What Do the Purified Solow Residuals Tell Us about Japan's Lost Decade?

Takuji Kawamoto

In the 1990s, measured productivity growth decelerated dramatically in Japan. However, the standard Solow residuals may reflect factors other than changes in the rate of technological progress. This paper attempts to construct a measure of "true" aggregate technical change for the Japanese economy over the years 1973–98, controlling for increasing returns, imperfect competition, cyclical utilization of capital and labor, and reallocation effects. We find little *or* no *evidence of a decline in the pace of technological change during the 1990s. Both cyclical utilization and reallocations of inputs have played an important role in lowering measured productivity growth relative to true technology growth. Our results thus cast doubt on the explanation of Japan's "lost decade" that attributes the prolonged slump to the observed productivity slowdown.*

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Institute for Monetary and Economic Studies, Bank of Japan (E-mail: takuji.kawamoto@boj.or.jp)

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I. Introduction

Japan's economic performance over the last decade has been miserable. The average growth rate of Japanese real GDP was a mere 1 percent in the 1990s, compared to around 4 percent in the previous two decades. Following the collapse of the "asset price bubble" in early 1990, Japanese growth rates steadily deteriorated through the first half of the decade, rebounded briefly at mid-decade, but has been generally weak since then. Despite repeated fiscal cum monetary stimuli, the Japanese economy has remained in a deep recession. Why has the economy stagnated for so long? What is the fundamental cause of the protracted slump? These are puzzling questions not just for policymakers, but also for academic economists.[1]

Recent work by Hayashi and Prescott (2002) provides a clear-cut but provocative account of Japan's "lost decade." They first note that the measured total-factor-productivity (TFP) growth decelerated substantially in the 1990s, interpreting such movements in TFP as the result of exogenous technology shocks (or to a small extent, measurement errors). They then develop a quantitative real-business-cycle model of the Japanese economy and examine the predictions of the model economy in response to the exogenous productivity slowdown.[2] Their main finding is that a calibrated version of their model can explain quite well the behavior of the Japanese economy in the 1990s. They thus conclude that "the only puzzle is why the TFP growth was so low subsequent to 1991" (Hayashi and Prescott [2002, p. 207]).[3]

Indeed, Japan's productivity slowdown in the 1990s appears to be a stylized fact. Table 1 shows different sets of estimates of the Solow residuals for the Japanese economy over various periods, including the estimates by Hayashi and Prescott (2002). The result—that TFP growth declined markedly in the 1990s—appears to be *qualitatively* robust, although the magnitude of that decline depends on the estimates. For example, the average annual growth rate of TFP over 1990–98 based on the Japan Industry Productivity (JIP) database was just 0.5 percent, compared with 1.6 percent in the 1980s. Figure 1 also plots the *levels* of TFP from the selected estimates. We can detect a clear break in these series around 1990: there is a steadily upward trend in TFP until about 1990, when the trend flattened (except for a blip over 1995–97). Thus, to the extent that the Solow residuals are a valid measure of changes in the available production technology, Japan's lost decade is likely to be better understood as a period of low technology growth.

1. For example, Blanchard (2003) has stated, "Japanese economic policy bashing is also a popular sport, and it strikes me also as largely unwarranted. Japanese policy was not that crazy for most of the 1990s. Interest rates were decreased, in retrospect a bit too slowly. Expansionary fiscal policy was used, admittedly with the ebbs and flows, but who would not be scared about running such large deficits for so long? . . . How many of the current critics predicted this outcome in the early 1990s? A major question is why this fiscal cum money expansion was insufficient to avoid getting to the trap. I do not know the answer."
2. They also argue that an *exogenous* decline in the workweek, which occurred from 1988 to 1993, played an important role in the anemic performance of the Japanese economy over the 1990s.
3. They conjecture that the low TFP growth stems from an inappropriate policy that subsidizes inefficient firms and declining industries. Preliminary work by Caballero, Hoshi, and Kashyap (2003) attempts to attribute the low productivity to the "misallocation of bank credit."

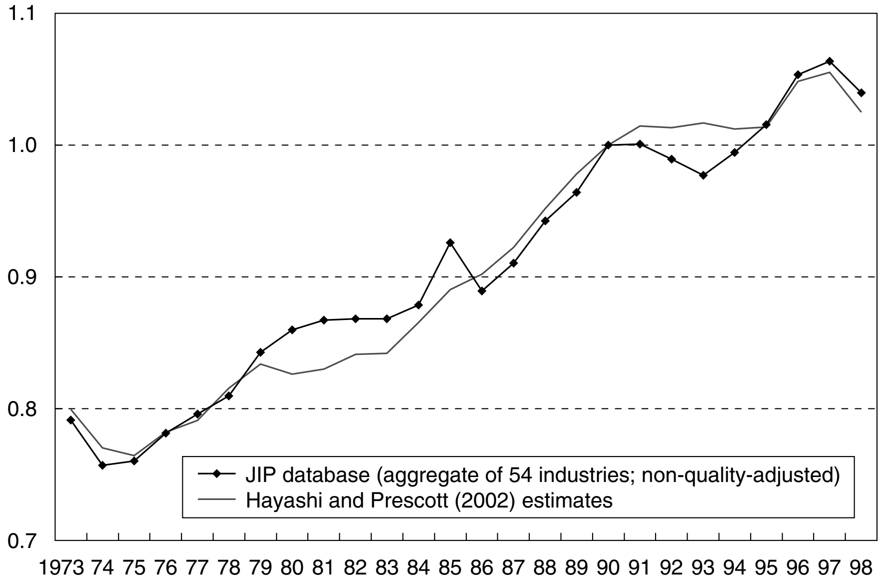
Table 1 Aggregate Solow Residuals

Percent per year

	1960–70	1970–80	1980–90	1990–2000
JIP database (54 industries)				
Without labor quality adjustment	n.a.	1.2[1]	1.6	0.5[2]
With labor quality adjustment	n.a.	0.3[1]	0.9	0.3[2]
Gust and Marquez (2000)	n.a.	n.a.	2.0[3]	1.0[4]
Hayashi and Prescott (2002)	4.8	0.8	1.9	0.3
Ministry of International Trade and Industry *White Paper* (cited in Yoshikawa [2000])	3.7	0.7	1.0	0.0

Notes: 1. 1973–80.
2. 1990–98.
3. 1980–89.
4. 1989–98.
5. Section II describes the method for calculating the Solow residuals based on the Japan Industry Productivity (JIP) database. See Fukao *et al.* (2003, 2004) for details of the JIP database. The estimates of Gust and Marquez (2000) are taken from table 4 presented in their paper. The estimates of Hayashi and Prescott (2002) are taken from the Excel file they provide at http://www.e.u-tokyo.ac.jp/~hayashi/hp (file: rbc, sheet: growth accounting, column: C).

Figure 1 Levels of Total Factor Productivity

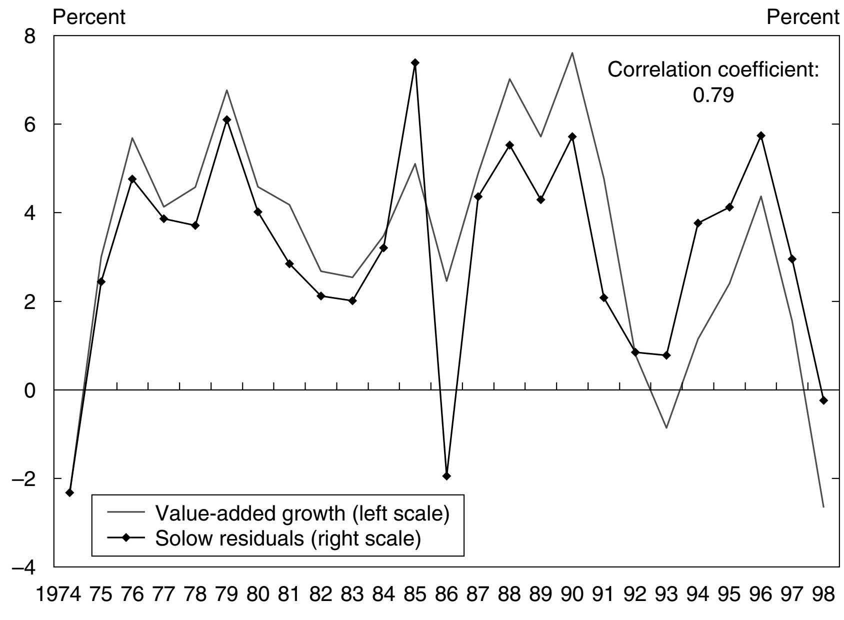


Note: Levels of the series are normalized to equal one in 1990. See Section II for a detailed description of the method for calculating the aggregate Solow residuals based on the JIP database. See also Section III and Fukao *et al.* (2003, 2004) for details of the JIP database. The estimates of Hayashi and Prescott (2002) are taken from the Excel file they provide at http://www.e.u-tokyo.ac.jp/~hayashi/hp (file: rbc, sheet: growth accounting, column: C).

