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90s: Is the New Economy Still Alive?**

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# Measuring Productivity Growth over the 90s: Is the New Economy Still Alive?\*

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## Abstract

This paper presents an updated estimation of the total factor productivity (TFP) of the U.S. economy following the two preceding empirical studies, Basu et al. (2001) and Burnside et al. (1995). Based on these two estimation approaches, both of which carefully handle the potential estimation bias stemming from cyclical utilization, we verified that the TFP growth in the late 90s was, to some extent, higher than that in the 80s. Further, our estimation results support the following views; (i) the effect of the higher growth of TFP on the *level* of output was permanent, however, (ii) the acceleration of *growth rate* of output was transitory in the sense that the TFP growth rates after 1999 turn out to be nearly the same as those in the 80s and early 90s.

Key Words: TFP, New Economy, capital utilization

JEL Classification: E23, E32

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# 1 Introduction

The purpose of this paper is to provide updated estimates of the recent productivity growth of the U.S. economy. There seems now to be a broad consensus that the productivity growth of the U.S. economy accelerated in the second half of the 90s, perhaps due to the industrial “revolution” based on computers and information technology (IT). Indeed, there is a substantial body of empirical studies supporting what is called the “New Economy” view. Among them, Oliner and Sichel (2001), Jorgenson and Stiroh (2000) and Whelan (2001) are frequently cited empirical studies reporting the positive effects of IT on productivity growth in the late 90s. In addition to these aggregate level empirical studies, Stiroh (2001) examines the role of IT capital and labor productivity based on industry level data to conclude that IT use is closely related to (labor) productivity gain and such IT oriented productivity growth is widespread throughout the economy. As Stiroh (2001) states, however, “not everyone is convinced.” From this standpoint, Gordon (2000, 2003), for example, argues that the majority of the higher growth of U.S. productivity in the late 90s is due to cyclical utilization and, therefore, adopts a skeptical view of the New Economy arguments.

Although this study is motivated by this controversy to some extent, the main focus is not on the link between IT and (labor) productivity, but on measuring the “purified” total factor productivity (TFP) of the U.S. economy by industry. Total factor productivity is, if measured sufficiently precisely, the most appropriate measurement of technology in the economic sense, as discussed in growth/business cycle theories. However, in measuring TFP, the problem of estimation bias stemming from cyclical utilization of input factors always arises. But only a few preceding empirical studies handle this problem in a sufficiently careful way, as pointed out by Gordon (2003), Basu, Fernald and Shapiro (2001) and others. In this line of literature, estimation of purified TFP, Basu, Fernald and Shapiro (2001) adopt a sophisticated treatment of the cyclical utilization bias. This study extends their estimation, which is based on a sample ending in 1999, to 2001. Since as discussed so far measured TFP is significantly affected by the business cycle, it is of great interest to extend the BFS’s estimation of true/purified TFP beyond 2000, when the recent downturn of the U.S. economy started. The fundamental question to be addressed in this paper is, given the New Economy was indeed present, to some extent, at least until 1999, whether such acceleration of productivity growth is still observed beyond 2000.<sup>1</sup> To answer this question, in addition to the

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<sup>1</sup>Actually, BFS asked in their paper whether the increase (in TFP) is just a bit of temporary good fortune. Then they argue, “the answers to the question cannot be definitive until more time passes.”

BFS’s methodology, we apply an alternative estimation method proposed by Burnside, Eichenbaum and Rebelo (1995), which handles the cyclical utilization bias in a unique way different from BFS. Based on these two estimation results extended to 2001, our answer to the question is actually *no*, in the sense that the productivity growth beyond the 90s is nearly the same as that in the early 90s and 80s.

This paper is organized as follows. After briefly introducing the two approaches in simplified fashion in section 2, section 3 presents estimation results. In section 4, we discuss to what extent the U.S. economic growth accelerated in the late 90s from multiple perspectives. Section 5 concludes the paper.

## 2 Measuring productivity: two theoretical frameworks

### 2.1 Solow residuals and the SRIRL problem

Basically, we need to extract the pure technology component from the Solow residuals measured in the recent decade as attempted by preceding studies. Hence the natural starting point is the “naive” measurement of Solow residuals based on the following growth account estimation,

$$dz_t = dy_t - s_K \times (dk_t + du_t) - s_L \times (dn_t + dh_t + de_t) \quad (1)$$

where  $z_t$ ,  $y_t$ ,  $k_t$ ,  $u_t$ ,  $n_t$ ,  $h_t$  and  $e_t$  denote TFP, output, capital, capital utilization, employment, labor hours and labor effort, respectively.  $s_K$  and  $s_L$  are constant parameters which should be equal to capital and labor cost share under the conditions discussed later. Note that all the variables are expressed in terms of growth rate ( $dx_t = d \log X_t$ ). As demonstrated in Hall (1989), we need to make the following assumptions for eqn (1) to properly capture the true TFP. That is, (i) perfect competition in the final goods market, (ii) a Cobb-Douglas production function with constant-returns-to scale (CRS) and (iii) no measurement error in capital utilization and labor effort,  $u_t$  and  $e_t$ . Among these three, (iii) is obviously violated for certain industries where such data is not available at all. Moreover, Shapiro (1986) argues that the data available on capacity utilization released by BEA does not depict real capital utilization in the economic sense, but merely detrended output. The assumptions (i) and (ii) are of debatable validity, and so should be examined empirically using a general framework which is compatible with imperfect competition and non-CRS technology. Naturally, it is not reasonable to regard all the

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Now in 2003, it is a good occasion to reconsider the question.

final goods market to be perfectly competitive with constant-returns-to-scale technology. If the above conditions are not satisfied, there will be non-negligible estimation bias  $\varepsilon_t$  such that

$$\begin{aligned}\varepsilon_t &= dz_t - d\check{z}_t \\ &= (\gamma - 1) \times dx_t + s_K \times (du_t - d\check{u}_t) + s_L \times de_t\end{aligned}\quad (2)$$

where  $d\check{z}_t$  and  $d\check{u}_t$  denote distorted TFP and capital utilization data with measurement error.  $\gamma$  is a parameter denoting returns-to-scale/mark-up and  $dx_t \equiv s_K dk_t + s_L \times (dn_t + dh_t)$ . Essentially, if cyclical factor utilization is not properly controlled due to the lack of precisely measured data, there will be significant estimation bias in eqn (1) as shown here. A great deal of empirical studies indicate that estimation result of eqn (1) is likely to provide  $s_L > 1$ , which is called the short-run-increasing-returns-to-labor (denoted as SRIRL, hereafter). Now, table 1 reports a “naive” estimation of eqn (1). Obviously, the estimated  $s_L$  does not coincide with observed labor share, which is always smaller than unity by definition.<sup>2</sup>

Table 1: OLS estimation results (1987-2001)

Dependent variable: Output growth		
	Labor	Capital
Manufacturing, durables	1.80* (0.70)	-0.39 (0.59)
Manufacturing, non-durables	1.55** (0.46)	0.66 (0.58)

Notes: Numbers in () are standard errors. \*,\*\* indicate 5% and 1% level significant respectively.

Behind this SRIRL, the following two reasons can be detected. One is simply that the production function is indeed increasing returns to labor. Note that if this is the case, there must be imperfect competition in the final goods market. The other possibility is the cyclical utilization bias as discussed here in eqn (2). In either case, it is implied that the obtained  $s_L$  is not a consistent estimator any more, since one of the necessary conditions for eqn (1) to be valid, either (i) or (ii), is violated.

It is frequently noted by many empirical studies that the distortion incurred by imprecisely measured utilization of capital is not negligible.<sup>3</sup> Having characterized the difficulty with the empirical method, we apply two proxies for capital utilization, namely,

<sup>2</sup>A very similar estimation result showing SRIRL is presented in Burnside et al. (1995).

<sup>3</sup>See Shapiro (1986) for example.

average labor hours and electricity consumption in the following two subsections. The former is taken from Basu, Fernald and Shapiro’s (2001) approach, which is capable of controlling many other factors inducing distortion simultaneously, such as non-constant returns to scale production or imperfect competition in the final goods market. The latter is originally introduced by Burnside, Eichenbaum and Rebelo (1995) (denoted as BER hereafter) with a simple Solow-Hall type growth regression. Although BER’s approach is not as theoretically sophisticated as that of BFS, the simplicity of their approach is the great advantage, making it possible to provide clear and robust estimation results. We start with introducing BFS’s approach in the following subsection.

## 2.2 Basu, Fernald and Shapiro’s (2001) approach

BFS argues that there are three potential estimation biases in measuring TFP, namely, cyclical utilization, adjustment costs and aggregation. Among them, our focus is mainly on the cyclical utilization bias, which incurs the most serious distortion between measured TFP and true TFP. Actually, BFS’s estimation results exhibit little discrepancy induced by the latter two biases. Hence, here in this section we introduce how the cyclical utilization bias can be eliminated by the method proposed by BFS.

