Is Embodied Technology the Result of Upstream R&D?

Industry-Level Evidence[1]

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Abstract:

In this paper I present industry-level indices of embodied R&D that are meant to capture the extent of research and development applied to the capital goods in which an industry invests. Compiling and adjusting data from various National Science Foundation and Commerce Department sources, I construct industry-level, time-series measures of these indices and investigate their properties. The data indicate that the overall growth in embodied R&D over the last three decades is nearly entirely due to increased R&D done on capital goods rather than changes in the asset composition of capital.

The measures of embodied R&D are compared to rates of embodied technological change estimated using plant-level manufacturing data. The level of embodied R&D is found to be positively and significantly related to the estimated rates of embodied technological change, but its growth rate is not. Likewise, the level rather than the growth rate of embodied R&D is shown to have a positive and significant effect on productivity growth as measured by the Solow Residual. This suggests that the constructed measures of embodied R&D are 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 (2000) 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,” but other than subjective priors, we have no way of quantifying how high-tech an industry’s capital goods are.

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 two alternative indices that are meant to capture the amount of research and development (R&D) embodied in an industry’s capital and then investigate the effectiveness of each index in explaining embodied technological change. Each index is a weighted average of past and present R&D performed on the (upstream) capital goods purchased by a (downstream) industry. To construct these indices, 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*.

After discussing many of the interesting features of the constructed indices, 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. It turns out

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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)).

that the *level*, but not the *growth rate*, of embodied R&D is positively and significantly related to both the Solow Residual and the estimates of embodied technological change.[3] This mirrors the relationship I find between the product-oriented R&D applied to equipment assets and the rates of technological change in these assets implied by their relative price movements.

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 (2000). 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:
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

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[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.

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

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

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 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 (2000)). 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]

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

A natural choice for a variable that is likely to be related to 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." So if R&D is how technology is produced (I provide 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 two alternative indices which are weighted averages of past and present R&D done on an industry's equipment capital. As opposed to inferring embodied technology from an industry's asset composition, embodied R&D has the advantage of being a single 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 each asset type. The hope is that these indices will be useful predictors of either the level or the change in embodied technology. We can define the level of embodied technology for investment of vintage t-s in terms of equation (2) as:

$$q_{t-s} = (1+\gamma)^{t-s-t_0} \tag{4}$$

Note that from equation (2) it is clear that q refers to the level of embodied technology *per unit* of investment.[5]

The indices 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. The literature on indirect/embodied R&D is concerned with measuring the extent to which upstream R&D affects the productivity of downstream industries. 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)

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

[5]As discussed in Sakellaris & Wilson (2000), the proper unit of measurement for I_{t-s} is nominal investment deflated by the PCE deflator.

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]

For the purposes of comparison and to avoid confusion with more traditional measures of embodied R&D, it will be helpful to see the measure of indirect R&D in capital generally used in the R&D spillover literature:

$$\mathrm{IRD}_i(t) = \sum_j B_{ji}(t) \cdot \frac{\mathrm{RD}_j(t)}{Y_j} \qquad (5)$$

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

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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.

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

> 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.

For the purposes of predicting either q or 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, q is the level of embodied technology *per unit* of investment and therefore should be independent of the scale of an industry's investment (as should its growth rate). Thus, in the indices described below, I use investment shares rather than investment flows.

The first index I construct is based on the premise that an industry's q in a given year is simply a weighted average of the level's of embodied technology in each of the capital goods the industry purchases. So, let us define the first index, denoted Φ^1, as:

$$\Phi_i^1(t) = \sum_{p=1}^{13} x_{pi}(t) \cdot q_p(t) \tag{6}$$

where x_{pi} is the share of industry i's equipment investment spent on capital good p, and q_p is the level of technology embodied in capital of asset category (product field) p. We can proxy for q_p with a perpetual inventory accumulation of past and present R&D done on that product field (assuming some depreciation rate), normalized to be 1 in the base year of the prices used to deflate nominal investment:

$$q_p(t) = [(1-d)q_p(t-1) + r_p(t)] / q_p(t_{Base}) \tag{7}$$

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. Given that the real marginal product must be equal across all types of equipment (a necessary condition for the existence of an equipment capital stock) and the fact that real units are identical to nominal units in the base year, q_p must be equal across p in the base year.