However, these Solow residuals need not be interpreted as exogenous technology shocks. Figure 2 presents the Solow residual and percent change in annual output for the private-sector Japanese economy over 1973–98. Clearly, we can confirm the widespread observation that measured productivity is highly procyclical.[4] In every year in which output fell, TFP also fell. Indeed, if one accepts the Solow residuals as a measure of year-to-year changes in technology as would an advocate of real-business-cycle theory, it seems very easy to explain *all* major recessions over the sample period including the lost decade! There is, however, significant evidence that the Solow residuals reflect factors other than changes in the pace of technological innovation. Researchers point out several reasons that fluctuations in output arising from sources other than technology shocks can make measured Solow residuals procyclical. The leading possibilities are (1) increasing returns to scale, (2) varying utilization of capital and labor, and (3) the cyclical reallocation of inputs across different sectors.[5]

From this standpoint, the present paper attempts to construct a measure of "true" aggregate technical change for the Japanese economy during the years 1973–98, controlling for increasing returns, imperfect competition, cyclical utilization of capital

Figure 2 Solow Residuals and Output Growth



Note: Aggregates of 54 industries. Data are from the JIP database.

4. Hall (1987) writes, "Hardly any fact about the United States economy is better established than the procyclical behavior of productivity."
5. The evidence based on the U.S. data suggests that cyclical utilization matters, and provides less support for increasing returns. Relatively less work has been done on reallocation. See Shapiro (1993, 1996), Basu (1996), Basu and Kimball (1997), and Burnside, Eichenbaum, and Rebelo (1996a, b) for the importance of variable utilization in cyclical productivity. Basu and Fernald (1997, 2002) stress the reallocation of inputs across industries with different returns to scale.

and labor, and reallocation effects. In particular, we first estimate technical change at a disaggregated (54-industry) level, allowing for non-constant returns to scale and variations in the utilization of capital and labor. We then aggregate sectoral technical change into an economy-wide index in an appropriate manner. By doing so, we hope to assess the plausibility of the productivity slowdown hypothesis for the decade-long Japanese slowdown.

Our method for constructing aggregate technical change primarily draws on Basu, Fernald, and Kimball (2002), who in turn build on their own previous studies such as Basu and Kimball (1997) and Basu and Fernald (1997, 2002). Basu and Kimball (1997) propose simple *model-based* proxies for unobserved fluctuations in the utilization of capital and labor. In correcting for cyclical utilization, we follow their basic insight that firms will push on each utilization margin—hours of workers, labor effort, and workweek of capital—to equalize the cost of using each margin, and hence an *observed* margin of adjustment can be used as a proxy for other *unobserved* margins. Basu and Fernald (1997, 2002) emphasize the importance of reallocations in cyclical productivity. Following their framework, we consider how shifts in the composition of input growth across industries with different returns to scale create a wedge between measured productivity and true technology in the Japanese economy.

The main findings in this paper can be summarized as follows:

(1) Most importantly, according to our measures of true aggregate technical change, there is *little* or *no* evidence of a decline in the pace of technological progress during Japan's lost decade. We thus conclude that fluctuations in the Solow residuals are a poor measure of exogenous technology shocks, and that the slowdown in measured productivity in the 1990s is not indicative of a decline in the rate of technological progress. Moreover, we find a considerably larger gap between measured productivity and true technology in the 1990s than in the previous two decades.

(2) Durable manufacturing shows slow growth in technology in the 1990s relative to its good performance over the previous two decades. By contrast, nondurable manufacturing and non-manufacturing show relatively strong growth in technology in the 1990s. Because non-manufacturing constitutes most of GDP, technology improvements in non-manufacturing contributed significantly to maintaining the pace of aggregate technological progress in the 1990s.

(3) Estimated returns to scale vary greatly across sectors. Durable manufacturing appears to have increasing returns, whereas nondurable manufacturing and non-manufacturing appear to have decreasing returns.

(4) Not surprisingly, variations in the utilization of capital and labor are highly procyclical. In particular, cyclical utilization played the most important role in lowering measured productivity growth relative to true technology growth in the first half of the 1990s.

(5) Reallocation effects appear to be *countercyclical* for the Japanese economy, contrasting sharply with the evidence for the United States provided by Basu and Fernald (2001). In Japan, industries with low returns to scale expand disproportionately in booms and contract disproportionately in recessions,

so that reallocations make aggregate productivity *less* procyclical. Such reallocation effects significantly lowered measured productivity growth during the (short-lived) recovery years of 1995–97.

(6) Our main conclusion—that there was little or no deceleration in the rate of aggregate technology growth in the 1990s—appears robust to the estimates of the returns to scale and the quality adjustment of labor-input data.[6]

These results cast doubt on the productivity slowdown hypothesis discussed above. Indeed, if one accepts our results, the "low TFP growth puzzle" that Hayashi and Prescott (2002) emphasize in explaining Japan's lost decade is not a puzzle, but a figment of cyclical errors in measuring productivity: after correcting the aggregate Solow residuals for imperfect competition, varying utilization, and reallocations, we find little or no evidence of a decline in the pace of technological progress in the 1990s. Our results thus provide a strong motivation for moving beyond a simple real-business-cycle explanation that ultimately attributes the prolonged slump to the observed productivity slowdown.[7] Even if this strong conclusion is not accepted, our findings suggest that there is substantial room for factors other than *negative* technology shocks as causal elements in the decade-long Japanese slowdown.[8]

The paper is structured as follows. Section II discusses our method for identifying sectoral and aggregate technical change. Section III describes the data and estimation methods, and Section IV presents baseline results. Section V checks the robustness of the results, and Section VI briefly discusses investment-specific technology change. Finally, Section VII offers a conclusion.

II. Theoretical Framework

This section describes our basic method for identifying aggregate technical change, following Basu and Kimball (1997), Basu and Fernald (2001, 2002), Basu, Fernald,

6. Besides the major results regarding the "neutral" technological progress, we briefly explore the implications of another notion of technology change: "investment-specific technology change," as originally proposed by Solow (1960) and recently revived by Greenwood, Hercowitz, and Krusell (1997, 2000). Specifically, we follow these studies by interpreting the secular decline in the real price of investment goods as being the result of investment-specific, not neutral, technology change. We then find no evidence that the pace of such technology growth has slowed in the 1990s.
7. Our results are surely not irrelevant to the "liquidity trap" hypothesis regarding the current Japanese slump. Krugman (1998) originally proposes this hypothesis using a two-period sticky-price model, which has recently been elaborated into an infinite-horizon model by Eggertsson and Woodford (2003). In these models, economies fall into the liquidity trap when the "natural rate of interest" (i.e., the full employment level of the real interest rate holding with flexible price) is *negative*, and emerge from the trap when this rate turns positive again. Because those models do *not* incorporate endogenous capital, the natural rate of interest is determined solely by the expected growth rate of exogenous technology according to a consumption Euler equation (some researchers call this Euler equation a "new IS" equation), given the expected growth rate of government expenditures. Hence, the natural rate becomes negative for a period of *negative technology growth*, holding constant fiscal policy. However, if one accepts the results in this paper, it would be difficult to identify which factors caused the natural rate to be negative during Japan's lost decade.
8. The results in this paper may also have some implications for the celebrated "missing productivity growth" puzzle (see Basu *et al.* [2004], among others). In the United States, TFP growth *accelerated* in the 1990s, probably reflecting the diffusion of information and communications technology (ICT). By contrast, as many researchers (e.g., Gust and Marquez [2000]) document, TFP growth *decelerated* in the European Union overall and in Japan in the same decade, although these countries should also have enjoyed advances in ICT. Our results indicate, however, that once one purifies the Solow residuals, the missing productivity growth puzzle disappears, at least for Japan.

and Shapiro (2001), and Basu, Fernald, and Kimball (2002). Section II.A discusses how to estimate technical change at a disaggregated (industry) level, allowing for non-constant returns to scale and variations in the utilization of capital and labor. Section II.B presents our method of aggregating sectoral technical change into an economy-wide index.