As a remedy for the SRIRL problem and other distortions, Basu and Kimball (1997) first proposed a unique technique to control such bias. Here we present their argument, which is incorporated in BFS, in a slightly simplified fashion. A basic insight of Basu and Kimball (1997) is that a cost minimizing firm operates on all margins simultaneously, so the first order conditions can be used to relate observable factors to unobservable factors. The following demonstration is mainly taken from BFS. Consider a firm’s cost minimization problem as follows,

$$\begin{aligned} \min \quad & WN \times G(H, E) \times V(U) + C(K) \\ \text{s.t.} \quad & Y = F(UK, EHN) = \Gamma((UK)^{s_K} (EHN)^{s_L}) \times Z \end{aligned}$$

where  $G(H, E)$  represents the function of how the wage rate depends on hours and efforts. We do not mention the cost function with respect to capital  $C(K)$ , since the property of  $C(K)$  does not matter in the following argument. Note that each variable in capital letters stands for raw levels of the corresponding lower-lettered variable. The key device introduced here is  $V(U)$ , function of “shift premium” of hourly wages. Shapiro (1986) finds the first empirical evidence that the SRIRL disappears when labor hours is used as a proxy for capital utilization.<sup>4</sup> Later, Basu and Kimball (1997) demonstrate

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<sup>4</sup>Shapiro (1986) re-calculated labor hours by explicitly taking multiple labor shifts into account.

that introducing  $V(U)$ , a shift premium increasing in capital utilization, will theoretically assure labor hours to be used as a proxy for capital utilization. Their argument is as follows. Taking the first order conditions of the cost minimization problem, we obtain,

$$\lambda F_1 K = W N G(H, E) V'(U) \quad (3)$$

$$\lambda F_2 E = W G_H(H, E) V(U) \quad (4)$$

$$\lambda F_2 H = W G_E(H, E) V(U) \quad (5)$$

where  $\lambda$  denotes the Lagrange multiplier. Before handling capital utilization bias, we need to eliminate labor effort  $E$  in advance. Eliminating  $\lambda$  from the FOCs yields the following equation implicitly relating  $E$  and  $H$ :

$$H \times \frac{G_H(H, E)}{G(H, E)} = E \times \frac{G_E(H, E)}{G(H, E)}. \quad (6)$$

This implies elasticity of labor cost with respect to  $H$  and  $E$  must be equal. Under the regularity conditions<sup>5</sup> on  $G(H, E)$ , eqn (6) has the unique, upward-sloping  $E$ - $H$  expansion path, so that it can be written as,  $E = E(H)$  with  $E'(H) > 0$ . This is why unobservable labor effort  $E$ , can be replaced by a function of observed labor hours. Finally, by defining the elasticity of effort with respect to labor hours  $\zeta = H^* E'(H^*)/E(H^*)$ , the growth rate of effective labor input can be written as follows.

$$d \ln(EHN) = dn + dh + de = dn + (1 + \zeta)dh. \quad (7)$$

where each lower-case letter denotes the log of the corresponding capital letter variables.

Similar procedure can be applied to find a proxy for capital utilization. Eliminating  $\lambda$  from eqn (3) and eqn (4) leaves

$$\frac{F_1 UK/F}{F_2 EHN/F} = \frac{G(H, E)}{H G_H(H, E)} \times \frac{U V'(U)}{V(U)}. \quad (8)$$

Further, since the left-hand-side of eqn (8) is the ratio of output elasticities with respect to input factors, they must be proportional to each factor cost share  $s$ 's as demonstrated in Hall (1990). Here, we define  $g(H)$  and  $v(U)$  as the elasticity of cost with respect to labor hours and marginal shift premium divided by average shift premium, respectively, such that

$$g(H) = \frac{H G_H(H, E(H))}{G(H, E(H))}$$

$$v(U) = U \times \frac{V'(U)}{V(U)}.$$

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<sup>5</sup>See the BFS paper for details.

Plugging them into eqn (8) leaves  $v(U) = (s_K/s_L) \times g(H)$ , the log-linearization of which is,

$$du = \frac{\eta}{\nu} \times dh \quad (9)$$

where the constant parameters  $\eta$  and  $\nu$  indicate the rates at which elasticity of labor cost with respect to labor hours/capital utilization increases. Thus, labor effort (an unobservable variable) is now expressed by labor hours proportionally under the given conditions.

Since the steady state output elasticity with respect to  $i$ th input is equal to  $i$ th cost share  $s_i$  ( $= C_i/PY$  where  $PY$  denotes total revenue) multiplied by mark-up  $\mu$ , it can be written as,

$$\frac{F_i}{F} = \mu \times \frac{C_i}{PY} = \mu s_i$$

assuming zero profit at the steady state. Note that the returns-to-scale  $\gamma$  is linked to mark-up  $\mu$  by the relation  $\mu(1 - s_\pi) = \gamma$ , where  $s_\pi$  denotes profit share. The zero profit assumption, which can be applied by following Chamberlin's monopolistic competition model, will result in the simple relation  $\mu = \gamma$ .

Putting everything together, eqn (1) is now turned into the following generalized form, which is compatible with imperfect competition and non-constant returns to scale without utilization variables explicitly.

$$\begin{aligned} dy &= \gamma(s_K \times (dk + du) + s_L \times (dn + dh + de)) + dz \\ &= \gamma dx + \xi dh + dz. \end{aligned}$$

Recall  $dx_t \equiv s_K dk_t + s_L \times (dn_t + dh_t)$ , so that it is completely observable and therefore, estimating only two coefficients, returns-to-scale  $\gamma$  on  $dx$  and cyclical utilization  $\xi$  on  $dh$ , is perfectly sufficient for our purpose in this paper.

### 2.3 Burnside, Eichenbaum and Rebelo's (1995) approach

BER's approach is even more simple than BFS's. Basically, they use electric power usage as a proxy for working capital ( $U \times K$ ). Note that in their approach, not only capital utilization, but capital stock itself is replaced by the proxy. Potential measurement error in capital stock data is not negligible as often indicated by early studies in the literature. The difficulty in measuring capital stock arises mainly from the difficulty in measuring depreciation. If there exists a complete used capital market, then the re-evaluated market price is a good measurement of capital stock. However, such a market is very limited, and depreciation of capital is only imprecisely estimated.



As we have discussed here in this paper, the SRIRL is frequently accompanied by the statistically insignificant role of capital input just as shown in table 1. This is further evidence of non-negligible measurement error in capital service/stock.

BER's approach is indeed simple. Essentially, they assume working capital needs electric power, and thus unobserved capital service is highly positively correlated with electricity consumption of the productive sector, which is obviously observable. For slightly more formal argument, they assume very low elasticity of substitution between working capital and electricity. Suppose capital service  $S_t$  is written as the CES function of working capital  $U_t K_t$  and electricity use  $E_t$ , such that

$$S_t = [\mu (U_t K_t)^\rho + (1 - \mu) E_t^\rho]^{1/\rho} \quad (10)$$

where,  $\rho < 1$ .

Combining with a standard Cobb-Douglas production function  $Y_t = (S_t)^{s_K} (H_t N_t)^{s_L} Z_t$ , eqn (10) yields the following relation.

$$dy_t = \beta_1 \times (dn_t + dh_t) + \beta_2 dq_t + \beta_3 dp_t + dz_t \quad (11)$$

where  $\beta_1 = s_L + s_K/\rho$ ,  $\beta_2 = s_K - s_K/\rho$  and  $\beta_3 = -s_K/\rho$ .  $q_t$  and  $p_t$  indicate the log of electric power use and relative price of electricity, respectively. It is easy to show  $\beta_1 = s_L$ ,  $\beta_2 = s_K$  and  $\beta_3 = 0$  when the elasticity of substitution between capital service and electricity use is zero ( $\rho = -\infty$ ). Thus, using electric power usage as a proxy for capital service can be justified under the condition such that capital service and electricity are highly complement each other.

### 3 Estimation results

#### 3.1 Data and some statistics

Our empirical work in this paper utilizes data from publicly available statistics sources. Average labor hours and employment data are published by the Bureau of Labor Statistics (BLS). Output data is taken from the GDP (value added) by industry, which runs from 1987 to 2001, released by the Bureau of Economic Analysis (BEA). As for the rest of the sample, i.e. from 1978 to 87, only contributions of each industry to aggregate output are available from the same source. However, this is sufficient for our purpose in this paper, since output growth of each industry can be derived from the contributions and aggregate output. Our measures of electric power use is the monthly index of total electrical power usage in the manufacturing sector published as *Official*

*Energy Statistics* released by the Energy Information Administration. Capital stock data by industry is constructed using the private non-residential real cost net stocks and real cost investment released by BEA. Details of the data compilation process are provided in the appendix.

Before presenting our estimation results, here we introduce fundamental statistics regarding the U.S.'s industrial structure focusing the late 90s. Figure 1 indicates output growth by industry in the 90s. The figure reveals that the major fraction of the U.S.'s economic growth in the 90s was achieved by the non-manufacturing sector. This was especially true of the second half of the 90s, when the average growth rate of the U.S. economy was 3.8%. Of this 3.8%, the contribution of the non-manufacturing sector amounted to 3.2% points. Figure 2 shows the output share of each sector in the U.S.'s aggregate output. As can be seen, non-manufacturing share is nearly 70%, while manufacturing share accounts for only 17% of the macroeconomy. Figure 3 presents a more detailed decomposition of U.S. growth in the 90s. The upper panel reveals that the vast majority of the growth in manufacturing is attributable to the durable goods sector. Indeed, the contribution of the non-durable goods sector, may even be said to be marginal. On the other hand, in the non-manufacturing sector, as shown in the lower panel, a variety of subsectors, such as the service sector and financial sector, make substantial contributions to higher growth in the 90s. These basic facts will help us evaluate the impact of higher TFP growth in each industry reported in the following subsections.

### **3.2 Manufacturing sector**

Table 2 reports the estimation results of the BFS approach for the manufacturing sector. In spite of the small sample size, it detects only a little degree of increasing returns to scale for both durables and non-durables. These values of  $\gamma$  are slightly higher than the original estimates of BFS, but roughly consistent with the stylized facts in the literature. The estimates of utilization ( $\xi$ ) of non-durables seem less precise than of  $\gamma$ . We therefore also conducted a constrained estimation with  $\gamma = 1$  to check for robustness. In this case, estimate of  $\xi$  turns out to be significant at the 5% level, as shown in table 2.