It is possible that the productivity of a new capital good depends on the composition of capital in place in a firm or industry. Under this hypothesis, past changes in asset mix should affect an industry's current level of embodied technology. An index which allows for this possibility is defined by the following equations:

$$\Phi_i^2(t) = (1-d)\Phi_i^2(t-1) + r_i(t)\text{, where} \tag{8}$$

$$r_i(t) = \sum_{p=1}^{13} x_{pi}(t) \cdot r_p(t)$$

Here a weighted average of current R&D spending on capital goods is fed into a perpetual inventory accumulation. So past R&D as well as past changes in the composition of an industry's capital determine the current level of Φ^2.

An interesting issue is whether Φ_i^2 should be a predictor of q_i, the *level* of embodied technology, or for γ_i, the *growth rate* of embodied technology. Perhaps the composition of capital in place affects not how productive the current vintage of investment is (relative to the base year), but rather how much more productive the current vintage is than last year's vintage. This is left as an open question; in sections 6 and 7, both the level and the growth of Φ_i^2 will be compared to the Solow Residual and the estimated rates of γ_i.

4. Data

The principal source for industrial R&D data in the U.S. is the survey of companies done by the Census Bureau and financed by the NSF. This survey has been done on an irregular basis between 1957 and 1997.[9] Among other things, the NSF asks respondents how much R&D they spent in each "product field." The vast majority of these product fields correspond to categories of equipment. The industry aggregates of this data are published in the NSF's *Funds for Research and Development in Industry*.[10] Unfortunately, there are many holes in the 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 vehicles R&D to total transportation equipment R&D in the nearest adjacent year. Third, in 1957 data was 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.

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[9]It was not conducted in 65, 66, 69, 78, 80, 82, 84, 86, 88, 90, 92, 94, and 96.

[10]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.

Another discontinuity in the data comes from the fact that after 1983, 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 above, 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 were applied for, on average, in 1974. It seems reasonable to assume that the split between process- and product-orientation in patents is similar to that in R&D and also that this split is relatively stable over time.[11] Subject to these assumptions, the resulting share of each product field's R&D that is product-oriented is shown in Table 3. 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 $r_p(t)$'s in equations (7) and (8) above.

The other data ingredient necessary for creating the desired embodied R&D indices 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 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 3. 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_{pi}'s in equations (7) and (8) above.

The x_{pi}'s and r_p's are used, according to equations (7) and (8), to construct each of the two

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[11]There is very little evidence on the stability of the process vs. product R&D split over time. Stability was assumed given the lack of evidence to the contrary.

[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 indices I construct exclude R&D embodied in structures. This is appropriate since γ refers only to embodied technological change in equipment .

indices. The depreciation rate, d, is assumed to equal 15%, which is commonly used in the R&D literature when direct R&D stocks are constructed. There is also evidence that, at least for R&D directed towards an industry's product (rather than its capital), a depreciation rate closer to zero may be more appropriate (see Griliches and Lichtenberg (1984)). Therefore, as an alternative, I also construct indices using a 2% depreciation rate. The choice turns out to have very little effect on the growth of an index or its correlation with the Solow Residual or estimated γ. For both of these stocks, a unit bucket adjustment is made to "fill in" the stock for early periods (see Almon (1994), p. 87).

