Investment-specific Technological Change and Labor Composition: Evidence from the U.S. Manufacturing[1]

Chun-Yu Ho[2]
Boston University

Abstract

This paper examines the impact of investment-specific technological change on labor composition in U.S. manufacturing industries from 1974 to 1994. I show that investment-specific technological change increases the relative demand of non-production workers to production workers, while TFP growth does not change labor composition. Moreover, I find that the demand of skilled labor is stronger in the durable goods sector whereas the deskilling effect is stronger in the non-durable goods sector.

Keywords: Employment Structure, Equipment Investment, Technological Change

JEL Classification: J21, O33

[1] This paper is a revised version of my MPhil Thesis at the Hong Kong University of Science and Technology. I am very grateful to Jang-Ok Cho for providing the data and invaluable advice. I also thank Vivian Chiu, David Cook, Wai-Yip Alex Ho, Aditi Mehta and the participants at the Macro reading group in Boston University and Midwest Macroeconomic Meeting 2005 for their helpful comments and suggestions. I am also indebted to an anonymous referee for valuable comments. I acknowledge financial support from the Institute of Economic Development of Boston University.
[2] Tel.: +1 617 3533743; Fax: +1 617 3534449; Email: chunyu@bu.edu; URL: http://people.bu.edu/chunyu; Address: Department of Economics, Boston University, 270 Bay State Road, Boston, MA 02215.

1. Introduction

Motivated by the dramatic technological change in capital goods since the 1970s, recent studies examine the effects of investment-specific and neutral technological changes on the economy.[3] Investment-specific technology improves only new vintages of capital goods whereas neutral technological change (TFP) affects the productivities of all production inputs equally. Hulten (1992), Greenwood et al. (1997) and Cummins and Violante (2002) argue that investment-specific technological change is important to explain output growth in the U.S.

Figure 1 shows that the ratio of non-production (skilled) workers to total workers has increased since the 1970s. This pattern is dramatic in the durable goods sector which more intensively uses technology. Recent research identifies two ways in which technological changes affect labor composition. First, Greenwood and Yorukoglu (1997) argue that an increase in skilled labor facilitates the adoption of new technologies. Second, Caselli (1999) shows that new technologies are more likely assigned to skilled labor if these workers face a smaller cost of using the new technologies. The productivity of skilled labor improves resulting in increases demand of skilled labor during a technological revolution. On the other hand, new technologies can reduce the need of skilled labor by deskilling the production process.[4] Caselli (1999) argues that a deskilling technological revolution can occur if the adoption cost is lower for new technologies. However, there is no study which specifically investigates the effects of investment-specific technological change on labor composition. This paper fills this gap in the literatures by showing the effects of investment-specific technological change on labor composition.

Using panel data of 457 4-digit U.S. manufacturing industries from 1974 to 1994, my empirical results show that investment-specific technological change increases the demand for non-production workers more than for production workers, but TFP growth does not change labor composition. Moreover, the skill-biased effect is stronger in the

[3] See Hercowitz (1998) for an excellent review.

durable goods sector while the deskilling effect is stronger in the non-durable goods sector.

The paper is organized as follows: Section 2 and 3 describe the data and model respectively. Section 4 presents the results. The final section concludes.

2. Data

The annual 4 digit industry-level data is extracted from the *NBER-CES Manufacturing Industry Database* which largely represents the information in the *Annual Survey of Manufacturing*. It covers 457 industries from 1958 to 1996. It contains output, employment, equipment and structure investment, TFP, and various industry-specific price indices classified by the 1987 Standard Industrial Classification (SIC) codes.

Greenwood et al. (1997) argue that quality improvements in newly invested equipment reduce the price of equipment relative to the price of consumption goods in a competitive environment.[5] The relative price of consumption goods to equipment, q_t, is a measure of the quality.

$$q_t = \frac{p_t^c}{p_t^e} \tag{2.1}$$

Production utilizes capital stock rather than only the latest vintage of investment, thus the latest technology may not represent the technology used in production. In order to capture the technology embedded in the capital stock, I construct an index for equipment quality using a weighted average of quality for all vintages of equipment investment as follows:

[4] Goldin and Katz (1998) suggest that the assembly line substitutes for the skilled worker in the early twentieth century.
[5] For example, a computer in year 1990 sold at $1000. If the price of a computer with the same function and speed at year 2000 was listed at $100, the quality is considered to be improved by a factor of 10.

$$Q_t = \frac{(1-\delta)^t x_0}{\sum_{k=0}^{t}(1-\delta)^{t-k} x_k} q_0 + .. + \frac{(1-\delta) x_{t-1}}{\sum_{k=0}^{t}(1-\delta)^{t-k} x_k} q_{t-1} + \frac{x_t}{\sum_{k=0}^{t}(1-\delta)^{t-k} x_k} q_t \tag{2.2}$$

