Is Embodied Technology the Result of Upstream R&D?

Industry-Level Evidence

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Abstract:

This paper provides an exploratory analysis of whether data on the research and development (R&D) spending directed at particular technological/product fields can be used to measure industry-level capital-embodied technological change. Evidence from the patent literature suggests that the R&D directed at a product, as the main input into the "innovation" production function, is proportional to the value of the innovations in that product. I confirm this hypothesis by showing that the decline in the relative price of a good is positively correlated with the R&D directed at that product. The hypothesis implies that the technological change, or innovation, embodied in an industry's capital is proportional to the R&D that is done ("upstream") by the economy as a whole on each of the capital goods that a ("downstream") industry purchases. Using R&D data from the National Science Foundation, I construct measures of capital-embodied R&D. I find they have a strong effect on conventionally-measured TFP growth, a phenomenon that seems to be due partly to the mismeasurement of quality change in the capital stock and partly to a positive correlation between embodied and disembodied technological change. Finally, I find the cross-industry variation in empirical estimates of embodied technological change accord with the cross-industry variation in embodied R&D.

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1. Introduction

In order 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 long been an important goal in economics, as has the dual problem of distinguishing between obsolescence and physical depreciation on the price/cost-side. The channel through which most economic public policies work is business investment; thus separately identifying these phenomena is crucial to determining how much of aggregate labor productivity growth is affected by the economy's investment decisions and is thereby promotable by public policy.

Because of its important policy implications, a great deal of empirical research has sought to estimate the rate of embodied technological change, i.e., the rate at which the quality of capital goods is improving, and its contribution to overall labor productivity growth. Hulten (1992); Hornstein and Krusell (1996); Greenwood, Hercowitz, and Krusell (1997); Cummins and Violante (2001) and others have shown that given certain assumptions one can interpret the decline in the price of a constant-quality unit of investment relative to a consumption deflator as the rate of embodied technological change. The contribution of embodied technological change to output and productivity growth can then be measured via growth accounting techniques and/or model simulation. Researchers in this field generally use the price indexes constructed by Gordon (1990) to form their constant-quality price deflator for investment. Depending on certain assumptions, the implied rate of embodied technological change is between 3 and 4 percent.

Other researchers have estimated embodied technological change through regression analysis using production data. Nelson (1964); McHugh and Lane (1983, 1987); and Bahk and Gort (1993) include the average age (or vintage) of capital as an additional regressor with the usual factor inputs in a production regression in order to capture the effects of embodiment on productivity. Sakellaris and Wilson (2001) go one step further and essentially include the entire historical investment distribution, net of physical depreciation, in place of a preconstructed capital stock in an otherwise straightforward production regression. The variation in historical investment distributions across manufacturing plants allows us to estimate the increased effects on productivity of newer vintages of investment relative to older vintages, i.e., embodied technological change. The production-side approach to estimating embodied technological change has tended to yield much higher estimates, generally around 10 to 15 percent.

Given such a wide range of estimates using different approaches, it seems appropriate for the literature to stop and ask: What exactly is embodied technological change and where does it come from? And if we can identify the source(s) of it, can we use this information to evaluate whether estimates of embodied technological change in the literature make sense?

In particular, a number of recent studies have moved beyond the aggregate estimation of embodied technological change and derived estimates at the industry-level. The question of which industries are experiencing the greatest gains in terms of the technological progress of their capital goods is naturally of great interest to policymakers as well as academics. But 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.[2]

In order to evaluate the realism of estimated rates of embodied technological change and explore the sources of this kind of innovation, I propose an index that captures the amount of research and development (R&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 the past and present R&D performed on the (upstream) capital goods that are 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*.

In the following section, I present the basic theoretical underpinnings for using R&D data to capture embodied technological change. In section 3, I discuss the data, the construction of the index of capital-embodied R&D, and the ranking of industries according to this index. The 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 in Section 4 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. I search for some reduced-form relationships between embodied R&D and various measures of total-factor productivity (TFP) in Section 5. Finally, in Section 6, I estimate the relationship between embodied R&D and various industry-level estimates of embodied technological change in the literature. Embodied R&D turns out to be positively and significantly related to both conventionally-measured TFP and estimates of embodied technological change, implying that the R&D done "upstream" by producers of capital goods *is* responsible for the measured productivity growth of "downstream" customer industries.[3]

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

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[2]Throughout this paper, the term "innovation" will used as a synonym for technological change.

