HIGH-TECH CAPITAL FORMATION AND ECONOMIC PERFORMANCE IN U.S. MANUFACTURING INDUSTRIES: AN EXPLORATORY ANALYSIS

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ABSTRACT

To what extent have investments in "high-tech" office and information technology capital "delivered" in terms of reducing costs and facilitating productivity growth? In this paper we report results of an exploratory effort examining relationships between investments in high-tech office and information technology capital (OF) and alternative industry performance measures such as labor and multifactor productivity, gross returns to capital, real *ex post* internal rates of return, and markups over variable costs.

Our data is at the two-digit manufacturing level of detail, annual from 1968 through 1986. The capital data on high-tech investment and capital is taken from the capital stock study published by the US Bureau of Economic Analysis, which in turn is based on BEA capital flow tables, input-output tables, and data from the Census and Annual Survey of Manufactures. The high-tech OF capital data is a Divisia quantity index comprising office, computing and accounting machinery, communications equipment, scientific and engineering instruments, and photocopy and related equipment.

Our principal findings are as follows. We find only very limited evidence indicating a positive correlation between industry profitability and OF/K, the share of OF capital in the total physical capital stock. However, when we employ industry-specific output deflators, results change considerably. For example, in terms of multifactor productivity (MFP) growth, we find that increases in OF/K are *negatively* correlated with growth in MFP; furthermore, rather than being aggregate labor-saving, increases in OF/K tend to be labor-using.

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I. INTRODUCTION

It is widely recognized that "high-tech" office and information (micro-electronic chip) technology has enormous potential for achieving major cost savings, particularly with respect to labor. Whether in practice such potential benefits to increased labor and multifactor productivity have in fact been realized is not nearly as well-recorded.[1] Indeed, in an earlier paper based on a highly structured dynamic model of cost and production (Morrison-Berndt [1991]), we obtained results suggesting that by 1986, in most two-digit US manufacturing industries, the marginal benefits of high-tech capital investments were less than marginal costs.

In this paper we report results of a much less structured approach, and thereby implicitly examine whether our earlier findings were simply due to our use of a highly structured, parameter-rich econometric model of production. In particular, using a variety of traditional measures of economic performance and multiple regression analysis, we report results of an examination of the extent to which high-tech capital has "delivered" as promised in US manufacturing industries.

That a topic such as this is addressed in a volume honoring the intellectual achievements of Zvi Griliches on the occasion of his 60th birthday is most fitting. Zvi's research on the diffusion of hybrid corn in the US agriculture sector (Griliches [1958]) pioneered in emphasizing the role of economic analysis in helping to understand the diffusion process -- the supply, the rate of acceptance and the equilibrium usage of a new product. This paper follows on that paradigm -- here we examine the cost and profitability effects of the diffusion of high-tech capital into US manufacturing industries. Moreover, throughout his distinguished research career, Zvi has emphasized the importance of measurement issues in undertaking and interpreting empirical research.[2] As we shall see, measurement issues are particularly important in interpreting findings concerning the impacts of high-tech capital formation.

It is also the case that Zvi's research has often focused on the labor market implications of various forms of technical progress, e.g., capital-skill complementarity as a framework for understanding why rates of return to education did not decline in the face of substantial increases in the supply of educated workers. Whether in US industries the increased diffusion of high-tech capital affects workers with varying skills and occupations in a neutral or non-neutral manner is an equally important issue today.[3] Finally, although Zvi has made numerous contributions to econometric theory and has employed the entire gamut of econometric tools in his empirical research, his research modus operandi has typically tended to favor the simpler rather than the more sophisiticated econometric artillery. In this paper, our econometric toolkit is a rather modest one -- ordinary least squares and multiple regression analysis.

Our focus in this exploratory data analysis paper is on the relationship between high-tech capital formation and various annual measures of overall economic performance for two-digit US manufacturing industries, 1968-86. We concentrate on the manufacturing industries since these industries have experienced substantial productivity growth in the last decade. If high-tech capital formation has had positive productivity impacts, one could argue that these impacts are most likely to reveal themselves through an analysis of the successful manufacturing industries. It is worth noting that, although sales of high-tech capital in the US are much greater to the non-manufacturing and service sectors than to manufacturing, it is the non-manufacturing sectors that have fared worst in terms of productivity growth, perhaps due in part to notorious difficulties in reliably measuring their real output growth.[4] Hence, here we limit our attention to the relatively successful two-digit manufacturing industries.

II. Measurement and Data Issues

> "Then the officers of the children of Israel came and cried unto Pharaoh, saying, Wherefore dealest thou thus with thy servants?
> There is no straw given unto thy servants, and they say to us, Make brick: and behold the servants are beaten; but the fault is in thine own people.
> But he said, Ye are idle, ye are idle: Therefore ye say, Let us go and do sacrifice to the Lord.
> Go therefore now, and work; for there shall no straw be given you, yet shall ye deliver the tale of bricks."
>
> Exodus 5:15-18[5]

IIa. DATA CONSTRUCTION AND INTERPRETATION

We begin with a discussion of measurement and data issues, starting with the concept of information and office technology equipment. Clear guidelines are not available to help define the concept of information technology capital, in part because there is as yet no well-articulated theory on precisely what tasks information technology performs.[6] For practical purposes, our possibilities are constrained considerably by the limited availability of public domain data, which at this point in time appears to be restricted to the data series constructed by John A. Gorman et al. [1985] and John Musgrave [1986] of the Bureau of Economic Analysis (BEA), U.S. Department of Commerce.

The interpretation of this BEA investment and capital stock data is somewhat problematic, since little documentation concerning data sources and data construction procedures is available. According to Gorman et al. [1985] and Musgrave [1986], U.S. National Income and Product Accounts (NIPA) annual investment expenditures by type of asset and by industry were allocated proportionally using two control totals. First, the BEA capital flow tables for 1963, 1967, 1972 and 1977 were employed so that asset types distributed to each industry summed to match industry investment control totals for equipment and for structures, where control totals were taken from the Census of Manufactures (1947, 1954, 1958, 1963, 1967, 1972 and 1977) or the Annual Survey of Manufactures.[7] Second, the sum of investment types by asset category across industries was set to equal the corresponding annual national control totals used in the NIPA.[8] Moreover, the equipment and structures control totals by industry were also adjusted to include capital expenditures by central administrative offices and auxiliaries, using data from the quinquennial Census Bureau publication, Enterprise Statistics. Other adjustments involved company vs. establishment units, a transformation from a use to an ownership basis, and from an input-output to a NIPA industry classification.

Based on this BEA investment and capital stock data, for each two-digit manufacturing industry we have constructed a "high tech" capital aggregate of office and information technology capital (hereafter, OF) as an implicit Divisia quantity index of four asset codes in the BEA data set: 14 -- office, computing and accounting machinery (including computing and related machines, typewriters, scales and balances, and office machines not elsewhere classified); 16 -- communications equipment; 25 -- scientific and engineering instruments; and 26 -- photocopy and related equipment. We have also constructed an equipment aggregate EQ consisting of all 24 components of non-OF producers' durable equipment, and a structures aggregate ST incorporating all 22 non-residential structure assets from the manufacturing industries.

The other set of data used in this paper is the annual output and input price and quantity data by two-digit manufacturing industry to 1986, provided us by Michael Harper of the US Bureau of Labor Statistics. The data series on gross output Y, aggregate labor L (where hours are computed as a sum of production and non-production worker hours), aggregate energy input N, and non-energy intermediate materials M were constructed by BLS personnel using data from the Census of Manufactures and the Annual Survey of Manufactures. The output and input deflators dealing with computers reflect adjustments for quality change incorporated by the Bureau of Economic Analysis.[9]

It should also be emphasized that these L, N and M data refer only to inputs utilized at production establishments, and do not incorporate input usage at the central administrative offices and auxiliaries of manufacturing firms. While this difference might affect the L, N and M measures, presumably the firm's measure of output is not materially affected by excluding central administrative offices and auxiliaries.

In terms of the L measure, attempts were made to obtain data based on the March CPS of households that asked respondents how many weeks they worked in the previous year, how many hours they worked in the survey week, what was their occupation and educational attainment, and in what industry did they do most of their work. In principle, such data should include hours estimates at the central administative offices and auxiliaries of manufacturing firms (hours excluded in the Census and ASM plant surveys), and also account for hours at work rather than hours paid for. Based on this data organized by Larry Rosenblum of the BLS, we had hoped to construct estimates of levels of hours by occupation, educational attainment, and industry. However, a preliminary data analysis suggested that this data, while perhaps appropriate for measuring the *distribution* of hours by industry, education and occupation, was not reliable for estimating the *level* of hours. For example, in four of the twenty industries (food, tobacco, apparel and miscellaneous manufacturing), simple correlations between the traditional BLS and this measure were *negative*, and in only four industries were the simple correlations greater than 0.8. For manufacturing in total, the simple correlation was 0.427. Given the uncertainties of the CPS-based data, we decided to retain the more "official" BLS data series on L constructed by Michael Harper and based on the Census of Manufactures and the ASM.[10]

Using tax and depreciation data series, BLS officials have also constructed annual rental price measures for the various types of capital equipment and structures.[11] We have modified their ex post rental price computation to obtain an ex ante measure by incorporating Moody's Baa corporate bond yield as the ex ante interest rate, and have set the capital gains term in the traditional Hall-Jorgenson rental price formulae to zero for each component of capital.[12] A Divisia price index was then constructed separately for the rental prices P_{EQ}, P_{ST} and P_{OF}, and implicit Divisia quantity indexes for EQ, ST and OF were also computed.

