Productivity, Computerization, and Skill Change

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November 23, 2001

Main Findings:

1. Using pooled cross-section, time-series data for 44 industries over the decades of the 1960s, 1970s, and 1980s in the United States, I find no econometric evidence that computer investment is positively linked to TFP growth (over and above its inclusion in the TFP measure).
2. However, computerization is positively associated with occupational restructuring and changes in the composition of intermediate inputs and capital coefficients.
3. There is modest evidence that the growth of worker skills is positively related to industry productivity growth. The effects are very modest -- adding at most 0.07 percentage points to annual labor productivity growth.

Outline:

Section 1 reviews some of the pertinent literature on the role of skill change and computerization on productivity changes in the U.S. economy.

Section 2 introduces the accounting framework and model.

Section 3 presents descriptive statistics on postwar productivity trends. Descriptive statistics are also presented for key variables that have shaped the pattern of productivity growth over the postwar period.

In Section 4, multivariate analysis is conducted on the industry level to assess their influence.

Concluding remarks are made in Section 5.

1. Review of Previous Literature

Human capital theory views schooling as an investment in skills and hence as a way of augmenting worker productivity (see, for example, **Schultz, 1960**, and **Becker, 1975**).

Griliches (1970) estimated that the increased educational attainment of the U.S. labor force accounted for one-third of aggregate technical change between 1940 and 1967.

Denison (1979) estimated that about one-fifth of the growth in U.S. national income per person employed between 1948 and 1973 could be attributed to increases in educational levels of the labor force.

Jorgenson and Fraumeni (1993) calculated that improvements in labor quality accounted for one fourth of U.S. economic growth between 1948 and 1986.

Yet, some anomalies have appeared in this line of inquiry. **Denison (1983)** in his analysis of the productivity slowdown in the U.S. between 1973 and 1981, reported that the growth in national income per person employed (NIPPE) fell by 0.2 percentage points whereas increases in educational attainment contributed a **positive** 0.6 percentage points to the growth in NIPPE.

Maddison (1982) reported similar results for other OECD countries for the 1970-1979.

Wolff (2001), using various series on educational attainment among OECD countries, found no statistically significant effect of the growth in mean years of schooling on the growth in GDP per capita among OECD countries over the period from 1950 to 1990.

Most of the earlier studies failed to find any excess returns to IT

Bailey and Gordon (1988) examined aggregate productivity growth in the U.S. and found no significant contribution of computerization.

Loveman (1988) reported no productivity gains from IT investment

Parsons, Gotlieb, and Denny (1993) estimated very low returns on computer investments in Canadian banks

Berndt and Morrison (1995) found negative correlations between labor productivity growth and high-tech capital investment in U.S. manufacturing industries.

Wolff (1991) found that the insurance industry had a negative rate of total factor productivity growth over the 1948-1986 period in the U.S. even though it ranked fourth among 64 industries in terms of computer investment.

The later studies generally tend to be more positive.

Both **Siegel and Griliches (1992)** and **Steindel (1992)** estimated a positive and significant relationship between computer investment and industry-level productivity growth.

Oliner and Sichel (1994) reported a significant contribution of computers to aggregate U.S. output growth.

Lichtenberg (1995) estimated firm-level production functions and found an excess return to IT equipment and labor.

Siegel (1997), using detailed industry-level manufacturing data for the U.S., found that computers are an important source of quality change and that, once correcting output measures for quality change, computerization had a significant positive effect on productivity growth.

Brynjolfsson and Hitt (1996, 1998) found a positive correlation between firm-level productivity growth and IT investment over the 1987-1994 time period when accompanied by organizational changes.

Lehr and Lichtenberg (1998) used data for U.S. federal government agencies over the 1987-1992 period and found a significant positive relation between productivity growth and computer intensity.

Lehr and Lichtenberg (1999) investigated firm-level data among service industries over the 1977-1993 period and also reported evidence that computers, particularly personal computers, contributed positively and significantly to productivity growth.

Ten Raa and Wolff (2000), developing a new measure of direct and indirect productivity gains, found that the computer sector was the leading sector in the U.S. economy during the 1980s as a source of economy-wide productivity growth. They also found very high productivity spillovers between the computer-producing sector and sectors using computers. In their imputation procedure, these large spillovers were attributable to the high rate of productivity growth within the computer industry.