[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 only affect disembodied technological change and thus are separate from the embodied effects of R&D discussed in this paper.

To answer the question of whether the capital of one industry is undergoing faster technological change than that of another industry, one needs to quantify the innovation embodied in an industry's capital stock. Related studies often associate innovation embodied in an industry's capital with the extent to which the industry invests in "high-tech" capital as measured in capital flows tables. Though such a technique is useful for determining the productivity impact of investment in a particular type of capital (e.g., computers and telecommunications equipment), 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 versus 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.

Evidence for using R&D as an indicator of innovation value

A natural choice for a variable that is likely to be related to the true rate of embodied technological change 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.[4] Earlier studies have also found that R&D in a particular technological field is proportional to technological change as measured by either simple patent counts (Jaffe (1986)) or citation-weighted patent-counts (Trajtenberg (1990)).

So if R&D is the main input into the innovation production function (I provide further evidence of this below), then R&D directed toward the equipment assets used by an industry is the main input into the "production" of its capital-embodied innovation (specifically, the production of the productive *value* of its capital-embodied innovation). 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 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 predictor of embodied technological change.

Theoretical Basis for Downstream Productivity Benefits of R&D

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

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

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 the 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.[5] These smaller downstream gains that would occur in this case, 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 prevents the nominal price of newly-invented capital from increasing in proportion to the increase in quality (i.e., they are the result of the flow of consumer surplus downstream). On the other hand, if prices are not adjusted 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. Regardless of whether the downstream measured productivity gains are due to mismeasured capital prices or to pure rent spillovers, these gains reflect investment-specific technological change since they would cease to appear if the downstream industry did not invest.[6]

Traditional Measures of Indirect R&D

The index I construct in this paper is 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 consider the measure of indirect R&D in capital generally used in the R&D spillover literature:

$$\mathrm{IRD}_i(t) = \sum_j B_{ji}(t) \cdot \frac{\mathrm{RD}_j(t)}{Y_j} \tag{1}$$

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

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[5]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.

[6]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.

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.[7]

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 the misidentification of industry R&D with product R&D, for the purposes of measuring embodied technological change, 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, the rate of 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.

Should the R&D Directed at a Product Be Scaled?

Another element of the Terleckyj measure that is inappropriate for capturing embodied technological change is the scaling of R&D by dividing it by the sales of the R&D-performing industry. Recall that the patent evidence mentioned above shows that the value of a specific innovation is correlated with the R&D spent on the innovation, not the R&D spending divided by sales. For example, in 1997 the U.S. economy devoted about three times as much R&D to computers as it did to scientific and measuring instruments, while the sales of the computer producing industry were about twice those of scientific and measuring instruments.[8] Should a dollar's investment in scientific and measuring instruments then be considered as embodying

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

[8]These numbers come from the NSF data described in this paper and manufacturing shipments data from the Bureau of Economic Analysis (BEA).

three times or 1.5 times the technology as is embodied in a dollar's worth of scientific instruments? I argue the appropriate answer is three. Why should the technological value of a given expenditure on computers be the less for the size of the computer industry, and by implication, be reduced by increases in demand for computers?

An Alternative Index of Embodied R&D

Let us first define embodied technological change in the context of the standard definition of the productive capital stock. Let J_{it} be the stock of equipment capital in industry i in year t:

$$J_{it} = \sum_{s=1}^{T} I_{i,t-s} D_{i,t,t-s} (1+\gamma_i)^{t-s-t_0} \qquad (2)$$

where:
$I_{i,t-s}$ = Real investment in vintage t-s equipment (deflated using a non-hedonic deflator);
$D_{i,t,t-s}$ = the fraction of one dollar's worth of vintage t-s investment that is still used in production in year t;
γ_i = 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.

$D_{t,t-s}$ captures physical depreciation (wear and tear) and often appears in its more familiar but restrictive geometric form: $D_{t,t-s} = (1 - \delta)^s$. The extra term $(1+\gamma)^{t-s-t_0}$ may seem foreign but in fact it is always there in any capital stock construct. Conventionally, this term reflecting embodied technological change is assumed to be subsumed in the quality-adjusted price deflator for investment. However, if embodied technological change is defined as the quality change in capital goods relative to consumption goods, then one can separate out this term by deflating investment by a consumption deflator. Separating identifying γ, the rate of embodied technological change, in our definition helps us focus on our attention on how embodied technological change affects the overall capital stock and thereby productivity.