A. Measuring Sectoral Technical Change

We assume that the representative firm in each industry has a production function for gross output:

$$Y_i = F^i(S_i K_i,\ E_i H_i N_i,\ M_i,\ Z_i).$$

The firm produces gross output Y_i using the capital stock K_i, employees N_i, and intermediate inputs M_i. To have a coherent model of variable factor utilization, we assume that the capital stock and number of employees are quasi-fixed, so that changing their levels involves adjustment costs.[9] Yet the firm may vary the intensity with which it uses these quasi-fixed inputs: H_i is hours worked per employee; E_i is the effort of each worker; and S_i is the capital utilization rate (i.e., the workweek of capital). Total labor input L_i is the product $E_i H_i N_i$. The firm's production function F^i is assumed to be (locally) homogeneous of arbitrary degree γ_i in total inputs. Z_i indexes gross output-augmenting technology. We adopt the gross output rather than the value-added production function because the former is desirable for estimating technical change in an economy with increasing returns to scale and imperfect competition.[10]

Following Solow (1957) and Hall (1988, 1990), we define technical change as the fraction of output growth that cannot be attributed to the growth rate of inputs, via a *first-order* (log-linear) approximation. For any variable J, we define dj as its logarithmic growth rate ($\equiv d\ \log J$), and J^* as its steady-state value. The log-linearization of the production function and the standard first-order conditions from cost minimization imply

$$\begin{aligned} dy_i &= \left(\frac{F_1 SK}{F}\right)_i^* (ds_i + dk_i) + \left(\frac{F_2 EHN}{F}\right)_i^* (de_i + dh_i + dn_i) + \left(\frac{F_3 M}{F}\right)_i^* dm_i + dz_i \\ &= \gamma_i\ [c_{Ki}^*(ds_i + dk_i) + c_{Li}^*(de_i + dh_i + dn_i) + c_{Mi}^* dm_i] + dz_i \\ &= \gamma_i\ (dx_i + du_i) + dz_i, \qquad (1) \end{aligned}$$

9. See Basu, Fernald, and Kimball (2002) for this point.

10. According to equation (A.16) in Appendix 2, the growth rate of value-added dv_i depends on materials intensity $dm_i - dy_i$ in addition to primary input growth dx_i^V, utilization variation du_i^V, and technological progress dz_i^V (note that with increasing returns and imperfect competition, the coefficient multiplying $dm_i - dy_i$ is not zero). Thus, there is an "omitted variable" in the estimating equation that uses value added as the output measure. See Basu and Fernald (1995, 1997) for the details.

where dx_i is the cost-share-weighted average of *observed* input growth:

$$dx_i \equiv c^*_{Ki} dk_i + c^*_{Li}(dh_i + dn_i) + c^*_{Mi} dm_i,$$

du_i is the weighted average of *unobserved* variation in capital utilization and labor effort:

$$du_i \equiv c^*_{Ki} ds + c^*_{Li} de,$$

and c_{Ji} is the share of input J in total cost, so $c_{Ki} + c_{Li} + c_{Mi} = 1$. The first-order approximation requires us to treat the output elasticity of each input $\gamma_i c^*_{Ji}$ as constant. In practice, we assume that returns to scale γ_i do not vary over time, and use the sample average of the annual cost shares as a proxy for c^*_{Ji}.[11]

Lack of an observable counterpart to utilization growth du_i is the barrier to estimating equation (1).[12] However, Basu and Kimball (1997) propose a simple *model-based* method of relating du_i to observable variables. Their basic idea is that a cost-minimizing firm operates on all margins simultaneously, so the firm's first-order conditions imply a relationship between observed and unobserved variables. Specifically, Basu and Kimball (1997) show that if the sole cost of changing the workweek of capital is a "shift premium"—firms need to pay higher wages to compensate employees for working at night, or at other undesirable times—then changes in hours per worker can proxy appropriately for unobserved changes in *both* labor effort and capital utilization. The important point to note is that Basu and Kimball's (1997) model uses only the cost minimization problem and the assumption that firms are price takers in factor markets; it does not require any assumptions about the firms' price-setting behavior in output markets. Based on their model, Appendix 1 shows that

$$du_i = \left(c^*_{Ki} \frac{\eta_i}{\omega_i} + c^*_{Li} \zeta_i \right) dh_i, \tag{2}$$

where η_i is the rate at which the elasticity of labor costs with respect to hours increases, ω_i is the rate at which the elasticity of labor costs with respect to capital utilization increases, and ζ_i is the elasticity of effort with respect to hours per worker. The reason why hours per worker proxies for capital utilization as well as labor effort is that the shift premium creates a link between the workweek of capital and labor costs. See Appendix 1 for the detailed derivation.

11. By contrast, a second-order Törnqvist approximation to the production function tries to estimate the "time-varying" elasticity by using the high-frequency variations in observed shares. However, this procedure would be valid only if the observed cyclical fluctuations in factor prices were *allocative* (i.e., actual factor prices always equaled *shadow* prices). See Basu and Fernald (2001) for the problems with such a higher-order approximation approach.
12. In Japan, the Ministry of Economy, Trade, and Industry (METI) publishes an index of "capacity utilization" for manufacturing and mining industries. Note, however, that this is not necessarily an economically meaningful measure of "capital utilization." Indeed, METI's capacity utilization measures actual output relative to potential output rather than capital's workweek. See Shapiro (1989) for the crucial difference between capital utilization and capacity utilization.

Finally, combining (1) and (2) gives us the following estimating equation:

$$dy_i = \gamma_i dx_i + \gamma_i \left(c_{Ki}^* \frac{\eta_i}{\omega_i} + c_{Li}^* \zeta_i \right) dh_i + dz_i$$

$$= \gamma_i dx_i + \beta_i dh_i + dz_i, \tag{3}$$

where $\beta_i \equiv \gamma_i (c_{Ki}^* (\eta_i / \omega_i) + c_{Li}^* \zeta_i)$. This specification controls for both labor effort and capital utilization, as well as non-constant returns to scale and imperfect competition. Since we treat cost shares and other structural parameters as constants, we can simply estimate β_i as well as γ_i. We interpret the resulting residual dz_i as representing "true" technical change for each industry.

B. Aggregate Technical Change

We now aggregate sectoral technical change dz_i into an economy-wide index. Following Basu, Fernald, and Kimball (2002), we define aggregate technical change as the increase in aggregate output, holding fixed not only aggregate primary inputs, but also their distribution across industries and the materials-gross output ratio for each industry. In particular, this measure of aggregate technical change equals

$$dz^V \equiv \sum_i w_i dz_i^V \equiv \sum_i w_i \frac{dz_i}{1 - \gamma_i c_{Mi}^*}, \tag{4}$$

where w_i is the industry's share in aggregate *real* value added:[13]

$$w_i \equiv \frac{Y_i - M_i}{\sum_i (Y_i - M_i)} \equiv \frac{V_i}{V}.$$

(Henceforth, we use a superscript V to denote the value-added version of variables previously defined in a gross-output context.) Conceptually, this measure first converts the sectoral, gross output-augmenting technology shocks to a value-added basis by dividing through by $1 - \gamma_i c_{Mi}^*$ (note that gross output-augmenting technology shocks translate to *larger* value-added augmenting technology shocks). These value-added technology shocks are then weighted by the industry's share in aggregate real value added. The key aspect of this definition is that aggregate technology changes only if industry-level technology changes.

It is useful to relate our definition of aggregate technical change to the aggregate Solow residual. First, we define the aggregate Solow residual dp as

$$dp \equiv dv - dx^V, \tag{5}$$

13. We use the "double deflation" method to define real value-added V_i. See the discussion in Appendix 2.

where dv is the aggregate real value-added growth:

$$dv \equiv \sum_i w_i dv_i,$$

and dx^V is the share-weighted average of sectoral *primary-input* growth dx_i^V:

$$dx^V \equiv \sum_i w_i dx_i^V \equiv \sum_i w_i \left[\frac{c_{Ki}^*}{1 - c_{Mi}^*} dk_i + \frac{c_{Li}^*}{1 - c_{Mi}^*} (dh_i + dn_i) \right].$$

Note that we use the shares of capital and labor in value-added-based total cost to compute dx_i^V. Next we define the value-added returns to scale as[14]

$$\gamma_i^V \equiv \frac{\gamma_i (1 - c_{Mi}^*)}{1 - \gamma_i c_{Mi}^*}. \tag{6}$$

This formula implies that since value added is only a fraction of gross output, increasing returns in the production of gross output translates to larger increasing returns in the production of value added.