Table 2: SURHAC estimation results (1978-2001)

Dependent variable: Output growth				
	Returns-to-scale		Utilization	
	Unconstrained	CRS	Unconstrained	CRS
Manufacturing, durables	1.23** (0.09)	1 -	0.71** (0.18)	0.91** (0.17)
Manufacturing, non-durables	1.18** (0.15)	1 -	0.33 (0.32)	0.47* (0.21)

Notes: Numbers in () are standard errors. \*,\*\* indicate 5% and 1% level significant, respectively.

Based on these estimation results, figure 4 depicts the measured TFP (which we call the *true* TFP due to the applied prescription for estimation bias) of the manufacturing sector from 1978 to 2001. The upper panel in figure 4 shows the growth rate of TFP in the durable goods sector in comparison with the naive estimates of the Solow residuals. Although not much difference can be seen, the bold line (TFP) may be found in closer inspection to be slightly smoother than the thinner line (Solow residuals). The lower panel is the TFP of the non-durable goods sector. Again it seems that there is not much difference, but a closer look gives the impression that the TFP turns out to be slightly lower than the Solow residuals in the 90s.

Table 3 reports the estimation results of the same manufacturing sector using BER's approach. These estimation results present a sharp contrast as compared with table 1. As can be seen, the SRIRL completely disappears in this estimation using electrical power usage as a proxy for capital service. As for returns to scale, it is slightly higher than one for durables and almost equal to one for non-durable. Note that these estimated values are close to those obtained in BFS's estimation. Figure 5 shows measured TFP based on BER's method. Again, measured TFP is slightly smoother than the Solow residuals in the durable goods sector, implying that cyclical utilization bias is well controlled. Further, measured TFP in the non-durable goods sector as shown in the lower panel turns out to be slightly higher than the Solow residuals. This is somewhat inconsistent with the result obtained by the BFS method and we can not infer the possible reason behind this. However, as we discussed based on figure 3, this does not affect our main argument much, since the contribution of the non-durable goods sector to U.S. growth in the 90s is nearly negligible.

Table 3: OLS estimation results (1975q1-2002q3)

Dependent variable: Output growth		
	Labor	Electricity usage
Manufacturing, durables	0.976** (0.082)	0.138* (0.060)
Manufacturing, non-durables	0.827** (0.040)	0.137** (0.049)

Notes: Numbers in () are standard errors. \*,\*\* indicate 5% and 1% level significant respectively.

### 3.3 Non-manufacturing sector

As we have already seen, the non-manufacturing sector covers the majority of the U.S. productive sector. Hence inspecting the TFP of this broad sector is critical in understanding the New Economy argument. Unfortunately, however, there exists no electric power usage statistics for the non-manufacturing sector. Therefore, we present the estimation results obtained by BFS's method only.

Table 4 reports the estimates of industry level  $\gamma$ 's and  $\xi$ 's in the non-manufacturing sector obtained by the BFS method. First, although the value of each  $\gamma$  varies considerably between industries, the  $\gamma$ 's are generally quite precisely estimated for all industries. On the other hand, estimates of  $\xi$ 's are again less precise than those of  $\gamma$ 's. In contrast to the manufacturing sector, those estimates of  $\xi$  do not alter much, except for construction, even in the constrained estimation as shown in the last column of the table 4. One possible reason for this might be the imprecise measurement of labor hours in some industries, such as Transportation & public utilities and Retail. If average labor hours are not measured precisely in those industries (non-reported overwork, for example), then average labor hours are insufficient proxy to control cyclical utilization of capital. In other words, true labor hours could be more strongly procyclical.

Table 4: SURHAC estimation results (1978-2001)

Dependent variable: Output growth				
	Returns-to-scale		Utilization	
	Unconstrained	CRS	Unconstrained	CRS
Transportation & public utilities	0.74** (0.23)	1 -	-0.34 (0.46)	-0.42 (0.23)
Wholesale	1.56** (0.23)	1 -	2.17* (1.34)	3.27** (1.38)
Retail	1.83** (0.26)	1 -	0.25 (0.48)	0.58 (0.50)
Service	0.97** (0.13)	1 -	0.88** (0.43)	0.75** (0.39)
Finance, insurance and real estate	0.44** (0.13)	1 -	1.71** (0.32)	1.73** (0.35)
Construction	0.89** (0.10)	1 -	1.13* (0.60)	0.15 (0.43)

Notes: Numbers in () are standard errors. \*,\*\* indicate 10% and 5% level significant respectively.

The panels in figure 6 show the TFP growth of the non-manufacturing sector by industry. The most notable feature can be found in the panel for finance, insurance and real estate. It turns out that true/measured TFP growth in the 90s has been 1 to 2% point higher than the measured Solow residuals, where cyclical utilization is controlled by BFS's methodology. This result seems reasonable when we recall the rapid popularization of internet banking and other on-line financial trading offered by retail bankers and insurance companies, such as Bank One, Progressive and State Firm, as well as the remarkable performance of major investment banks on Wall Street. Further, we can observe slightly higher TFP growth in the wholesale sector in the late 90s than before. On the other hand, the panel for retail sector might be striking. Although the TFP growth of retailers in the late 90s is indeed about 3% points higher than the early 90s and the 80s, the panel reveals that the true/measured TFP growth is not as high as the measured Solow residuals in the same period. Given our estimation is precise, the widely accepted argument which emphasizes the role of "big box" retailers, such as Wall Mart, Home Depot or Best Buys, in explaining the emergence of the New Economy might possibly be overstated to some extent.

Let us turn finally to the service sector. The corresponding panel shows service sector performed fairly poorly in terms of TFP growth all through the recent two decades.

Provided that our estimates are sufficiently accurate, the TFP of the service sector had been diminishing in the 90s. This seems counter-intuitive considering the nature of technology. Regarding this little puzzle, we may recall the greater heterogeneity of the service sector. As we have seen in the previous subsection, service sector's share of the U.S. GDP is the largest among SIC-2 digit divisions. If we examine the contents of the service sector, we find that it contains various different types of business as shown in figure 2. One would find a considerable degree of "heterogeneity" between AMC movie theaters and Valvoline oil change stores, both of which are classified together in the service sector. It is pointed out not only by BFS but some other studies that heterogeneity can generate significant aggregation bias in estimating TFP. Suppose there are two subsectors A and B in one sector, and subsector A has higher TFP than subsector B. If a unit of employment is then reallocated from subsector A to subsector B, what will we observe? The resulting observation is a decrease in sector-wide TFP, since output in that sector decreases while the employment input is unchanged. If each subsector is highly homogeneous, such reallocation is not only neutral, but unlikely to happen spontaneously. Henceforth, considering the high heterogeneity of service sector, we should detect this kind of estimation bias distorting the observed TFP in the panel. Unfortunately, however, further decomposition is extremely difficult due to the limitations of the data.

#### 4 Discussions: What was the source of U.S. growth in the 90s?

Having estimated the production function parameters in the previous section, now we turn to evaluate the magnitude of higher TFP growth from macroeconomic viewpoints. The panels in figure 7 show the decomposition of output growth of each manufacturing and non-manufacturing sector in the 90s. The upper panel implies that the average growth rate of the manufacturing sector in the second half of the 90s is 4.2%. As can be seen in the panel, the main source of the economic growth during this period is TFP rather than input of labor and capital. Actually, the average contribution of TFP growth in the manufacturing sector amounts to 3.8% points. This implies roughly 90% of output growth is attributable to TFP growth.

On the other hand, a sharp contrast can be found in the lower panel showing a decomposition of output growth in the non-manufacturing sector.<sup>6</sup> The non-manufacturing

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<sup>6</sup>Note that "non-manufacturing sector" indicated here contains construction and mining industry to

sector in the U.S. achieved remarkable performance in terms of output growth in the late 90s. Average growth rate in the period is 4.9%, however, out of which only 1.4% points is the contribution of TFP growth. This means that more than 70% of the economic growth is attributed to increases in labor input and capital accumulation rather than technological changes. Here, we recall attention to the industrial structure of the U.S. economy as shown in figure 2. U.S. economic growth in the 90s was mainly driven by the non-manufacturing sector. We do find evidence of some acceleration of TFP growth in the non-manufacturing sector as discussed in section 3, but such acceleration cannot explain the majority of U.S. economic growth in the late 90s. Further, the two panels in figure 7 reveal TFP growth of both sectors in 2001 to be much lower than the average of that in the second half of the 90s. Note that our estimation can extract pure TFP better than naive growth account regressions. Although the measured TFP presented in this paper might not yet be completely free from estimation bias, especially in 2001, we consider it very unlikely for the U.S. TFP to accelerate even faster after 2000. For illustrative purpose, we aggregate sector level TFP to construct economy-wide TFP.<sup>7</sup> Figure 8 vividly illustrates what happened to the U.S. economy in the 90s and after. Roughly speaking, the TFP growth of the U.S. economy had been stable for a long time until the midst of the 90s. We observe strong growth of TFP starting in 1995, but that acceleration soon diminishes and eventually comes back to the initial speed around 2000.

To shed light on this issue from an alternative viewpoint, we additionally estimate the U.S. potential output growth using a structural VAR originally proposed by Blanchard and Quah (1989). As is well known, the Blanchard and Quah technique enables us to distinguish permanent and transitory shocks in output fluctuation. Hence it is possible to construct potential output by accumulating permanent shocks extracted from the residuals of the VAR estimation. Since technology changes are usually considered to be permanent shocks, such higher TFP growth, if exists, should be reflected in potential output growth to some extent. Our specification of the structural VAR is taken from Dupasquier et al. (1997), whose estimation sample ends in 1995, but with a longer sample period ending in 2002. Consider a trivariate system comprised of log-differenced

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capture the broad macroeconomic impact of the TFP growth, although the shares of construction and mining industry are not that large.