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 that the industry purchases:

$$\gamma_{it} = \sum_{p} x_{pit} \cdot \gamma_{pt} \qquad (3)$$

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, by all sources (including international sources), at capital type p, R_{pt}:

$$\gamma_{pt} = A \cdot R_{pt} \tag{4}$$

where A is a factor of proportionality.

This equation assumes constant returns to R&D. If there were increasing returns as is assumed in many endogenous growth models (e.g., Romer (1990), Grossman and Helpman (1991, Ch. 4)), then R_{pt} would be replaced in the above equation by $(R_{pt})^{\theta}$ where θ is greater than one. Conversely, it is possible that because of coordination failures and secrecy, as economy-wide R&D devoted to a product type increases, more and more researchers engage in duplicate research activities and thus there are decreasing returns to R&D (Kortum, 1993). There is, in fact, some empirical evidence of decreasing returns at the firm-level. However, this evidence does not account for the positive industry- and economy-wide spillovers beyond the R&D-performing firms. There may be substantial complementarities involved with research on a particular subject suggesting increasing returns to R&D. Yet, the empirical research that is most relevant for assessing the returns of R&D to innovation value in a technological field is the patent research mentioned above (particularly Scherer (1999)), which suggests constant returns. Nonetheless, there is no conclusive evidence in the literature regarding θ, thus applying Occam's Razor, I proceed under the simplest assumption, $\theta = 1$.

Equation (4) essentially treats R_{pt} as exogenous. In reality, R_{pt} is the sum of R&D spending (in product field p) by every firm in the economy. Each firm chooses R&D spending based on the size of the market for that field's products and the technological opportunities in the field. For example, if the market for IT goods is increasing, then profit-maximizing research firms will increase IT research. Since productivity in the IT-using industries will help determine the size of the market for IT goods, it will affect how much R&D is targeted toward IT goods. So in this way, downstream productivity can affect upstream R&D. However, current productivity in using industries will mostly affect future upstream R&D and current upstream R&D will mostly affect future TFP. Therefore, in the regressions of current downstream TFP on past and present upstream R&D presented in section 5, endogeneity bias should not be a serious problem.

It should also be noted that empirically I will assume that the distribution of R&D spending across product fields is approximately the same outside the U.S. as it is inside the U.S.. Thus, R_{pt} as measured in the U.S. is proportional to R_{pt} as would be measured globally if such data existed, which it does not. This assumption is unrealistic if both the international distribution of R&D across product fields is significantly different from the U.S. distribution *and* American industries import a substantial share of their equipment capital.

I measure this stock of R&D as a perpetual inventory of past and present R&D expenditures:

$$R_{pt} = (1 - d)R_{p,t-1} + r_{pt} \tag{5}$$

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:

$$g_{it} = \sum_{p} x_{pit} R_{pt} \,, \tag{6}$$

which implies:

$$\gamma_{it} = A \cdot g_{it} \tag{7}$$

The implications of equation (7) will be discussed and evaluated in Sections 5 and 6.

3. Data

The principal source for industrial R&D data in the U.S. is the firm-level Survey of Industrial Research and Development conducted by the Census Bureau and financed by the NSF. This survey began in 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 only 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, computers, aircraft, etc.). The industry aggregates of the survey data are published in the NSF's *Funds for Research and Development in Industry*.[9]

Imputation of Missing Data Values

Unfortunately, there are many holes in the aggregate data due to nondisclosure 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 eight 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 six product fields within machinery. The value of R&D for each

[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.

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 effect 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 nonrespondents 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 nonrespondents 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 rows corresponding to nonequipment fields (e.g., Chemicals) are omitted from the matrix. 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."

Netting Out Process-Oriented R&D

As mentioned in Section 2, 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. The appropriate year here was 1974 because the sampled patents 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 for patents. In fact, Scherer (1984) finds that approximately 74% of patents are product-oriented whereas Cohen and Walsh (2000) find the share of R&D that is product-oriented to be only 67%.[10] It is difficult, however, 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

[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).

responses), or statistical error.[11] Thus, I use the patent-based shares from Scherer because of their disaggregate availability (the R&D-based shares are not available at the industry-level). 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.

Summary of Data on R&D by Product Field

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 1. 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 (5). 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.

Data on Investment by Capital Type

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 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 1. 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 (6) above.

Results of the Construction of the Embodied R&D Indexes

The x_{pi}'s and r_p's are used, according to equations (5) and (6), to construct g_{it}, the index of

[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%.

[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 .

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).