IIb. DATA TRENDS

With this outline of data construction procedures in mind, we turn now to an overview of summary statistics and notable trends. We begin with the capital and investment data. As is seen in Table 1, from 1976 to 1986 the aggregate capital intensity (computed as the simple sum of the three capital stock components, $K' \equiv EQ + ST + OF$, all divided by gross output Y, each in 1971$) has risen in seventeen of the twenty industries, with the only decreases in intensity occuring in textiles, lumber & wood and rubber. For total manufacturing, the increase from 1976 to 1986 has been about 25%. Thus the predominant trend across industries is one of increasing aggregate capital intensity in the last decade.

The composition of this net investment has also been changing in the last decade, as is shown in the final six columns of Table 1. In particular, from 1976 to 1986 the share of OF net investment in total EQ + ST + OF investment has increased dramatically -- by more than twenty percentage points

-- in ten of the twenty industries. It has increased by more than ten percentage points in four industries, and has fallen slightly (by less than ten percentage points) in only four industries. For total manufacturing, it has increased from 25.3% in 1976 to 36.8% in 1986. By 1986, in some industries the OF share of total investment is very large, e.g., 57% in printing and publishing, 66% in clay and glass, and 77% in non-electric machinery. Over the same 1976-86 time period, the share of non-OF equipment investment EQ has been falling in most industries (in all but food, leather and rubber), while the structures share of investment has fallen in fourteen and risen in six industries. Hence the dominant trend in the composition of net investment is one of increasing shares of OF investment, and decreasing shares of both EQ and ST investment.

Since capital stocks by asset type are constructed using the perpetual inventory method, the increasing share of OF *net investment* since 1976 should be expected to be reflected in corresponding increases in the share of *capital stocks* by asset type. Shares of stocks for EQ, ST and OF capital in selected years from 1968 onward are given in Table 2. As is seen in the first four columns of Table 2, in all industries except petroleum and fabricated metals, the EQ share of total capital stock has been falling over the 1968-1986 time period. Similarly, in all industries except apparel, rubber and leather, the ST share of total capital stock has been decreasing as well. But in 19 of the 20 industries (the lone exception is leather), the OF share of the total capital stock has been increasing; by 1986, the OF share is greater than 60% in non-electric machinery, and is larger than 40% in the printing and publishing, clay and glass, and instrument industries. For manufacturing industries in total, the EQ share of capital stock fell from 59% in 1968 to 49% in 1986, for ST the share fell from 35% to 25%, but for OF it increased from 6% to 26%.

In brief, the investment and capital stock data indicate quite clearly that in almost all US manufacturing industries, not only has the aggregate capital-output ratio risen implying enhanced capital intensity, but the share of office and information technology equipment in the total capital stock has also increased dramatically since 1968.

We now turn to the labor data. In the first column of Table 3, we tabulate the average annual growth rates (AAGR) of L over the 1968-86 time period, by industry. In thirteen industries, the AAGR is negative (the decline is greater than 2% in tobacco, leather, and primary metals), while in seven industries it is positive (larger than 1% in printng and publishing, rubber, and instruments). For manufacturing in total, the AAGR is -0.18%.

In the next four columns of Table 3, we present measures of aggregate labor intensity (L divided by gross output Y) for 1968, 1976, 1981 and 1986, while in the last column we tabulate the AAGR of the L/Y ratio. Noting that growth in average labor productivity is the negative of growth in the L/Y ratio, we see that labor intensity declined (labor productivity increased) in all industries, with particularly large increases in labor productivity occurring in food, textiles, apparel, paper, chemicals, machinery, electric machinery and instruments. For total manufacturing, the AAGR of labor productivity was 2.08%.

With these data trends in mind, we now move on to a discussion of results obtained from regression analysis, in which we relate industry profitability, multifactor productivity and labor productivity to overall capital intensity and changes in its composition.

III. REGRESSION ANALYSIS

We begin by focusing on alternative indicators of profitability, and then analyze effects on multifactor and average labor productivity.

IIIa. ECONOMIC PERFORMANCE AND HIGH-TECH CAPITAL FORMATION

To assess whether high-tech office and information technology equipment (OF) has a differential impact on industry profitability, we employ three alternative indicators of profitability: (i) economic or total input profitability, defined as revenue divided by total costs, where the capital components employ rental prices with ex ante costs of capital; (ii) accounting or variable input profitability, measured as the ratio of revenue to variable costs, where variable costs are total costs minus imputed costs to the various types of capital equipment and structures; and (iii) the ex post internal rate of return, computed as returns to capital (revenue minus variable costs, deflated by the Producer Price Index) divided by the aggregate capital stock K in constant 1971\$.[13] Notice that none of these profitability measures requires deflation of output by industry.

Each of these alternative profitability measures is regressed on a constant term, aggregate capital intensity K/Y (where K is a Divisia index of the various types of capital), the ratio of OF capital to total capital stock (OF/K), the ratio of EQ capital to total capital stock (EQ/K), and a time trend term; all variables except time are in logarithmic form.[14]

We begin with regressions by industry where the dependent variable is economic or total input profitability (revenue divided by total costs, or equivalently, the unit cost markup, defined as price over unit total cost). Results from such "within industry" regressions, using annual 1968-86 data, are presented in Table 4. As is shown in Table 4, in most (15 of 20) industries variations in aggregate capital intensity K/Y are positively correlated with economic profitability. However, in 13 of the 20 industries, the coefficient on OF/K is negative (often significant), implying that ceteris paribus, increases in the OF share of capital are correlated with *decreases* in industry economic profitability. A similar negative relationship occurs with the EQ ratio, and in fact this negative coefficient is typically larger in absolute value than the coefficient on OF/K. Finally, the estimated parameter on the time trend term is of mixed sign, being negative in 12 of the 20 industries, thereby reflecting the predominant negative trend in industry profitability over time.

As an alternative to these within industry regressions, we have introduced cross-sectional variation by estimating a pooled model with industry-specific intercepts, but common slope coefficients. This yields the estimated regression equation (hereafter, absolute values of t-statistics are in parentheses)

$$\begin{array}{l} \text{LUCMKP} = \text{dummies} - \underset{(1.97)}{0.042}{*}\ln(K/Y) + \underset{(2.74)}{0.022}{*}\ln(OF/K) + \underset{(0.74)}{0.038}{*}\ln(EQ/K) - \underset{(10.85)}{0.009}{*}t \end{array}$$

with an R^2 of 0.838, where LUCMKP denotes the logarithm of the unit cost markup. Notice that when cross-sectional variation is included, the slope coefficients have signs that differ from the predominant trends in the within industry regressions. In particular, profitability is negatively correlated with aggregate capital intensity, it is positively correlated with the high-tech intensity of the aggregate capital stock, and is positively correlated with EQ/K, although this last correlation is not statistically significant.

For completeness, we have also simply summed the various underlying variables across the two-digit industries to obtain total manufacturing measures, and then ran a regression using total manufacturing data. This yielded

$$\text{LUCMKP} = \underset{(0.36)}{0.484} - \underset{(2.09)}{0.230}{*}\ln(K/Y) - \underset{(0.89)}{0.059}{*}\ln(OF/K) - \underset{(0.51)}{0.340}{*}\ln(EQ/K) - \underset{(0.41)}{0.002}{*}t$$

with an R^2 of 0.781 and a Durbin-Watson of 1.202. Here the coefficients have signs consistent with predominant trends in Table 4, which is not surprising given that this is also a "within industry" regression. Apparently, these within regressions attribute the declining profitability of industries over time to simultaneous increases in aggregate capital intensity and high rates of OF capital formation, thereby generating negative coefficients. The differing pooled results suggest that some of this correlation may be spurious, and that accounting for this spurious correlation, the partial effect of OF/K on profitability may be positive.

In Table 5 we report regressions based on our second measure of profitability -- variable input or accounting profitability -- defined as the ratio of revenue to variable (non-capital) costs, and interpreted alternatively as the markup over variable costs. In these regressions LREVVC (the logarithm of revenue over variable costs) is the dependent variable, and the regressors are the same as in the previous profitability equation.

As is seen in Table 5, in 14 of the 20 industries, increases in K/Y are positively correlated with LREVVC (although only two are significant at the 95% confidence level), whereas in 14 of the 20 industries increases in OF/K are negatively correlated with LREVVC (five are significant). The predominant trend is that increases in EQ/K are also negatively correlated with LREVVC (in 15 of 20 industries, six of them statistically significant), and that a downward trend occurs with time (12 of 20 coefficient estimates are negative).

When pooled data are employed to introduce cross-sectional variation, the estimated equation becomes

$$\underset{}{\text{LREVVC}} = \text{dummies} + \underset{(4.23)}{0.068*\ln(K/Y)} + \underset{(0.27)}{0.002*\ln(OF/K)} - \underset{(0.02)}{0.010*\ln(EQ/K)} - \underset{(3.06)}{0.002*t}$$

with an R^2 of 0.948. Notice that the coefficient on aggregate capital intensity remains positive and significant (as was the predominant trend in the within regressions of Table 5), but that coefficients on the OF/K and EQ/K capital composition variables become much smaller in absolute value and are now statistically insignificant. Hence it appears that there is little support for increases in OF/K, <u>ceteris paribus</u>, being related to increases in this type of industry profitability, although profitability is positively related to aggregate capital intensity.

Finally, when data are summed to the total manufacturing level, we obtain the following regression result:

$$\underset{}{\text{LREVVC}} = \underset{(2.03)}{-1.095} + \underset{(2.73)}{0.119*\ln(K/Y)} - \underset{(0.93)}{0.025*\ln(OF/K)} - \underset{(3.10)}{0.827*\ln(EQ/K)} - \underset{(2.07)}{0.005*t}$$

with an R^2 of 0.841 and a Durbin-Watson of 1.952. Notice that while the coefficient on K/Y remains positive and significant, that on OF/K is negative and insignificant. High-tech capital appears to be no different than other capital in its effects on the ratio of revenue to variable costs.

