated under the assumption that non-respondents have a similar product field decomposition of their total R&D as have respondents. After these adjustments were made to the raw data, what was left was a matrix of applied R&D by product field for 1957-97. For the purposes of this project I was only interested in the R&D applied to equipment product fields and thus I omit from this matrix rows corresponding to non-equipment fields (e.g. Chemicals). The field "Electrical Equipment" contains one subfield, "Electronic Components," whose applied R&D consists mainly of semiconductor research. In the LRD (as well as in the NIPA), semiconductors are considered an intermediate input rather than a capital asset and therefore I subtracted out all "Electronic Components" product field R&D from that of "Electrical Equipment."

As mentioned in Section 3, the type of R&D that causes downstream productivity gains is the product-oriented type. Unfortunately, the NSF survey does not distinguish between product- and process-oriented R&D. Scherer (1984), however, does provide a detailed industry-level table of the percentages of issued patents, sampled between June 1976 and March 1977, that were product-oriented. Using Scherer's table, I aggregated these percentages to the NSF product field level by taking weighted averages of the percentages for the component industries that comprise a product field. For each component industry, the weight was its 1974 R&D divided by the 1974 R&D for the product field as a whole. 1974 was the relevant year here since the sampled patents

[9]Hard copies of the tables, one for each year of the survey, containing total R&D by product field, were generously compiled and provided by Raymond Wolfe of the NSF.

were applied for, on average, in 1974.

There is some potential that these patent-based product-orientation percentages may not be appropriate measures of the product-orientation of R&D. Survey findings by Levin, Klevorick, Nelson, and Winter (1987) and Cohen and Walsh (2000) indicate that patents are less effective for processes than products in appropriating the returns to innovative activity. Therefore, product innovations may be more likely to be patented and the share of R&D devoted to product innovations may be less than the corresponding share of patents. In fact, Scherer (1984) finds that approximately 74% of patents are product-oriented whereas Cohen and Walsh (2000) find the share of product-oriented R&D products to be only 67%.[10] However, it is difficult to know whether this difference is persistent and accurate or whether it is due to the different time periods covered, the different data collection techniques (patent citations versus survey responses), or statistical error.[11] Thus, I use the patent-based shares from Scherer because of their disaggregate availability. Nonetheless, for robustness, all of the analyses of this paper were also done without adjusting for the process/product splits and the results did not substantively change.

The resulting share of each product field's R&D that is product-oriented (subject to the above assumptions) is shown in the second column of Table 2. The shares are quite high with the lowest, 77.5%, occurring in "Aircraft and parts." Multiplying these shares by the corresponding product fields' R&D for 1957-97 gives the r_{pt}'s in equation (7). To give an impression of the variation in r_{pt} across capital types, Figure 1 displays their 1997 levels as well as their average over 1957-97 for each capital type. One can see that Electrical Equipment, Aircraft and Parts, Office Computing and Accounting Machines (OCAM), and Motor Vehicles and Equipment are the targets of the majority of the U.S. economy's equipment-oriented R&D. Specifically, these four types of equipment account for just over three-quarters of the total over the 13 types. This implies that industries which invest heavily in these four types of equipment should exhibit high rates of embodied technological change (which is in fact what I find in Section 5). Figure 1 also shows that, according to the most recent year of data (1997), Electrical Equipment and Motor Vehicles receive much more real R&D today than they have on average over the past four decades, whereas real R&D on Aircraft and Parts has fallen. In fact, real R&D directed to Aircraft and Parts was as low in 1997 as it was in any year over the past 40 years and has fallen rapidly since its peak in 1987.

The other data ingredient necessary for creating the desired embodied R&D index is a capital flows matrix by year. I use the BEA's unpublished table of nominal investment by asset type for 62 industries for 1957-97 provided in the *Fixed Reproducible Tangible Wealth in the*

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[10]Unfortunately, the share of R&D that is product-oriented from Cohen and Walsh (2000) is not available at a disaggregated level or it could be used rather than the disaggregate patent-based share from Scherer (1984).

[11]The standard error around mean share of R&D that is product-oriented, 66.7%, is 9.6%. Thus, this 67% is not statistically significantly different from 74%.