The table in Appendix B summarizes the results of constructing g_{it} for each of the 62 industries in the BEA investment data set. 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 that is 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 service industries 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 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.

4. Does the R&D directed at a Capital Good Explain its Technological Change?

[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.

The use of g_{it} as an indicator of embodied technological change rests on the premise, formalized in equation (4), that technological change in a capital type is proportional to the stock of R&D directed at that capital type. This is a nontrivial statement. Evidence for this hypothesis is based on identifying technological change via patent counts and/or the perceived value of new patents. Given that much innovation is never patented, it seems worthwhile to confirm this hypothesis using alternative, non-patent-based indicators of technological change prior to using the constructed 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 1 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 2 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 1, 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 a modest decline in relative prices despite high R&D, and the two Instruments-related product 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 (4).

5. Is TFP Invariant to Embodied R&D?

To begin investigating whether there is a relationship between the R&D embodied in an industry's capital stock and the industry's embodied technological change, I test whether g_{it} is a good predictor of the Solow Residual (SRD). Consider the generally established definition of the cost-based Solow Residual, first established by Hall (1990)[14]:

$$SRD = \Delta(Q) - c_L\Delta(L) - c_J\Delta(J_{\gamma=0}) - c_S\Delta(S) - (1 - c_L - c_J - c_S)\Delta(M) \qquad (8)$$

where Δ is the log first-difference operator, c_i is the cost share of input i, Q is real output, L is labor input, M is materials, S is structures, J is equipment as defined in equation (2), and γ is the rate of embodied technological change. A distinguishing feature between the cost-based Solow Residual (hereafter simply the Solow Residual or SRD) 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 will be an upwardly biased estimator of true total factor productivity (TFP) growth. Furthermore, 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.[15]

Using industry-level data from the BEA and other sources, I construct cost-based Solow Residuals for 54 industries spanning the U.S. private economy. Appendix A describes the data and the construction of SRD. I constructed Solow Residuals myself rather than using available data sources on TFP so as to ensure that embodied technological change was not already being partially accounted for in the underlying construction of the capital stock. As can be seen in equation (2) and the definition of SRD above, the property that γ=0 must be built into the construction of the capital stock through the use of a consumption price index to deflate nominal investment and the non-use of depreciation data that partially reflects obsolescence (as do the BEA economic depreciation rates). By contrast, available data on TFP such as that from the Bureau of Labor Statistics (BLS) or Jorgenson and Stiroh (2000) make some effort to at least partially account for capital quality changes. Below I compare the results of relating SRD to g_{it} versus relating these measures of TFP to g_{it}.

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[14]The original Solow Residual (Solow (1957)) uses revenue shares rather than cost shares and requires, *inter alia*, an assumption of perfect competition in product markets in order to be interpreted as total-factor productivity growth. The cost-based Solow Residual, on the other hand, is robust to imperfect competition (see Hall (1990)).

[15]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.

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.[16] 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 3 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. Industries considered to be measurable are those in Agriculture, Mining, Manufacturing, Transportation, Communications, and Utilities. 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 results generally show a positive a significant relationship between embodied R&D and the Solow Residual. The results are strongest for the between regressions. The R^2 for the full sample between 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 content (or signal-noise ratio) 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 technological change and that capital good price deflators do not fully account for quality change,

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

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.

Are Existing Measures of TFP invariant to Embodied R&D?

As I explained above, I chose to construct my own measures of the Solow Residual rather than use available data on total factor productivity growth because, to the extent that TFP is measured correctly, it may be invariant to embodied technological change and therefore g_{it}, something that is not true for the Solow Residual. Or, at the least, if TFP is affected by embodied R&D, the effect should not be due to quality mismeasurement in the capital stock. Thus, the above regressions were really a one-sided test: if SRD as measured above is *not* affected by g_{it}, either g_{it} is a poor indicator of embodied technological change or embodied technological change is zero, which is highly unlikely. But if SRD is affected by g_{it}, and we have determined that it is, we do not know if this is solely because embodied technological change is "corrupting" the residual (i.e., is captured in SRD) or if is also partly because embodied and disembodied technological change are correlated in reality. Looking at actual measures of disembodied technological change, i.e., TFP, can help us determine if the relationship between g_{it} and SRD is partly a real phenomenon.

