The Downstream Effects of R&D Performed on Capital Goods

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PRELIMINARY DRAFT - NOT FOR QUOTATION

Abstract:

In this paper I present two possible industry-level indices of embodied R&D that were meant to capture the extent of research and development done on 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 measure of these indices and investigate their properties. According to one index (which is highly correlated with the other), 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 which capital goods are used.

The measures of embodied R&D were compared to rates of embodied technological change that were estimated using plant-level manufacturing data from the Census Bureau's Longitudinal Research Database. 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 measure of embodied R&D is likely to be proportional to true embodied technological change.

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 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). However, hedonic methods require very specific time-series and cross-sectional data on prices and product characteristics -- data which is not available for most 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. We estimate this model using plant-level manufacturing data from the Longitudinal Research Database (LRD) available at the U.S. Census Bureau. I extend this method to allow the estimates of embodied technological change to vary by industry. Nonetheless, there remains two inherent limitations to 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 sensibility of these estimates. That is, how does one know whether it is sensible for one industry to have a higher 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 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. 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 found at the plant-level or conventionally-measured total factor productivity (TFP). It turns out that the *level*, but not the *growth rate*, of embodied R&D is positively and significantly related to both TFP and the estimates of embodied technological change.[1]

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 essentially be summarized in four equations:

Capital Services

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

where:
J = equipment capital stock in efficiency units
U^J = equipment capital utilization rate
E = Energy usage
J_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

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

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 production in year t
(= 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.

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[1]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, product field, input-output linkages, etc.. These types of R&D are likely to affect disembodied technological change and thus are not relevant for this paper.

Production

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

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

The services of structures capital, S*, is defined analogously to (1) and (2) except that (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 $J_S = J_J$, and adding an error term yields a single regression equation that can be used to estimate ", $, (, 0, 2, J, and the coefficients on the control variables using nonlinear least squares. A simple extension can be done to allow (to vary by sector/industry (while constraining the other coefficients to be the same across all plants in the sample).

The estimates of (by sector are shown in Table 1. The estimates seems sensible 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. It seems reasonable to interpret these negatives as findings of (=0 for these sectors and thus I replace the negative ('s with zero for constructing quality-adjusted capital stocks. The absurdly high ('s in 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 (which just so happen to be in sector 19). I have also tried estimating the model using the PCE deflator (which has some theoretical justification as discussed in Sakellaris and Wilson 2000). Yet, this results in strongly negative ('s for these two industries which is clearly unrealistic. Therefore, throughout the paper I use the ('s in Table 1, with the caveat that the relative rank of (may be more informative than the actual levels.

3. The Relationship between estimates of (and Investment Asset Shares

In order to impute nonmfg ('s as well as to evaluate the sensibility of their rank across industries, it would be nice if there were observable variables that vary by industry and which are likely to be proportional to the true rate of ETC. Since (can be thought of as a weighted average of the rates of ETC for each particular capital asset, the asset mix of an industry (from the BEA's Fixed Reproducible Tangible Wealth, FRTW) is one possibility. However, given only 24 sectors, these asset shares had to be combined into a small number (n<24 is required for identification if (is regressed on asset shares). Ideally, we would like to aggregate them into a small number of groups that differ according to the levels of technology. Thus, the disadvantage of using asset shares is that the process of aggregation requires some arbitrary decisions on what assets are considered "high-tech" vs. "low-tech."

The NIPA uses an equipment asset breakdown consisting of 4 categories: 1) "Information processing and related equipment," 2) "Industrial equipment," 3) "Transportation and related equipment," and 4) "Other equipment" (see Table 5.8 - NIPA). Using this classification scheme, I aggregate the FRTW's data on industries' investment in each of 35 equipment assets to investment by NIPA category. For each industry, the share of total investment in each of the four asset categories is calculated and averaged from 1972-96.