United States, 1925-1997.[12] First, a many-to-one mapping was made between the BEA's asset types and the NSF's equipment product fields. This mapping is shown in Table 2. The mapping was used to convert the capital flows matrix to one that is by product field rather than by asset type. This flows matrix was then converted into a coefficients (shares) matrix using the industry investment totals (over all equipment product fields). The elements of this matrix correspond to the x_{pit}'s in equation (7) above.

The x_{pi}'s and r_p's are used, according to equations (7) and (8), to construct g_{it}, the index of capital-embodied R&D. The depreciation rate, d, is assumed to equal 2%. This assumption is based on evidence that the depreciation rate for direct R&D stocks is close to zero (see Griliches and Lichtenberg (1984)). To ensure the robustness of my analyses, I also construct the R&D stocks using two alternative depreciation rates: 15%, as is commonly assumed in the literature, and 12%, the rate estimated by Nadiri & Prucha (1996). The choice turns out to have virtually no effect on the analyses in this paper. A unit bucket adjustment is made to "fill in" the stocks for early periods (see Almon (1998), p. 87).

Table 3 summarizes the results of the construction of g_{it}. The industries are ordered according to their mean g_{it} over the 1957-97 period which is shown in Column 2. The ranking of industries seems quite reasonable. The Telephone and Telegraph industry tops the list with an average value of capital-embodied R&D nearly double the economy-wide average. This is not at all surprising given this industry's high shares of investment in electrical equipment and OCAM. Transportation by air also has very high embodied R&D due to its heavy investment in aircraft.[13] Trucking and Warehousing is also near the top thanks mostly to its high share of investment in Motor Vehicles. Emulating the historical decline in R&D directed at Motor Vehicles, the index of embodied R&D for Trucking and Warehousing has also declined over time (not shown). One can see that the service industries tend to be high on the list. Though services are not capital-intensive, what investments they do make tend to be in high-tech equipment such as computers and communications equipment.

The bottom of the list also fits with our a priori notions of which industries tend to use relatively low-tech equipment. The bottom five are Farms, Water Transportation, Coal Mining, Motor Vehicles and Equipment, and Rubber and Miscellaneous Plastic. The fact that the Motor Vehicle *industry* has a low value of embodied R&D despite the historically very high levels of R&D directed at the production of Motor Vehicle *products* is not only sensible but helps to illustrate the distinction between technological change embodied in an industry's product versus that embodied in its capital. The R&D across the economy directed at motor vehicles and related equipment has generated rapid innovation in this type of capital good. And the Motor Vehicle industry may very well have benefitted from this disembodied technological change (disembodied in the sense that it is not embodied in the industry's own capital stock) by being able to increase

[12]Investment in non-equipment asset types was dropped from the matrix. Of the 37 NSF product fields, only the 13 which referred to equipment assets were kept. Thus, the embodied R&D index I construct excludes R&D embodied in structures. This is appropriate since γ refers only to embodied technological change in equipment .

[13]The value of embodied R&D in "Transportation by air" may be artificially high since the R&D on aircraft includes R&D on military planes financed by the Defense Department.

its prices to reflect their higher quality product. But the industry does not observe high embodied technological change because it does not itself invest in motor vehicles nor any other "innovative" capital equipment. In fact, the Motor Vehicle industry invests mostly in metalworking machinery which one can see from Figure 1 has historically received the least amount of R&D.

5. Is Embodied R&D Proportional to Estimates of Embodied Technology?

The use of g_{it} as an indicator of embodied technological change rests on the premise, formalized in equation (6), that technological change in a capital type is proportional to the stock of R&D directed at that capital type. This is a non-trivial statement. Evidence for this hypothesis is based on identifying technological change via new patent counts and/or the value of new patents. Given that much innovation is never patented, it seems worthwhile to confirm this hypothesis using another measure of technological change prior to using R&D stocks to measure downstream embodied R&D. Additionally, one would like to confirm that the hypothesis holds equally well at the more aggregate level of the NSF equipment product fields. Of course, there are no observables of true technological change so one must look to the literature for evidence on the rates of technological change in equipment assets.