Table 3 shows the annual growth rate of Φ^1 (assuming a 15% depreciation rate) for each industry from 1972-96, ranked in descending order. 1972-96 is the relevant period for comparing embodied R&D to γ since γ refers to the rate of embodied technological change between 1972-96. The annual growth for the overall economy, shown at the bottom of the table, has been about 2%. Notice that services, particularly financial services, tend to have the fastest growth in embodied R&D while manufacturing industries exhibit far slower growth. This could be because services have been changing their capital asset mix, relative to manufacturing, towards higher-tech equipment (e.g. computers), or because the equipment goods service industries traditionally invest in have undergone rapid increases in R&D (causing high growth in q_p), or both. More generally, we would like to know for the overall economy, as well as for individual industries, whether the growth in embodied R&D over the past few decades is driven more by changes in capital composition or growth in R&D spending.

The following equation provides just such a decomposition:

$$\begin{aligned}\Delta\Phi^1 &\equiv \Phi^1(T_1) - \Phi^1(T_0) \\ &= \sum_p \Delta q_p \cdot x_{pi}(T_0) + \sum_p \Delta x_{pi} \cdot q_p(T_0) + \sum_p \Delta x_{pi} \cdot \Delta q_p \end{aligned} \tag{9}$$

The first term in the decomposition captures the contribution to total change from changes in R&D embodied in capital goods holding constant the composition of capital. The second term gives the contribution from changes in asset mix holding constant R&D embodied in specific goods. The third is an interaction term, giving the contribution from the covariance of changes in R&D embodied in goods with changes in asset mix. Dividing both sides of (9) by $\Phi^1(T_0)$ yields a growth rate decomposition.

Figure 1 graphs this decomposition for the 1972 to 1997 growth rates across industries. The industries are ordered from left to right according to their total growth rate. The figure also gives the unweighted averages across industries. The chart shows that the primary driver of increases in embodied R&D, as measured by Φ^1, has been increases in R&D spent on equipment assets rather than changes in asset mix. We can also see that the difference in embodied R&D growth between those industries with high growth such as services and those with low growth such as manufacturing, is primarily due to fact that high growth industries channel a higher fraction of their total investment into goods whose embodied R&D is growing rapidly. It is *not* because they have been changing the composition of the goods in which they invest.

Recall that the q_p's that go into the equation for Φ^1 were normalized, as theory dictates, to equal one in the base year of the price deflator. This is because the real marginal product of investment must be equal across asset types.[13] This means that by construction $\Phi^1(t)$, which is just a weighted average of the q_p's, will be one in the base year. Therefore, differences across industries in the *level* of Φ^1 only imply interindustry differences in the *growth* of embodied R&D relative the base year.

The base year value of index Φ^2, on the other hand, does not necessarily have to be equal across industries nor equal to one. This is true whether Φ^2 is proportional to the true industry q_i or to the true industry γ_i. Neither q_i nor γ_i must be equal across industries, even in the base year. Nonetheless, since the actual levels of Φ_i^2 (t) are only meaningful in their relation to index values for other years or industries, I normalize Φ_i^2 (t) to be one for average value (over the 1972-96 period) of the index for the overall private economy. All Φ^2's are thus relative to the average extent of R&D embodied in capital economy-wide.

Table 4 displays the results of the construction of Φ^2. Column 2 shows the mean level of the index over the 1972-96 period. The third column gives its annual growth rate over the same period. The industries are ordered according to their mean value of Φ^2. For the overall economy, the growth rate of the index was about 3.3%. The ranking of industries seems quite reasonable. Transportation by air tops the list which is not unexpected since a great deal of R&D is done on airplanes.[14] One can also 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. The bottom of the list also fits with our a priori notions of which industries tend to use relatively low-tech equipment. The final four are Construction, Coal Mining, Trucking and Warehousing, and Farms.