Sitroh (1998) and **Jorgenson and Stiroh (1999, 2000)** used a growth accounting framework to assess the impact of computers on output growth. Jorgenson and Stiroh (1999) calculated that one sixth of the 2.4 percent annual growth in output can be attributed to computer outputs, compared to about zero percent over the 1948-1973 period. The effect came from capital deepening rather than from enhanced productivity growth.

Oliner and Sichel (2000) provides strong evidence for a substantial role of IT in the recent spurt of productivity growth during the second half of the 1990s. Using aggregate time-series data for the U.S., they found that both the use of IT in sectors purchasing computers and other forms of Information Technology, as well as the production of computers, appear to have made an important contribution to the speed-up of productivity growth in the latter part of the 1990s.

Hubbard (2001) investigated how on-board computer adoption affected capacity utilization in the U.S. trucking industry between 1992 and 1997. He found that their use improved communications and resource allocation decisions and led to a 3 percent increase in capacity utilization within the industry.

2. **Modeling Framework**

I begin with a standard neoclassical production function f_j for sector j:

$$(1) \qquad X_j = Z_j f_j(K_{Cj}, K_{Ej}, K_{Sj}, L_j, N_j, R_j)$$

where X_j is the (gross) output of sector j, K_{Cj} is the input of IT-related capital, K_{Ej} is the input of other machinery and equipment capital goods, K_{Sj} is the input of plant and other structures, L_j is the total

labor input, N_j are total intermediate inputs, R_j is the stock of research and development (R&D) capital, and Z_j is a (Hicks-neutral) total factor productivity (TFP) index that shifts the production function of sector j over time. This is a modification of Stiroh (2002)'s framework.

$$(2) \quad d \ln X_j = d \ln Z_j + \varepsilon_{Cj}\, d \ln K_{Cj} + \varepsilon_{Ej}\, d \ln K_{Ej} + \varepsilon_{Sj}\, d \ln K_{Sj} + \varepsilon_{Lj}\, d \ln L_j + \varepsilon_{Nj}\, d \ln N_j + \varepsilon_{Rj}\, d \ln R_j$$

where ε represents the output elasticity of each input and $d \ln Z_j$ is the rate of Hicks-neutral TFP growth. If we now impose the assumption of competitive input markets and constant returns to scale, it follows that an input's factor share (α_j) will equal its output elasticity. Let us now employ the standard measure of TFP growth p_j for sector j:

$$(3) \quad p_j \equiv d \ln X_j/dt - \alpha_{Cj}\, d \ln K_{Cj}/dt - \alpha_{Ej}\, d \ln K_{Ej}/dt - \alpha_{Sj}\, d \ln K_{Sj}/dt - \alpha_{Lj}\, d \ln L_j/dt - \alpha_{Nj}\, d \ln N_j/dt$$

It then follows that:

$$(4) \quad p_j = d \ln Z_j/dt + \alpha_{Rj}\, d \ln R_j/dt$$

In particular, in the standard neoclassical model, there is no special place reserved for IT capital in terms of its effect on TFP growth.

As Stiroh (2002) argues, there are several reasons why we might expect the standard necoclassical model to fail in the case of the introduction of a radically new technology that might be captured by IT investment. These include the presence of productivity spillovers from IT, problems of omitted variables, the presence of embodied technological change, measurement error in variables, and reverse causality. If for one of these reasons, the output elasticity of IT ε_{Cj} exceeds its measured input share α_{Cj} , say by u_{Cj}, then

$$(5) \quad p_j = d \ln Z_j/dt + \alpha_{Rj}\, d \ln R_j/dt + u_{Cj}\, d \ln K_{Cj}/dt$$

In other words, conventionally measured TFP growth p_j will be positively correlated with the growth in ICT capital.

A similar argument applies to labor productivity growth, LP, defined as:

(6) $LP_j \equiv d \ln X_j/dt - d \ln L_j/dt$

If we again impose the assumption of competitive input markets and constant returns to scale, it follows that:

(7) $LP_j = d \ln Z_j/dt + \alpha_{Cj}\, d \ln k_{Cj}/dt + \alpha_{Ej}\, d \ln k_{Ej}/dt + \alpha_{Sj}\, d \ln k_{Sj}/dt + \alpha_{Nj}\, d \ln n_j/dt + \alpha_{Rj}\, d \ln R_j/dt$

where lower case symbols indicate the rate of growth of the input per worker. If for the reasons cited above there is a special productivity "kick" from IT investment, then the estimated coefficient of k_{Cj}/dt should exceeds its factor input share.