<sup>7</sup>Our aggregation procedure is heuristic in the sense that we simply calculated weighted sum of obtained industry-level TFPS. This simple method is not entirely bias-free, especially in the presence of increasing returns to scale. As discussed in BFS, however, the aggregation bias stemming from this problem is not serious, so that we present this simply aggregated data just for illustrative purpose.

output, log of average propensity of consumption and differenced FF rate. The system can be written as

$$\begin{bmatrix} dy_t \\ c_t - y_t \\ di_t \end{bmatrix} = \mathbf{A}(\mathbf{L})\mathbf{u}_t$$

where  $y_t$ ,  $c_t$  and  $i_t$  denote output, consumption and FF rate.<sup>8</sup>  $\mathbf{u}_t$  is a  $3 \times 1$  vector of structural errors. To identify the structural errors, we impose long-run restrictions as applied in Dupasquier et al. That is, we assume  $\mathbf{A}(\mathbf{1})$  to be lower triangular. Then, the third element identified in  $\mathbf{u}_t$  is the permanent shock, in which the major component can be interpreted as technological changes vis-a-vis our TFP estimation in the previous section. Now figure 9 depicts the growth rate of potential output (=permanent shocks) identified by the structural VAR. Since the measured permanent shocks are extremely noisy, it is not easy to interpret the result. However, we can at least say that any apparent and sustained increase in potential output growth cannot be found after the midst of the 90s as appeared in the figure. Essentially, it seems that the VAR result implies the New Economy to be illusory in terms of the *growth rate* of potential output. Although it cannot be related directly to our estimation results for TFP, the fact is that the structural VAR does not detect a permanent increase in potential output growth in/after the 90s.

## 5 Concluding remarks

Numerous empirical studies on the link between IT and productivity have stirred up a great deal of controversy over the magnitude of the New Economy emerging in these years. To avoid unnecessary confusion, we focused on TFP growth in/after the 90s without concerning ourselves with the source of technological changes. As a result, we found evidence of acceleration of TFP growth. However, this does not provide a definitive answer to the question about future U.S. productivity growth. One agreement among the proponents (Oliner and Sichel 2001, for example) and skeptics (such as Gordon 2000) in the controversy over the New Economy is that it is not easy to predict the sustainability of the accelerated technological growth (if it exists) in the future. A currently ongoing technological change is always a latent variable. As BFS argues, the methodologies applied in this paper cannot detect the momentum of such technological changes. What then, do we learn from our estimation results vis-a-vis the

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<sup>8</sup>The basic rationale for this specification is the standard permanent income theory. See Dupasquier et al. (1997) for detailed arguments.



future U.S. economy? Essentially, our conclusion is exactly the same as that of BFS. Namely, based on the estimation results extended to 2001, the embodied technological changes still remains. In other words, the effect on the level of output is permanent, while the acceleration of growth rate was transitory as reflected in figure 8.

## A Appendix: Construction of capital stock datasets

We use the following datasets to construct our capital stock data: (1) private nonresidential real cost net stocks and (2) real cost investment released by BEA, both of which are disaggregated by detailed industry and assets. The BEA's capital stock data is available yearly from 1947 to 2000. To calculate capital stock and investment of  $i$ th industry in year  $t$ , we aggregate capital stock and investment over assets and detailed industries, so that

$$\begin{aligned} K_t^i &= \sum_{j \in J_i} \sum_{n \in N_i} K_{t,j,n}^i \\ I_t^i &= \sum_{j \in J_i} \sum_{n \in N_i} I_{t,j,n}^i \end{aligned}$$

where subscripts  $j$  and  $n$  denote index of asset and detailed industry. Capital stocks by industry in 2001, data on which is not available at the moment, we estimate using the following procedure. Since industry-level investment data in 2001 is already available, we can calculate the capital stock in 2001 if annual depreciation is known. We assume the depreciation rate of capital to be equal to the recent 5-year average. The  $i$ th industry's current capital stock is thus calculated as follows:

$$K_{2001}^i = \left( 1 - \sum_{h=1996}^{2000} (1/5) \delta_h^i \right) \times K_{2000}^i + I_{2001}^i$$

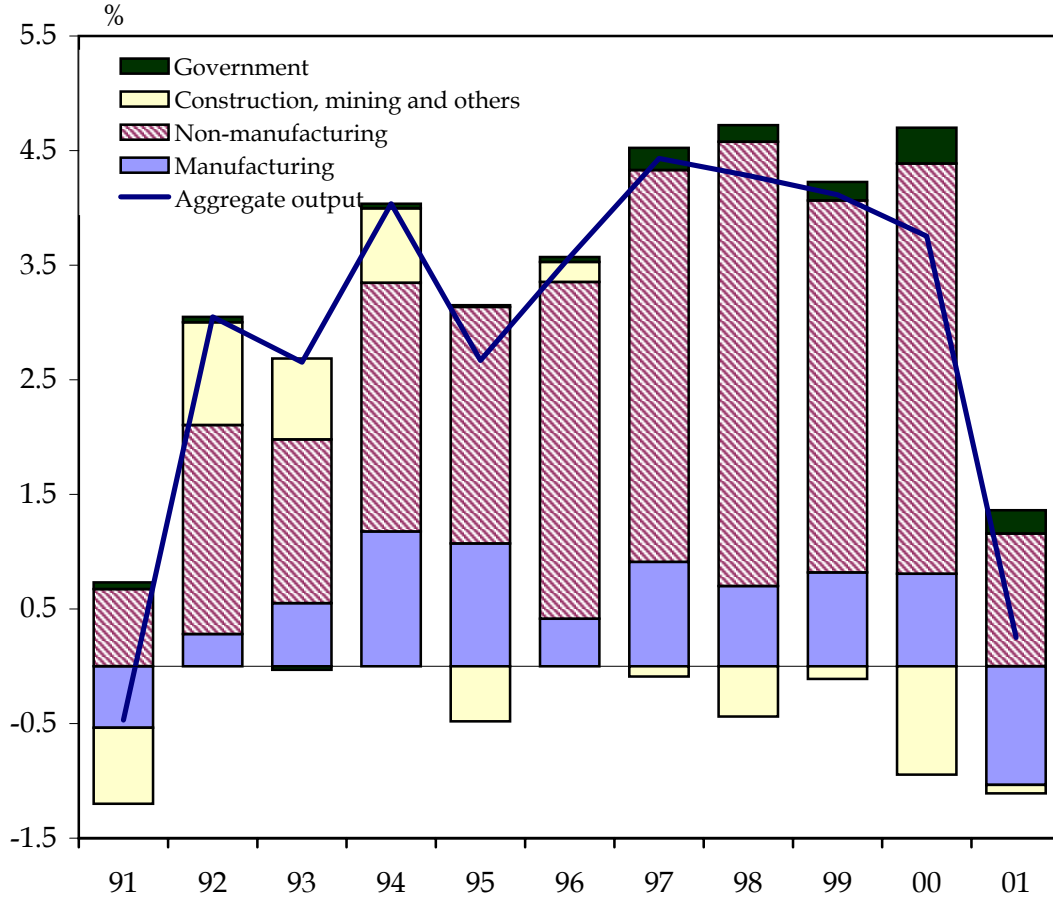
where  $\delta_h^i$  indicates the depreciation rate of capital of  $i$ th industry in year  $h$ .

## References

- [1] Basu, S. (1996), "Procyclical productivity: Increasing returns or cyclical utilization?" *Quarterly Journal of Economics* 111, 719-751.
- [2] Basu, S. and M. Kimball (1997), "Cyclical productivity with un-observable input variation." NBER working paper 5915.
- [3] Basu, S., J. Fernald and M. Shapiro (2001), "Productivity growth in the 1990s: Technology, utilization, or adjustment?" *Carnegie-Rochester conference paper on public policy*.