Jorgenson and Stiroh (2000) construct measures of TFP for 33 industries which are generally aggregates of the 62 industries listed in Appendix B. Regressing the sample average from 1960-96 for each industry and regressing it on g_{it} (after aggregating it up to the 33 industry level by simple averaging of the many g_{it}'s within each aggregate industry) yields the following results:

$$\begin{pmatrix}\text{Average Growth}\\ \text{Rate of TFP}\end{pmatrix}_i = B_0 + \underset{(0.38)}{-0.22}\left(\overline{g_t}\right)_i \quad , \mathrm{R}^2 = 0.01 \text{, 33 industries}$$

So embodied R&D seems to have no effect on Jorgenson and Stiroh's measure of TFP. However, it could be that both g_{it} and this measure of TFP are noisy, or mismeasured in an idiosyncratic way, making a significant relationship unlikely.

To check if this result is driven by idiosyncratic measurement error in the data, I repeat the above regression using the subsample of manufacturing industries, where measurement error should be far less problematic. This yields the following results:

$$\begin{pmatrix}\text{Average Growth}\\ \text{Rate of TFP}\end{pmatrix}_i = B_0 + \underset{(0.70)}{1.47}\left(\overline{g_t}\right)_i \quad , \mathrm{R}^2 = 0.18 \text{, 21 industries.}$$

Embodied R&D turns out to have a positive and significant coefficient suggesting that the insignificance found in the full sample may simply be due to noise. This can be further confirmed by repeating the regression using the TFP data set constructed by the Bureau of Labor Statistics (BLS) multifactor productivity group.[17] Doing this, I find a coefficient on embodied

[17]The BLS TFP data is at the 2-digit SIC level (20 industries), but data is not available for two industries, leaving TFP series for 18 industries. These industries have a one-to-one mapping with the Jorgenson and Stiroh industries and the BEA industries for which g_{it} is available, with

R&D of 1.82, which is significant at the 10% level, and an R^2 of 0.16. Thus, there does appear to be a robust relationship between the embodied R&D index in this paper and the available data measures of either TFP or the Solow Residual.

Explanations for a positive relationship between embodied R&D and available TFP measures

Capital-embodied R&D may be positively related to these measures of TFP either because capital quality change is not being correctly accounted for and so it wrongly ends up in the TFP residual, or because embodied R&D is correlated with other variables that are correlated with TFP. For instance, an industry's capital mix (and therefore g_{it}) may be correlated with labor quality which, if the TFP data does not adequately account for labor quality changes, could be correlated with the TFP measure. There may also be *true* knowledge spillovers within an industry from technology-heavy investment to actual disembodied/total-factor productivity growth stemming from the business interactions between suppliers and customers.

Table 4 shows the correlation matrix, for the manufacturing subsample, for the following variables: g_{it}, BLS TFP growth, Jorgenson and Stiroh's TFP growth, growth in the Jorgenson and Stiroh's capital composition component, and growth in their labor quality/composition component. It turns it that not only is TFP growth positively correlated with embodied R&D, but capital composition is as well, with a correlation coefficient of 0.66. Notice also that according to the Jorgenson and Stiroh data, changes in capital composition are positively correlated with TFP. These findings suggest a non-measurement-error explanation for the positive relationship between TFP measures and embodied R&D. It seems likely that these measures of TFP do account for part, though not all, of capital quality growth by accounting for changes in industries' capital composition. This is why we find a positive correlation between embodied R&D and Jorgenson and Stiroh's capital composition change. Furthermore, it is likely that industries with higher embodied technological change tend to have higher disembodied technological change as well. This explains the high positive correlation between Jorgenson and Stiroh's capital composition change and their TFP growth and the even higher positive correlation between embodied R&D and their TFP growth. There is a small but significantly positive correlation between g_{it} and Jorgenson and Stiroh's labor quality growth, but it is too small to explain the high correlation between g_{it} and TFP. Thus, I conclude that the positive relationship found here between embodied R&D and TFP is a real phenomenon, not merely an artifact of mismeasurement.

A Note on Potential Endogeneity Bias

In production or productivity regressions, the possibility of productivity shocks simultaneously affecting the independent variables and therefore biasing the coefficients is often a concern. It must be noted, however, that in the case of the regressions above, such endogeneity bias is unlikely. A productivity (or, equivalently, disembodied technology) shock, whether it is transitory or persistent, may cause a firm/industry to increase total investment but, assuming the

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the exception that the BLS industry set does not separate Transportation Equipment (SIC 37) into Motor Vehicles (371) and Other Transportation Equipment (372-379) as is done in the other two sets.

capital mix was optimal before the shock, the shock will not cause the capital mix to change according to any homogenous production function.