In the estimation, I use the price deflator of Gross Domestic Product (GDP) and price deflators of equipment at the industry level to construct the quality measures.[6] Due to the limited data on the price deflator of equipment, the empirical analysis is restricted to the sample period 1973–1994. Figure 2 shows the quality index, q_{it}, for durable and non-durable goods sectors.[7]

3. Empirical Framework

To exploit the structure of the panel data, I apply fixed effect estimation to control for the industry effect on labor composition. However, there is still a possible endogeneity bias in the estimation. For example, business cycle fluctuation affects both investment-specific technological change or TFP growth and also unexplained changes in the labor composition. In order to reduce this endogeneity bias, I divide the sample into two periods, namely 1974–1983 and 1984–1994, and compute the average for each variable over each sub-period. The utilization of technology in durable and non-durable goods sectors is substantially different, thus I investigate these two sectors separately in order to reveal the differentiated impact of technological changes.

To investigate the effects of investment-specific technology, TFP and capital on labor composition, I estimate the following model:

$$lnrationp_{it} = \alpha_i + \beta_Q lnIST_{it} + \beta_{TFP} lnTFP_{it} + \beta_K lnk_{it} + \beta_Y year + \varepsilon_{it} \tag{2.3}$$

where i and t denote the industry and year, respectively. The log of the ratio of non-production workers to total workers is represented by $lnrationp_{it}$, $lnTFP_{it}$ is the log of 5-

[6] The deflators are created by first generating a 3-digit industry real net capital stock value. The 3-digit data are converted to the 4-digit level by assuming that the industry-asset type flows are the same for all 4-digit industries within a 3-digit industry. With this information, 4-digit investment deflators are created for equipment and structures separately. Furthermore, this deflator incorporates the hedonic adjustment for quality changes in computers.

factor TFP, lnk_{it} is the log of capital, *year* is the dummy variable for the period 1984–1994 and α_i is the industry fixed effect. I employ two proxies for $lnIST_{it}$, namely the log of variables q_{it} and Q_{it}. If there is substitution (complementarity) of investment-specific technological change for non-production workers, a negative (positive) coefficient of $lnIST_{it}$ is expected. The coefficient on $lnTFP_{it}$ can be interpreted similarly. The capital k_{it} measures the capital intensity operated by a worker and is computed by adding capital equipment and structure and then dividing by the total employment. A negative (positive) coefficient on lnk_{it} implies substitution (complementarity) between non-production workers and capital, conditional on the technological level.

4. Empirical Results

Table 1 shows the empirical results.[8] Column (1) includes only a constant term and year dummy. It shows that there was an increase in the share of non-production workers during the period between 1984 and 1994. In the manufacturing sample the coefficients on both proxies of investment-specific technology are significant. The coefficient estimates on lnq_{it} in Column (2) and on lnQ_{it} in Column (3) are 0.181 and 0.246, respectively. This indicates that quality improvements in newly invested equipment and capital equipment increase demand for skilled workers, thus investment-specific technology is skill-biased. Moreover, the labor composition is more responsive to the embedded technology in capital (Q_{it}) than to the technology in recently invested equipment (q_{it}). It suggests labor productivity depends more on the average technology than the latest technology.

Comparing Columns (4) and (7), the share of non-production workers is higher and increases more rapidly in the durable goods sectors. The coefficient estimates of $dlnq_{it}$ and $dlnQ_{it}$ for the durable goods sector (0.105 and 0.153) are smaller than those for the non-durable goods sector (0.226 and 0.297). This shows that the durable goods sector has a higher share of skilled labor than the non-durable goods sector, but that share is less

[7] The rise and fall pattern also appears in the Figure 1 in Greenwood et al. (1997). Also, it is consistent with the sharp negative growth in investment-specific technological change in the Figure 1 in Cummins and Violante (2002).

[8] I also estimate the model with an output term to account for cyclical differences and allow labor to be quasi-fixed. However, there is no qualitative change in the results.

responsive to technological changes. On the other hand, the insignificant coefficients on $lnTFP_{it}$ in all of the specifications indicate that TFP growth does not affect the labor composition.

The coefficients on capital are negative in all of the specifications. This shows that conditional on the technological level, capital accumulation induces demand of production workers. Increasing capital intensity provides more opportunities for workers to upgrade their skills in utilizing machinery and hence it facilitates the technology adoption. This is consistent with the deskilling hypothesis which asserts that if the adoption cost of new technologies decreases the demand for unskilled workers will increase. Moreover, the coefficient on lnk_{it} for the durable goods sector is less negative than that for the non-durable goods sector. This indicates that skilled workers are better complements to capital in the durable goods sector which utilizes more advanced technology and the deskilling phenomenon is more significant in the non-durable goods sector. The opposing signs of investment-specific technology and capital explain that the capital-skill complementarity in Krusell et al. (2000) is driven by the improvement of technology embedded in the capital but not due to the usage of capital, i.e., increasing capital to labor ratio.