Our estimates of (were then regressed on the four 1972-96 average asset shares.[2] The results of this regression are shown in Table 2. The first column contains the R^2 and coefficient estimates from performing OLS regression. The second contains the results from a quadratic programming algorithm which minimizes the sum of squared error subject to the constraint that the coefficients on the asset shares are greater than zero. This was done in order to ensure that imputed ('s for nonmfg would be positive (negative ('s are unrealistic). The estimated coefficients in the unrestricted case are very imprecise and 3 of the 4 are negative. The only sensible results of this regression is that the coefficient on "Information processing" is, as one would expect, positive (though the standard error is quite large). The linear programming coefficients seem more realistic, however they are extremely imprecise. Thus, it appears that a relationship between asset shares and (cannot be estimated with a sufficiently high degree of precision to be useful for imputing rates of ETC in nonmfg.

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

Another natural choice for a variable that is likely to be related to (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, 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

[2]These shares sum to 1, therefore a constant cannot be included in this regression in order to maintain full rank in the regressor matrix.

equipment capital. As opposed to the asset shares discussed in Section 3, 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.[3]

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. As pointed out by Scherer (1982) and Griliches (1979), much of measured downstream benefits 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 productivity gains (if there were any) in the capital-supplying industry and not in the downstream industries. On the other hand, if prices do not adjust for quality and, due to competition in the upstream industry, the nominal price of capital does not increase in proportion to the increase in quality, then real output of the supplying industry and real investment of purchasing industries will be understated. In this case, increases in measured productivity should show up mainly in the downstream industries. It is this kind of R&D spillover, due to quality-mismeasurement in equipment price deflators, that I am attempting to capture.[4]

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:

$$IRD_i(t) = \sum_j B_{ji}(t)[RD_j(t) / Y_j] \tag{5}$$

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

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

[4]There may also be pure rent spillovers from embodied R&D, in addition to those due to mismeasurement. These spillovers are still contributors to investment-specific technological change since an industry can only reap the benefits of them if they invest.

and then summed across industries. This measure was developed by Terleckyj (1974) and has been used in numerous studies.[5]

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.

For the purposes of predicting either q or (, 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 M^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 (or 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

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

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 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 M^2.

An interesting issue is whether M_i^2 should be a predictor of q_i, the *level* of embodied technology, or for $(_i$, 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 M_i^2 will be compared to TFP and the estimated rates of $(_i$.

5. Data

The one and only source for industrial R&D 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 (it was not done in 65, 66, 69, 78, 80, 82, 84, 86, 88, 90, 92, 94, and 96). Among other things, the NSF asks respondents how much R&D they spent in each "product field." This data is published in the NSF's *Funds for Research and Development in Industry*.[6] Unfortunately, there are many holes in the data due to non-disclosure of certain values and changes in the product field classification over time. These holes were filled in by imputation using available information in adjacent years. Data for years in which the survey was not done were interpolated.

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

[6]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.

these adjustments were made to the raw data, what was left was a matrix of applied R&D by product field for 1957-97.[7] This 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*.[8] 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 asset type. This flows matrix was then converted into a coefficients (shares) matrix using the industry investment totals (across the 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 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 TFP or estimated (. 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 4 shows the annual growth rate of M^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 (since (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:

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[7]Unfortunately, product- and process-oriented R&D is not distinguished in the product field R&D data. Ideally, I would use only the product-oriented R&D in each product field. This will not alter our indices if either the split between product- and process-oriented R&D is constant over time and product field, or the fraction of R&D that is process-oriented is very small. There is some evidence of the latter: Scherer (1984) finds three-fourths of all R&D is product-oriented.

[8]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 (refers only to embodied technological change in equipment .

$$\Delta\Phi^1 \equiv \Phi^1(T_1) - \Phi^1(T_0)$$
$$= \sum_p \Delta q_p \cdot x_{pi}(T_0) + \sum_p \Delta x_{pi} \cdot q_p(T_0) + \sum_p \Delta x_{pi} \cdot \Delta q_p \qquad (9)$$

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 $M^1(T_0)$ 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 M^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 M^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.[9] This means that by construction $M^1(t)$, 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 M^1 only imply interindustry differences in growth in embodied R&D relative the base year.