Following the steps described in Basu and Fernald (2001, 2002), Appendix 2 shows that taking a weighted sum of equation (1) over the entire economy and substituting definitions (4), (5), and (6) yields the following decomposition for aggregate productivity:

$$dp = (\bar{\gamma}^V - 1) dx^V + R_\gamma + R_M + du^V + dz^V, \tag{7}$$

where

$$\bar{\gamma}^V \equiv \sum_i w_i \gamma_i^V, \tag{8}$$

$$R_\gamma \equiv \sum_i w_i (\gamma_i^V - \bar{\gamma}^V) dx_i^V, \tag{9}$$

$$R_M \equiv \sum_i w_i \left[\gamma_i^V \left(\frac{c_{Mi}^*}{1 - c_{Mi}^*} \right) - \frac{s_{Mi}}{1 - s_{Mi}} \right] (dm_i - dy_i), \tag{10}$$

$$du^V \equiv \sum_i w_i \gamma_i^V du_i^V \equiv \sum_i w_i \gamma_i^V \left(\frac{c_{Ki}^*}{1 - c_{Mi}^*} ds_i + \frac{c_{Li}^*}{1 - c_{Mi}^*} de_i \right), \tag{11}$$

with $s_{Mi} \equiv M_i / Y_i$.

14. See Appendix 2 for the derivation.

Equation (7) shows the difference between aggregate productivity and aggregate technology. First, the $(\bar{\gamma}^V - 1)dx^V$ term captures the average scale effect: if the average value-added returns to scale are increasing, fluctuations in aggregate primary inputs cause procyclical fluctuations in aggregate productivity. Second, the R_γ term represents the effect of reallocation of inputs across industries with different returns to scale: if returns to scale vary across industries, productivity growth receives an extra boost when industries with above-average increasing returns also experience above-average input growth. Third, the R_M term corrects for mismeasurements in value added: value added is computed using s_{Mi} as a measure of the output elasticity of materials, but with non-constant returns the output elasticity differs from materials' revenue share. Finally, the du^V term captures the effect on aggregate productivity of a change in value-added-based utilization.

Note that if all firms are perfectly competitive and do not vary utilization, then all four terms discussed above disappear: if all firms are perfectly competitive with a constant returns production function, $\gamma_i^V = 1$ and $c_{Mi}^* = s_{Mi}^*$ for all i. Hence, the first three terms in equation (7) always equal zero. Furthermore, if there is no utilization variation, it is obvious that the last term also equals zero. Then aggregate Solow residual dp equals aggregate technology change dz^V. However, with imperfect competition (non-constant returns) and cyclical variations in utilization, productivity and technology are generally not equivalent.

III. Data and Estimation Method

A. The Data

We use the JIP database compiled by Fukao *et al.* (2003) on industry-level inputs and outputs. This database is part of the research project at the Economic and Social Research Institute (ESRI), Cabinet Office, Government of Japan, aimed at measuring TFP growth at the industry level. The data consist of a panel of 84 industries covering the entire Japanese economy for the years 1973–98.[15] In each sectoral account, output is measured as gross output, and inputs are separated into capital, labor, and materials. Labor input data are available both with and without a quality adjustment. For a complete description of the database, see Fukao *et al.* (2003; 2004, appendix A).[16]

15. Fukao *et al.* (2003, chapter 1) do not report the data on gross output and materials in 1971 and 1972, because there is no extended table of the Input-Output Table for both these years. Thus, our sample period runs from 1973.
16. These data are available in Excel file format (in Japanese) at the ESRI's website, http://www.esri.go.jp/jp/archive/bun/bun170/170index.html.

Among the 84 industries in the JIP database, our analysis focuses on 54 industries belonging to the "non-farm, non-mining private economy" that is our primary interest.[17] These 54 industries constitute about 70 percent of GDP for the sample period. For the list of industries used in the estimation, see Table 2. For labor input, we use the non-quality-adjusted data in our benchmark estimation. In Section V, we assess the robustness of our benchmark results using the quality-adjusted data.

To construct the cost shares c_{Ji}, one generally needs to calculate required payments to capital. Fukao *et al.* (2003) estimate the user cost of capital and compute the series of factor cost shares for each industry. To calculate the steady-state value c_{Ji}^*, we take the time average of the cost shares over the sample period.

For the dh_i term in the utilization adjustment, we use the annual growth rate of industry's "nonscheduled hours" per worker, which is taken from the establishment survey conducted by the Government of Japan's Ministry of Health, Labour and Welfare (the survey is entitled "Maitsuki Kinro Tokei Chosa"). In this survey, the total number of hours per worker is divided into "scheduled" working hours and "nonscheduled" working hours. Scheduled hours are defined as the number of hours worked between the starting and ending time that are determined by the work regulations of the establishment, whereas nonscheduled hours are defined as the number of hours for which employees work early in the morning, overtime in the evening,

Table 2 Industry Classification

Durable manufacturing (14 industries, share: 14 percent)		Nondurable manufacturing (17 industries, share: 9 percent)	
JIP code	Industry	JIP code	Industry
21	Lumber & wood	11	Livestock products
22	Furniture	12	Processed marine products
32	Stone, clay & glass	14	Other foods
35	Nonferrous metal	15	Beverages
36	Metal products	16	Tobacco
37	General machinery	18	Spinning
38	Electrical machinery	19	Other textile products
39	Electrical machinery for households	20	Apparel
40	Other electrical machinery	23	Paper
41	Motor vehicles	24	Publishing & printing
42	Ships	25	Leather
43	Other transportation equipment	26	Rubber products
44	Instruments	27	Basic chemicals
45	Miscellaneous manufacturing	28	Chemical fibers
		29	Other chemicals
		30	Petroleum products
		31	Coal products

17. Although these industries are interpreted as belonging to the non-farm, non-mining private sector, we exclude the following four industries with serious data problems: rice polishing & flour milling (JIP code 13); silk (17); iron & steel (33); and other iron & steel (34). We also exclude the real estate (57) industry from our analysis, taking into account the possibility that it might be incomplete to subtract imputed housing rents from this industry's output. See Fukao *et al.* (2003, chapter 1) for details of these data problems.

Table 2 (continued)

Non-manufacturing (23 industries, share: 47 percent)		Excluded (30 industries, share: 30 percent)	
JIP code	Industry	JIP code	Industry
46	Construction	1	Rice & wheat
47	Civil engineering	2	Other farms
48	Electric utilities	3	Stockbreeding & sericulture
49	Gas utilities	4	Veterinary & agricultural services
53	Wholesale trade	5	Forestry
54	Retail trade	6	Fishing
55	Finance	7	Coal mining
56	Insurance	8	Metal mining
59	Railroad transportation	9	Oil & gas extraction
60	Trucking	10	Other mining
61	Water transportation	13	Rice polishing & flour milling
62	Transportation by air	17	Silk
63	Other transportation services	33	Iron & steel
64	Telephone & telegraph	34	Other iron & steel
70	Advertising	50	Waterworks
71	Rental of office equipment	51	Water services for industrial sector
72	Other business services	52	Waste disposal
73	Amusement & recreation services	57	Real estate
74	Radio & television	58	Housing services (imputed rent)
75	Restaurants	65	Postal services
76	Hotels & other lodging places	66	Educational services (private, nonprofit)
77	Laundry, barber, & public bath	67	Research
78	Other personal services	68	Medical services (private)
		69	Other social services
		79	Educational services (government)
		80	Medical services (government)
		81	Other services (government)
		82	Medical services (nonprofit)
		83	Other services (nonprofit)
		84	Statistical discrepancy

on emergency call-up, and on a day off. Reflecting declines in scheduled working hours, most of which are enforced by government fiat, total working hours have a low-frequency downward trend unrelated to cyclical utilization. (See Figure 3.) Since our utilization measure is the cyclical change in hours per worker, we take the growth rate of nonscheduled working hours as the dh_i term in the benchmark estimation.

B. The Estimation Method

Following Basu, Fernald, and Shapiro (2001) and Basu, Fernald, and Kimball (2002), we group all 54 industries into three broad sectors: (1) durable manufacturing (14 industries); (2) nondurable manufacturing (17 industries); and (3) non-manufacturing (23 industries). (See Table 2 for our classification of industries.) We allow the returns to scale parameter γ_i and the utilization parameter β_i to vary across these broad sectors. Yet we constrain these coefficients to be equal within

Figure 3 Number of Hours Worked

Note: All industries. Data are from the establishment survey conducted by the Ministry of Health, Labour and Welfare.

sectors.[18,19] The estimated equations also include industry-level constants to allow for differences in growth rates across industries, i.e., the estimated equations have industry-level fixed effects. These constants are added back in to our estimates of growth in technology.

18. In principle, we could allow for more heterogeneity across industries. Some experimentation suggested, however, that coefficients in several industries are often estimated rather imprecisely. To mitigate this problem, we opt to restrict the parameters to be constant within sectors.
19. Note that although the *gross-output* returns to scale parameters are restricted to be equal within sectors, we (implicitly) allow for industry heterogeneity in the *value-added* returns to scale defined by equation (6), reflecting differences in materials cost share.