Gordon's (1990) major study of durable goods provides alternative price indexes for equipment from 1947-1983 which *inter alia* attempt to account for quality change. Hornstein and Krusell (1996) and others, using a 2-sector model of investment and consumption, argue that the growth rate of Gordon's aggregate producer durable equipment (PDE) price index relative to the consumption deflator is equal to the negative of the rate of embodied technological change. Thus, one can use the rate of relative price decline of each equipment product field, according to Gordon's indexes, as a proxy for the rate of technological change in that field. It should be noted that an equipment asset's relative price may fluctuate not only due to technological change but also due to substitution effects between equipment assets. However, one would expect substitution between such broad product fields as those in Table 2 to be quite limited.

From the 22 PDE categories for which Gordon constructed price indexes, I constructed 13 Törnqvist price indexes corresponding to the 13 equipment product fields. I then compute the annual growth rates of these prices relative to the PCE deflator from 1957 (the R&D data does not begin until 1957) to 1983. These growth rates can be compared to the average (or total) amount of R&D directed each capital type. I also investigate whether there is any relationship between technological change and the growth rate of R&D.

Table 4 shows the ordinary and rank correlations between the average relative growth of Gordon's price indexes to three variables defined over the 1957-1983 period: (1) mean of R_p (the stock of R&D), (2) annual growth of R_p, and (3) annual growth of r_p. The correlations are perfectly consistent with the hypothesis that an asset's technological change is proportional to the stock R&D directed at that asset. It is the mean level of R&D and not its growth rate that is strongly related to technological growth. The average stock of R&D applied to an equipment type has a negative correlation with the growth rate of that equipment type's relative price of -0.504 (significant at the 10% level) and a negative rank correlation of -0.674 (significant at the 5% level). The other two variables are not significantly different from zero.

The significant correlation between the 1957-83 averages of the R&D stocks and the price declines is illustrated in Figure 2 which presents a scatter plot of these two series. The label next to each data point is the initials of the product field corresponding to that point (see Table 2, Column 1 for the product field titles). There is clearly a strong relationship here though there are some minor outliers. For instance, Motor Vehicles and Equipment have experienced only modest decline in relative prices despite high R&D, and the two instruments fields (SMMI and OSPOI) experienced large relative price declines despite modest R&D. In general, these results provide strong support for the hypothesis of equation (6).

Given equation (6), it follows that the rate of embodied technological change in an industry should be proportional to the index of capital-embodied R&D (see equation (9)). Table 5 shows the ordinary and Spearman's rank correlations, among the 22 manufacturing industries, between the estimated rate of technological change, $\hat{\gamma}$, and mean of g_{it} over 1972-96 (the period for which $\hat{\gamma}$ was estimated). The mean of g_{it} is positively correlated with $\hat{\gamma}$, with an ordinary correlation coefficient of 0.49 and a rank correlation is 0.44, both significant at the 95% level.

Viewed as a test of the reasonableness of the Sakellaris and Wilson (2001) estimated rates of embodied technological change, this exercise yields encouraging results. This seems to be powerful evidence that these estimated rates are positively and significantly correlated with observable patterns of R&D spent on capital goods.

6. Relationship Between Embodied R&D and the Solow Residual

To further investigate whether the positive correlation found above between (average) g_{it} and $\hat{\gamma}$ is indicative of a *true* relationship between g_{it} and embodied technological change, I test whether g_{it} is a good predictor of the Solow Residual. Consider the generally established definition of the Solow Residual:

$$SRD = \Delta(Q) - c_L\Delta(L) - c_J\Delta(J_{\gamma=0}) - c_S\Delta(S) - (1 - c_L - c_J - c_S)\Delta(M) \qquad (10)$$

where Δ is the log first-difference operator; c_i is the cost share of input i; and Q, L, J, S, and M are as defined in equations (2) and (3). A distinguishing feature between the Solow Residual and true total factor productivity (TFP) growth is that the rate of embodied technological change is assumed to be zero in the former. The growth rate of equipment capital (J) is an increasing function of γ; therefore true TFP growth is decreasing in γ. If there is embodied technological change, the Solow Residual (SRD) will be an upwardly biased estimator of true total factor productivity (TFP) growth. This bias increases with γ. Therefore, if the embodied R&D index is positively proportional to the true γ, then it should also have a positive effect on SRD.[14]