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

Table 5 displays the results of the construction of M^2. Column 1 shows the mean level of the index over the 1972-96 period. The second column gives its annual growth rate over the same period.

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[9] Consider a simple Cobb-Douglas production function where there are two types of capital goods 1 and 2: $Y_t = K_t^{"} L_t^{\$}$ where $K_t = K_{t-1}(1-*) + i_t^1 q_t^1 + i_t^2 q_t^2$. 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 "Yq^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.

The industries are ordered according to their mean value of M^2. For the overall economy, the growth rate of the index was about 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.[10] 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 low-tech equipment. The final four are Construction, Coal Mining, Trucking and warehousing, and Farms.

6. The Relationship Between Estimates of (and Embodied R&D

To compare our two indices to the rates of embodied technological change (() that were estimated for manufacturing industries using plant-level Census data, I had to convert each index from the BEA 21-industry classification to a 22-industry scheme (spanning manufacturing) that is consistent with the 22 industries for which I have estimates of (.

In section 3 I argued that M^1 should proxy for the level of embodied technology and therefore its growth rate should proxy for the rate of embodied technological change ((). I also argued that either the level or the growth rate of M^2 should be proportional (though not necessarily serve as a proxy) to (. Table 6 shows the ordinary and Spearman's rank correlations, among the 22 manufacturing industries, between 8 and each of 3 variables: 1) the 1972-96 annualized growth in M^1, 2) the 1972-96 annualized growth in M^2, and 3) the 1972-96 mean of M^2.[11] Neither of the growth rate appear to be correlated with 8. Yet, the mean of M^2 is positively correlated 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.[12]

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 M^2), or

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[10]As was pointed out by Douglas Meade at Inforum, the value of embodied R&D in Transportation by air may be artificially high since the R&D on airplanes includes R&D on military planes financed by the Defense Department.

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

[12]Another interesting finding, not shown, is that the growth in M^1 has a Pearson's correlation with the mean of M^2 of 0.54 and a Spearman's correlation of 0.65, both of which are significant at the 99% level.

whether they imply that our λ's are actually capturing an industry's *level* of embodied technology and not its rate of change, one cannot say.

A third possibility is that the growth rates of embodied R&D, as measured by growth in either M^1 or M^2, are badly mismeasured since the time-series dimensions of either the BEA capital flows tables or 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 reason unrelated to capital mix. The NSF data underlying the annual R&D by product field tables constructed in this paper has 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 M^1 because the normalization that causes M^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 M^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 M^1 and M^2 have with λ; it cannot explain why the growth of M^2 would actually have a positive and significant correlation.

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

One way of sorting out whether the positive correlation between M^2 growth and λ is due to λ measuring the level and not the growth rate of embodied technological change or rather to the level of M^2 being a good predictor of the true rate of embodied technological change, is to see if either the growth or level of M^2 is a good predictor of the Solow Residual.[13] 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 or indices are positively proportional to the true γ, then they should have a positive effect on SRD.

The panel nature of the measured data on M^1 or M^2 allows us to separately investigate the effect of these indices on SRD over the cross-industry dimension (emphasizing long-run/growth patterns), the time-series dimension (emphasizing short-run fluctuations), or both.[14] 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

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[13]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.