Our third and final indicator of industry profitability is the <u>ex post</u> internal rate of return. Regression results with LEXPT as the dependent variable (the logarithm of the <u>ex post</u> internal rate of return, calculated as revenue minus variable costs, both deflated by the overall finished goods PPI, all divided by the constant 1971$ capital stock), based on the within industry estimations are presented in Table 6. There it is seen that, as expected given diminishing returns to capital, marginal increases in K/Y tend to reduce the average <u>ex post</u> internal rate of return (this occurs in 15 of 20 industries). The effect of OF/K is mixed, being negative in 13 and positive in 7 industries, and is seldomly significant. Changes in the EQ/K capital composition have a more consistent sign effect (negative in 16 industries), but parameter estimates vary sometimes rather wildly across industries.[15] The estimated time trend coefficient is negative in 12 of the 20 industries.

The pooled cross-section, time series regression of this industry profitability equation turns out to differ again somewhat from the predominant trends based on the within-industry regressions. Specifically, we obtain

$$\text{LEXPT} = \text{dummies} - \underset{(4.61)}{0.538*\ln(K/Y)} + \underset{(1.00)}{0.053*\ln(OF/K)} + \underset{(1.77)}{0.489*\ln(EQ/K)} - \underset{(4.02)}{0.018*t}$$

with an R^2 of 0.771. Notice that, as for the within industry regressions, the coefficient on aggregate capital intensity is negative, and here it is strongly significant. Although both capital composition coefficients are positive (unlike the preponderance of within-industry regressions), neither is significant at the 95% confidence level. Hence increases in the high-tech OF/K capital composition do not appear to have a significant impact on the real <u>ex post</u> internal rate of return, other things equal.

Finally, when the data are summed to the total manufacturing level, the regression equation obtained is of the form

$$\underset{(1.84)}{\text{LEXPT} = -7.619} - \underset{(0.16)}{0.054*\ln(K/Y)} - \underset{(0.72)}{0.146*\ln(OF/K)} - \underset{(2.22)}{4.534*\ln(EQ/K)} - \underset{(2.19)}{0.031*t}$$

with an R^2 of 0.769 and a Durbin-Watson test statistic of 1.939. Note that the signs of all four estimated slope coefficients are negative, but estimates on the aggregate capital intensity ln(K/Y) and high-tech capital share ln(OF/K) coefficients are statistically insignificant.

In summary, there is only a very limited amount of evidence suggesting that changes in the high-tech composition of aggregate capital (OF/K) are positively correlated with alternative indicators of profitability. This limited evidence emerges from the economic profitability (revenue over total cost) regressions, and occurs with pooled cross-section, time series data, rather than from the within-industry regressions. The predominant finding on profitability and high-tech capital is one of no significant relationship.

We now turn to multifactor productivity (MFP), another measure of industry performance. For each industry, we first compute the rate of MFP growth as the growth in output quantity minus the growth in aggregate input quantity, where aggregate input is a Divisia index of aggregate capital (with rental prices employing <u>ex ante</u> rates of return), labor, energy, and non-energy materials. The resulting growth rates of MFP are cumulated over time, cumulated MFP growth is then exponentiated, and the resulting time series is normalized to unity in the first year of the sample (1968).

In Table 7 we present regression results when the logarithm of MFP (LNMFP) is regressed on a constant term, time, and logarithms of K/Y, OF/K and EQ/K. There it is seen that the predominant trends are that changes in aggregate capital intensity are negatively correlated with LNMFP (in 15 of 20 industries), as are changes in the high-tech composition of capital (15 of the 20 OF/K coefficient estimates are negative). For equipment, the picture is more mixed, with 12 of the 20 coefficients being positive. Not surprisingly, most of the time coefficients (16 of 20) are positive (9 are statistically significant).

Since these within-industry time series regressions are potentially vulnerable to spurious contemporaneous negative correlations between OF/K and LNMFP, it is particular interesting to examine the pooled cross-section, time series results. These turn out to be

$$\underset{}{LNMFP} = \text{dummies} - \underset{(14.44)}{0.265}*\ln(K/Y) - \underset{(5.58)}{0.038}*\ln(OF/K) - \underset{(6.17)}{0.268}*\ln(EQ/K) + \underset{(11.01)}{0.008}*t$$

with an R^2 of 0.763. Notice that the coefficient on ln(OF/K) is small, negative and statistically significant, and smaller in absolute value than the coefficients on the ln(K/Y) and ln(EQ/K) variables. Apparently, the greater rates of investment in aggregate capital, and in the OF and EQ components of capital, have not resulted in greater growth in multifactor productivity. Similar results occur when the data is summed to the total manufacturing level, in which case the OLS equation turns out to be

$$LNMFP = \underset{(1.58)}{-1.017} - \underset{(0.76)}{0.039}*\ln(K/Y) - \underset{(2.50)}{0.079}*\ln(OF/K) - \underset{(1.07)}{0.340}*\ln(EQ/K) + \underset{(5.47)}{0.012}*t$$

with an R^2 of 0.943 and a Durbin-Watson test statistic of 1.563. It might also be noted that this empirical finding that increases in the high-tech composition of the capital stock, <u>ceteris paribus</u>, are correlated with lower multifactor productivity growth is robust to the inclusion of ln(Y) as a regressor.[16] Regressions with ln(Y) included are presented in Table 12.

This finding on the negative correlation between growth in OF/K and MFP is a provocative one, and opens up a number of issues. One perspective on this can be pursued by examining an alternative measure of productivity growth, that of average labor productivity, defined as Y/L. As noted in the previous section, labor intensity, defined as L/Y, is the reciprocal of average labor productivity. In the next sub-section, therefore, we examine trends in aggregate labor intensity in greater detail.

IIIb. HIGH-TECH CAPITAL FORMATION, LABOR INTENSITY, AND LABOR PRODUCTIVITY

Before presenting our empirical results on labor intensity and average labor productivity, we believe it is useful to digress briefly and provide some background about how one might interpret these regressions.

Suppose that one specified a Cobb-Douglas production function

$$\ln Y = \ln A + \beta_1 \cdot \ln L + \beta_2 \cdot \ln K^* + \beta_3 \cdot t \qquad (1)$$

where K^* is a "quality-adjusted" measure of aggregate capital affected by the composition of high-tech office and automation equipment OF and non-high tech equipment EQ, such that

$$K^* = K \cdot (OF/K)^{\delta} \cdot (EQ/K)^{\gamma}, \qquad (2)$$

which in logarithmic form is written as

$$\ln K^* = \ln K + \delta \cdot \ln(OF/K) + \gamma \cdot \ln(EQ/K). \qquad (3)$$

If high-tech capital is more productive per dollar of services than, say, other capital, then one would expect δ to be positive. On the other hand, if OF capital (and EQ capital) do not have any differential impact, then $\delta = \gamma = 0$.[17] If one substitutes (3) into (1), imposes constant returns to scale in L and K^* so that $\beta_1 + \beta_2 = 1$, and then solves for ln(L/Y), one obtains

$$\ln(L/Y) = \alpha_1 + \alpha_2 \cdot \ln(K/Y) + \alpha_3 \cdot \ln(OF/K) + \alpha_4 \cdot \ln(EQ/K) + \alpha_5 \cdot t \qquad (4)$$

where

$$\alpha_1 \equiv -\ln A/\beta_1,\ \alpha_2 \equiv (\beta_1-1)/\beta_1,\ \alpha_3 \equiv -\delta\cdot(1 - \beta_1)/\beta_1$$

$$\alpha_4 \equiv -\gamma\cdot(1 - \beta_1)/\beta_1, \text{ and } \alpha_5 \equiv -\beta_3/\beta_1. \tag{5}$$

Provided that $\beta_1 \neq 0$ (according to the Cobb-Douglas model, it should be positive and less than one), a test of the null hypothesis that high-tech capital is no different in its productivity than other capital is a test of $\delta = 0$, which in turn implies that α_3 in (4) is zero. On the other hand, if high-tech capital is more productive per dollar of services than other capital, then provided $0 < \beta_1 < 1$, $\delta > 0$ implies $\alpha_3 < 0$. Intuitively, if high-tech capital is more productive per dollar of services, then it should show up in reduced labor intensity, other things equal. A similar argument holds for EQ capital, in which case the γ and α_4 coefficients have analogous interpretations.

We have estimated the aggregate labor intensity equation (4); results from the within-industry regressions are presented in Table 9. As is seen there, only in one of the twenty industries (chemicals) is the coefficient on ln(OF/K) negative; this implies that, _ceteris paribus_, in the within-industry regressions increases in the share of high-tech capital OF/K are positively correlated with labor intensity, and therefore are negatively correlated with average labor productivity. Notice also that according to the Cobb-Douglas model (4), substitutability between capital and labor implies that α_2 (the coefficient on ln(K/Y) in (4)) should be negative; in the within industry regressions of Table 9, however, this coefficient is positive in 14 of the 20 industries. Hence there is a problem in trying to give these regression estimates a structural interpretation. It is also worth noting that the sign of the estimated coefficient on ln(EQ/K) is mixed, being evenly divided between negative and positive in the twenty industries. However, the coefficient on t is negative in all 20 industries.

When cross-sectional variation is introduced by estimating a pooled cross-section, time series model, the finding that increases in ln(OF/K) are positively correlated with aggregate labor intensity (and hence negatively correlated with average labor productivity) persists:

$$\begin{array}{l} \text{LNLY} = \text{dummies} + \underset{(9.57)}{0.239*\ln(K/Y)} + \underset{(4.67)}{0.043*\ln(OF/K)} + \underset{(5.97)}{0.352*\ln(EQ/K)} - \underset{(22.14)}{0.022*t} \end{array}$$

with an R^2 of 0.981. The coefficient on ln(EQ/K) is positive and even larger than that on ln(OF/K), and the coefficient on ln(K/Y) is also positive, consistent with the predominant trend in the within-industry regressions of Table 9.