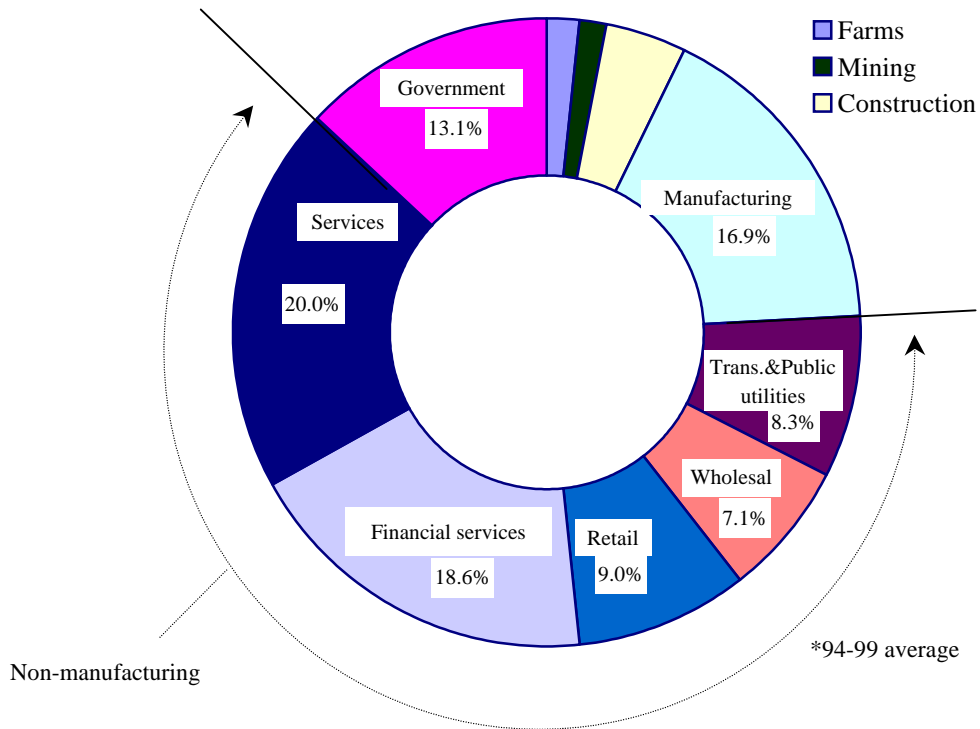
- [4] Burnside, C., M. Eichenbaum and S. Rebelo (1995), "Capital utilization and returns to scale." NBER working paper 5125.
- [5] Blanchard, O. and D. Quah (1989) "The dynamic effect of aggregate demand and supply disturbances." *American Economic Review* 79, 655-673.
- [6] Cochrane, J. (1994), "Permanent and transitory components of GNP and stock prices." *Quarterly Journal of Economics* 61, 241-265.
- [7] Dupasquier, C., A. Guay and P. St-Amant (1997), "A comparison of alternative methodologies for estimating potential output and the output gap," Bank of Canada working paper 97-5.
- [8] Gordon, R. (2000), "Does the 'New Economy' measure up to the great inventions of the past?" *Journal of Economic Perspectives* 14, 49-74.
- [9] Gordon, R. (2003), "Hi-tech innovation and future productivity growth: Does supply create its own demands?" Manuscript, Northwestern University.
- [10] Hall, R. E. (1990) "Invariance properties of Solow's productivity residuals." *Growth/Productivity/Employment*, Ed. P. A. Diamond, Cambridge, MA, MIT Press.
- [11] Jorgenson, D. and K. Stiroh. (1999), "Information technology and growth." *American Economic Review, Papers and Proceedings* 89 (2), 109-115.
- [12] Jorgenson, D. and K. Stiroh (2000), "Rasing the speed limit: U.S. economic growth in the information age." *Brookings Papers on Economic Activity* 2000 (1), 125-211.
- [13] Ogaki, M. and K. Jang, (1999), "Structural Macroeconometrics." Book manuscript.
- [14] Oliner, S. D. and D. E. Sichel (2001), "The resurgence of growth in late 1990s: Is information technology the story?" *Journal of Economic Perspectives* 14, 3-22.
- [15] Shapiro, M. (1986), "Capital utilization and accumulation : Theory and evidence." *Journal of Applied Econometrics* 1, 211-234.
- [16] Stiroh, K. (2001), "Information technology and the U.S. productivity revival: What do the industry data say?" *American Economic Review*, forthcoming.
- [17] Whelan, K. (2000), "Computers, obsolescence and productivity," FEDS working paper 2000-35.

Figure 1: Output growth by industry (1)



**Figure 2: Industry structure of the U.S.**

(1) Output by industry



(2) Contents of service sector

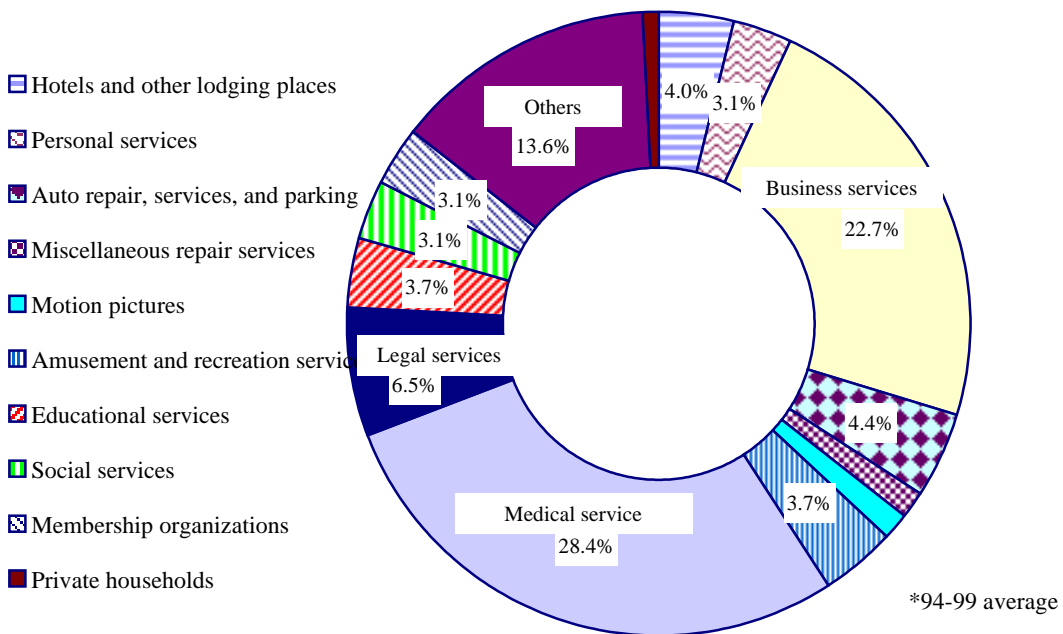
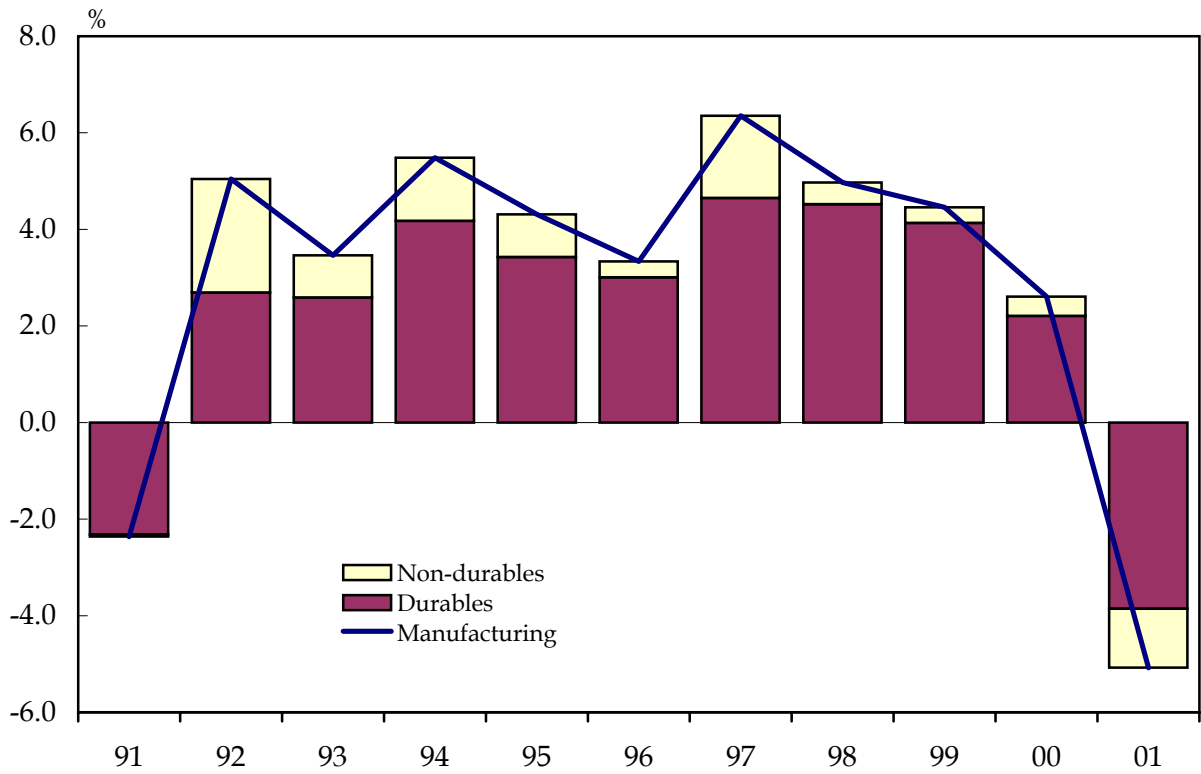
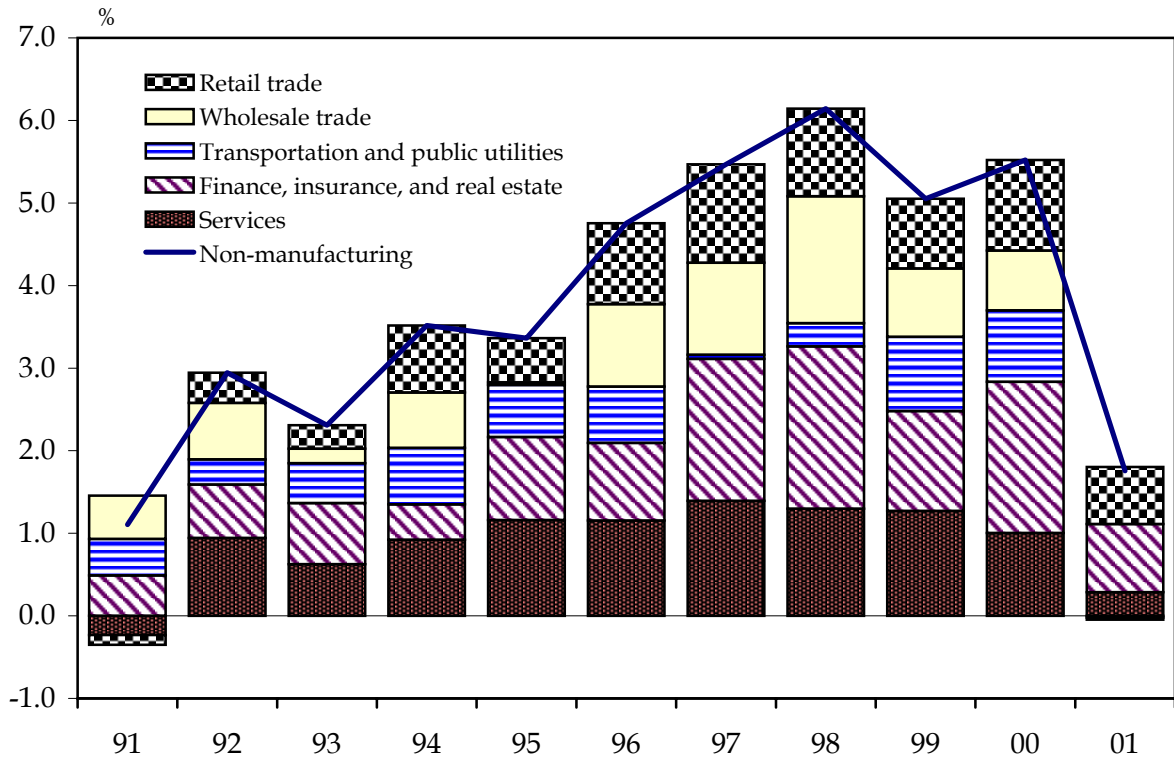