I now include the change in average worker skills in the production function. There are two possible approaches. Let the effective labor input E = QL, where Q is a measure of average worker quality (or skills). Then (1) can be rewritten as:

(10) $X_j = Z_j f^*_j(K_{Cj}, K_{Ej}, K_{Sj}, E_j, N_j, R_j)$

Again assuming competitive input markets and constant returns to scale (to the traditional factors of production) and still using (6) to define labor productivity growth, we obtain:

(11) $LP_j = d \ln Z_j/dt + \alpha_{Cj}\, d \ln k_{Cj}/dt + \alpha_{Ej}\, d \ln k_{Ej}/dt + \alpha_{Sj}\, d \ln k_{Sj}/dt + \alpha_{Nj}\, d \ln n_j/dt + \alpha_{Lj}\, d \ln Q_j/dt + \alpha_{Rj}\, d \ln R_j/dt$

In this formulation, the rate of labor productivity growth should increase directly with the **rate of growth** of average worker quality or skills.

The second approach derives from the standard human capital earnings function. From Mincer

(1974),

$$\text{Ln } w = a_o + a_1 S$$

where w is the wage, S is the worker's level of schooling (or skills), and a_0 and a_1 are constants. It follows that

$$(d\text{Ln } w)/dt = a_i(dS/dt)$$

By definition, the wage share in sector j is $\alpha_{Lj} = wL_j/Y_j$. Under the assumptions of competitive input markets and constant returns to scale, $\alpha_{Lj} = \varepsilon_{Lj}$, a constant. Therefore, $Y_j/L_j = w/\varepsilon_{Lj}$. In this case, effective labor input E is given by the equation: Ln E = Q + ln L.It follows from (6) that

$$(12) LP_j = d \ln Z_j/dt + \alpha_{Cj}\, d \ln k_{Cj}/dt + \alpha_{Ej}\, d \ln k_{Ej}/dt + \alpha_{Sj}\, d \ln k_{Sj}/dt + \alpha_{Nj}\, d \ln n_j/dt + \alpha_{Lj}\, dQ_j/dt + \alpha_{Rj}\, d \ln R_j/dt$$

In other words, the rate of labor productivity growth should be proportional to the **change in the level** of average worker quality or skills over the period.

Productivity growth and changes in input composition usually go hand in hand. To see this, let me first introduce three new matrices:

A = 45-order matrix of technical interindustry input-output coefficients, where a_{ij} is the amount of input i used per constant dollar of output j.

C = 45-order matrix of capital coefficients, where c_{ij} is the net stock of capital of type i (in 1992 dollars) used per constant dollar of output j.

M = occupation-by-industry employment coefficient matrix, where m_{ij} shows the employment of occupation i in industry j as a share of total employment in industry j.

Since for any input I in sector j, $\alpha_{Ij} = p_I I_j / p_j X_j$, where p is the price, I can rewrite equation (3):

(8) $$p_j = - [\Sigma_i \; p_i \, da_{ij} \; + \Sigma_i \; p_{i,c} \, dc_{ij} \; + \Sigma_i \; w_i \, db_{ij}] / p_j$$

where p_i is the price of intermediate input i, $p_{i,c}$ is the price of capital input i, $b_{ij} = m_{ij} L_j / X_j$ is the total employment of occupation i per unit of output in industry j, and w_i is the wage paid to workers in occupation i. In this formulation, it is clear that measured TFP growth reflects changes in the composition of intermediate inputs, capital inputs, and occupational employment. Using the multiplication rule for derivatives, we can rewrite equation (8) as:

(9) $$p_j = - [\Sigma_i \; p_i \, da_{ij} \; + \Sigma_i \; p_{i,c} \, dc_{ij} \; + \Sigma_i \; w_i \lambda_j \, dm_{ij} + \Sigma_i \; w_i m_{ij} \, d\lambda_j] / p_j$$

where $\lambda_j = L_j / X_j$. From (5) it follows that in the circumstances enumerated above, there may be a positive correlation between measures of coefficient changes (such as da_{ij}, dc_{ij} , and dm_{ij}) and IT investment.