When the underlying data are summed to the total manufacturing level, the time series regression results are as follows:

$$\text{LNLY} = \underset{(1.73)}{-1.752} - \underset{(2.12)}{0.174*\ln(K/Y)} + \underset{(2.15)}{0.107*\ln(OF/K)} - \underset{(1.69)}{0.849*\ln(EQ/K)} - \underset{(10.02)}{0.035*t}$$

with an R^2 of 0.983 and a Durbin-Watson test statistic of 1.432. Note that in this total manufacturing equation, the coefficient on ln(OF/K) remains positive and statistically significant.

We conclude, therefore, that based on these aggregate labor intensity regressions, the rapid accumulation of high-tech office and automation equipment capital has not been labor-saving, but instead is correlated with increases in labor intensity and decreases in average labor productivity. Moreover, this finding is robust among the various time series and pooled cross-section, time series regressions.

In the final two tables of this paper we present results from log-log regressions without the Cobb-Douglas constant returns to scale and capital quality structural interpretations imposed. Specifically, in Table 10 the dependent variable is LNL (the natural logarithm of labor hours -- in levels, not the input-output coefficient), and the regressors include a constant term, a time trend, and natural logarithms of levels of OF, EQ, ST and Y (note that ln K is not included as a regressor, since all its components are separate regressors). As is seen in Table 10, coefficient estimates on ln(OF) are positive in 13 industries (significantly so in seven of them), coefficient estimates on ln(EQ) are also positive in 13 industries, but estimates on ln(ST) are negative in 14 of 20 industries. The coefficient on ln(Y) is positive and less than unity in all industries, consistent with short-run increasing returns to aggregate labor; the time trend coefficient is negative in all 20 industries.

The pooled cross-section, time series data of this unconstrained Cobb-Douglas equation yield the following regression results:

$$\underset{}{LNL} = \text{dummies} + \underset{(4.85)}{.038*\ln(OF)} + \underset{(3.67)}{.115*\ln(EQ)} - \underset{(2.13)}{.075*\ln(ST)} + \underset{(25.81)}{.616*\ln(Y)} - \underset{(19.53)}{.018*t}$$

with an R^2 of 0.997. When instead the underlying data are summed to the total manufacturing level of aggregation, we obtain

$$LNL = \underset{(0.96)}{0.384} + \underset{(4.34)}{.121*\ln(OF)} - \underset{(1.78)}{.375*\ln(EQ)} + \underset{(0.31)}{.054*\ln(ST)} + \underset{(10.91)}{.997*\ln(Y)} - \underset{(7.95)}{.029*t}$$

with an R^2 of 0.935 and a Durbin-Watson test statistic of 1.301. In both cases the coefficient on ln(OF/K) is positive and significant.

We conclude, therefore, that the preponderant finding from these aggregate labor level regressions is that holding output and other types of capital stocks fixed, increases in high-tech office and information technology equipment are positively correlated with aggregate labor hours; consistent with our earlier findings, high-tech capital formation does not appear to be aggregate labor-saving.

As yet one more check on the robustness of these results, we have estimated a Cobb-Douglas production function equation (Eq. (1) with Eq. (3) substituted in, but without the constant returns to scale restrictions imposed) where the dependent variable is the natural logarithm of value-added (deflated gross output minus deflated intermediate materials). Results are presented in Table 11. Again, the striking finding from this table is that in 15 of the 20 industries, the coefficient on ln(OF) is negative -- and significantly so in six cases. Increases in high-tech capital, ceteris paribus, have not contributed commensurately to growth in output.

IV. INTERPRETATION OF RESULTS

For economists studying rational choices made by profit-maximizing firms, it is somewhat difficult at best to conclude that, like lemmings gone to sea, US manufacturing firms have irrationally over-invested in high-tech office and information technology capital. While it is possible that the results reported above could be interpreted in such a manner, we are most reluctant to do so -- if for no other reason than the fact that both authors of this paper are admitted high-tech "junkies" convinced that computerization offers enormous potential benefits. But how might one explain our findings? What mis-specifications or measurement issues might help interpret these results?

One possible hypothesis is that installing computer equipment, transferring files from one computer and operating system to another, and learning how to use new hardware and software takes time, i.e., there are adjustment costs. One should not expect this year's investment to generate productivity this year, but perhaps in a year or two, after learning and other adjustments have occurred. This suggests that it would be useful to examine how robust the results are when one includes as additional regressors one or more lagged terms involving ln $(INOF/K)_{t-\tau}$, where INOF is annual real gross investment in high-tech capital, divided by that year's entire capital stock.[18]

We have performed additional pooled cross-section, time series regressions in which each of the five performance variables is regressed on a constant, ln(K/Y), ln (OF/K), ln (EQ/K), t, as well as the lagged variables ln $(INOF/K)_{t-12}$ and ln $(INOF/K)_{t-2}$. In terms of the profitability variables, hardly anything changes. In the unit markup equation with LUCMKP as regressand, although the coefficient estimate on ln $(INOF/K)_{t-1}$ is positive and significant (.032, t=3.31), that on ln $(INOF/K)_{t-2}$ is insignificant (-.011, t=1.17), but that on ln (OF/K) changes minimally from .022 (t=2.74) to 0.020 (t=2.45). With LREVVC (accounting or variable cost profitability) as regressand, neither of the two lagged ln (INOF/K) terms is significant, and the parameter estimate on ln (OF/K) remains essentially unchanged -- from .002 (t=0.27) to .005 (t=0.74). Finally, with LEXPT (log of the real ex post internal rate of return) as dependent variable, again neither of the two lagged ln (INOF/K) terms is significant, and the coefficient on ln (OF/K) falls slightly from .053 (t=1.00) to .042 (t=0.94). Hence, none of the profitability equations is changed substantively when lagged high-tech investment terms are incorporated.

The strongly negative findings in the two productivity equations are also robust to inclusion of these lagged terms. When LNMFP (multifactor productivity) is the regressand, the coefficient on ln$(INOF/K)_{t-1}$ is positive and significant (.026, t=3.22), that on ln $(INOF/K)_{t-2}$ is insignificant (-.007, t=0.86), but the parameter estimate on ln (OF/K) becomes slightly more negative -- changing from -.038 (t=5.58) to -.040 (t=5.75). When in addition ln Y is included to account for possible pro-cyclicality of MFP growth, the coefficient on ln (OF/K) falls even more -- to 0.042 (t=6.27). In the labor intensity equation with LNLY as regressand, the estimated adverse impact of high-tech capital intensity is even larger when lagged investment terms are added. While the coefficient estimate on ln $(INOF/K)_{t-1}$ is negative and significant indicating some gradual adjustment (-.047, t=4.31), that on ln $(INOF/K)_{t-2}$ is insignificant (.007, t=0.65), but that on the high-tech capital intensity variable ln (OF/K) increases from .043 (t=4.67) to 0.49

(t=5.22). These results suggest, therefore, that allowing for lagged adjustment does not change any of qualitative findings concerning the effects of high-tech capital formation.

However, it is of interest to note that while high-tech capital formation appears to have "delivered" in terms of one profitability measure -- the unit cost markup (recall that the estimate on ln (OF/K) remains positive and significant), it is in the two productivity equations that high-tech capital intensity appears consistently to have the most adverse impact. An intriguing hypothesis that emerges is that in these two productivity equations industry-specific output deflators are employed, and thus it is possible that errors in adjusting for quality change in the measurement of output lead to the apparent adverse impact of computerization on productivity. In our judgment, this measurement issue merits careful attention in future research.

V. SUMMARY AND CONCLUDING REMARKS

Our purpose in this paper has been to report results from an exploratory effort examining empirical relationships among investments in high-tech office and information technology capital and industry performance measures such as labor productivity, multifactor productivity, and various profitability measures.

Our findings can be summarized as follows. While limited evidence indicates a positive relationship between one measure of profitability and the high-tech intensity of industry capital stock, for both other measures of profitability the relationship is insignificantly different from zero. However, for both measures of productivity (labor and multifactor productivity), there is a statistically significant negative relationship between productivity growth and the high-tech intensity of the capital stock. All these findings are robust to the inclusion of lagged investment terms, suggesting that the results cannot be explained as simply reflecting the lagged effects of learning and gradual adjustment. It is also worth noting that the results suggesting adverse productivity impacts of high-tech capital intensity are based on data construction procedures involving use of industry-specific output deflators. Hence it is possible that the negative productivity results are due to measurement problems in failing to account properly for quality changes in the measurement of real output.

In placing our findings into context, it is useful to comment briefly on other related recent research. In a paper by J. Bradford DeLong and Lawrence H. Summers [1990] based on an international cross-section of country data, it is argued that social rates of return to equipment investment are greater than 30%, that the spillovers from equipment investment are very substantial, and that equipment investment has a highly beneficial impact on economic growth. The DeLong-Summers data base does not permit them to separate high-tech from other equipment capital, a distinction that is central to this paper. More importantly, however, DeLong-Summers note that when the data sample is confined to high-productivity countries, the relationship between equipment investment and economic growth disappears, for the "identifying variance" in their regressions comes "...from a comparison of East Asia to South America" ([1990, p. 20]).[19] Note that the data in this study come from the twenty two-digit manufacturing industries of the US -- all from a high-productivity country.

Finally, a related set of recent studies has examined the effects of computerization on the wage rates of employees. An intriguing finding reported by Alan Krueger [1991] is that employees whose work involves computers receive an approximate 15% wage premium over other workers, when controlling for education, age, experience and computer use at home. Similarly, Ann P. Bartel and Frank R. Lichtenberg [1991] find that industries with relatively young or immature technologies pay higher wages to workers of given age and education than do industries with mature technologies.