Figure 3: Output growth by industry (2)

(1) Manufacturing

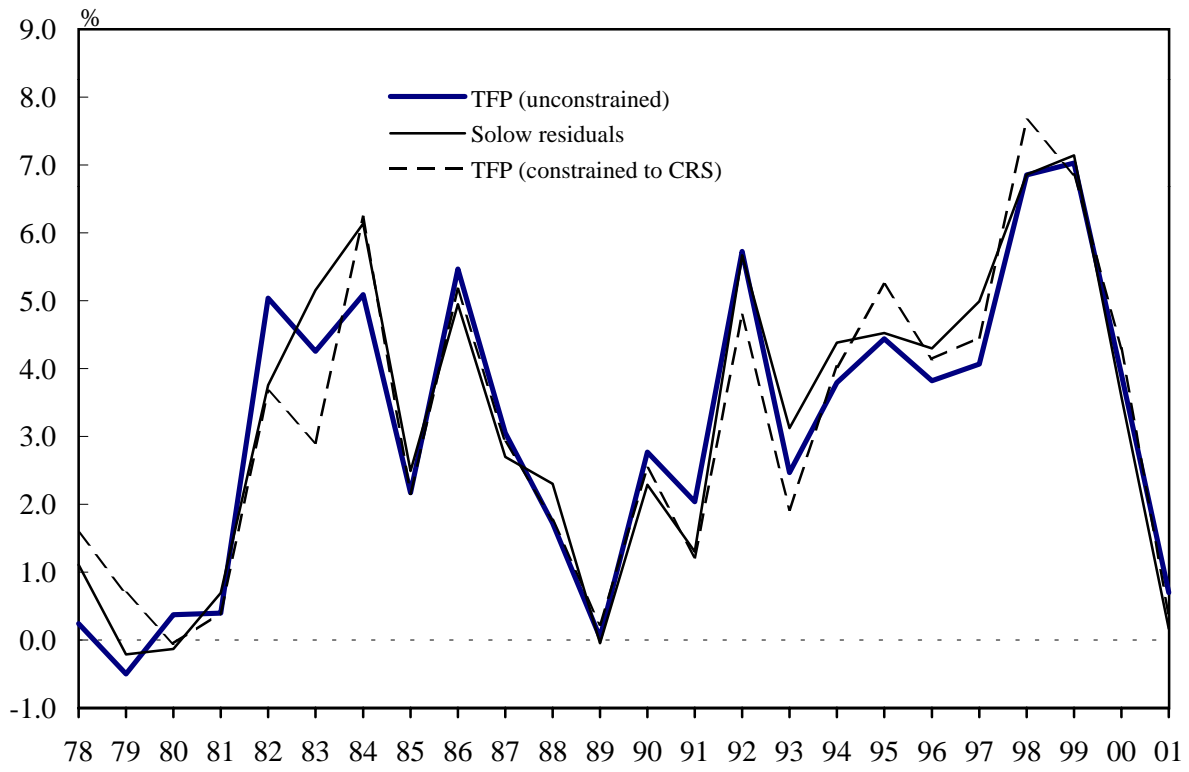


(2) Non-manufacturing

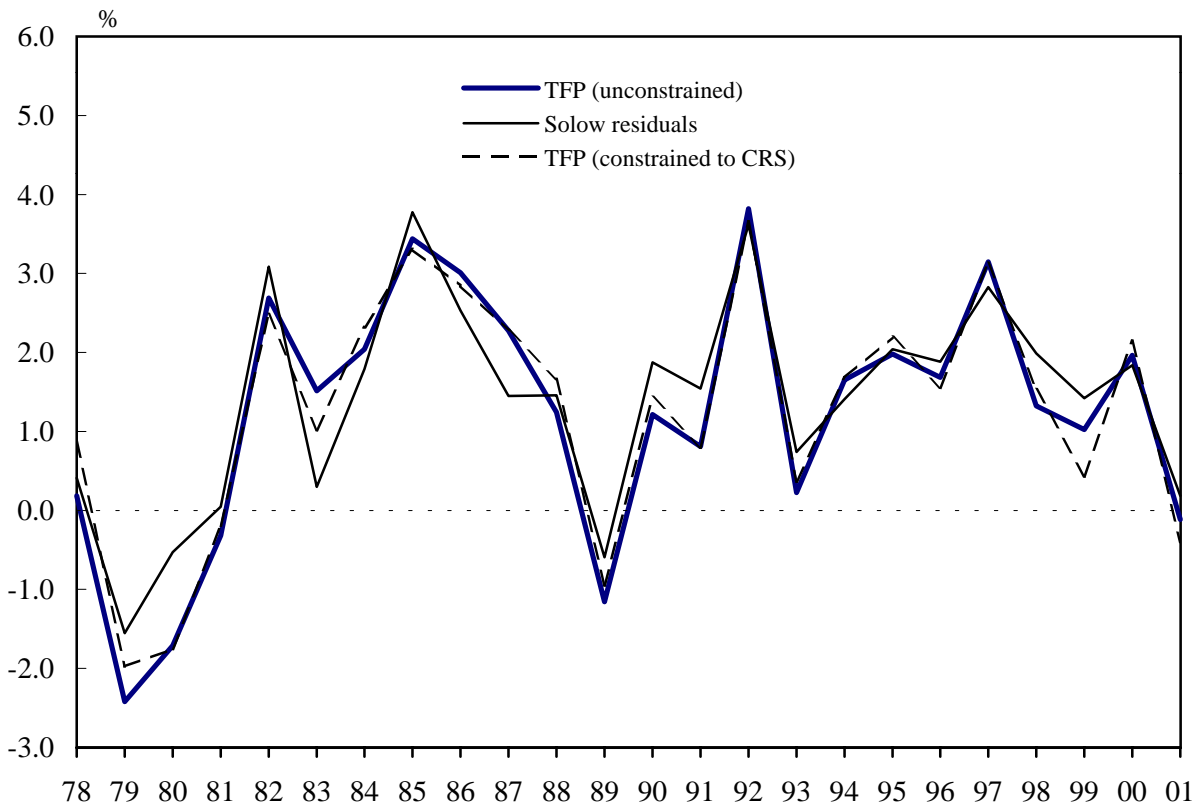


**Figure 4: TFP by BFS method, manufacturing sector**

(1) Durables

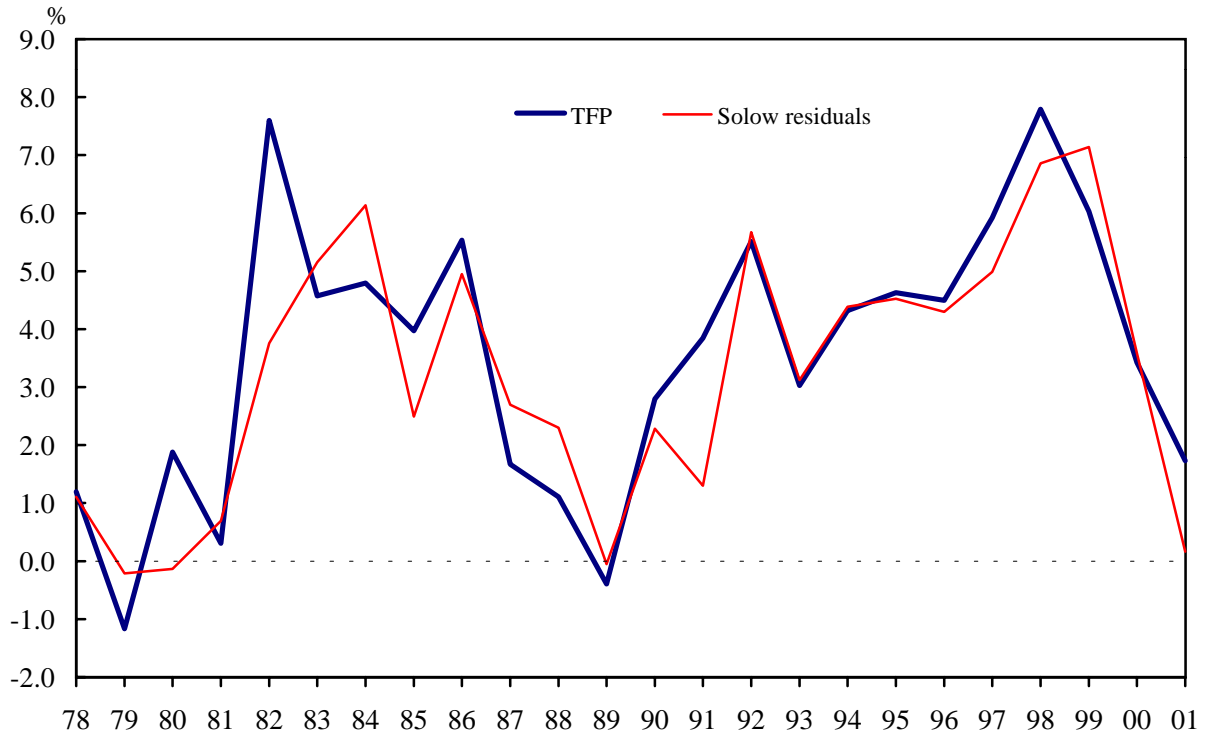


(2) Non-durables

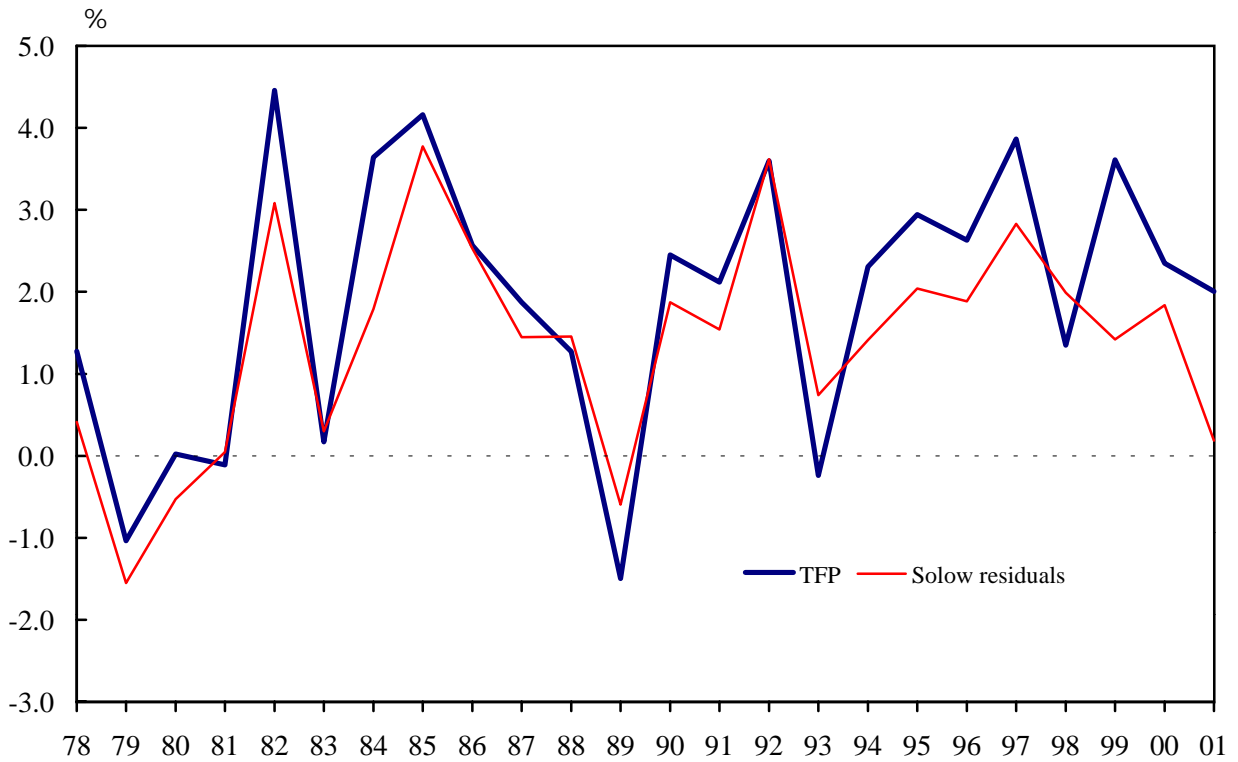


**Figure 5: TFP by BER method, manufacturing sector**

(1) Durables



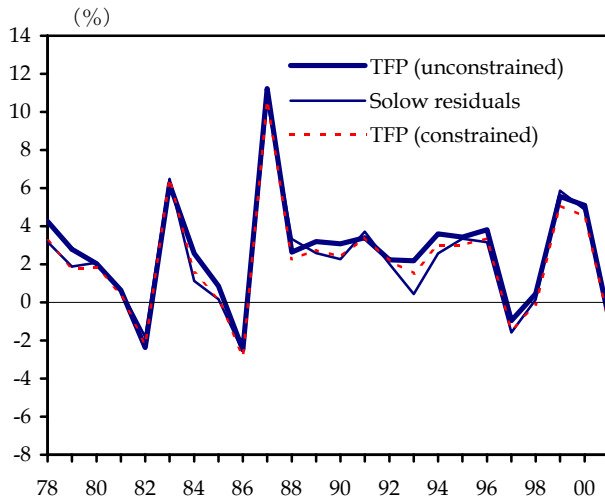