Though productivity growth and changes in input composition are algebraically related, there are several reasons why they may deviate. First, there are costs of adjustments associated with radical restructuring of technology, so that there may be a considerable time lag between the two (see David, 1991, for example). Second, while new technology is generally used to lower costs and hence increase measured output per unit of input, new technology might be used for other purposes such as product differentiation or differential pricing. Third, in the case of services in particular, output measurement problems might prevent us from correctly assessing industry productivity growth. This problem could, of course, be partly a consequence of product differentiation and price discrimination. Measures of structural change may therefore provide a more direct and robust test of the effects of computerization on changes in technology than standard measures of productivity growth. This is particularly so in the case when a radically new technology is introduced and the consequent adjustment period is lengthy.

3. **Descriptive Statistics**

(13) $$SI^{12} = \frac{S_i\, m^1_{ij} m^2_{ij}}{[S_i\, (m^1_{ij})^2 \;\; S_i\, (m^2_{ij})^2]^{1/2}}$$

(14) $$DIOCCUP^{12} = 1 - SI^{12}$$

(15) $$DIACOEFF^{12} = 1 - \frac{S_i\, a^1_{ij} a^2_{ij}}{[S_i\, (a^1_{ij})^2 \;\; S_i\, (a^2_{ij})^2]^{1/2}}$$

(16) $$DIKCOEFF^{12} = 1 - \frac{S_i\, c^1_{ij} c^2_{ij}}{[S_i\, (c^1_{ij})^2 \;\; S_i\, (c^2_{ij})^2]^{1/2}}$$

B. Skills

1. Substantive Complexity (SC) is a composite measure of skills derived from a factor analytic test of DOT variables. It was found to be correlated with General Educational Development, Specific Vocational Preparation (training time requirements), Data (synthesizing, coordinating, analyzing), and three worker aptitudes - Intelligence (general learning and reasoning ability), Verbal and Numerical.

2. Interactive Skills (IS) can be measured, at least roughly, by the DOT "People" variable, which, on a scale of 0-8, identifies whether the job requires mentoring (0), negotiating (1), instructing (2), supervising (3), diverting (4), persuading (5), speaking-signaling (6), serving (7) or taking instructions (8). For comparability with the other measures, this variable is rescaled so that its value ranges from 0 to 10 and reversed so that mentoring is now scored 10 and taking instructions is scored 0.

3. Motor Skills (MS) is another DOT factor-based variable. Also scaled from 0 to 10, this measure reflects occupational scores on motor coordination, manual dexterity and "things" - job requirements that range from setting up machines and precision working to feeding machines and handling materials.

4. Composite Skills (CS). I also introduce a measure of composite skill, CS, which is based on a regression of hourly wages in 1970 on SC, MS, and IS scores across the 267 occupations. The resulting formula is:

$$CS = 0.454\ SC + 0.093\ MS + 0.028\ IS$$

SC is the dominant factor in determining relative wages in 1970, followed by MS and then IS.

Average industry skill scores are computed as a weighted average of the skill scores of each occupation, with the occupational employment mix of the industry as weights. Computations are performed for 1950, 1960, 1970, 1980, and 1990 on the basis of consistent occupation by industry employment matrices for each of these years constructed from decennial Census data. There are 267 occupations and 64 industries.

5. **Conclusion and Interpretation of Results**

First, the regression results provide some modest evidence that skill growth is positively linked with productivity growth. The coefficients of the growth in both cognitive skills (SC) and the Composite Skill index are marginally significant (at the ten percent level). The effects are not large -- elasticities of 0.125 and 0.202, respectively. Between 1947 and 1997, cognitive skills have grown at an average annual rate of 0.41 percent, and Composite Skills by 0.33 percent. The growth of cognitive skills over this period would have added .05 percentage points to the growth of annual labor productivity, while the growth of Composite Skills would have added 0.07 percentage points. On the other hand, the coefficient of the growth of the mean education of the work force, while positive, is not statistically significant. Its estimated elasticity is 0.110. Since mean education grew, on average, by 0.69 percent per year over the 1947-1997 period, its growth would have added 0.07 percentage points to annual labor productivity growth.

Second, there is no evidence that computer investment is positively linked to TFP growth. In other words, there is no residual correlation between computer investment and TFP growth over and

above the inclusion of OCA as normal capital equipment in the TFP calculation. This result holds not only for the 1960-1990 period but also for the 1970-1990, 1980-1990, 1977-1997, and 1987-1997 periods. The result also holds among exclusively goods-producing industries and among exclusively manufacturing industries. This finding is not inconsistent with recent work on the subject. Oliner and Sichel (2000), for example, found a strong effect of computers on productivity growth only beginning in the mid-1990s, which is beyond my period of analysis.