Together these intriguing findings point to a mystery: What is it that these high-tech workers do, for which they are paid a premium, but does not seem to show up in measured output and productivity growth? That is indeed a fascinating issue, and pointing to this empirical puzzle is a most appropriate way of concluding a paper celebrating the 60th birthday of Zvi Griliches.

FOOTNOTES

[1]For recent surveys, see Brynjolfsson [1991], Wilson [1992], and the references cited therein. Also see Bresnahan [1986], Dudley-Lasserre [1989], Jonscher [1987], Morrison-Berndt [1991], Parsons et al. [1990] and Osterman [1986]. The effects of a more general notion of high-tech capital are examined by Bregman, Fuss and Regev [1991].

[2]For a set of representative discussions, see Part I in Griliches [1988].

[3]Due to overall space and paper length constraints, in this paper we are not able to address the issue of the employment distribution impacts of high-tech capital formation; see, however, Berndt, Morrison and Rosenblum [1992].

[4]For a recent discussion of measurement issues, see Zvi Griliches [1992].

[5]Quoted by Zvi Griliches [1974], p. 971.

[6]On this, see Kevin Crowston and Thomas Malone [1988].

[7]For years prior to 1963, the 1963 table was employed, and for years after 1977, the 1977 table was used. For other years in the 1963-86 time period, interpolations were performed between the 1963, 1967, 1972 and 1977 tables. The 1982 input/output table, incidentally, is to be available in mid-1992.

[8]As we understand it, the NIPA breakdown by asset type is based on domestic production, export and import data; direct data on investment by detailed asset type are not available for use in estimating asset-specific national investment.

[9]On this, see Cole et al. [1986], Cartwright [1986], and Berndt-Griliches [1990].

[10]For further discussion, see Berndt-Morrison [1992].

[11]Discussion of rental price construction methods and references to appropriate BLS publications are found in Harper et al. [1989].

[12]In the BLS data base, the depreciation rates for each asset follow a hyperbolic pattern and are not necessarily constant over time; depreciation rates for the EQ, ST and OF composites also vary across industries and time due to changes in the composition of the stocks. In fact, however, the depreciation rates tend to be very stable over time for each asset. For 1986, the capital stock-weighted average depreciation rates for EQ in the machinery, chemicals and iron and steel industries are approximately 6, 8 and 6%, respectively, for ST they are all about 4%, and for OF the weighted-average depreciation rates for these three industries are 17, 15 and 14%, respectively.

[13]The data series on the Producer Price Index is that for total finished goods, and is taken from the 1990 Economic Report of the President, Table C-63, p. 365.

[14]Results of regressions using a linear rather than a log-log functional form yielded qualitatively similar results, and are available from the authors upon written request.

[15]This volatility may be due in part to the fact that in some industries, the EQ/K ratio is virtually constant from 1968 to 1986.

[16]Note that one might want to include ln Y as a regressor, since it is widely believed that growth in productivity is procyclical. However, our measure of the rental price of capital that weights capital growth uses an <u>ex ante</u> cost of capital, rather than the <u>ex post</u> internal rate of return. With the pooled cross-section time series data, the results are

$$\underset{}{\mathrm{LNMFP}} = \text{dummies} - \underset{(8.09)}{0.175*\ln(K/Y)} - \underset{(6.67)}{0.043*\ln(OF/K)} - \underset{(6.07)}{0.248*\ln(EQ/K)}$$

$$+ \underset{(8.21)}{0.006*\text{time}} + \underset{(6.88)}{0.146*\ln(Y)} \qquad R^2 = 0.791$$

Results based on data summed to the total manufacturing level are

$$\mathrm{LNMFP} = \underset{(1.38)}{-1.120} - \underset{(0.69)}{0.038*\ln(K/Y)} - \underset{(2.41)}{0.788*\ln(OF/K)} - \underset{(1.06)}{0.360*\ln(EQ/K)}$$

$$+ \underset{(4.18)}{0.012*t} + \underset{(0.22)}{0.012*\ln(Y)} \qquad R^2 = 0.943, \quad DW = 1.58$$

[17]This formulation of quality is closely related to that put forth in the education and labor context by Zvi Griliches [1970].

[18]For a related approach, see Pakes-Griliches [1984].

[19]Further, there is a considerable literature on the measurement of investment spillovers, much of it in the context of assessing social rates of return to research and development expenditures. More credible ways of measuring spillovers, as discussed in, for example, Griliches [1988, Part III) and Griliches [1991], are not considered by DeLong-Summers.

Table 1

CAPITAL INTENSITY AND INVESTMENT COMPOSITION, U.S. MANUFACTURING

	Aggregate K' Intensity		Net Investment Shares (%)					
			EQ		ST		OF	
Industry	1976	1986	1976	1986	1976	1986	1976	1986
Food	.743	.788	46.7	48.6	31.6	29.2	21.6	22.3
Tobacco	.608	1.571	58.4	42.9	24.7	24.9	16.9	32.2
Textiles	1.454	1.279	61.1	56.7	33.6	26.7	5.3	16.6
Apparel	.424	.432	47.8	23.2	37.3	41.2	14.9	35.7
Lumber & Wood	1.491	1.206	73.3	50.4	24.0	34.1	2.7	15.5
Furniture & Fixture	.676	.775	29.8	25.3	52.3	25.3	18.0	49.5
Paper	2.001	2.176	73.0	57.4	17.2	13.6	9.8	29.1
Printing & Publish	1.040	1.426	44.9	28.3	28.3	14.5	26.8	57.2
Chemicals	2.371	2.490	39.8	37.8	15.8	24.1	44.4	38.1
Petroleum	1.613	2.167	45.0	39.0	38.6	44.8	16.4	16.3
Rubber	1.368	1.109	69.4	72.4	26.7	24.5	3.9	3.1
Leather	.554	.860	49.0	50.4	54.3	47.1	-3.3	2.5
Clay & Glass	2.002	2.891	51.2	20.7	17.8	13.4	31.0	66.0
Primary Metals	2.353	3.387	61.5	60.3	18.0	22.4	20.4	17.3
Fabricated Metals	.975	1.247	68.3	54.9	26.3	17.6	5.4	27.5
Machinery	1.080	1.819	35.6	15.1	22.1	7.7	42.3	77.2
Electric Machinery	1.084	1.336	45.6	33.3	26.0	17.1	28.4	49.6
Instrument	.869	1.298	46.0	28.3	33.5	13.2	20.5	58.5
Transporta tion Equi	1.035	1.260	64.6	45.9	21.2	19.1	14.2	35.1
Misc. Mfg.	.799	1.094	57.8	37.9	30.8	28.1	11.4	34.0
Total Mfg.	1.227	1.531	51.1	42.2	23.6	21.1	25.3	36.8

Notes: The aggregate capital intensity K'/Y is computed as the simple sum of the three capital stock components (EQ, ST and OF) divided by gross output, all in 1971$.

Table 2

CAPITAL STOCK COMPOSITION -- EQ, ST and OF CAPITAL SHARES, U.S. MANUFACTURING (%)

Industry	EQ/K' 1968	1976	1981	1986	ST/K' 1968	1976	1981	1986	OF/K' 1968	1976	1981	1986
Food	56.5	54.2	52.1	50.4	38.2	37.0	34.2	32.2	5.4	8.8	13.7	17.5
Tobacco	52.3	49.7	50.5	46.2	39.1	39.0	37.4	32.6	8.6	11.3	12.0	21.2
Textiles	65.4	66.1	66.3	63.6	30.5	29.3	29.2	28.5	4.0	4.7	4.5	7.8
Apparel	62.6	59.2	54.2	44.1	31.9	32.4	30.3	34.0	5.5	8.4	15.5	21.9
Lumber & Wood	64.1	69.5	69.7	63.3	33.3	29.0	26.9	30.5	2.6	1.5	3.4	6.3
Furniture & Fixtures	51.3	50.4	43.7	35.0	45.5	45.1	42.2	35.9	3.2	4.4	14.0	29.1
Paper	70.6	70.7	70.8	66.0	28.0	25.7	21.6	18.3	1.5	3.6	7.6	15.7
Printing & Publishing	62.5	59.3	51.2	39.4	32.7	32.5	27.2	20.3	4.8	8.2	21.6	40.3
Chemicals	59.8	54.6	48.0	44.3	31.2	27.1	23.8	23.7	9.0	18.3	28.3	32.0
Petroleum	24.7	33.1	37.8	38.3	71.4	60.7	51.0	46.7	3.9	6.2	11.2	15.0
Rubber	74.9	73.8	72.6	71.7	23.3	24.3	24.8	25.7	1.8	1.9	2.6	2.6
Leather	62.4	61.0	59.8	58.5	34.1	36.4	37.7	39.2	3.5	2.6	2.5	2.3
Clay & Glass	62.9	63.5	51.4	39.2	34.5	29.4	22.2	19.3	2.6	7.1	26.3	41.5
Primary Metals	62.8	64.0	62.4	61.4	33.7	29.8	25.3	23.8	3.5	6.1	12.3	14.8
Fabricated Metals	62.8	66.9	66.6	63.0	31.1	29.4	26.4	23.5	6.1	3.7	7.0	13.5
Machinery	53.4	46.9	35.7	24.8	31.5	29.3	21.0	13.8	15.1	23.9	43.3	61.4
Electric Machinery	52.4	55.4	47.9	40.0	35.4	31.0	26.2	21.4	12.2	13.6	25.9	38.6
Instruments	51.1	51.4	46.9	37.4	38.6	37.7	32.8	22.0	10.3	10.8	20.3	40.6
Transportation Equipt.	67.0	68.6	66.7	58.1	29.4	26.8	22.3	21.6	3.6	4.6	11.0	20.4
Misc. Mfg.	49.5	53.7	54.0	48.8	39.3	37.7	34.5	32.7	11.2	8.6	11.5	18.5
Total Mfg.	**59.0**	**58.6**	**54.8**	**49.3**	**35.0**	**31.8**	**27.4**	**25.0**	**6.0**	**9.5**	**17.8**	**25.7**

Notes: Total capital K' in this table is defined as K'≡EQ+ST+OF, where all are in constant 1971 dollars. The shares are defined accordingly.