Using industry-level data from the BEA and other sources, I construct Solow Residuals for 54 industries spanning the private economy. Appendix A describes the data and the

[14]Recall that the index is independent of the total amount of investment done by an industry. Rather, they depend on the R&D done on each capital type and the industry's investment composition across capital types. Therefore, there is no danger of reverse causation from productivity shocks (affecting SRD) simultaneously affecting the embodied R&D index through their effect on total investment.

construction of SRD.

The panel nature of the measured data on g_{it} allows us to separately investigate its effect on SRD over the cross-industry dimension (emphasizing long-run/growth patterns), the time-series dimension (emphasizing short-run fluctuations), or both.[15] The cross-industry relationship can be estimated using a "between" regression which regresses the intertemporal mean of the dependent variable on the intertemporal mean of the regressor. A "within" regression isolates the time-series relationship by regressing the dependent variable net of its intertemporal mean on a similarly demeaned regressor. Lastly, I estimate the total effect via a first-difference regression: the change in the dependent variable between t and t-1 regressed on the change in the independent variable. The first-differencing simply allows for the intercept to vary by industry.

Table 6 shows the results from estimating these three different types of regressions. The dependent variable in these regressions is the Solow Residual. The second column reports results for regressions using the full set of industries. Since the output of many industries is notoriously difficult to measure, I follow Griliches (1994) in distinguishing between "measurable" and "unmeasurable" industries. To ensure that my results are not affected by this output measurement error, I repeat the regressions using the subset of measurable industries. The results using this subset are given in the third column. The signs and confidence intervals found in the between regression, which is the most comparable to the simple correlations of Table 5, are quite similar to those estimated correlations. Yet again, the coefficient on the mean of g_{it} is found to be positive and significant. The R^2 for this regression is 0.21, implying that 21% of the cross-industry variation in the Solow Residual can be explained by variation in embodied R&D as measured by g_{it}.

The within and first-difference regressions also find a positive effect of embodied R&D on SRD, though the relationship is only significant in the subset of well-measured industries. The weaker relationship found in these regressions may be due to intertemporal measurement errors that are likely in the data on g_{it}. The annual capital flows tables used in constructing g_{it} are based on input-output studies that 1) are only done every five years, and 2) are largely based on the occupational composition of industries, which may fluctuate due to reasons unrelated to capital mix. In addition, the NSF data underlying the annual R&D by product field tables constructed in this paper have many missing years that were filled in by interpolation as well as other discontinuities that had to be dealt with. For these reasons the time series informational of g_{it} may be less reliable than the cross-sectional content.

These results are quite consistent with other studies on indirect R&D which generally find stronger effects on productivity in the cross-section than in the time-series. Interestingly, they are also very similar to the findings of Bartelsman, Caballero, and Lyons (1994). They find that upstream suppliers' activity (as measured by cost-share-weighted input growth) does not have a significant effect on downstream productivity in their within estimates but does in their between estimates. It is possible that upstream activity is simply a good predictor of upstream R&D spending (or more broadly, upstream innovation), for they are certain to be correlated. Then, under the joint hypothesis that embodied R&D, as measured by g_{it}, is proportional to embodied

[15]See Griliches & Mairesse (1995) for a discussion of the advantages and disadvantages of different panel data estimation techniques.

technological change and that capital good price deflators do not fully account for quality change, some of what Bartelsman, et al. find may be due to "spillovers" stemming from this price mismeasurement -- the same spillovers that cause upstream embodied R&D to have downstream effects on measured productivity.