Third, in contrast, computerization is strongly and positively associated with other dimensions of structural change. These include occupational restructuring and changes in the composition of intermediate inputs. The evidence is a bit weaker for its effects on changes in the composition of industry capital stock.

The bottom line is that the diffusion of IT appears to have "shaken up" the U.S. economy, beginning in the 1970s. However, it is a technological revolution that shows up more strongly in measures of structural change rather than in terms of productivity, if the previous literature is a good guide on the latter issue. In particular, the strongest results of the effects of OCA on productivity growth are found for the late 1990s in the U.S. My results seem to indicate that OCA has had strong effects on changes in occupational composition and input structure dating from the early 1970s.

Table 1. Total Factor Productivity (TFP) Growth By Major Sector, 1950-1990
(Average annual growth in percentage points)

Sector	1950-60	1960-70	1970-80	1980-90	1950-90
A. Goods-Producing Industries					
Agriculture, forestry, and fisheries	1.54	1.05	-2.33	5.52	1.45
Mining	2.22	3.19	-3.41	3.06	1.27
Construction	4.00	-2.36	-4.48	0.49	-0.59
Manufacturing, durables	1.95	1.72	2.19	3.12	2.25
Manufacturing, nondurables	0.40	1.59	1.07	2.23	1.32
Transportation	1.10	2.97	0.13	0.88	1.27
Communications	2.99	2.55	2.94	1.46	2.49
Electric, gas, and sanitary services	5.35	3.47	2.66	0.62	3.03
B. Service Industries					
Wholesale and retail trade	1.08	0.60	-1.01	0.86	0.38
Finance, insurance, and real estate	1.41	0.14	0.37	-1.53	0.10
General services	0.12	-0.05	0.25	-0.35	-0.07
Government and government enterprises	0.59	-0.66	0.15	-0.03	-0.28
Total goods	2.12	1.50	0.25	2.04	1.48
Total services	0.70	0.58	0.58	0.07	0.48
Total economy (GDP)	1.39	0.96	0.38	0.77	0.88

Table 2. Dissimilarity Index (DIOCCUP) of the Distribution of Occupational Employment by Major Sector, 1950-1990

Sector	1950-60	1960-70	1970-80	1980-90	Average 1950-1990
A. Goods Industries					
Agriculture, forestry, and fisheries	0.000	0.001	0.001	0.017	0.005
Mining	0.022	0.025	0.020	0.045	0.028
Construction	0.040	0.025	0.005	0.053	0.031
Manufacturing, Durables	0.100	0.039	0.014	0.096	0.062
Manufacturing, Nondurables	0.077	0.050	0.023	0.088	0.060
Transportation	0.030	0.024	0.014	0.048	0.029
Communications	0.032	0.061	0.043	0.128	0.066
Electric, gas, and sanitary services	0.078	0.169	0.053	0.105	0.101
B. Service Industries					
Wholesale and retail trade	0.026	0.019	0.029	0.078	0.038
Finance, insurance, and real estate	0.043	0.117	0.033	0.080	0.068
General Services	0.061	0.091	0.029	0.047	0.057
Government and government enterprises	0.046	0.054	0.042	0.045	0.047
Total Goods	0.063	0.061	0.014	0.110	0.062
Total Services	0.022	0.056	0.026	0.077	0.045
All Industries	0.050	0.056	0.019	0.095	0.055

Note: Computations are based on employment by occupation aggregated for each of the major sectors.

Table 7. Cross-Industry Regressions of Industry TFP Growth (TFPGRTH) on R&D Intensity and OCA Investment