Table 3

LABOR GROWTH RATES (1968-86, %AAGR) and LABOR-OUTPUT RATIOS

Industry	AAGR L	Aggregate Labor Intensity L/Y 1968	1976	1981	1986	AAGR %
Food	-0.61%	.207	.162	.148	.133	-2.43%
Tobacco	-2.01	.143	.118	.112	.109	-1.50
Textiles	-1.88	.502	.355	.306	.262	-3.55
Apparel	-1.16	.468	.390	.343	.312	-2.23
Lumber & Wood	0.34	.445	.373	.358	.309	-2.01
Furniture & Fixtures	0.61	.433	.345	.312	.311	-1.82
Paper	-0.08	.420	.341	.304	.258	-2.67
Printing & Publishing	1.93	.493	.456	.434	.426	-0.81
Chemicals	0.01	.384	.293	.271	.241	-2.55
Petroleum	-0.38	.112	.095	.109	.084	-1.59
Rubber	1.94	.408	.359	.356	.313	-1.46
Leather	-4.73	.484	.439	.415	.392	-1.16
Clay & Glass	-0.39	.421	.381	.379	.352	-0.99
Primary Metals	-2.81	.389	.348	.326	.319	-1.10
Fabricated Metals	-0.76	.372	.361	.354	.324	-0.76
Machinery	0.21	.496	.381	.321	.236	-4.04
Electric Machinery	0.54	.534	.407	.333	.275	-3.62
Instruments	1.61	.544	.377	.353	.316	-2.97
Transportation Eqpt	-0.38	.420	.316	.350	.294	-1.96
Misc. Mfg.	-0.63	.424	.348	.332	.346	-1.12
Total Mfg.	**-0.18**	**.387**	.313	.301	**.265**	**-2.08**

Notes: AAGR denotes average annual growth rate. L is the sum of production and nonproduction worker labor hours calculated by the BLS, using data from the Census and Annual Survey of Manufactures.

Table 4

ECONOMIC PROFITABILITY OR UNIT TOTAL COST MARKUP ($p_Y/[C/Y]=p_Y \cdot Y/C$) REGRESSIONS
(absolute value of t-statistics in parentheses)

Industry	C	ln(K/Y)	ln(OF/K)	ln(EQ/K)	t	R^2
Food	-1.362 (2.10)	.157* (3.09)	-.256* (2.49)	-3.731* (2.42)	-.006 (1.20)	.837
Tobacco	1.097 (1.72)	.859* (7.35)	-.229* (2.37)	.246 (0.93)	-.045* (9.30)	.939
Textiles	.333 (0.34)	.274 (1.38)	.037 (0.29)	.078 (0.06)	-.002 (0.27)	.771
Apparel	-.389 (0.79)	.031 (0.41)	-.058 (0.72)	-.231* (3.16)	-.002 (0.32)	.833
Lumber & Wood	-1.592* (2.30)	.148 (0.52)	-.181* (2.46)	-1.448 (2.02)	.010 (1.32)	.515
Furniture & Fixtures	-.233 (0.17)	.160 (1.22)	.018 (0.22)	-.346 (0.49)	-.009 (1.14)	.368
Paper	-.709 (1.41)	.205 (1.58)	.094 (0.89)	-4.023* (2.58)	-.008 (0.54)	.716
Printing & Publishing	1.120 (1.87)	.282* (5.41)	.102* (2.55)	.675 (0.74)	-.009* (2.44)	.700
Chemicals	.257 (1.01)	.309* (3.07)	-.050 (0.68)	.971 (2.11)	.014* (2.41)	.863
Petroleum	-1.057* (2.28)	.054 (0.41)	-.094 (2.13)	-1.134* (2.99)	.018* (2.44)	.768
Rubber	-1.791 (1.61)	.093 (0.57)	-.115 (1.31)	-3.331 (1.36)	-.014 (1.92)	.632
Leather	-2.637* (3.46)	.212* (3.36)	-.308 (2.09)	-.722 (1.95)	-.040* (7.30)	.951
Clay & Glass	-.664 (1.72)	-.010 (0.04)	-.098 (1.81)	-.300 (0.68)	.012 (1.12)	.461
Primary Metals	1.483 (1.56)	-.221* (2.18)	.143 (1.14)	5.882* (2.29)	-.003 (0.37)	.864
Fabricated Metals	-3.399* (3.36)	.052 (0.73)	-.234* (3.61)	-6.308* (3.57)	.036* (3.17)	.694
Machinery	1.051 (0.76)	-.030 (0.55)	.157 (0.51)	2.152 (1.03)	.023 (1.70)	.866
Electric Machinery	-.901 (0.69)	-.053 (0.49)	-.205 (0.76)	-.827 (0.79)	.003 (0.23)	.600
Instruments	-.872 (1.02)	.105 (1.37)	.029 (1.27)	-1.231 (1.33)	-.006 (1.37)	.866
Transportation Equipt	-1.683* (3.96)	-.320* (3.33)	-.143* (2.30)	-4.222* (4.62)	-.003 (0.48)	.864
Misc. Mfg.	-.819 (0.87)	.169 (1.39)	-.099 (1.30)	-.457 (0.93)	.003 (0.40)	.479

Table 5

ACCOUNTING PROFITABILITY OR UNIT VARIABLE COST MARKUP ($p_Y \cdot Y/VCOST$) REGRESSIONS
(absolute value of t-statistics in parentheses)

Industry	C	ln(K/Y)	ln(OF/K)	ln(EQ/K)	t	R^2
Food	-2.183* (2.87)	.110 (1.84)	-.323* (2.67)	-6.199* (3.42)	-.015* (2.50)	.563
Tobacco	1.751 (1.58)	.827* (4.08)	-.108 (0.65)	.281 (0.61)	-.028* (3.28)	.669
Textiles	-.824 (1.97)	.155 (1.80)	-.062 (1.12)	-1.664* (2.89)	.004 (1.09)	.650
Apparel	.402 (1.05)	.016 (0.27)	.056 (0.90)	.073 (1.28)	-.003 (0.59)	.368
Lumber & Wood	- .484 (1.51)	.205 (1.55)	-.083* (2.43)	-.668 (2.00)	.007 (2.10)	.452
Furniture & Fixtures	-.327 (0.90)	.063 (1.85)	.009 (0.44)	-.380 (2.07)	-.003 (1.77)	.714
Paper	.241 (1.16)	.041 (0.78)	.133* (3.07)	-2.182* (3.40)	-.016* (2.68)	.692
Printing & Publishing	.455 (1.09)	.091* (2.50)	.044 (1.60)	.049 (0.08)	-.004 (1.61)	.631
Chemicals	-.058 (0.38)	.214* (3.59)	-.156* (3.59)	-.168 (0.62)	.005 (1.56)	.885
Petroleum	-1.356* (2.27)	.147 (0.87)	-.147* (2.60)	-1.562* (3.21)	.026* (2.65)	.805
Rubber	-.935 (2.09)	.058 (0.89)	-.063 (1.78)	-2.065 (2.08)	-.008* (2.76)	.743
Leather	-.965* (2.37)	-.145* (4.28)	-.092 (1.17)	-.260 (1.31)	-.0002 (0.05)	.707
Clay & Glass	-.135 (0.82)	.066 (0.52)	-.040 (1.72)	-.317 (1.68)	.005 (0.99)	.307
Primary Metals	.118 (0.29)	-.137* (3.18)	-.009 (0.17)	.415 (0.38)	-.0006 (0.17)	.843
Fabricated Metals	-1.309* (3.18)	.010 (0.34)	-.085* (3.23)	-2.572* (3.58)	.017* (3.73)	.755
Machinery	.700 (0.53)	-.001 (0.02)	.093 (0.32)	.983 (0.50)	.008 (0.58)	.649
Electric Machinery	.007 (0.008)	-.024 (0.32)	-.006 (0.34)	-.178 (0.25)	-.002 (0.23)	.151
Instruments	-.434 (0.67)	.016 (0.28)	.049* (2.81)	-.922 (1.31)	-.009* (2.70)	.879
Transportation Equipt	-.561 (1.38)	-.138 (1.50)	-.028 (0.47)	-2.558* (2.93)	-.009 (1.72)	.771
Misc. Mfg.	-.610 (0.80)	-.021 (0.22)	-.032 (0.52)	-.402 (1.00)	.007 (1.25)	.319

Table 6

EX-POST INTERNAL RATE OF RETURN REGRESSIONS IN LOGARITHMS
(absolute value of t-statistics in parentheses)