Given our relative confidence in the measurement of the across-time means of g_{it}, and their demonstrated correlation with $\hat{\gamma}$ and the Solow Residual, I then use these means to impute γ's for nonmanufacturing industries (where $\hat{\gamma}$'s are not available) via the estimated relationship obtained from a linear regression across manufacturing industries of $\hat{\gamma}$ on a constant and the 1972-96 mean of g_{it}.[16] This regression yielded the following:

$$\hat{\gamma} = \underset{(0.048)}{-0.038} + \underset{(0.063)}{0.069}\times(\text{mean } g_{it});\ R^2 = 0.062.$$

The imputed values of γ for nonmanufacturing sectors, computed using this estimated relationship, are shown in Table 7. The γ's range from 0 to 11%. It should be noted that the estimated coefficients in the above regression have large standard errors, thus the imputed γ's have correspondingly large standard errors associated with them. Nonetheless, the magnitudes and the cross-sectoral ranking of these rates of embodied technological change seem quite reasonable. By construction, these industries' rates of embodied technological change vary according to their mean values of g_{it}. For instance, mining industries were near the bottom of our rankings of g_{it} in table 3 and thus the lowest imputed rates of embodied technological change are found in mining industries. These imputed rates provide at least some indication of the embodied technological change occurring in nonmanufacturing industries, which seems useful given a complete lack of rival estimates, precise or otherwise, in the literature.

7. Conclusion

The title of this paper asks "Is embodied technology the result of upstream R&D?" The answer seems to be a cautious yes. If the R&D applied to an industry's capital goods is not the actual *cause* of the industry's embodied technological change, it is at the very least highly correlated with whatever the true cause or causes are. This is evidenced by the finding that the extent of R&D embodied in an industry's capital is highly correlated with both the industry's estimated rate of embodied technological change as well as the industry's productivity growth as measured by the Solow Residual. Furthermore, the extent of R&D applied to a particular capital good is found to be highly correlated to the relative decline in the price of that good, providing further evidence that technological advances in capital are the result of R&D oriented toward the creation of new capital goods. As for the possibility of reverse causation, given the lags between R&D and innovation it is difficult to imagine how increases in an industry's embodied technology could actually cause increased past and present R&D spending by capital goods suppliers.

The results of this paper show that data on upstream product-field R&D can be used to

[16]For this regression, I exclude "Computers" and "Electronic Components" which have unrealistic outlier $\hat{\gamma}$'s of 2.93 and 0.77, respectively.

measure the relative differences among industries in their rates of embodied technological change, which are an inherently unobservable. Armed with estimates of embodied technological change in manufacturing industries, where plant-level longitudinal data is available, I was able to use the constructed measures of embodied R&D to impute rates of embodied technological change for nonmanufacturing industries. Thus, aside from its other contributions, this paper provides the first industry-level estimates of embodied technological change spanning the entire private economy.

Appendix A - Construction of the Solow Residual

The Solow Residual (SRD) is defined as:

$$\mathrm{dlog}(Y) - c_L \mathrm{dlog}(L) - c_J \mathrm{dlog}(J) - c_S \mathrm{dlog}(S) - (1- c_L - c_J - c_S)\mathrm{dlog}(M),$$

where Y is gross output, L is labor, J is equipment, S is structures, and M is materials. c_i is the share of input i in total costs. Data by industry on real equipment investment, structures investment, and materials come from the BEA. Equipment and structures capital stocks were constructed via the perpetual inventory methods using industry-level physical depreciation schedules derived from the Federal Reserve Board's Capital Stock study (Mohr and Gilbert (1996)). Cost shares for equipment and structures are constructed according to the Hall-Jorgenson user cost of capital formula using data from BEA. The rate of return used in the user costs was the AAA corporate bond rate minus the rate of CPI inflation.

Data on real output, labor, and hourly labor compensation in manufacturing industries come from the Annual Survey of Manufacturers (Census). Labor hours and hourly labor compensation for all other industries come from the Bureau of Labor Statistics (BLS). Labor quality is captured only to the extent that worker skill/quality is reflected in wages. Real output data for most nonmanufacturing industries is from the BLS's Office of Employment Projections (exceptions listed below). According to the November 1999 Monthly Labor Review, data sources for nonmanufacturing industries "include the Service Annual Survey, National Income and Product Accounts (NIPA) data on new construction and personal consumption expenditures, IRS data on business receipts, and many other sources. The constant dollar industry output estimates for the most recent years are based on BLS employment data and trend predictions of productivity." It is unclear how the BLS obtains real output prior to "recent" years.