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

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 mean I compared to γ in Section 6 and Table 6. They are the level of M^2, the growth of M^2, and the growth of M^1. The signs and confidence intervals found in the between regression, which is the most comparable to the simple correlations of Table 6, are quite similar to those correlations. Again, the mean of M^2 is the only variable found to be positive and significant. This seems to lend support to the hypothesis that the positive correlation found between γ and the mean level of M^2 is due to M^2 being a good predictor of true embodied technological change, rather than γ 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 M^1 and M^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, M^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 M^1 or M^2 again has no significant effect on SRD. The one exception is the growth rate of M^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. 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 does in their between estimates. It is possible that upstream activity is simply a good predictor of upstream R&D spending, for they are certain to be correlated. Then, under the joint hypothesis that embodied R&D, as measured by M^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 the cause upstream embodied R&D to have downstream effects on productivity.

Given our relative confidence in the measurement of the across-time means of M^2, and their demonstrated correlation with γ and the Solow Residual, I then use these means to impute γ’s for nonmanufacturing industries (where γ‘s are not available) via the estimated relationship obtained from a linear regression across manufacturing industries of γ on a constant and the 1972-96 mean of M^2. This regression yielded a constant of -0.041 (with a standard error of 0.039), an embodied R&D coefficient of 0.058 (0.041), and an R^2 of 0.102.

The imputed values of (for nonmfg sectors, computed using this estimated relationship, are shown in Table 8. There were five negative imputed values which were replaced with zero's. The ('s range from 0 to 19%. The magnitudes and the cross-sectoral ranking of these rates of embodied technological change seem quite reasonable.

8. Conclusion and Suggestion for Further Research

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

In future work, I plan to use the rate of embodied technological change to construct quality-adjusted measures of industry-level capital stocks. These capital stocks, along with other factor inputs, will be used to estimate labor productivity equations to be used in a structural macro model.

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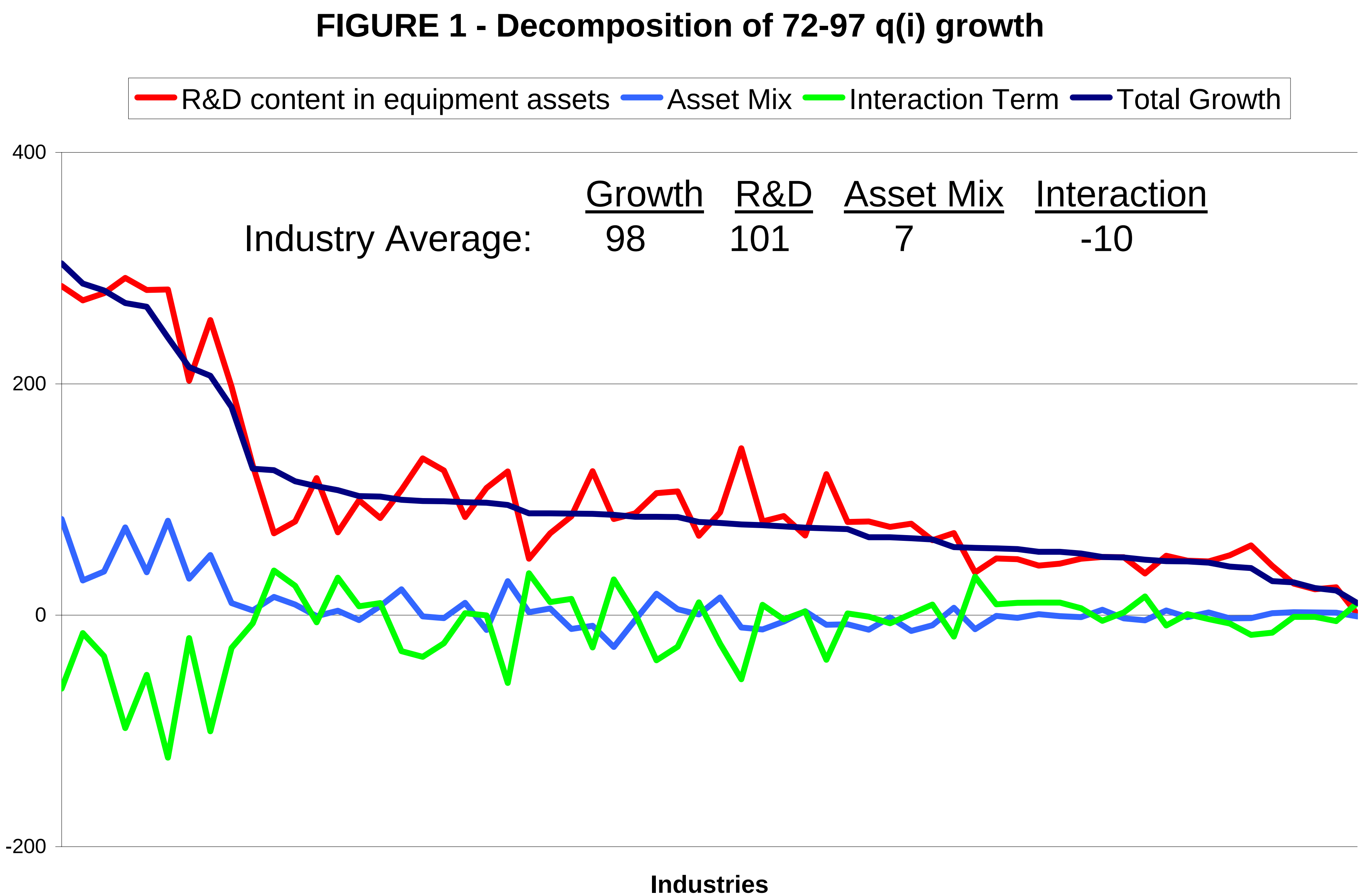