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

In section 4 I argued that Φ^1 should proxy for the level of embodied technology and therefore its growth rate should proxy for the rate of embodied technological change (γ). I also argued that either the level or the growth rate of Φ^2 should be proportional (though not necessarily serve as a proxy) to γ. Table 5 shows the ordinary and Spearman's rank correlations, among the 22 manufacturing industries, between $\hat{\gamma}$ and each of 3 variables: 1) the 1972-96 annualized growth in Φ^1, 2) the 1972-96 annualized growth in Φ^2, and 3) the 1972-96 mean of

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[13]Consider a simple Cobb-Douglas production function where there are two types of capital goods 1 and 2: $Y_t = K_t^{\alpha} L_t^{\beta}$ where $K_t = K_{t-1}(1-\delta) + i_t^1 q_t^1 + i_t^2 q_t^2$. In the base year, the marginal product of a current dollar's worth of investment is identical to the marginal product of a constant-quality unit of investment as quality is defined relative to the base year's level. The marginal product of a current dollar's worth of investment in good j (i^j) is $\alpha Y q^j/K$. Equalizing across goods yields $q^1 = q^2$. In non-base years, the equality between nominal and real marginal products breaks down and thus q^1 need not equal q^2.

[14]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.

Φ^2.[15] Neither of the growth rates appear to be correlated with $\hat{\gamma}$. Yet, the mean of Φ^2 is positively correlated with $\hat{\gamma}$, with an ordinary correlation coefficient of 0.54, which is significant at the 99% level. The rank correlation is 0.42, significant at the 95% level.[16]

Viewed as a test of the reasonableness of the Sakellaris and Wilson estimated rates of embodied technological change, this exercise yields mixed results. It is encouraging that we have found strong evidence that these estimated rates are positively and significantly correlated with observable patterns of R&D spent on capital goods. Yet, the nature of the correlation is not as one would expect. Whether these results reflect that interindustry differences in true embodied technological change are proportional to interindustry differences in the average level of embodied R&D (as defined by Φ^2), or whether they imply that our $\hat{\gamma}$'s are actually capturing an industry's *level* of embodied technology and not its rate of change, is difficult to say.

A third possibility is that the growth rates of embodied R&D, as measured by growth in either Φ^1 or Φ^2, are badly mismeasured since the time-series dimensions of both the BEA capital flows tables and the NSF product field R&D tables are highly suspect. The annual capital flows tables 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. 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 dimension of the indices constructed in this paper may be less reliable than the cross-sectional dimension. This is especially problematic for Φ^1 because the normalization that causes Φ^1 to equal one in all industries in the base year implies its interindustry differences in levels are really determined by the time series movements. Interindustry differences in the level of Φ^2, on the other hand, should be fairly reliable though differences across growth rates may not be. Nonetheless, this intertemporal measurement error can only explain the lack of correlation that Φ^1 and the growth of Φ^2 have with $\hat{\gamma}$; it cannot explain why the mean level of Φ^2 would actually have a positive and significant correlation.

One way of sorting out whether the positive correlation between Φ^2 growth and $\hat{\gamma}$ is due to $\hat{\gamma}$ measuring the level and not the growth rate of embodied technological change or rather is due to the level of Φ^2 being a good predictor of the true rate of embodied technological change, is to go back to the data on product-oriented R&D by product field and ask whether it is the level or growth in R&D that predicts technological change at the product field level. 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

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[15]The correlations shown refer to Φ^1 and Φ^2 constructed using a 15% depreciation rate. Assuming a 2% rate yield very similar results.

[16]Another interesting finding, not shown, is that the growth in Φ^1 has a Pearson's correlation with the mean of Φ^2 of 0.53 and a Spearman's rank correlation of 0.62, both of which are significant at the 99% level.

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.

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 levels and growth rates of the r_p's and q_p's constructed above. 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.

Table 6 shows the ordinary and rank correlations between this average relative growth of Gordon's price indexes to three variables defined over the 1957-1983 period: 1) growth of q_p, 2) growth of r_p, and 3) mean of r_p. The correlations are perfectly consistent with those found in Table 5. Again, it is the mean level of R&D and not its growth rate that is strongly related to technological growth. The mean of product-oriented R&D applied to an equipment type (r_p) 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 insignificantly 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).