Real output data for Construction , Health Services, and Educational and Social Services are based on PCE for the corresponding categories in the unpublished NIPA. Data on real output in the mining industries is from the Minerals Yearbook, Energy Statistics Sourcebook. That for Agriculture, Forestry and Fisheries is from the USDA. Finally, quantity and price data for output of Air Transportation is based on data from the U.S. Statistical Abstract.

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Table 1

Sector	Sector Title	SIC (1987 basis)	$\hat{\gamma}$
1	Food & Tobacco	20 and 21	-0.056 (0.021)
2	Textiles and knitting	22	0.098 (0.030)
3	Apparel	23	0.004 (0.025)
4	Paper	26	-0.064 (0.027)
5	Printing & publishing	27	-0.053 (0.023)
6	Chemicals	28	-0.004 (0.024)
7	Petroleum refining & Fuel Oil	29	0.017 (0.039)
8	Rubber & Plastic products	30	0.084 (0.026)
9	Shoes & leather	31	-0.046 (0.052)
10	Lumber	24	0.007 (0.023)
11	Furniture	25	-0.056 (0.028)
12	Stone, clay & glass	32	0.006 (0.026)
13	Primary metals	33, 3462, 3463	0.080 (0.029)
14	Metal products	34, exc. 3462,3463	-0.005 (0.022)
15	Industrial Equipment, except computers & office eqp.	35, exc SIC's in sector 16	0.031 (0.024)
16	Computers & other office equipment	3571,3572,3575,3577,3578, 3579	2.927 (0.202)
17	Electrical eqp. except communications and elec. components	36, exc. 366, 367	0.049 (0.029)
18	Communication equipment	366	0.141 (0.044)
19	Electronic components	367	0.766 (0.059)
20	Motor vehicles & parts	371	-0.064 (0.028)
21	Non-motor vehicle transportation equipment	37, exc. 371	0.098 (0.033)
22	Scientific Instruments	38, exc. 384, 385	-0.023 (0.034)
23	Other instruments	384, 385, 382, 386, 387	0.087 (0.039)
24	Miscellaneous manufacturing	39	0.029 (0.032)

Table 2

NSF Product Field	Percent Product-Oriented	BEA Asset Type
Other fabricated metal products (OFMP)	83.9	Other fabricated metal products
Engines and turbines (ET)	91.7	Internal combustion engines
		Steam engines
Farm machinery and equipment (FME)	98.3	Agricultural machinery, except tractors
		Farm tractors
Construction, mining, and materials handling machinery (CMMHM)	99.1	Construction tractors
		Construction machinery, except tractors
		General industrial, including materials handling, equipment
		Mining and oilfield machinery
Metalworking machinery and equipment (MME)	98.5	Metalworking machinery
Office, computing, and accounting machines (OCAM)	94.5	Mainframe computers
		Personal computers
		Direct access storage devices
		Computer printers
		Computer terminals
		Computer tape drives
		Computer storage devices
		Other office equipment
Other machinery, except electrical (OMEE)	96	Special industry machinery, n.e.c.
		Service industry machinery
Electrical equipment (EE)	81.8	Electrical transmission, distribution, and industrial apparatus
		Communication equipment
		Household appliances
		Other electrical equipment, n.e.c.
Motor vehicles and equipment (MVE)	94.9	Autos
		Trucks, buses, and truck trailers
Other transportation equipment (OTE)	99.5	Ships and boats
		Railroad equipment
Aircraft and parts (AP)	77.5	Aircraft
Scientific and mechanical measuring instruments (SMMI)	97.5	Instruments
Optical, surgical, photographic, and other instruments (OSPOI)	93.2	Photocopy and related equipment