Owing to the simultaneous determination of inputs and technology, we estimate each system by instrumental variables. Valid instruments need to be uncorrelated with technology shocks and correlated with the inputs and hours growth on the right-hand side of the equation. Good instruments are of course hard to find. Here we use the following variables as instruments: (1) the growth rate of the price of oil deflated by the GDP deflator;[20] (2) annual versions of the Romer dates for Japanese monetary policy that are identified by the author (a dummy variable that is one in 1973, 1980, and 1990 when there was a pronounced monetary contraction induced by the BOJ and zero otherwise);[21] and (3) a "banking crisis shock" variable (a dummy variable that is one in 1997 when several major financial institutions in Japan collapsed and zero otherwise).

Since the disturbances are somewhat correlated across industries, there are efficiency gains from re-estimating a system of equations with an estimated covariance matrix. We thus estimate the system by three-stage least squares, using the instruments noted above.

IV. Baseline Results

A. Parameter Estimates

Table 3 gives the estimates of the returns to scale and utilization parameters from equation (3). The returns to scale parameters γ_i are precisely estimated for all sectors. For the durable manufacturing sector, the estimated returns to scale is 1.06, indicating statistically significant evidence of increasing returns. For nondurable

Table 3 Parameter Estimates: Baseline Case

$$dy_i = \gamma_i dx_i + \beta_i dh_i + dz_i$$

	Durable manufacturing	Nondurable manufacturing	Non-manufacturing
Returns to scale, γ_i	1.06 (0.03)	0.81 (0.04)	0.65 (0.02)
Utilization, β_i	0.063 (0.012)	0.034 (0.024)	0.190 (0.015)
Without utilization adjustment Returns to scale, γ_i	1.14 (0.03)	0.84 (0.03)	0.67 (0.01)

Note: Estimation by three-stage least squares pooling across industries within sectors. Sample period is 1973–98. Data are from the JIP database and the establishment survey conducted by the Ministry of Health, Labour and Welfare. Non-quality-adjusted data on labor input are used. Instruments are (1) the contemporaneous and lagged value of the growth rate of the real oil price, (2) the contemporaneous and lagged value of the Romer date for Japan, and (3) a lagged "banking crisis" variable. Sectoral estimates include industry fixed effects (not reported). Standard errors are in parentheses.

20. Oil prices (customs clearance basis; yen) are taken from the Bank of Japan Financial and Economic Data CD-ROM. Data on the GDP deflator are from the Japanese National Accounts.

21. Kawamoto (2002) finds that these indicators of pronounced monetary tightness have the strong contractionary effects on real variables such as Romer and Romer (1989, 1994) find for the U.S. economy.

manufacturing and non-manufacturing, the estimates are 0.81 and 0.65, respectively, both displaying decreasing returns.[22] (Omitting the utilization correction term, the estimates rise slightly to 0.84 and 0.67 for nondurable manufacturing and non-manufacturing, respectively. Thus, the two sectors exhibit decreasing returns even without utilization correction.) Given these estimates, the returns to scale across sectors appear to demonstrate significant heterogeneity.

For comparison, Table 4 presents the estimates of the returns to scale for U.S. industries that are reported by Basu, Fernald, and Kimball (2002) and Basu, Fernald, and Shapiro (2001). Comparing Tables 3 and 4, we see that our estimates of the returns to scale are broadly similar to the U.S. estimates, although Japanese non-manufacturing exhibits much smaller returns to scale than U.S. non-manufacturing.

Our estimated returns to scale are also consistent with previous studies using Japanese data. For example, estimating translog production functions with data for Japanese manufacturing industries over the years 1955–90, Beason and Weinstein (1996) find that durable manufacturing industries have slightly increasing returns, while nondurable manufacturing industries have decreasing returns (see table 3 in their paper).

We now turn to the estimates of utilization-correction parameter β_i. In durable manufacturing and non-manufacturing, the estimates are positive and strongly statistically significant, both indicating the importance of the utilization adjustment. The estimate for nondurable manufacturing is estimated the least precisely. However, the share of nondurable manufacturing in GDP is relatively small (9 percent), so the statistical insignificance of β_i in this sector does not seem to be a major problem. Our empirical results are also not driven by any single industry: for example, omitting industries that look like "outliers" has little effect on our series of aggregate technology change presented below.

B. Estimated Growth in Technology

Table 5 shows the annual average growth rates of the estimates of technology over various periods. Focusing first on the entire private-sector economy that is our primary interest, the average growth rate of technology over 1990–98 was 2.1 percent, compared to 3.0 percent for 1973–80 and 2.3 percent for 1980–90. Omitting 1998 (in which a severe recession hit the economy) yields the average growth rate of 2.6 percent over the 1990s. Thus, we find little evidence of a significant decline in the

Table 4 Estimates of the Returns to Scale for U.S. Industries

	Durable manufacturing	Nondurable manufacturing	Non-manufacturing
Basu, Fernald, and Kimball (2002)	1.05	0.87	0.89
Basu, Fernald, and Shapiro (2001)	1.03	0.78	1.00

Note: See Basu, Fernald, and Kimball (2002, table 1) and Basu, Fernald, and Shapiro (2001, table 1). Since the former allow the returns to scale parameters to differ across industries within sectors, the estimates listed above are the value-added weighted averages. By contrast, the latter constrain the returns to scale parameters to be equal within sectors as in the present paper.

22. In Section V, we explore the implications of decreasing returns in the two sectors at length.

Table 5 Estimated Growth in Technology: Baseline Case

Percent per year

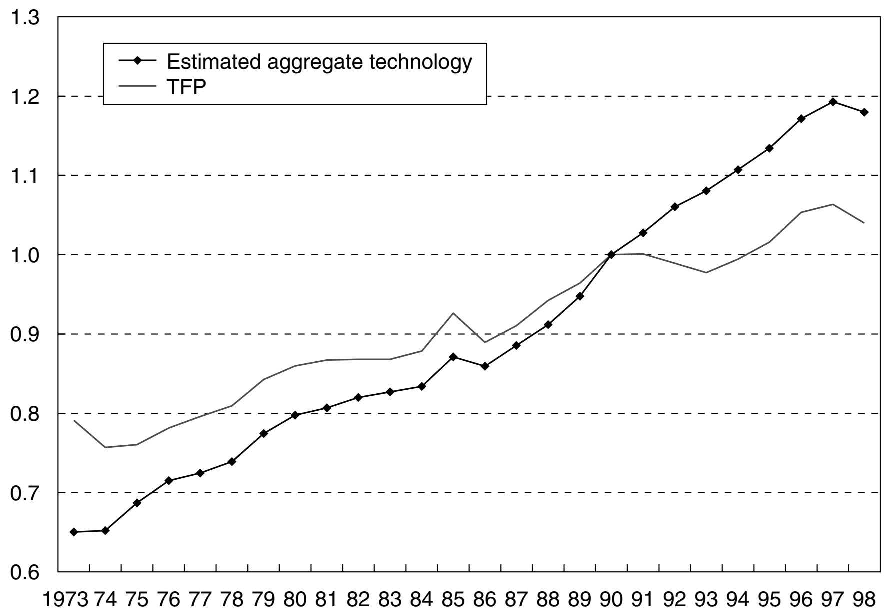
	1973–98	1973–80	1980–90	1990–98
Private sector	2.4	3.0	2.3	2.1
Durable manufacturing	3.6	5.6	3.5	2.1
Nondurable manufacturing	2.3	3.1	2.0	2.1
Non-manufacturing	2.1	2.3	2.0	2.1

Note: Estimates of technological change are based on the theoretical framework described in Section II and the parameter estimates given in Table 3.

pace of technological progress in the 1990s. Figure 4 underscores this point; the figure plots the *levels* of estimated aggregate technology as well as TFP. Both series are normalized to equal one in 1990, with the growth rates cumulated before and after. Both estimated aggregate technology and TFP grew steadily until about 1990. However, TFP slowed suddenly after 1990 as discussed in the introduction, whereas estimated aggregate technology continued to grow steadily through most of the decade.

We now turn to the sectoral results. Non-manufacturing showed a modest pickup in technology growth from 2.0 percent in the 1980s to 2.1 percent in the 1990s. Because non-manufacturing accounts for around 70 percent of private-sector GDP,

Figure 4 Levels of Estimated Aggregate Technology



Note: Levels of the series are normalized to equal one in 1990, with the changes cumulated before and after. Estimates of technological change are based on the theoretical framework described in Section II and the parameter estimates given in Table 3.

the technology non-deceleration in this sector contributed significantly to maintaining the pace of aggregate technological progress in the 1990s. Growth in nondurable manufacturing technology also increased slightly, from 2.0 percent in the 1980s to 2.1 percent in the 1990s. The exception to this pattern is durable manufacturing, in which the average growth rate of technology in the 1990s was 2.1 percent, a decrease of 1.4 percentage points relative to the 1980s and of 3.5 percentage points compared to the 1970s. This technology deceleration for durable manufacturing is somewhat puzzling, because information and communication *production* technology improved at a rapid rate during the 1990s, and Basu, Fernald, and Shapiro (2001) and many others naturally find substantial technology acceleration in the U.S. durable manufacturing sector.[23]

Summing up, our results indicate that the slowdown in measured productivity in the 1990s is not indicative of a decline in the rate of technological change: once the Solow residuals are purified by correcting for imperfect competition, cyclical utilization, and reallocations, there turns out to be little evidence of deceleration in the rate of technical progress in the lost decade. This conclusion naturally casts doubt on the Hayashi and Prescott (2002) hypothesis discussed in Section I. The question we must consider next is what factors explain such a large difference between measured productivity and true technology.