FIGURE 1 - Decomposition of 72-97 q(i) growth
R&D content in equipment assets
Asset Mix
Interaction Term
Total Growth
Growth
R&D
Asset Mix
Interaction
Industry Average:
98
101
7
-10
400
200
0
-200
Industries

Table 1

Sector	Sector Title	SIC (1987 basis)	[illegible]
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

	Coefficients unbounded	Coefficients bounded to be > 0
Info. Processing	1.818 (0.947)	0.058 (1.027)
Industrial Equipment	-2.043 (1.225)	0.168 (1.329)
Transportation and related	-1.396 (3.476)	0.019 (3.770)
Other Equipment	-3.215 (3.126)	0.000 (3.391)
$\underline{R}^2$	0.135	-0.018

Table 3

NSF Product Field	**BEA Asset Type**
Other fabricated metal products	Other fabricated metal products
Engines and turbines	Internal combustion engines
Engines and turbines	Steam engines
Farm machinery and equipment	Agricultural machinery, except tractors
Farm machinery and equipment	Farm tractors
Construction, mining, and materials handling machinery	Construction tractors
Construction, mining, and materials handling machinery	Construction machinery, except tractors
Construction, mining, and materials handling machinery	General industrial, including materials handling, equipment
Construction, mining, and materials handling machinery	Mining and oilfield machinery
Metalworking machinery and equipment	Metalworking machinery
Office, computing, and accounting machines	Mainframe computers
Office, computing, and accounting machines	Personal computers
Office, computing, and accounting machines	Direct access storage devices
Office, computing, and accounting machines	Computer printers
Office, computing, and accounting machines	Computer terminals
Office, computing, and accounting machines	Computer tape drives
Office, computing, and accounting machines	Computer storage devices
Office, computing, and accounting machines	Other office equipment
Other machinery, except electrical	Special industry machinery, n.e.c.
Other machinery, except electrical	Service industry machinery
Electrical equipment	Electrical transmission, distribution, and industrial apparatus
Electrical equipment	Communication equipment
Electrical equipment	Household appliances
Electrical equipment	Other electrical equipment, n.e.c.
Motor vehicles and equipment	Autos
Other transportation equipment	Trucks, buses, and truck trailers
Other transportation equipment	Ships and boats
Other transportation equipment	Railroad equipment
Aircraft and parts	Aircraft
Scientific and mechanical measuring instruments	Instruments
Optical, surgical, photographic, and other instruments	Photocopy and related equipment