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

To further investigate whether the positive correlation found above between (average) Φ^2 and $\hat{\gamma}$ is indicative of a true relationship between Φ^2 and embodied technological change, we can see if either the growth or level of Φ^2 is a good predictor of the Solow Residual. 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 is larger the larger is γ. Therefore, if the indices are positively proportional to the true γ, then they should have a positive effect on SRD.[17]

The panel nature of the measured data on Φ^1 or Φ^2 allows us to separately investigate the effect of these indices on SRD over the cross-industry dimension (emphasizing long-run/growth

[17]Recall that indices are 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 indices by affecting total investment.

patterns), the time-series dimension (emphasizing short-run fluctuations), or both.[18] 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 7 shows the results from estimating these three different types of regressions. The dependent variable in these regressions is the Solow Residual. The first column lists the independent variable used. The estimated coefficient (and standard error) on that variable, when all industries are included in the regression, is shown in the second column. The independent variable (aside from the constant), which is denoted X in the table, is one of the three variables whose average I compared to $\hat{\gamma}$ in Section 5 and Table 5. They are the level of Φ^2, the growth of Φ^2, and the growth of Φ^1. 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.[19] Yet again, the mean of Φ^2 is the only variable found to be positive and significant. This seems to lend even further support to the hypothesis that the positive correlation found between $\hat{\gamma}$ and the mean level of Φ^2 is due to Φ^2 being a good predictor of true embodied technological change, rather than $\hat{\gamma}$ inadvertently capturing the level and not the growth in embodied technology.

The within and first-difference regressions find no significant effect of these indices on SRD. This may be due to the intertemporal measurement errors, discussed above, that are likely in the data on Φ^1 and Φ^2.

On the Solow Residual side of the equation, data, particularly real output data, outside of manufacturing is generally considered less reliable than manufacturing data. Thus, the third column gives the estimated coefficients obtained when only manufacturing industries are included. Now, Φ^2 shows up as positive and significant in all three types of regressions (although in the between regression its coefficient is no longer significant at the 5% level but rather at the 10%). With but one exception, the growth rate of Φ^1 or Φ^2 again has no significant effect on SRD. The one exception is the growth rate of Φ^2 in the first-difference regression.

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,

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

[19] The R^2 for this regression is 0.22, implying that 22% of the cross-industry variation in the Solow Residual can be explained by variation in embodied R&D as measured by Φ^2.

under the joint hypothesis that embodied R&D, as measured by Φ^2, is proportional to embodied 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 Φ^2, 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 Φ^2.[20] This regression yielded the following:

$$\underset{}{\hat{\gamma}} = \underset{(0.047)}{-0.036} + \underset{(0.051)}{0.054}\times(\text{mean } \Phi^2);\ R^2 = 0.060.$$

The imputed values of γ for nonmanufacturing sectors, computed using this estimated relationship, are shown in Table 8. There were five negative imputed values which were replaced with zero’s. The γ’s range from 0 to 19%. 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. These imputed rates provide at least some indication of the embodied technological change occuring 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

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[20] 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:

$$dlog(Y) - c_L dlog(L) - c_J dlog(J) - c_S dlog(S) - (1- c_L- c_J-c_S)dlog(M),$$

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 prodctions 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	Other 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	83.9	Other fabricated metal products
Engines and turbines	91.7	Internal combustion engines Steam engines
Farm machinery and equipment	98.3	Agricultural machinery, except tractors Farm tractors
Construction, mining, and materials handling machinery	99.1	Construction tractors Construction machinery, except tractors General industrial, including materials handling, equipment Mining and oilfield machinery
Metalworking machinery and equipment	98.5	Metalworking machinery
Office, computing, and accounting machines	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	96	Special industry machinery, n.e.c. Service industry machinery
Electrical equipment	81.8	Electrical transmission, distribution, and industrial apparatus Communication equipment Household appliances Other electrical equipment, n.e.c.
Motor vehicles and equipment	94.9	Autos Trucks, buses, and truck trailers
Other transportation equipment	99.5	Ships and boats Railroad equipment
Aircraft and parts	77.5	Aircraft
Scientific and mechanical measuring instruments	97.5	Instruments
Optical, surgical, photographic, and other instruments	93.2	Photocopy and related equipment