C. Difference between Aggregate Productivity and Aggregate Technology

Based upon equations (7)–(11), Table 6 decomposes the difference between measured aggregate productivity and true aggregate technology into various correction terms. In addition, focusing on the 1990s, our primary interest, Figure 5 shows the *levels*

Table 6 Difference between Aggregate Productivity and Aggregate Technology

$$dp = dv - dx^V$$
$$= (\bar{\gamma}^V - 1)dx^V + R_\gamma + R_M + du + dz^V$$

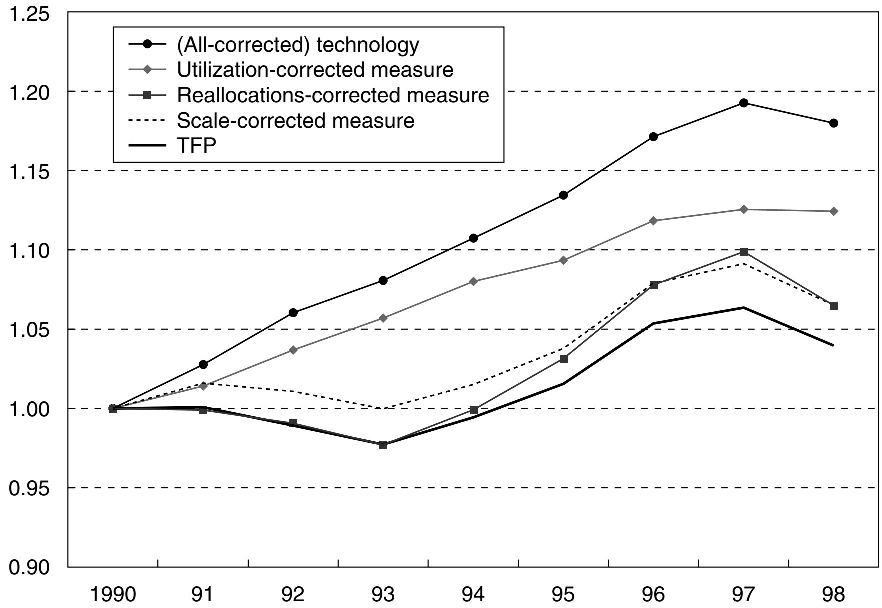
Percent per year

	1973–98	1973–80	1980–90	1990–98
Value-added growth dv	3.3	3.8	4.6	1.4
– Input growth dx^V	2.2	2.5	3.0	0.9
= Solow residual dp	1.1	1.2	1.6	0.5
– Average scale effect $(\bar{\gamma}^V - 1)dx^V$	–0.8	–0.9	–1.0	–0.3
– Reallocations $R_\gamma + R_M$	–0.2	–0.4	0.0	–0.3
– Utilization du	–0.3	–0.4	0.3	–1.0
= Technology growth dz^V	2.4	3.0	2.3	2.1

Note: Decomposition of the difference between measured productivity growth and estimated technology growth (see equations [7]–[11] in the text). Estimates are based on the parameter estimates given in Table 3.

23. There are two possible explanations for this puzzling fact. First, our data may *underestimate* real output growth in durable manufacturing due to an increasing upward bias of price indexes for durable goods. Second, Japanese durable manufacturing industries significantly increased foreign direct investment during the 1990s (probably because of the continuing yen appreciation), and hence a large amount of ICT production has shifted outward. Further investigation of this issue would be particularly interesting, but is beyond the scope of this paper.

Figure 5 Aggregate Productivity and Aggregate Technology in the 1990s

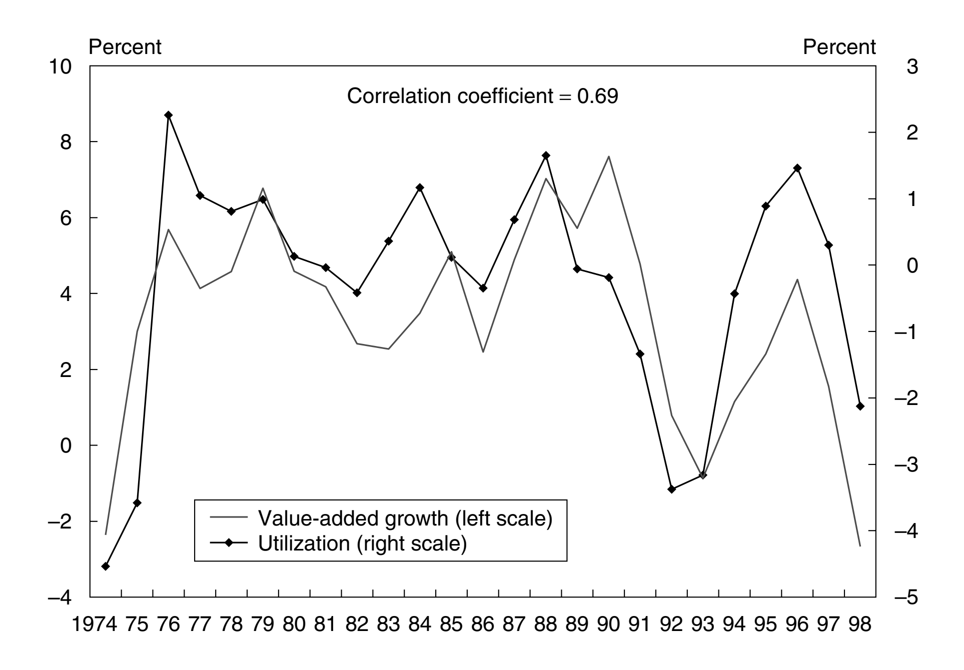


Note: Levels of the series are normalized to equal one in 1990, with the estimated growth rates cumulated thereafter. Estimates of technological change and various corrected measures are based on the theoretical framework described in Section II and the parameter estimates given in Table 3.

of (1) productivity, (2) the scale-corrected measure, (3) the utilization-corrected measure, (4) the reallocations-corrected measure, and (5) (all-corrected) true technology. (The levels of all five series are normalized to equal one in 1990, with the estimated growth rates cumulated thereafter. Thus, for example, the difference between productivity and the utilization-corrected measure in this figure represents the *cumulative effects* of the utilization correction.) Several interesting results emerge.

First, cyclical utilization of capital and labor has played the most prominent role in lowering measured productivity growth relative to true technology growth in the 1990s. Utilization correction has caused the Solow residual to understate technological change by an average annual rate of 1.0 percent over 1990–98, as shown in Table 6. A glance at Figure 5 also reveals that utilization correction accounts for most of the differences between productivity and technology in the first half of the 1990s. To see the cyclical properties of utilization, Figure 6 shows our estimated utilization series, plotted against real value-added growth. Not surprisingly, utilization is highly procyclical: the correlation of utilization with real value added is strongly positive at 0.69. We thus confirm that "true" inputs are more cyclical than measured inputs, so that measured productivity is spuriously procyclical. In this light, the enormous gaps between measured productivity and true technology—especially in the first half of the 1990s—can be interpreted as reflecting the unprecedented

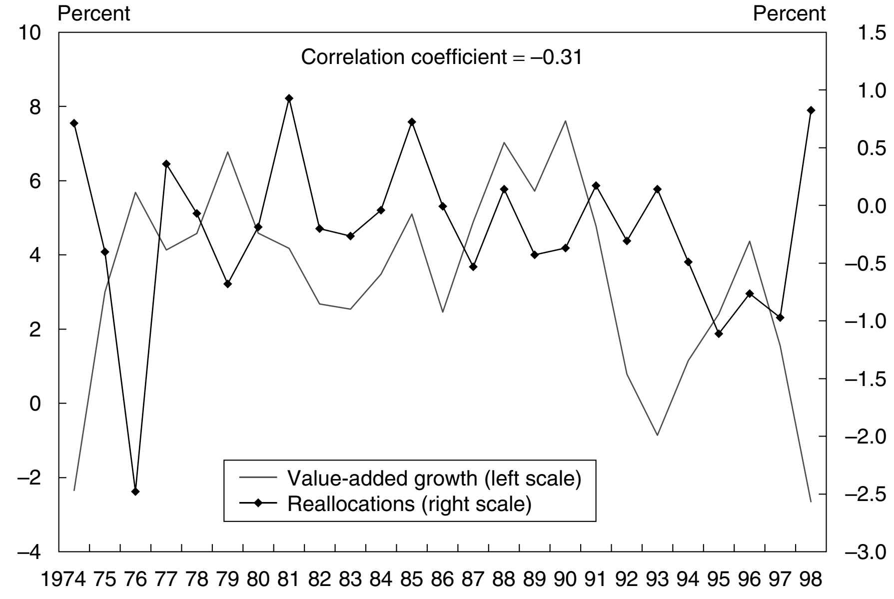
Figure 6 Cyclicality of Utilization



severity of the contemporaneous recession: since the 1991–93 recession following the collapse of the "asset price bubble" (this recession is called the "first Heisei recession") was so deep, the cyclical measurement error of input quantities in this period was significantly larger than in typical business cycles.