Table 3

INDUSTRY (i)	Mean g_{it} over 1957-97
Telephone and telegraph	1.951
Transportation by air	1.930
Radio and television	1.872
Trucking and warehousing	1.378
Legal services	1.377
Business services	1.329
Security and commodity brokers	1.323
Local and interurban passenger transit	1.306
Hotels and other lodging places	1.268
Insurance agents, brokers, and service	1.259
Electric services	1.232
Financial holding and investment offices	1.218
Pipelines, except natural gas	1.197
Real estate	1.196
Wholesale trade	1.189
Other services, n.e.c.	1.188
Auto repair, services, and parking	1.185
Insurance carriers	1.175
Nonfinancial holding and investment offices	1.148
Health services	1.132
Other depository institutions	1.124
Amusement and recreation services	1.112
Miscellaneous repair services	1.078
Educational services	1.057
Personal services	1.019
Electronic and other electric equipment	1.016
Federal reserve banks	1.010
Nondepository institutions	0.994
Retail trade	0.931
Gas services	0.916
Apparel and other textile products	0.842
Other transportation equipment	0.823
Industrial machinery and equipment	0.817
Metal mining	0.816
Agricultural services, forestry, and fishing	0.809
Construction	0.727
Sanitary services	0.688
Railroad transportation	0.685
Motion pictures	0.644
Instruments and related products	0.623
Primary metal industries	0.622
Stone, clay, and glass products	0.607

Leather and leather products	0.591
Transportation services	0.588
Oil and gas extraction	0.584
Printing and publishing	0.578
Tobacco products	0.572
Furniture and fixtures	0.564
Petroleum and coal products	0.561
Lumber and wood products	0.557
Food and kindred products	0.555
Paper and allied products	0.554
Chemicals and allied products	0.548
Nonmetallic minerals, except fuels	0.543
Miscellaneous manufacturing industries	0.507
Fabricated metal products	0.443
Textile mill products	0.408
Farms	0.374
Water transportation	0.372
Coal mining	0.357
Motor vehicles and equipment	0.318
Rubber and miscellaneous plastics products	0.296
ECONOMY-WIDE	**1**

Table 4

	Pearson's (ordinary) Correlation with the relative growth rate of Gordon's price indexes (p-value)	Spearman's Rank Correlation with the relative growth rate of Gordon's price indexes (p-value)
Cumulative r_p over 1957-83	-0.504 (0.079)	-0.674 (0.012)
Annual growth from 1957-83 in R_p	0.016 (0.959)	0.262 (0.388)
Annual growth from 1957-83 in r_p	-0.117 (0.704)	0.179 (0.558)

Table 5

	Pearson's (ordinary) Correlation with $\hat{\gamma}$ (p-value)	Spearman's Rank Correlation with $\hat{\gamma}$ (p-value)
1972-96 Mean of g_{it}	0.488 (0.021)	0.439 (0.041)

Table 6

	All Industries (n=54)	Measurable Industries Subset (n=43)
"Between" Regression: $\overline{SRD}_i = B_0 + B_1 \bar{g}_i + \varepsilon_i$		
Estimate of B_1 (std. error)	0.554*** (0.151)	0.539*** (0.187)
R^2	0.205	0.169
"Within" Regression: $SRD_{it} - \overline{SRD}_i = B_0 + B_1 \left(g_{it} - \bar{g}_i\right) + \varepsilon_{it}$		
Estimate of B_1 (std. error)	0.002 (0.001)	0.004** (0.002)
R^2	0.006	0.004
Total/First-difference: $SRD_{it} - SRD_{it-1} = B_0 + B_1 \left(g_{it} - g_{it-1}\right) + \varepsilon_{it}$		
Estimate of B_1 (std. error)	0.028 (0.019)	0.031* (0.019)
R^2	0.001	0.002

* - significant at the 10% level.
** - significant at the 5% level.
*** - significant at the 1% level.

Table 7 - Imputed γ's for Nonmanufacturing sectors

Sector Name	γ
Agriculture, forestry, and fisheries	0.009
Metal mining	0.027
Coal mining	-0.006
Natural Gas and Crude Petroleum extraction	0.013
Non-metallic mining	-0.001
Construction	0.026
Railroads	0.024
Air transport	0.109
Other transportation	0.058
Communication services	0.112
Electric utilities	0.056
Gas utilities, and water and sanitary services	0.033
Wholesale trade	0.066
Retail trade, and restaurant and bars	0.044
Finance and Insurance	0.065
Real Estate	0.065
Hotels, and personal and repair services (exc. auto)	0.061
Business services	0.078
Automobile services	0.063
Movies and amusement parks	0.037
Medical services	0.062
Education, social services, membership organizations	0.062