Table 3

Industry	Annual Growth in Φ^1 from 1972-96
Federal reserve banks	0.060
Security and commodity brokers	0.057
Financial holding and investment offices	0.056
Legal services	0.054
Educational services	0.054
Nonfinancial holding and investment offices	0.050
Insurance carriers	0.048
Other services, n.e.c.	0.045
Insurance agents, brokers, and service	0.041
Trucking and warehousing	0.039
Local and interurban passenger transit	0.037
Pipelines, except natural gas	0.037
Auto repair, services, and parking	0.032
Wholesale trade	0.031
Construction	0.030
Metal mining	0.029
Other depository institutions	0.028
Miscellaneous repair services	0.028
Transportation services	0.027
Industrial machinery and equipment	0.026
Gas services	0.026
Oil and gas extraction	0.026
Business services	0.025
Water transportation	0.025
Electric services	0.024
Leather and leather products	0.024
Amusement and recreation services	0.024
Personal services	0.024
Agricultural services, forestry, and fishing	0.023
Tobacco products	0.023
Radio and television	0.022
Sanitary services	0.021
Retail trade	0.021
Nonmetallic minerals, except fuels	0.021
Telephone and telegraph	0.021
Coal mining	0.021
Railroad transportation	0.020
Real estate	0.020
Nondepository institutions	0.019
Health services	0.019
Motion pictures	0.018
Hotels and other lodging places	0.017
Petroleum and coal products	0.017
Other transportation equipment	0.016

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Electronic and other electric equipment	0.016
Instruments and related products	0.016
Printing and publishing	0.016
Farms	0.015
Lumber and wood products	0.015
Apparel and other textile products	0.014
Miscellaneous manufacturing industries	0.014
Stone, clay, and glass products	0.014
Chemicals and allied products	0.014
Furniture and fixtures	0.013
Food and kindred products	0.013
Paper and allied products	0.013
Primary metal industries	0.012
Fabricated metal products	0.009
Textile mill products	0.006
Rubber and miscellaneous plastics products	0.005
Motor vehicles and equipment	0.005
Transportation by air	0.003
TOTAL	0.022

Table 4

INDUSTRY	Mean Φ^2 from 1972-96	Annual Growth in Φ^2 from 1972-96
Telephone and telegraph	1.644	1.673
Radio and television	1.596	1.738
Transportation by air	1.569	-0.100
Security and commodity brokers	1.286	4.988
Legal services	1.284	4.713
Trucking and warehousing	1.243	3.997
Insurance agents, brokers, and service	1.238	4.408
Financial holding and investment offices	1.184	4.473
Business services	1.149	3.222
Local and interurban passenger transit	1.124	2.798
Hotels and other lodging places	1.122	3.999
Other services, n.e.c.	1.121	4.796
Insurance carriers	1.119	3.688
Nonfinancial holding and investment offices	1.115	3.752
Wholesale trade	1.101	4.436
Pipelines, except natural gas	1.075	2.645
Auto repair, services, and parking	1.075	4.489
Other depository institutions	1.072	2.802
Real estate	1.044	4.172
Health services	1.022	3.568
Educational services	1.020	3.348
Amusement and recreation services	1.017	2.390
Electric services	1.014	1.751
Federal reserve banks	1.004	3.094
Miscellaneous repair services	0.986	6.658
Personal services	0.905	4.252
Electronic and other electric equipment	0.880	1.801
Nondepository institutions	0.865	5.049
Retail trade	0.854	4.177
Gas services	0.847	3.393
Industrial machinery and equipment	0.772	3.763
Apparel and other textile products	0.714	2.008
Other transportation equipment	0.699	4.223
Metal mining	0.678	4.189
Agricultural services, forestry, and fishing	0.676	2.899
Sanitary services	0.660	4.141
Construction	0.637	5.665
Motion pictures	0.620	5.939
Instruments and related products	0.579	6.202
Railroad transportation	0.577	5.414
Stone, clay, and glass products	0.565	4.381
Transportation services	0.564	8.177
Primary metal industries	0.548	2.035