Second, reallocations—the sum of R_γ (reallocations of primary inputs across industries with different returns-to-scale estimates) and R_M (reallocation of materials)—are also important in creating the wedge between measured productivity and true technology. We estimate that reallocation correction is –0.3 percent per year on average over the 1990s (Table 6). It is worth noting that such effects are concentrated during the short-lived recovery years of 1995–97 as shown in Figure 5. This implies that the industries having *below-average* returns to scale (i.e., the non-manufacturing sector) experienced *above-average* input growth over the mid-decade recovery, leading to lower productivity growth than technology growth. As in the case of utilization, Figure 7 shows our estimated reallocation series, plotted against real value-added growth. Somewhat surprisingly, reallocation effects appear to be *countercyclical* for Japan, contrasting sharply with the U.S. industry-level evidence provided by Basu and Fernald (2001) (the correlation of reallocations with real value-added growth is negative at –0.31). This implies that, in Japan, industries with low returns to scale expand disproportionately in booms and contract disproportionately in recessions, so that reallocations make aggregate productivity *less* procyclical. This pattern is not *prima facie* absurd. For example, if the income elasticity of goods produced by industries with low returns to scale is higher than that of goods by industries with high returns to scale, reallocations tend to be countercyclical. Another possibility is that

Figure 7 Cyclicality of Reallocations



increases in government spending driving business cycles were directed disproportionately toward industries with low returns to scale in the 1970s and 1990s, which led to *negative* reallocation effects in these periods.[24] Further investigation of this issue would be particularly useful, but is beyond the scope of this paper.

Finally, the *average* scale effect is strongly negative over all periods. This reflects our previous empirical result that a typical industry in Japan appears to have significantly decreasing returns to scale. However, widespread decreasing returns are internally inconsistent with any form of imperfect competition as discussed in the next section, so it appears to be too early to evaluate the quantitative importance of the scale effect.

In short, cyclical utilization accounts for most of the differences between measured productivity and true technology in the first half of the 1990s. After the mid-1990s, reallocation effects were important in lowering productivity growth relative to technology growth.

24. The correlation of reallocations with real value-added growth was –0.6 in the 1970s, –0.06 in the 1980s, and –0.54 in the 1990s.

V. Robustness Checks

In this section, we check the robustness of the results presented above in regard to two considerations. First, we impose constant returns to scale on nondurable manufacturing and non-manufacturing, for both of which we find decreasing returns in the baseline estimation. Second, we use labor-input data with a quality adjustment.

A. Imposing Constant Returns on Nondurable Manufacturing and Non-Manufacturing

Our estimates of the returns to scale in nondurable manufacturing and non-manufacturing were smaller than one (see Table 3). Note, however, that significant decreasing returns to scale are inconsistent with *any* form of imperfect competition, as long as free entry and exit are guaranteed (see the discussion in Basu and Fernald [1995, 1997]). To clarify this point, we consider the following well-known identity linking the returns to scale and the markup:

$$\gamma = \frac{AC}{MC} = \left(\frac{P}{MC}\right)\left(\frac{AC}{P}\right) = \mu(1 - s_{\pi}), \tag{12}$$

where $\mu \equiv P/MC$ is the markup of price over marginal cost and s_{π} is the share of economic profit in total (gross) revenue. Given that the economic profit rate should be small under free entry and exit, equation (12) shows that strongly decreasing returns (μ much less than one) imply that firms consistently price output below marginal cost (μ less than one). Since this is not a sensible result, we naturally expect that firm-level returns to scale must be either constant or increasing. Hence, the apparent decreasing returns in nondurable manufacturing and non-manufacturing give a caution to the previous baseline results.[25]

Motivated by this sort of consideration, we assess the sensitivity of our findings to the decreasing returns in nondurable manufacturing and non-manufacturing. In particular, we ask whether constraining the returns to scale parameters to be *constant* in the two sectors affects our basic conclusion that there is little or no evidence of a decline in the rate of technological progress in the 1990s.

Table 7 presents the utilization parameter estimates obtained when we impose constant returns upon nondurable manufacturing and non-manufacturing. The point estimates are, for the most part, little changed. The estimate of β_i for non-manufacturing remains statistically significant, although the size of the parameter

25. Note that such a "decreasing returns puzzle" is not a phenomenon specific to the Japanese industry data. For example, using data on (roughly) two-digit industries in the United States, Basu, Fernald, and Kimball (2002) report that the weighted averages of the estimated returns to scale are 0.87 and 0.89 for nondurable manufacturing and non-manufacturing, respectively (see Table 4). Using quarterly data on value added for three-digit manufacturing industries in the United States, Burnside, Eichenbaum, and Rebelo (1996a) also report that the estimated value-added returns to scale range from 0.8 to 0.9. One possible explanation for this puzzle is that "countercyclical within-industry reallocations" will tend to appear as decreasing returns, because *aggregated* data on industries are used in estimation. Investigating this sort of possibility would be of considerable interest, but is beyond the scope of this paper.

Table 7 Parameter Estimates: Imposing Constant Returns to Scale on Nondurable Manufacturing and Non-Manufacturing

$$dy_i - dx_i = \beta_i dh_i + dz_i$$

	Nondurable manufacturing	Non-manufacturing
Utilization, β_i	–0.014 (0.017)	0.122 (0.017)

Note: Estimation by three-stage least squares pooling across industries within sectors. Sample period is 1973–98. Data are from the JIP database and the establishment survey conducted by the Ministry of Health, Labour and Welfare. Non-quality-adjusted data on labor input are used. Instruments are (1) the contemporaneous and lagged value of the growth rate of the real oil price, (2) the contemporaneous and lagged value of the Romer date for Japan, and (3) a lagged "banking crisis" variable. Sectoral estimates include industry fixed effects (not reported). Standard errors are in parentheses.

becomes somewhat smaller than in Table 3. Thus, the decreasing returns and statistical significance of the utilization parameter for this sector do not seem to arise from a multicollinearity problem, where the inputs and hours growth are correlated. This result is particularly important, because it suggests that utilization correction is still necessary for the non-manufacturing sector, which accounts for most of private-sector GDP. Turning to the nondurable manufacturing sector, we find the estimate of β_i to be statistically insignificant. This is also similar to the baseline results in Table 3.

Table 8 and Figure 8 give estimated growth in technology based on the parameter estimates given in Table 7 (for durable manufacturing, we continue to use the parameter estimates given in Table 3). Overall, our basic conclusion is intact: the lost decade is *not* a period of low technology growth. The results for the entire private-sector economy show a pickup in technology from 1.2 percent in the 1980s to 1.8 percent in the 1990s: taken at face value, the Japanese economy experienced a 0.6 percentage point *acceleration* in technology growth in the lost decade! This acceleration comes mostly from the acceleration in technology growth for the non-manufacturing sector. Growth in non-manufacturing technology increased 0.9 percentage point, from 0.3 percent in the 1980s to 1.2 percent in the 1990s.