Independent Variables	Specification (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.015 **	0.016 **	0.014 *	0.014 **	0.011	0.020	0.010	0.005
	(3.45)	(3.59)	(2.59)	(2.63)	(1.38)	(1.53)	(1.24)	(0.35)
Ratio of R&D	0.203 *	0.212 *	0.199 #	0.205 #	0.338 *	0.348 #	0.171 *	0.131 #
Expenditures to Sales	(2.17)	(2.24)	(1.89)	(1.93)	(2.28)	(2.00)	(2.26)	(1.86)
Annual Growth		-0.039		-0.024	-0.053	-0.102	-0.060	-0.016
In OCA		(1.36)		(0.62)	(1.27)	(1.21)	(1.29)	(0.19)
Dummy Variable	-0.017 **	-0.017 **			-0.018 *		-0.032 **	-0.023 *
For Services	(3.47)	(3.34)			(2.47)		(3.08)	(2.10)
Dummy Variable for	-0.010 #	-0.006	-0.012 #	-0.009				
1970-1980	(1.89)	(0.95)	(1.74)	(1.05)				
Dummy Variable for	0.003	0.007	0.009	0.011	0.012 #	0.008	0.005	
1980-1990 (or 1987-97)	(0.59)	(1.13)	(1.22)	(1.37)	(1.95)	(0.80)	(0.81)	
R2	0.195	0.205	0.127	0.131	0.216	0.145	0.232	0.187
Adjusted R2	0.171	0.174	0.098	0.092	0.178	0.078	0.201	0.129
Standard Error	0.0249	0.0251	0.0280	0.0281	0.0286	0.0289	0.0267	0.0292
Sample Size	132	132	93	93	88	42	88	44
Sample	All	All	Goods	Goods	All	Goods	All	All
Period	1960-90	1960-90	1960-90	1960-90	1970-90	1970-90	1977-97	1987-97

Table 8. Cross-Industry Regressions of Industry Labor Productivity Growth on R&D Intensity, Capital Investment, and Skill Change, 1960-1990

Independent Variables	Specification (2)	(3)	(4)	(5)	(6)	(7)
Constant	0.033	0.031 **	0.030 *	0.038 *	0.017 **	0.014
	(1.47)	(3.23)	(3.39)	(2.00)	(2.81)	(1.74)
Ratio of R&D Expenditures to Sales	0.182 #	0.174 #	0.184 #	0.178 #	0.174 #	0.170
	(1.86)	(1.84)	(1.95)	(1.86)	(1.77)	(1.77)
Growth in Total Capital Per Worker	0.235 *	0.237 *	0.239 *	0.252 *	0.244 *	0.251
	(2.27)	(2.31)	(2.34)	(2.45)	(2.31)	(2.43)
Growth in Substantive Complexity (SC)	0.181	0.125 #				
	(1.19)	(1.78)				
Growth in Interactive Skills (IS)	-0.055					
	(0.44)					
Growth in Motor Skills (MS)	-0.015					
	(0.09)					
Growth in Composite Skills (CS)			0.202 #			
			(1.89)			
Growth in Mean Education				0.110		
				(1.14)		
Change in Substantive Complexity (SC)					0.224	
					(0.90)	
Change in Interactive Skills (IS)					-0.346	
					(1.04)	
Change in Motor Skills (MS)					0.006	
					(0.02)	
Change in Mean Education						0.056
						(0.66)
R2	0.236	0.234	0.237	0.223	0.226	0.218
Adjusted R2	0.186	0.197	0.200	0.186	0.176	0.180
Standard Error	0.0251	0.0249	0.0249	0.0251	0.0253	0.0252
Sample Size	132	132	132	132	132	132

Table 9. Cross-Industry Regressions of Indicators of Structural Change on Computer Investment

Independent Variables	Dependent Variable					
	DIOCCUP	DIOCCUP	DIACOEFF	DIACOEFF	DIKCOEFF	DIKCOEFF
Constant	0.048 **	0.055 **	0.001	-0.02 *	0.016 **	0.008
	7.29	(8.00)	(0.13)	(2.24)	(2.98)	(1.02)
Ratio of R&D	0.251	0.214	0.136	0.309	0.206	0.129
Expenditures/Sales	(1.10)	(0.97)	(0.59)	(1.57)	(1.17)	(0.71)
Investment in OCA	0.060 **	0.048 *	0.043 **	0.024 **		
Per Worker	(3.07)	(2.23)	(5.24)	(2.98)		
Initial Level of					0.032 #	0.031 #
OCA per Worker					(1.81)	(1.66)
Dummy Variable		0.008		0.017		0.026 **
for Services		(0.08)		(1.51)		(2.83)
Dummy Variable for		-0.021 *		-0.001		-0.007
1970-1980		(2.30)		(0.12)		(0.89)
R^2	0.112	0.145	0.250	0.271	0.135	0.165
Adjusted R^2	0.091	0.104	0.223	0.227	0.104	0.114
Standard Error	0.0470	0.0457	0.0429	0.0410	0.0339	0.0341
Sample Size	88	88	88	88	88	88
Industries	All	All	All	All	All	All