Figure 1 - R&D by product category

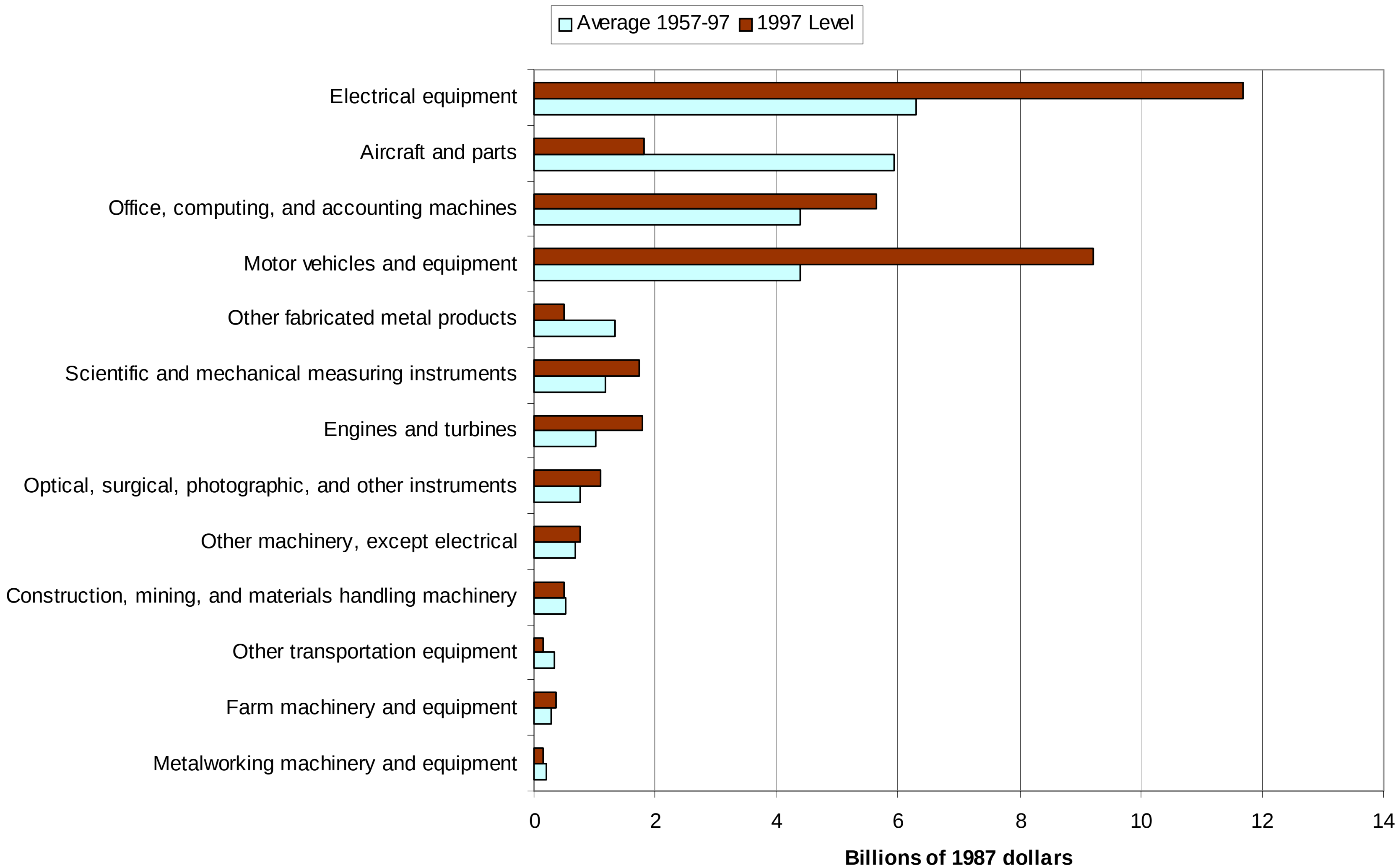

FIGURE 2 - R&D vs. Relative decline in Price (1957-83)