Industry	C	ln(K/Y)	ln(OF/K)	ln(EQ/K)	t	R^2
Food	-14.818*	-.256	-2.259*	-32.396*	-.048	.615
	(2.79)	(0.61)	(2.67)	(2.57)	(1.16)	
Tobacco	2.384	.610	-.197	.716	-.051*	.821
	(1.51)	(2.11)	(0.83)	(1.09)	(4.25)	
Textiles	-5.501	.112	-.037	-10.345*	-.008	.571
	(1.60)	(0.16)	(0.08)	(2.18)	(0.26)	
Apparel	2.166	-.612	.706	.153	-.067	.556
	(0.47)	(0.86)	(0.93)	(0.22)	(1.19)	
Lumber & Wood	-5.328*	.060	-.599*	-3.717	.044	.291
	(2.11)	(0.06)	(2.23)	(1.42)	(1.57)	
Furniture & Fixtures	-7.919	-.081	.048	-5.444*	-.049	.708
	(1.62)	(0.17)	(0.17)	(2.19)	(1.84)	
Paper	-1.049	-.629	.741*	-13.631*	-.081*	.517
	(0.87)	(2.03)	(2.94)	(3.66)	(2.38)	
Printing & Publishing	-.969	-.071	.244	-4.060	-.048*	.796
	(0.31)	(0.26)	(1.19)	(0.86)	(2.61)	
Chemicals	-1.119	.134	-.452	-.102	.020	.779
	(1.51)	(0.45)	(2.11)	(0.08)	(1.17)	
Petroleum	-3.234	.517	-.153	-4.784	.064	.637
	(1.17)	(0.66)	(0.59)	(2.12)	(1.44)	
Rubber	-10.619*	-.087	-.554	-18.883*	-.071*	.686
	(2.72)	(0.15)	(1.80)	(2.18)	(2.82)	
Leather	-15.012*	-2.529*	-.912	-4.049	-.015	.784
	(2.84)	(5.75)	(0.89)	(1.57)	(0.41)	
Clay & Glass	-3.110*	-.433	-.280	-2.091	.040	.277
	(2.47)	(0.45)	(1.59)	(1.46)	(1.09)	
Primary Metals	4.697	-2.495*	0.665	23.100	-.009	.827
	(0.73)	(3.66)	(0.79)	(1.34)	(0.17)	
Fabricated Metals	-16.337*	-.781*	-.974*	-26.816*	.181*	.560
	(3.83)	(2.58)	(3.56)	(3.59)	(3.82)	
Machinery	2.845	-1.166*	.527	8.382	.071	.814
	(0.21)	(2.27)	(0.18)	(0.42)	(0.54)	
Electric Machinery	-3.252	-1.025	-.318	-3.174	-.029	.482
	(0.35)	(1.32)	(0.16)	(0.42)	(0.35)	
Instruments	-4.860	-.839	.260	-5.891	-.070*	.827
	(0.94)	(1.81)	(1.86)	(1.06)	(2.56)	
Transportation Equipt	-21.423*	-2.701	-1.940	-54.853*	.022	.635
	(2.76)	(1.54)	(1.71)	(3.29)	(0.23)	
Misc. Mfg.	-5.303	-.888	-.148	-2.356	.044	.168
	(0.82)	(1.06)	(0.28)	(0.70)	(0.88)	

Table 7

MULTIFACTOR PRODUCTIVITY REGRESSIONS (IN LOGARITHMS)
(absolute value of t-statistics in parentheses)

Industry	C	ln(K/Y)	ln(OF/K)	ln(EQ/K)	t	R^2
Food	-1.276 (1.45)	.038 (0.55)	-.207 (1.48)	-2.460 (1.17)	.007 (1.07)	.887
Tobacco	-2.349* (4.73)	-.597* (6.57)	-.017 (0.23)	-.957* (4.63)	.015* (4.01)	.940
Textiles	.148 (0.18)	-.257 (1.52)	.003 (0.29)	.762 (0.67)	.009 (1.21)	.939
Apparel	-.653 (0.94)	-.116 (1.09)	-.125 (1.10)	.194 (1.87)	.026* (3.02)	.958
Lumber & Wood	-.450 (1.63)	.052 (0.46)	-.050 (1.70)	-.289 (1.01)	.013* (4.34)	.836
Furniture & Fixtures	.825 (1.52)	-.080 (1.55)	.049 (1.53)	.505 (1.83)	.005 (1.74)	.932
Paper	-1.282* (3.97)	-.121 (1.46)	-.074 (1.10)	-2.258* (2.26)	.024* (2.64)	.915
Printing & Publishing	.464 (1.01)	-.030 (0.76)	.017 (0.54)	.938 (1.34)	.004 (1.50)	.201
Chemicals	.355* (2.50)	-.134* (2.38)	.108* (2.62)	1.438* (5.53)	.024* (7.30)	.926
Petroleum	-.011 (0.07)	.019 (0.43)	-.094* (6.26)	.330* (2.54)	.003 (1.21)	.865
Rubber	-1.162 (1.85)	-.084 (0.92)	-.150* (3.03)	-.867 (0.62)	.007 (1.68)	.806
Leather	-1.425 (2.08)	-.122 (2.14)	-.453* (3.42)	.390 (1.17)	-.005 (0.99)	.670
Clay & Glass	-.240* (2.21)	.008 (0.10)	-.043* (2.82)	.018 (0.15)	.010* (3.34)	.486
Primary Metals	-.206 (0.21)	-.108 (1.03)	-.069 (0.53)	.433 (0.16)	-.001 (0.12)	.766
Fabricated Metals	1.444 (2.06)	-.026 (0.53)	.123* (2.74)	2.506 (2.05)	-.014 (1.83)	.766
Machinery	-1.637 (1.05)	-.019 (0.32)	-.285 (0.82)	-2.649 (1.13)	-.011 (0.71)	.956
Electric Machinery	-.536 (0.76)	-.123 (2.13)	-.040 (0.28)	-.254 (0.45)	.018* (2.94)	.981
Instruments	.483 (1.10)	-.045 (1.13)	-.082* (6.88)	.924 (1.94)	.017* (7.34)	.979
Transportation Equipt	-.938* (2.57)	-.202* (2.45)	-.111 (2.09)	-.861 (1.10)	.014* (3.09)	.673
Misc. Mfg.	-.409 (0.26)	.124 (0.62)	-.187 (1.50)	.052 (0.06)	.005 (0.44)	.317

Table 8

MULTIFACTOR PRODUCTIVITY REGRESSIONS (IN LOGARITHMS)
(absolute value of t-statistics in parentheses)

Industry	C	ln(K/Y)	ln(OF/K)	ln(EQ/K)	ln(Y)	t	R^2
Food	.371 (0.37)	.065 (1.07)	-.189 (1.57)	-3.331 (1.82)	-.403* (2.47)	.008 (1.42)	.923
Tobacco	-3.025* (5.64)	-.295 (1.85)	-.048 (0.70)	-.592* (2.40)	.850* (2.20)	.004 (0.69)	.956
Textiles	.581 (0.51)	-.256 (1.48)	-.00002 (0.002)	1.259 (0.86)	-.075 (0.56)	.010 (1.27)	.941
Apparel	-.601 (0.82)	-.133 (1.10)	-.141 (1.12)	.207 (1.83)	-.047 (0.35)	.028* (2.58)	.958
Lumber & Wood	-.286 (0.96)	-.030 (0.24)	-.074* (2.18)	-.304 (1.09)	-.136 (1.31)	.016* (4.31)	.856
Furniture & Fixtures	1.071 (1.82)	-.116 (1.88)	.051 (1.61)	.601 (2.08)	-.066 (1.06)	.007 (2.04)	.937
Paper	-1.169* (2.81)	-.124 (1.45)	-.078 (1.11)	-2.263* (2.19)	-.050 (0.45)	.026* (2.55)	.917
Printing & Publishing	.845 (1.41)	-.025 (0.63)	.033 (0.94)	1.025 (1.45)	-.090 (0.99)	.005 (1.72)	.257
Chemicals	.355 (0.86)	-.134 (2.10)	.108 (1.92)	1.427* (4.10)	.0002 (0.002)	.024* (5.49)	.926
Petroleum	-.101 (0.48)	.021 (0.47)	-.090* (5.38)	.290 (2.02)	.024 (0.69)	.003 (1.14)	.869
Rubber	-1.158 (1.69)	-.085 (0.84)	-.151* (2.87)	-.862 (0.59)	-.002 (0.02)	.007 (1.37)	.806
Leather	-1.428 (2.00)	-.126 (1.10)	-.458* (2.60)	.391 (1.13)	-.010 (0.04)	-.005 (0.57)	.670
Clay & Glass	-.422 (1.98)	.059 (0.61)	-.042* (2.77)	-.062 (0.42)	.067 (0.99)	.009* (2.79)	.522
Primary Metals	1.956 (1.31)	-.361 (2.14)	.045 (0.34)	3.712 (1.22)	-.346 (1.83)	-.001 (0.18)	.814
Fabricated Metals	2.067* (3.08)	.058 (1.01)	.195* (3.88)	4.340* (3.24)	.143* (2.29)	-.027* (3.07)	.833
Machinery	-3.443 (2.06)	.110 (1.31)	-.563 (1.65)	-4.418 (1.93)	.214 (2.03)	-.029 (1.76)	.967
Electric Machinery	-.611 (0.80)	-.142 (1.70)	-.070 (0.40)	-.382 (0.54)	-.027 (0.33)	.020* (2.16)	.981
Instruments	.413 (0.91)	-.027 (0.58)	-.077* (5.59)	.941 (1.95)	.060 (0.79)	.014* (2.92)	.980
Transportation Equipt	-1.056* (2.92)	.014 (0.08)	-.063 (1.02)	-.017 (0.02)	.185 (1.44)	.008 (1.30)	.718
Misc. Mfg.	-.932 (0.58)	.233 (1.06)	-.145 (1.12)	-.087 (0.11)	.248 (1.13)	.004 (0.30)	.378

Table 9

LABOR INTENSITY REGRESSIONS WITH LNLY AS DEPENDENT VARIABLE
(absolute value of t-statistics in parentheses)