As was mentioned in Section 2 regarding equation (4), it is also possible that a productivity shock in a subset of industries will cause increased demand for the types of capital goods that are disproportionately used by those industries. Firms may respond to this increase in demand by increasing R&D on those capital goods. If this response of upstream R&D firms to downstream productivity shocks takes place within the same period, or if productivity shocks are sufficiently persistent, this could yield an upward bias in our coefficient on g_{it}. However, these possibilities are unlikely. First, changes in the R&D stock of upstream firms in response to observed increases in demand are likely to be slow both because current investment is a small fraction of the total stock and because R&D projects often involve lengthly planning. Second, the positive relationship between g_{it} and TFP growth holds up in the first-difference regressions which control for permanent productivity differences across industries.

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

The previous two sections provided strong evidence that this paper's measures of capital-embodied R&D are proportional, at least at the industry-level, to true embodied technological change. It is natural to ask, then, how well do industry-level estimates of embodied technological change correlate with these measures of embodied R&D? Since the maintained hypothesis of this paper is that embodied R&D is proportional, not equal, to embodied technological change (recall the scale factor A in equation (7)), g_{it} cannot be used to evaluate whether a given estimate of embodied technological change is too high or too low. However, it can be used to answer the important question of which industries have the highest rates of embodied technological change and which the lowest. Thus, it provides a kind of "measuring stick" by which to judge the reasonableness of any set of industry-level rates of embodied technological change.

One set of industry-level estimates of embodied technological change is provided in this issue by Cummins and Violante (2001). These authors extend the 19 capital goods' price indexes constructed by Gordon (1990), which cover the period 1947-83, from 1984-2000. Then, as was done in Section 4 of this paper, they divide the price indexes by a consumption deflator and compute that ratio's percentage decline to arrive at the rate of technological change in each capital good type. Finally, each industry's embodied technological change is calculated by averaging the relative price declines over capital goods using the industry's investment shares, from the BEA data on investment by type, as weights. The ordinary correlation, across the 62 industries in the BEA data, between the average annual rate of embodied technological change between 1957 and 1997 as measured by Cummins and Violante, and the average embodied R&D index, g_{it}, averaged over 1957-97, is 0.52, which is significant above the 99% level. The two sets have a corresponding rank correlation of 0.61 – also significant above 99%.[18] The strong

[18]The estimates of embodied technological change from Cummins and Violante are from an earlier version of their paper that does not use R&D as an input in the equation that extends Gordon's price indexes to 2000. The authors have since added the stock of R&D directed at each

correlations are not surprising given that the high correlation found in Section 4 between the relative declines in Gordon's price indexes and the R&D directed at capital goods, and given that both g_{it} and Cummins and Violante's measures of embodied technological change used the same BEA data for industry investment shares. Nonetheless, the high correlations do seem to indicate that the Cummins and Violante estimates are realistic in their industry ordering.

As mentioned in the introduction, this price-based approach to estimating embodied technological change is not the only one. Sakellaris and Wilson (2001) develop a production-side approach that estimates embodied technological change using U.S. plant-level data on output, inputs, and the historical distributions of investment. The estimating equation is essentially a typical Cobb-Douglas gross-output production function in terms of labor, materials, structures stock, and equipment stock. However, the equipment stock, rather than being measured *a priori*, is specified as a parameterized stream of past investments adjusted for physical depreciation using the measures of physical depreciation constructed by the Federal Reserve Board in the process of constructing their industry-level capital stock series. Each vintage of past investment has a vintage weight assigned to it and investment is deflated using a consumption deflator so that each vintage weight should pick up the productivity in terms of consumption units of that vintage relative to some base vintage. The vintage weights are assumed to follow a geometric pattern and the geometric rate at which these weights increase, which is by definition the rate of embodied technological change, is estimated simultaneously with the other production function parameters. Sakellaris and Wilson find a rate of embodied technological change in manufacturing of 11.6% between 1972 and 1996.

Using the same data and an analogous regression equation, I extend Sakellaris and Wilson's results by allowing the rate of embodied technological change to vary by industry. The 22 industries for which I estimate embodied technological change are all within manufacturing and their level of aggregation is between the 2- and 3-digit SIC levels. The estimated rates are shown in Table 5. 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 and Electronic components. The negative values are not too disturbing given their rather high standard errors. They also occur in industries where one might expect low levels of embodied technology. The very high rates in Computers and Electronic Components are most likely a result of the use of the BEA's 4-digit level output (shipments) deflators. These deflators come from the BLS with two key exceptions: computers and semiconductors (semiconductors are a subcategory of Electronic Components). 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.