Table 4

Industry	Annual Growth in M[1] from 1972-96
Federal reserve banks	0.060223
Financial holding and investment offices	0.056326
Security and commodity brokers	0.056208
Educational services	0.054681
Legal services	0.054304
Nonfinancial holding and investment offices	0.051406
Insurance carriers	0.048055
Other services, n.e.c.	0.046981
Insurance agents, brokers, and service	0.043553
Metal mining	0.033859
Local and interurban passenger transit	0.03244
Construction	0.032087
Trucking and warehousing	0.031365
Miscellaneous repair services	0.030038
Other depository institutions	0.029107
Auto repair, services, and parking	0.027579
Transportation services	0.027511
Pipelines, except natural gas	0.027337
Agricultural services, forestry, and fishing	0.027015
Industrial machinery and equipment	0.026945
Oil and gas extraction	0.02675
Wholesale trade	0.02569
Leather and leather products	0.025068
Amusement and recreation services	0.024716
Personal services	0.024662
Water transportation	0.024662
Radio and television	0.023921
Sanitary services	0.023245
Electric services	0.022942
Tobacco products	0.02276
Business services	0.022741
Telephone and telegraph	0.02173
Gas services	0.021241
Coal mining	0.021213
Railroad transportation	0.02078
Nondepository institutions	0.020451
Real estate	0.020391
Health services	0.019346
Nonmetallic minerals, except fuels	0.018537
Motion pictures	0.018242
Retail trade	0.018131

Farms	0.016786
Other transportation equipment	0.016002
Petroleum and coal products	0.015897
Instruments and related products	0.01572
Electronic and other electric equipment	0.015656
Hotels and other lodging places	0.015067
Printing and publishing	0.015057
Miscellaneous manufacturing industries	0.014373
Apparel and other textile products	0.013819
Chemicals and allied products	0.013725
Stone, clay, and glass products	0.013693
Food and kindred products	0.013077
Paper and allied products	0.012345
Primary metal industries	0.012215
Furniture and fixtures	0.011988
Lumber and wood products	0.011389
Fabricated metal products	0.007708
Textile mill products	0.00629
Rubber and miscellaneous plastics products	0.005228
Motor vehicles and equipment	0.004761
Transportation by air	0.004177
TOTAL	0.021214

Table 5

INDUSTRY	Mean M^2 from 1972-96	Annual Growth in M^2 from 1972-96
Transportation by air	2.282	-0.521
Telephone and telegraph	2.229	1.280
Radio and television	2.099	1.152
Legal services	1.611	4.767
Security and commodity brokers	1.557	4.843
Financial holding and investment offices	1.463	4.362
Insurance agents, brokers, and service	1.446	3.697
Business services	1.413	2.971
Insurance carriers	1.397	3.696
Other depository institutions	1.388	2.416
Nonfinancial holding and investment offices	1.388	3.672
Health services	1.369	3.603
Real estate	1.336	3.949
Hotels and other lodging places	1.322	4.858
Other services, n.e.c.	1.319	4.210
Amusement and recreation services	1.302	1.859
Electric services	1.301	1.576
Educational services	1.244	3.128
Federal reserve banks	1.218	2.901
Electronic and other electric equipment	1.177	1.581
Nondepository institutions	1.062	4.938
Wholesale trade	1.052	6.126
Industrial machinery and equipment	0.971	3.523
Apparel and other textile products	0.907	1.909
Other transportation equipment	0.895	4.095
Retail trade	0.834	5.326
Local and interurban passenger transit	0.818	1.709
Auto repair, services, and parking	0.797	5.420
Miscellaneous repair services	0.774	6.051
Motion pictures	0.759	5.751
Railroad transportation	0.743	5.301
Instruments and related products	0.740	6.494
Primary metal industries	0.718	1.963
Personal services	0.715	2.840
Gas services	0.678	6.193
Sanitary services	0.664	3.381
Tobacco products	0.644	3.660
Chemicals and allied products	0.642	1.802
Paper and allied products	0.635	1.018
Printing and publishing	0.634	4.240
Transportation services	0.630	8.731
Petroleum and coal products	0.610	0.386