Industry	C	ln(K/Y)	ln(OF/K)	ln(EQ/K)	t	R^2
Food	-.436 (0.43)	.019 (0.23)	.091 (0.56)	2.496 (1.03)	-.017 (2.12)	.988
Tobacco	-.563 (1.18)	.106 (1.21)	.109 (1.51)	.342 (1.72)	-.027* (7.45)	.896
Textiles	-.848 (0.82)	-.067 (0.32)	.128 (0.93)	-1.759 (1.23)	-.040* (4.24)	.979
Apparel	1.206 (1.12)	.395* (2.39)	.281 (1.60)	-.106 (0.66)	-.051* (3.87)	.976
Lumber & Wood	.160 (0.44)	.204 (1.37)	.100* (2.59)	.400 (1.06)	-.022* (5.47)	.906
Furniture & Fixtures	-1.754 (1.97)	.276* (3.27)	.010 (0.18)	-1.004* (2.21)	-.029* (5.89)	.966
Paper	.009 (0.03)	.059 (0.66)	.010 (0.14)	1.681 (1.56)	-.030* (3.10)	.985
Printing & Publishing	-.778 (0.83)	.070 (0.86)	.026 (0.42)	-.782 (0.55)	-.018* (3.30)	.873
Chemicals	-1.958* (5.35)	.136 (0.94)	-.311* (2.95)	-2.994* (4.51)	-.050* (5.94)	.940
Petroleum	-1.541 (1.12)	-.178 (0.46)	.326* (2.51)	-.315 (0.28)	-.026 (1.16)	.481
Rubber	1.401 (1.67)	.045 (0.37)	.284* (4.27)	2.160 (1.16)	-.013* (2.31)	.889
Leather	-1.718 (1.54)	.051 (0.55)	.128 (0.59)	-.864 (1.59)	-.016 (1.97)	.754
Clay & Glass	-.798* (5.22)	-.003 (0.03)	.016 (0.74)	-.340 (1.95)	-.015* (3.47)	.892
Primary Metals	-.052 (0.09)	.218* (3.46)	.146 (1.88)	-.081 (0.05)	-.030* (6.08)	.895
Fabricated Metals	.906 (0.87)	-.015 (0.20)	.092 (1.37)	3.484 (1.91)	-.028* (2.44)	.903
Machinery	.191 (0.06)	-.072 (-.60)	.145 (0.21)	.921 (0.20)	-.033 (1.06)	.964
Electric Machinery	1.692 (1.82)	.184* (2.40)	.413* (2.15)	1.441 (1.93)	-.054* (6.62)	.992
Instruments	-.318 (0.40)	-.048 (0.67)	.172* (8.01)	-.581 (0.67)	-.047* (11.20)	.988
Transportation Equipt	2.341* (4.51)	.317* (2.70)	.456* (6.01)	3.727* (3.34)	-.058* (8.85)	.929
Misc. Mfg.	1.015 (0.75)	.578* (3.30)	.164 (1.50)	.564 (0.79)	-.023* (2.22)	.735

Table 10

AGGREGATE LABOR QUANTITY REGRESSIONS WITH LNL AS DEPENDENT VARIABLE
(absolute value of t-statistics in parentheses)

Industry	C	ln(OF)	ln(EQ)	ln(ST)	ln(Y)	t	R^2
Food	-.574 (0.42)	-.148 (1.11)	.889 (1.74)	-.747 (1.68)	.663* (2.74)	-.011 (1.74)	.928
Tobacco	-.230 (0.84)	.147* (3.16)	-.233 (1.48)	-.244 (1.83)	.097 (0.53)	-.011* (2.62)	.960
Textiles	.624* (2.22)	.102 (1.00)	.077 (0.20)	-.243 (0.54)	.703* (3.14)	-.035* (4.40)	.969
Apparel	1.733 (1.96)	.186 (1.04)	.016 (0.15)	.092 (0.69)	.422* (2.09)	-.037 (2.41)	.907
Lumber & Wood	-.152 (0.42)	.102* (2.25)	.238 (1.92)	-.123 (0.61)	.813* (4.95)	-.022* (4.50)	.825
Furniture & Fixtures	.221 (0.76)	.034 (0.69)	-.773 (1.88)	1.064* (2.16)	.762* (7.37)	-.032* (5.39)	.897
Paper	-.262 (0.65)	-.061 (1.05)	.480* (2.20)	-.387* (2.63)	.623* (6.93)	-.017* (2.45)	.882
Printing & Publishing	1.217 (1.92)	.095 (1.88)	.355 (0.65)	-.364 (0.70)	.392* (2.61)	-.009 (1.30)	.985
Chemicals	2.348* (10.18)	.204* (3.65)	-.805* (2.31)	.465 (1.57)	.457* (4.50)	-.030* (4.01)	.826
Petroleum	1.160 (1.56)	-.029 (0.28)	.628 (1.29)	-.795* (3.26)	.373 (1.46)	-.033* (2.24)	.723
Rubber	-.980 (1.41)	.193* (4.54)	1.005* (2.33)	-1.280* (2.74)	.806* (9.92)	-.001 (0.34)	.983
Leather	.263 (0.37)	.082 (0.29)	-.764 (1.48)	.686 (1.46)	.885* (3.70)	-.019 (1.31)	.980
Clay & Glass	-.224* (2.27)	-.002 (0.19)	-.090 (1.53)	-.128* (2.25)	.923* (15.99)	-.010* (4.41)	.985
Primary Metals	-2.134* (2.40)	-.151 (1.51)	3.053* (2.91)	-2.656* (2.99)	.704* (15.85)	-.055* (5.92)	.993
Fabricated Metals	-1.09* (2.57)	-.035 (1.97)	.735 (1.17)	-.751 (1.29)	.923* (10.38)	-.018 (1.63)	.947
Machinery	-.312 (0.29)	-.357 (1.23)	1.644 (0.99)	-1.856 (1.24)	.806* (6.88)	.022 (0.61)	.895
Electric Machinery	.669* (3.02)	.143* (2.80)	.375 (1.58)	-.512 (1.91)	.757* (12.51)	-.044* (5.34)	.968
Instruments	.367 (1.16)	.167* (2.77)	-.438 (0.90)	.152 (0.30)	.900* (9.04)	-.036* (4.97)	.985
Transportation Equipt	1.487* (3.30)	.247* (6.28)	-.054 (0.17)	-.383 (1.93)	.765* (7.39)	-.044* (5.63)	.899
Misc. Mfg.	1.256* (4.94)	.034 (0.62)	.648* (2.54)	-.372 (1.42)	.093 (0.77)	-.018* (3.44)	.832

Table 11

COBB-DOUGLAS REGRESSIONS WITH LV (Value Added) AS DEPENDENT VARIABLE
(absolute value of t-statistics in parentheses)

Industry	C	ln(OF)	ln(EQ)	ln(ST)	ln(L)	t	R^2
Food	3.137	-.150	-.272	.316	-.140	.035	.939
	(1.31)	(0.53)	(0.27)	(0.27)	(0.20)	(1.56)	
Tobacco	.954*	-.106	.762*	-1.047*	.551	.029*	.827
	(4.74)	(0.82)	(2.49)	(3.49)	(0.95)	(3.69)	
Textiles	-1.284	-.369*	2.008*	-1.454*	1.440*	.064*	.899
	(2.29*)	(3.07)	(2.64)	(2.29)	(4.05)	(8.21)	
Apparel	-1.072	-.061	-.462*	.591*	1.076*	.045	.941
	(0.82)	(0.24)	(2.68)	(4.37)	(3.16)	(1.71)	
Lumber & Wood	.255	-.100	.443	-.151	.700*	.026*	.886
	(0.61)	(1.38)	(1.66)	(0.79)	(2.83)	(3.55)	
Furniture & Fixtures	-.510	.030	-1.337	1.090	1.164*	.029*	.959
	(1.24)	(0.42)	(1.84)	(1.85)	(6.76)	(3.26)	
Paper	.207	.148	1.394*	-1.366	1.565*	.031	.947
	(0.18)	(0.86)	(2.98)	(1.96)	(4.25)	(1.85)	
Printing & Publishing	.459	-.057	-.574	.684	.613	.014	.971
	(0.50)	(0.76)	(0.82)	(0.94)	(2.08)	(1.48)	
Chemicals	-3.079*	-.373	-.524	1.376*	1.174*	.059*	.962
	(2.87)	(3.97)	(0.82)	(2.68)	(3.12)	(5.91)	
Petroleum	-.616	-.414*	.166	.929*	.438	.014	.908
	(0.97)	(5.64)	(0.51)	(2.29)	(1.69)	(0.86)	
Rubber	.949	-.305*	1.821*	-1.600*	1.145*	.009	.980
	(0.84)	(3.52)	(2.48)	(2.26)	(6.60)	(1.16)	
Leather	-2.867*	-.956*	-.580	1.592*	.811*	-.0001	.916
	(3.49)	(3.34)	(1.02)	(2.62)	(3.62)	(0.008)	
Clay & Glass	.024	-.033	.478*	-.169	.875*	.018*	.934
	(0.13)	(1.50)	(4.10)	(1.48)	(6.92)	(4.01)	
Primary Metals	7.826*	.478	9.153*	-10.616*	1.403*	.139*	.968
	(2.89)	(1.60)	(3.29)	(3.24)	(7.96)	(4.29)	
Fabricated Metals	1.124*	.087*	2.160*	-2.265*	1.134*	.046*	.918
	(2.22)	(3.67)	(2.58)	(2.51)	(8.97)	(2.76)	
Machinery	-.172	.235	.0002	.408	.741*	.003	.977
	(0.10)	(0.46)	(0.00007)	(0.14)	(3.40)	(0.05)	
Electric Machinery	-1.138*	-.042	.484	-.389	1.260*	.049*	.994
	(2.60)	(0.46)	(1.05)	(0.96)	(9.81)	(3.36)	
Instruments	-.174	-.140	-.172	.465	.771*	.037*	.993
	(0.38)	(1.60)	(0.25)	(0.69)	(5.50)	(6.49)	
Transportation Equipt	-2.065*	-.262*	.607	-.014	1.175*	.047*	.911
	(2.71)	(3.55)	(2.02)	(0.03)	(6.42)	(3.32)	
Misc. Mfg.	1.898	-.150	1.073	.285	-.316	-.010	.410

(0.94)	(0.58)	(0.76)	(0.19)	(0.23)	(0.28)

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