Overall, 15 industries have positive estimates of embodied technological change (nine which are significant) and nine industries have negative estimates (five significant). Aside from Computers and Electronic components, the industries of Communication equipment, Textiles, and Non-Motor Vehicle Transportation Equipment have the highest estimates. Paper, Motor

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capital good to their price equations because of the high correlations I find in this paper between technological change and the R&D stock.

vehicles, and Food and Tobacco have the lowest estimates.

There is approximately a one-to-one mapping between these 22 manufacturing industries and the 21 manufacturing industries in the classification scheme used in the BEA investment data. I generate a set of $\hat{\gamma}$'s and g_{it}'s that are at a comparable industry level and then calculate their average over the 1957-97 period.[19] The ordinary correlation over industries between the average embodied R&D index and the estimated rate of embodied technological change is 0.49 and the rank correlation 0.44, both significant above the 95% level. Thus, these production-based estimates of embodied technological change are positively and significantly correlated with observable patterns of industry investment and R&D spent of capital goods. Viewed as a test of the reasonableness of these production-based estimates of embodied technological change in terms of how industries compare to one another, this exercise yields encouraging results.

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. Evidence presented in this paper supports previous research that found that R&D spending within particular technological or product fields is the primary driver of technological change in those fields. Though this line of research develops various proxies for the value of technological change, i.e., the output of research activities, such as patent counts (weighted and unweighted), patent value, and firm market value, the true output of research is obviously much harder to measure than the inputs such as R&D.

Given that these output proxies of innovation are likely to have large and variable errors in predicting the true values of innovation, the approach of this paper was to use an input, R&D directed at specific technological fields, as a predictor of these values. It was judged that R&D would have a tighter link to the value of innovation than output variables that either do not take into account positive spillovers beyond the R&D-performing firm, as in the case of firm market value, or, in the case of patent variables, may not even apply for most innovations. In fact, based on a recent survey of manufacturing firms, Cohen, Nelson, and Welsh (2000) find that patenting tends to be the least important of the many mechanisms firms use to appropriate returns from R&D spending. Nonetheless, the use of R&D directed at capital goods as the predictor of innovation values is prototypical. Hopefully, better measures of the output of the inventive process will be developed and this paper can serve as a guide for using these measures to measure embodied technological change.

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[19] To generate series of $\hat{\gamma}$ and g_{it} at a comparable industry level, I simply assign the same g_{it} to each of the subindustries in the few cases where there are subindustries within the industry for which γ is estimated. When more than one of my industries map to a single BEA industry, I take a share-weighted average of the multiple $\hat{\gamma}$'s to create a $\hat{\gamma}$ for the more aggregate BEA industry, using investment shares as weights. The resulting comparable industry classification has 22 industries.

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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 hours, 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). In BLS data, labor hours are adjusted to reflect changes in education and skills of the workforce. In the Census data, labor hours are adjusted for quality by augmenting the hours of non-production workers by the ratio of their wages to those of production workers. Thus, there 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.

Appendix B – Industry Indexes of Embodied R&D

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 1

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 2

	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 3

	All Industries (n=54)	**Measurable Industries Subset (n=43)**
"Between" Regression: $\overline{SRD}_i = B_0 + B_1 \overline{g}_i + \varepsilon_i$		
Estimate of B_1 (std. error)	0.554^{***} (0.151)	0.539^{***} (0.187)
R^2	0.205	0.169
"Within" Regression: $SRD_{it} - \overline{SRD}_i = B_0 + B_1 \left(g_{it} - \overline{g}_i \right) + \varepsilon_{it}$		
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 4

	Embodied R&D	BLS TFP	Jorgenson & Stiroh (2000) TFP	Jorgenson & Stiroh (2000) Capital Composition	Jorgenson & Stiroh (2000) Labor Composition
Embodied R&D	1				
BLS TFP	0.40	1			
Jorgenson & Stiroh (2000) TFP	0.50	0.78	1		
Jorgenson & Stiroh (2000) Capital Composition	0.66	0.50	0.48	1	
Jorgenson & Stiroh (2000) Labor Composition	0.24	0.15	-0.04	0.06	1

Note: Variables are average annual growth rates for 18 manufacturing industries.