(2) Non-durables



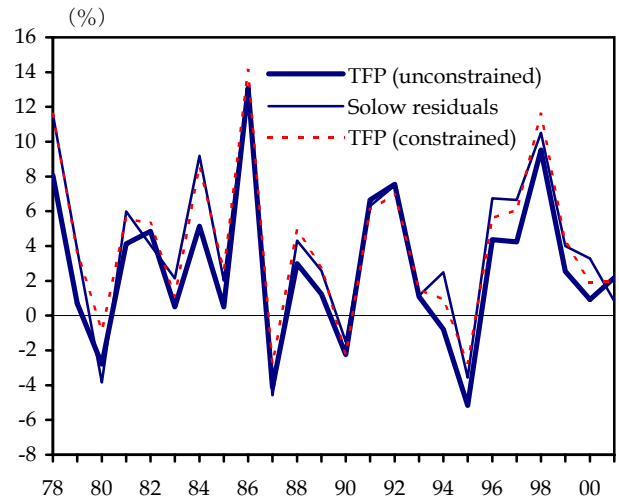


**Figure 6: TFP by BFS method, non-manufacturing sector**

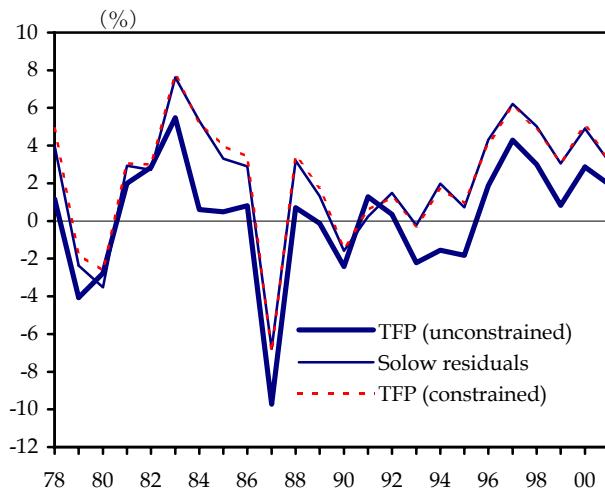
(1) Transportation & public utilities



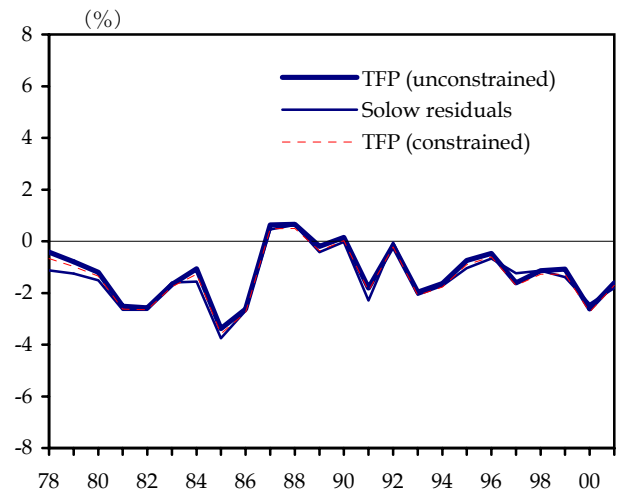
(2) Wholesale



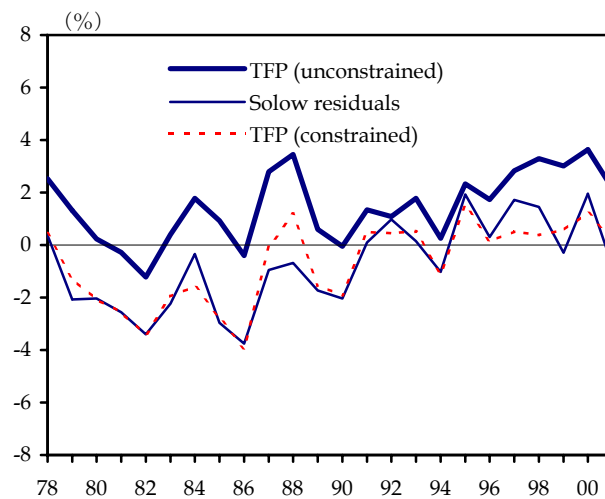
(3) Retail



(4) Services



(5) Finance, insurance and real estate



(6) Construction

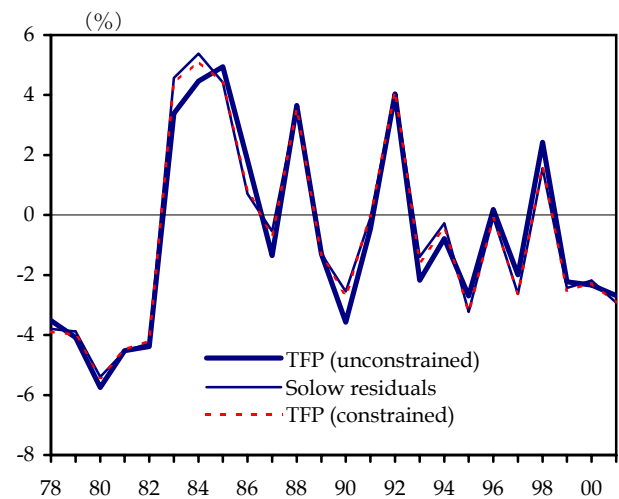