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Leather and leather products	0.548	3.755
Tobacco products	0.528	3.595
Printing and publishing	0.525	3.950
Furniture and fixtures	0.523	3.978
Oil and gas extraction	0.520	4.135
Lumber and wood products	0.507	2.293
Petroleum and coal products	0.501	0.581
Chemicals and allied products	0.499	2.015
Paper and allied products	0.492	0.995
Food and kindred products	0.486	2.566
Miscellaneous manufacturing industries	0.462	4.314
Nonmetallic minerals, except fuels	0.438	0.426
Fabricated metal products	0.382	1.817
Textile mill products	0.358	2.379
Coal mining	0.326	3.471
Water transportation	0.321	7.174
Farms	0.307	3.947
Motor vehicles and equipment	0.271	2.976
Rubber and miscellaneous plastics products	0.265	2.582
TOTAL	1.000	3.303

Table 5

	Pearson's (ordinary) Correlation with $\hat{\gamma}$ (p-value)	Spearman's Rank Correlation with $\hat{\gamma}$ (p-value)
1972-96 Annualized Growth rate of Φ^1	0.070 (0.757)	0.201 (0.370)
1972-96 Annualized Growth rate of Φ^2	-0.248 (0.265)	-0.183 (0.416)
1972-96 Mean of Φ^2	0.506 (0.016)	0.450 (0.036)

Table 6

	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)
Annual growth from 1957-83 in q_p	0.016 (0.958)	0.206 (0.498)
Annual growth from 1957-83 in r_p	-0.115 (0.710)	0.185 (0.546)
Mean r_p over 1957-83	-0.504 (0.079)	-0.674 (0.012)

Table 7

X	Estimate of B_1 (std error): All Industries (n=55)	Estimate of B_1 (std error): Manufacturing Subset (n=32)
"Between" Regression: $\overline{SRD_i} = B_0 + B_1 \cdot \overline{X_i} + \varepsilon_i$		
Φ^2	0.518*** (0.135)	0.544 (0.333)
dlog(Φ^2)	-0.139 (0.089)	-0.211 (0.144)
dlog(Φ^1)	-1.327 (8.312)	-21.314 (17.995)
"Within" Regression: $SRD_{it} - \overline{SRD_i} = B_0 + B_1 \cdot (X_{it} - \overline{X_i}) + \varepsilon$		
Φ^2	0.001 (0.002)	0.0055** (0.0027)
dlog(Φ^2)	0.032* (0.018)	0.0214 (0.0217)
dlog(Φ^1)	-0.002 (0.021)	-0.0010 (0.0238)
Total/First-difference: $SRD_{it} - SRD_{it-1} = B_0 + B_1 \cdot (X_{it} - X_{it-1}) + \varepsilon_i$		
Φ^2	0.030* (0.017)	0.0563** (0.0260)
dlog(Φ^2)	0.035** (0.018)	0.0555*** (0.0212)
dlog(Φ^1)	0.017 (0.025)	0.0077 (0.0324)

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

Table 8 - Imputed γ's for Nonmanufacturing sectors

Sector Name	γ
Agriculture, forestry, and fisheries	0.008
Metal mining	0.025
Coal mining	0.000
Natural Gas and Crude Petroleum extraction	0.011
Non-metallic mining	0.003
Construction	0.021
Railroads	0.016
Air transport	0.106
Other transportation	0.055
Communication services	0.111
Electric utilities	0.056
Gas utilities, and water and sanitary services	0.032
Wholesale trade	0.064
Retail trade, and restaurant and bars	0.041
Finance and Insurance	0.064
Real Estate	0.058
Hotels, and personal and repair services (exc. auto)	0.055
Business services	0.074
Automobile services	0.061
Movies and amusement parks	0.038
Medical services	0.056
Education, social services, membership organizations	0.061