Table 5

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)

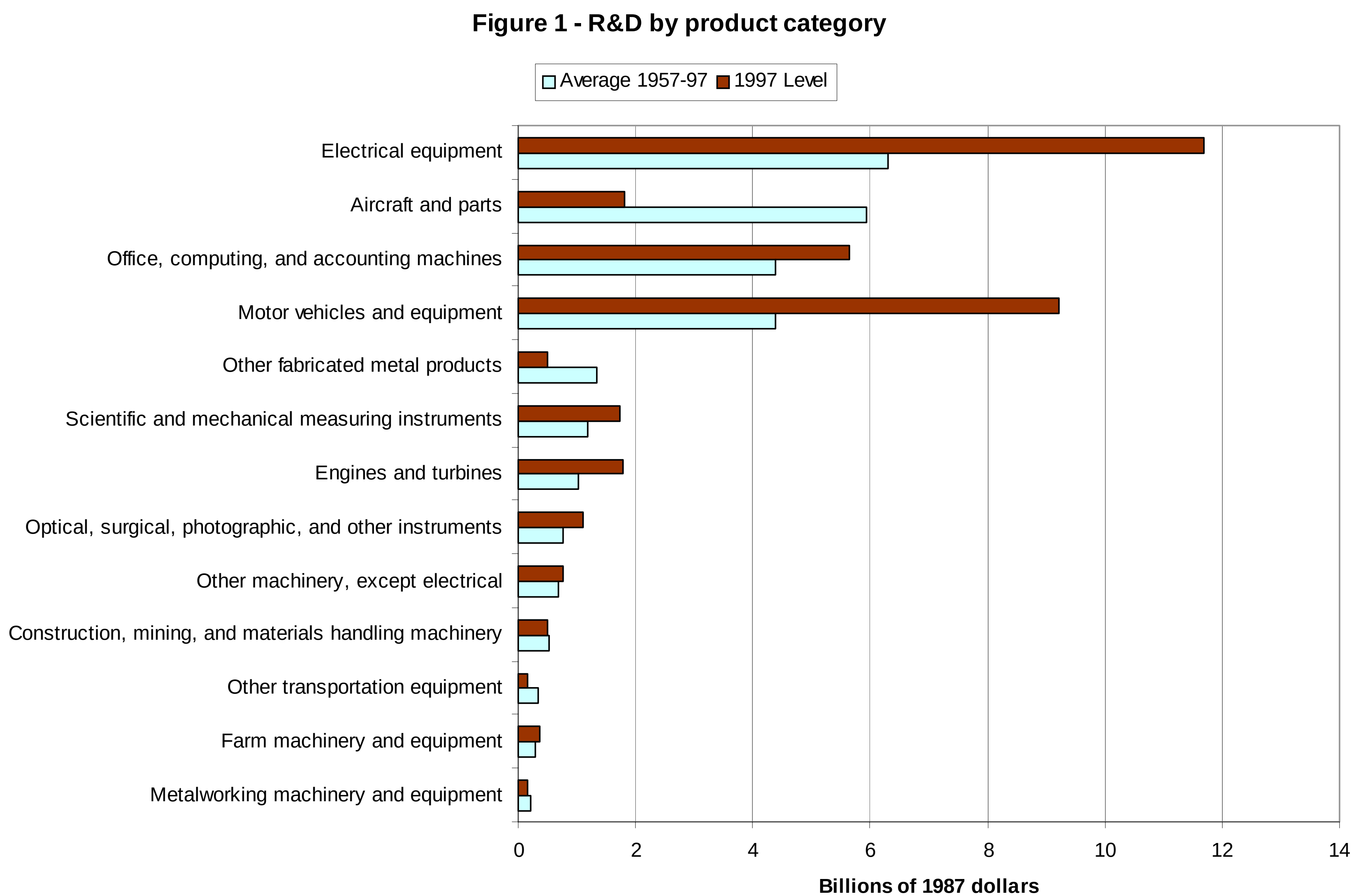
Figure 1 - R&D by product category
Average 1957-97
1997 Level
Electrical equipment
Aircraft and parts
Office, computing, and accounting machines
Motor vehicles and equipment
Other fabricated metal products
Scientific and mechanical measuring instruments
Engines and turbines
Optical, surgical, photographic, and other instruments
Other machinery, except electrical
Construction, mining, and materials handling machinery
Other transportation equipment
Farm machinery and equipment
Metalworking machinery and equipment
0
2
4
6
8
10
12
14
Billions of 1987 dollars

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