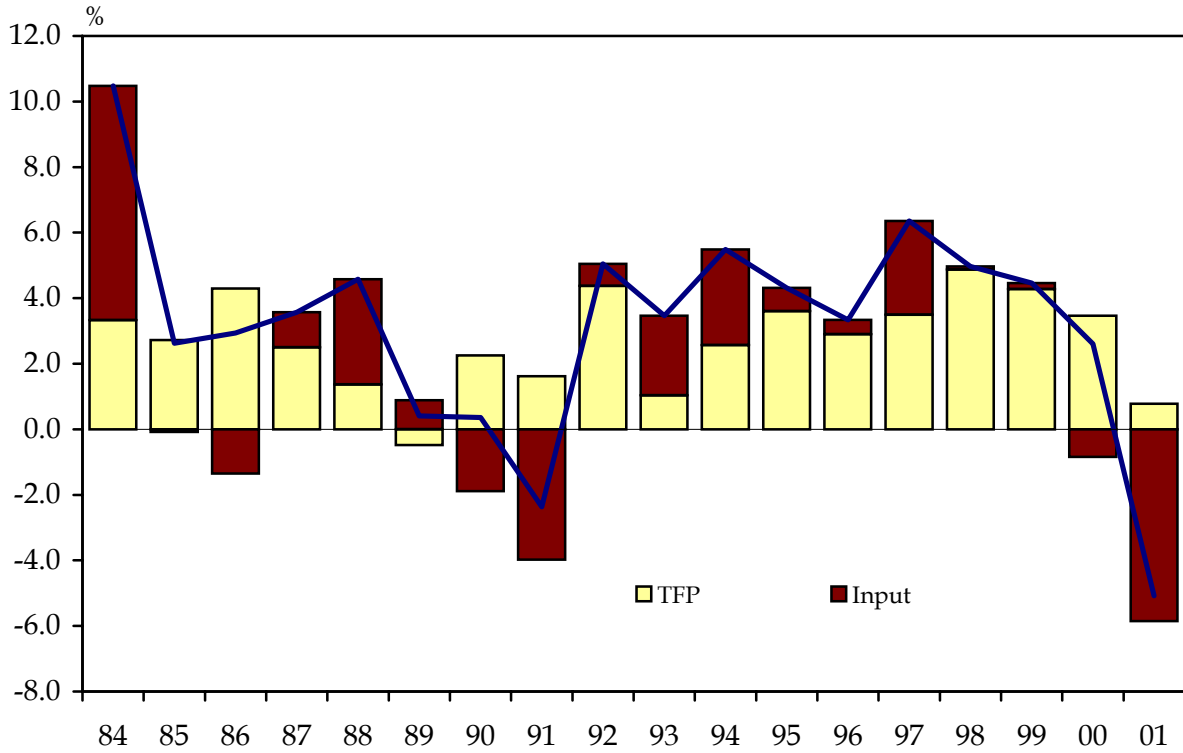
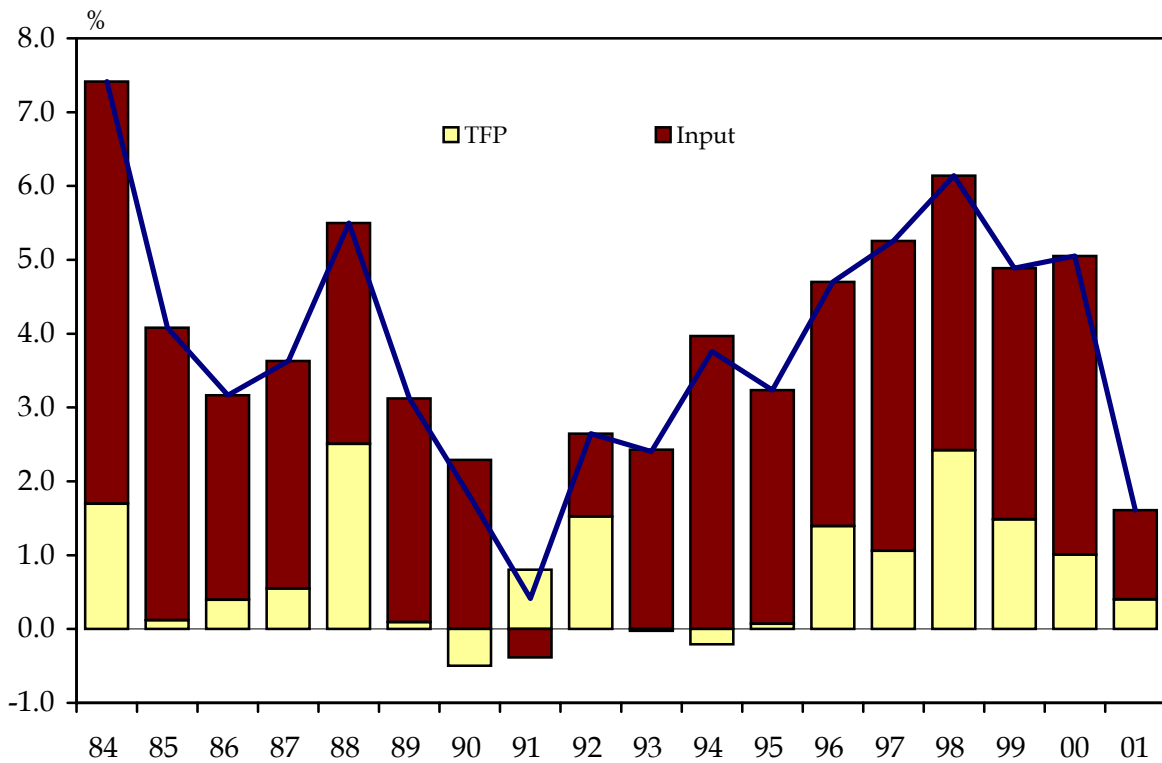


Figure 7: Source of growth

(1) Manufacturing

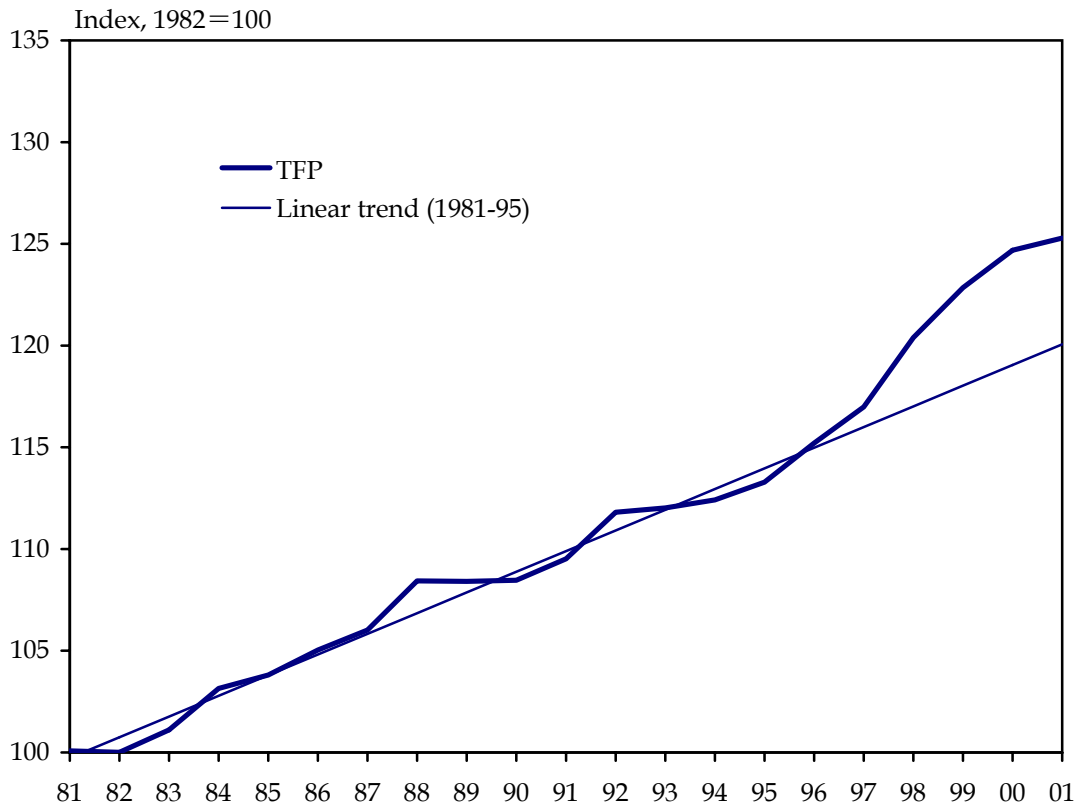


(2) Non-manufacturing + mining + construction



**Figure 8: Aggregated TFP**

○Entire non-farm business sector



\* Weighted sum of TFPs by industry, estimated by BFS's method

**Figure 9: Potential output growth**

○ Permanent shocks from structural VAR