Leather and leather products	0.592	3.023
Oil and gas extraction	0.586	3.643
Furniture and fixtures	0.543	4.400
Stone, clay, and glass products	0.538	5.499
Miscellaneous manufacturing industries	0.534	4.350
Food and kindred products	0.531	2.406
Agricultural services, forestry, and fishing	0.530	-1.469
Pipelines, except natural gas	0.493	5.254
Fabricated metal products	0.452	1.968
Textile mill products	0.439	2.615
Water transportation	0.411	7.846
Lumber and wood products	0.403	3.092
Nonmetallic minerals, except fuels	0.389	0.096
Metal mining	0.386	-1.357
Motor vehicles and equipment	0.337	3.027
Rubber and miscellaneous plastics products	0.306	2.466
Construction	0.296	1.545
Coal mining	0.287	2.061
Trucking and warehousing	0.286	4.461
Farms	0.137	1.383
TOTAL	1.000	3.091

<u>Table 6</u>

Variable	Pearson's (ordinary) Correlation with 8 (p-value)	Spearman's Rank Correlation with 8 (p-value)
1972-96 Annualized Growth rate of M^1	0.078 0.729	0.188 0.401
1972-96 Annualized Growth rate of M^2	-0.248 0.265	-0.183 0.416
1972-96 Mean of M^2	0.536 0.010	0.423 0.050

Table 7

X	Estimate of B_1: All Industries (n=55)	Estimate of B_1: Manufacturing Subset (n=32)
"Between" Regression: $\overline{SRD_i} = B_0 + B_1 \cdot \overline{X_i} + \varepsilon_i$		
M^2	0.449 (0.107)	0.517 (0.260)
dlog(M^2)	-0.049 (0.065)	-0.188 (0.260)
dlog(M^1)	-1.661 (8.211)	-19.697 (17.020)
"Within" Regression: $SRD_{it} - \overline{SRD_i} = B_0 + B_1 \cdot (X_{it} - \overline{X_i}) + \varepsilon$		
M^2	0.002 (0.002)	0.0051 (0.0026)
dlog(M^2)	0.013 (0.016)	0.0063 (0.0199)
dlog(M^1)	-0.003 (0.018)	-0.0092 (0.0238)
Total/First-difference: $SRD_{it} - SRD_{it-1} = B_0 + B_1 \cdot (X_{it} - X_{it-1}) + \varepsilon_i$		
M^2	0.024 (0.015)	0.0446 (0.0222)
dlog(M^2)	0.026 (0.015)	0.0448 (0.0194)
dlog(M^1)	0.025 (0.024)	0.0079 (0.0325)

Table 8 - Imputed ('s for Nonmfg sectors

Sector Name	(
Agriculture, forestry, and fisheries	0.0000
Metal mining	0.0000
Coal mining	0.0000
Natural Gas and Crude Petroleum extraction	0.0057
Non-metallic mining	0.0000
Construction	0.0000
Railroads	0.0305
Air transport	0.1038
Other transportation	0.0125
Communication services	0.1932
Electric utilities	0.0921
Gas utilities, and water and sanitary services	0.0131
Wholesale trade	0.0318
Retail trade, and restaurant and bars	0.0181
Finance and Insurance	0.0456
Real Estate	0.0751
Hotels, and personal and repair services (exc. auto)	0.0407
Business services	0.0604
Automobile services	0.0123
Movies and amusement parks	0.0409
Medical services	0.0857
Education, social services, membership organizations	0.0450