4. Conclusion

This paper shows that investment-specific technological change increases the relative demand of skilled to unskilled labor in the U.S. manufacturing industries from 1974 to 1994, but TFP growth does not change labor composition. Moreover, the demand of skilled labor is stronger in the durable goods sector while the deskilling effect is stronger in the non-durable goods sector. Further research should explore the driving forces behind the heterogeneous responses to investment-specific technological change across sectors.

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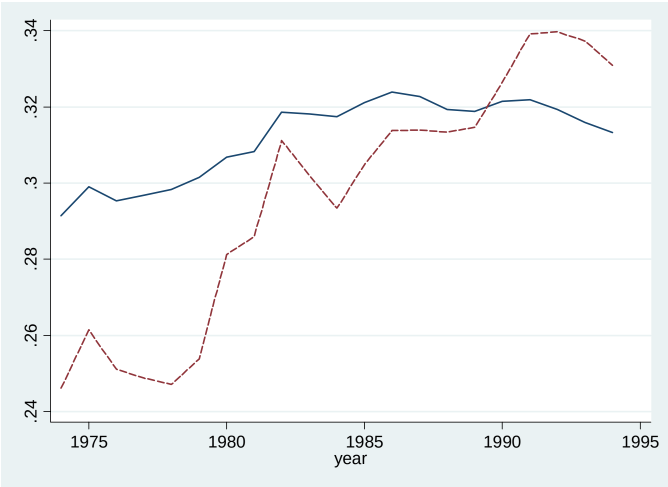
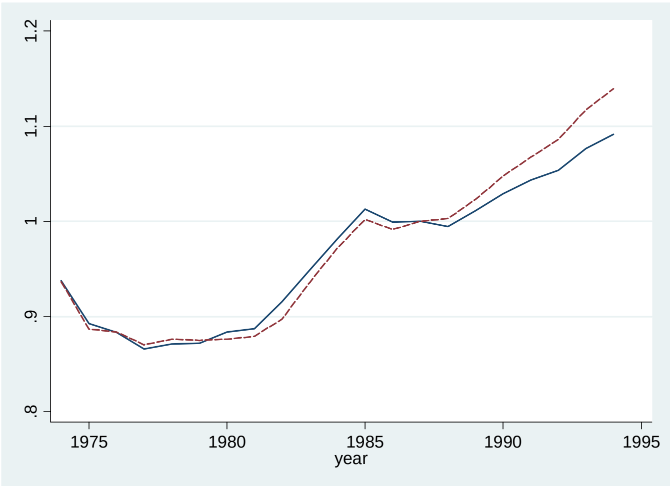
Figure 1: Ratio of non-production to total workers



Notes: Solid and dash lines represent non-durable and durable goods sectors, respectively. The variables are constructed by taking average over industries using real shipment as the weighting.
Sources: NBER Manufacturing Productivity Database

Figure 2: Investment-specific technological changes



Notes: Solid and dash lines represent non-durable and durable goods sectors, respectively. The variables are constructed by taking average over industries using real shipment as the weighting.
Sources: U.S. Department of Commerce, Bureau of Economic Analysis NIPA table for GDP deflator. NBER Manufacturing Productivity Database for real shipment. Author constructs q as described in the text.

Table 1: Empirical Results

	Manufacturing			Durable			Non-Durable		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnq		0.187			0.105			0.226	
		(0.051)			(0.067)			(0.085)	
lnQ			0.246			0.153			0.297
			(0.064)			(0.081)			(0.114)
lnTFP		-0.039	-0.045		-0.009	-0.019		-0.086	-0.077
		(0.032)	(0.032)		(0.036)	(0.037)		(0.071)	(0.071)
lnk		-0.050	-0.052		-0.028	-0.031		-0.068	-0.068
		(0.013)	(0.013)		(0.018)	(0.018)		(0.020)	(0.020)
Year	0.081	0.091	0.098	0.086	0.089	0.093	0.076	0.096	0.104
	(0.006)	(0.011)	(0.011)	(0.007)	(0.014)	(0.013)	(0.010)	(0.020)	(0.019)
constant	-1.442	-1.298	-1.288	-1.377	-1.296	-1.285	-1.528	-1.339	-1.331
	(0.004)	(0.034)	(0.035)	(0.005)	(0.046)	(0.047)	(0.007)	(0.053)	(0.053)
R^2	0.307	0.342	0.344	0.344	0.391	0.394	0.233	0.303	0.302
Obs	914	914	914	520	520	520	394	394	394

Notes: All variables are constructed by taking 10 averages over the periods 1974-83 and 1984-1994. An observation is at 4-digit SIC level. The numbers in the bracket are the standard errors. The dependent variable is lnrationp.
Sources: NBER Manufacturing Productivity Database for *rationp* and *TFP*. U.S. Department of Commerce, Bureau of Economic Analysis NIPA table for *GDP deflator*. Author constructs *q* and *Q* as described in the text.