FIGURE 1 - Decomposition of 72-97 q(i) growth

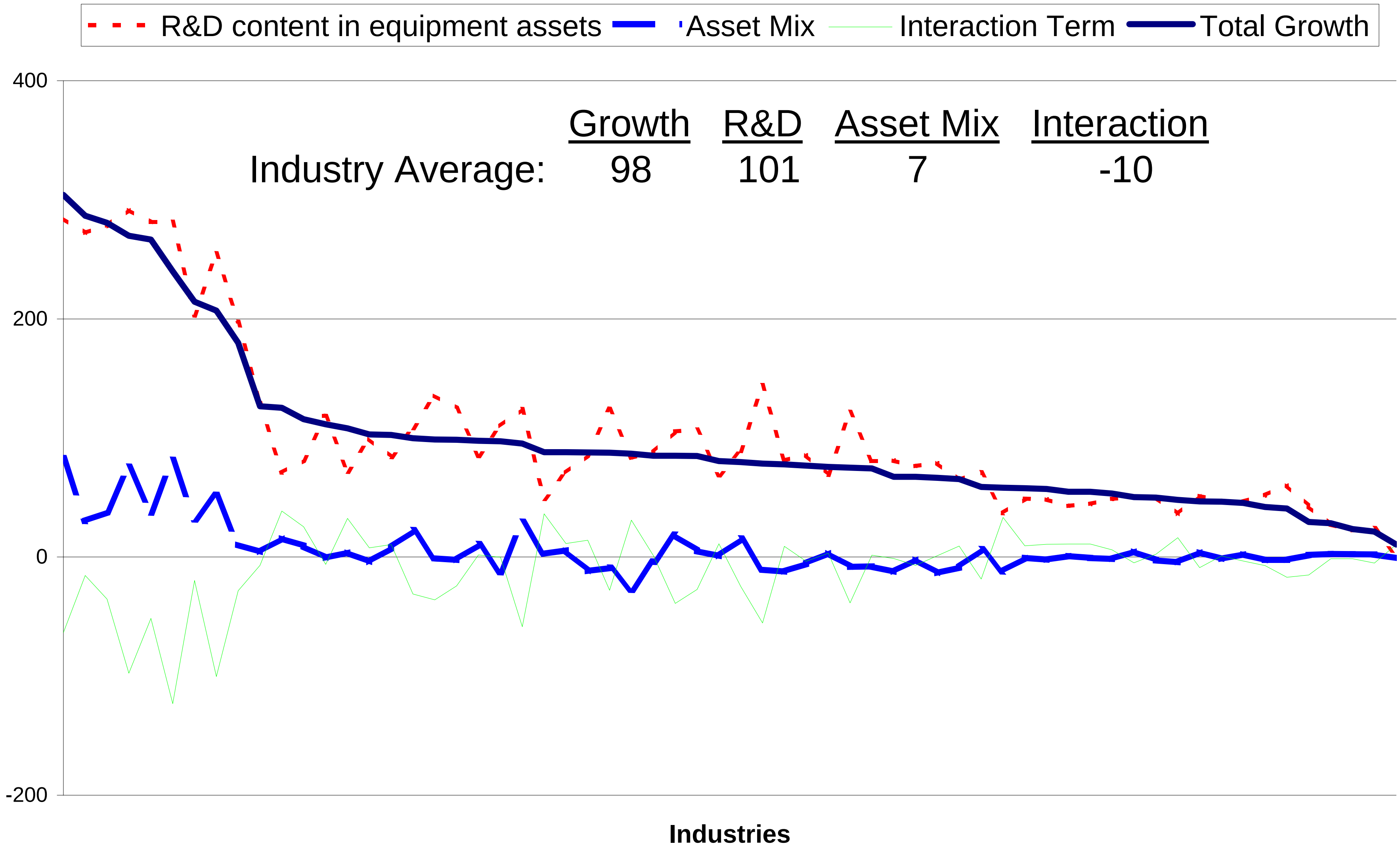

FIGURE 2 - R&D Stock vs. Relative decline in Price (1957-83)