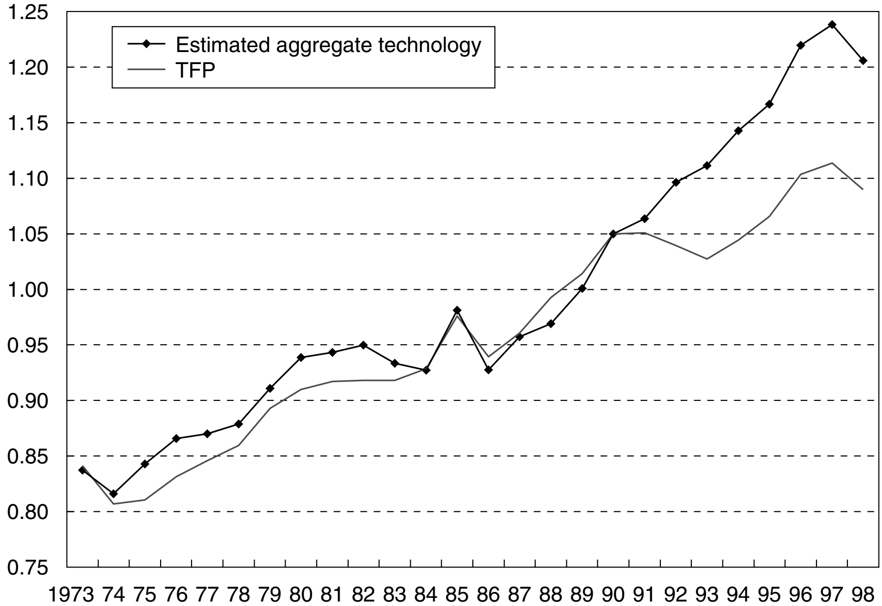
Table 8 Estimated Growth in Technology: Imposing Constant Returns to Scale on Nondurable Manufacturing and Non-Manufacturing

Percent per year

	1973–98	1973–80	1980–90	1990–98
Private sector	1.6	1.8	1.2	1.8
Durable manufacturing	3.6	5.6	3.5	2.1
Nondurable manufacturing	3.6	3.7	2.6	4.8
Non-manufacturing	0.6	0.5	0.3	1.2

Note: Estimates of technological change are based on the parameter estimates given in Table 3 for durable manufacturing and the parameter estimates given in Table 7 for nondurable manufacturing and non-manufacturing.

Figure 8 Levels of Estimated Aggregate Technology: Imposing Constant Returns to Scale on Nondurable Manufacturing and Non-Manufacturing



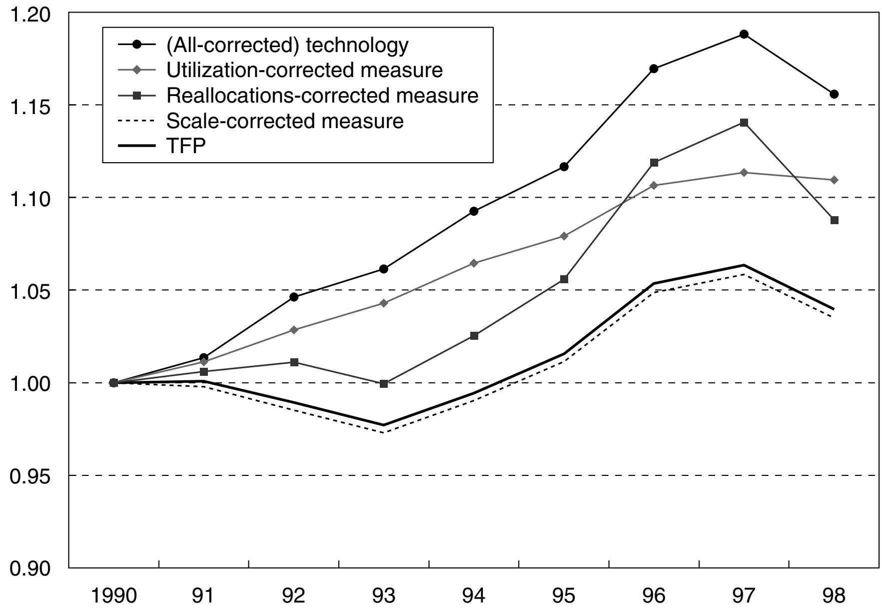
Note: Levels of the series are normalized to equal one in 1990, with the changes cumulated before and after. Estimates of technological change are based on the theoretical framework described in Section II and the parameter estimates given in Tables 3 and 7.

To examine which factors account for the difference between measured productivity and true technology, Figure 9 shows the *levels* of (1) productivity, (2) the scale-corrected measure, (3) the utilization-corrected measure, (4) the reallocations-corrected measure, and (5) (all-corrected) true technology when imposing constant returns on nondurable manufacturing and non-manufacturing. The results are strikingly similar to the pattern of the baseline case: cyclical utilization explains most of the gaps between productivity and technology in the first half of the 1990s. After the mid-1990s, reallocation effects played an important role in lowering productivity growth relative to technology growth.

B. Quality Adjustment to Labor Input

Thus far, we have continued to use "non-quality-adjusted" data on labor input. Without a quality adjustment, the measure of labor input in the JIP database is essentially standard hours worked, i.e., the product of the number of workers and the average annual hours per worker. From the perspective of a firm, however, the relevant measure of labor input might not be merely hours worked. It seems likely that the firm also cares about the *relative productivity* of different workers. From this standpoint, this subsection checks the robustness of our previous results by using quality-adjusted labor-input data.

Figure 9 Aggregate Productivity and Aggregate Technology in the 1990s: Imposing Constant Returns to Scale on Nondurable Manufacturing and Non-Manufacturing



Note: Levels of the series are normalized to equal one in 1990, with the estimated growth rates cumulated thereafter. Estimates of technological change and various corrected measures are based on the theoretical framework described in Section II and the parameter estimates given in Tables 3 and 7.

To construct data on labor with a quality adjustment, Fukao *et al.* (2003, 2004) take into account differences in sex, age, and educational background as labor "quality," assuming that observed wage differences reflect differences in relative marginal products. They then calculate quality-adjusted labor input by weighting the hours worked by different types of workers by relative wage rates. Hence, labor input can increase either because the number of hours worked increases, or because the quality of those hours increases.[26]

In Table 9, we show the same regressions as in Table 3, but using the quality-adjusted data on labor input. The estimation results are strikingly similar to those without the quality adjustment. We confirm that the estimated parameters are not altered by the quality adjustment.

26. See Fukao *et al.* (2003, chapter 2; 2004, appendix A.2) for a complete description of the quality adjustment.

Table 9 Parameter Estimates: Quality Adjustment to Labor Input

$$dy_i = \gamma_i dx_i + \beta_i dh_i + dz_i$$

	Durable manufacturing	Nondurable manufacturing	Non-manufacturing
Returns to scale, γ_i	1.07 (0.03)	0.81 (0.04)	0.65 (0.01)
Utilization, β_i	0.063 (0.012)	0.032 (0.024)	0.181 (0.010)

Note: Estimation by three-stage least squares pooling across industries within sectors. Sample period is 1973–98. Data are from the JIP database and the establishment survey conducted by the Ministry of Health, Labour and Welfare. The data used for labor input are quality-adjusted. Instruments are (1) the contemporaneous and lagged value of the growth rate of the real oil price, (2) the contemporaneous and lagged value of the Romer date for Japan, and (3) a lagged "banking crisis" variable. Sectoral estimates include industry fixed effects (not reported). Standard errors are in parentheses.

Table 10 shows the annual growth rates of estimated technology based on the parameter estimates given in Table 9. The results are qualitatively similar to the baseline case in Table 5, although making the quality adjustment lowers the growth rates of estimated technology for the *overall* period. The most important point to note is that we still find no evidence of a decline in the pace of technological change in the 1990s. Moreover, comparing Table 10 to Table 5, we see that the upward bias of technology growth, which arises from not accounting for quality changes in labor input, is much *smaller* in the 1990s than in other decades. This reflects the fact that the 1990s witnessed no substantial change in labor composition. We thus confirm that none of our main results are affected by the quality adjustment.

We conclude this section by noting that our basic conclusion appears quite robust to the estimates of the returns to scale and the quality adjustment. Different methods certainly generate different estimates of aggregate technical change. Nevertheless, we emphasize that these differences do not affect our *qualitative* conclusion that there is little or no evidence of a deceleration in the rate of technological progress in the 1990s. If one accepts these results, the 1990s in Japan were far from being a lost decade in terms of technological progress.

Table 10 Estimated Growth in Technology: Quality Adjustment to Labor Input

Percent per year

	1973–98	1973–80	1980–90	1990–98
Private sector	2.0	2.4	1.9	1.9
Durable manufacturing	2.9	4.6	2.8	1.4
Nondurable manufacturing	2.0	2.7	1.7	1.9
Non-manufacturing	1.8	1.9	1.6	2.1

Note: Estimates of technological change are based on the theoretical framework described in Section II and the parameter estimates given in Table 9.

VI. Another Look at Technology Change: Investment-Specific Technology Change

Up to this point, we have focused on "neutral" technology change that affects the production of all goods homogenously. This section briefly explores the implications of an alternative notion of technology change: "investment-specific technology change," originally proposed by Solow (1960) and recently revived by Greenwood, Hercowitz, and Krusell (1997, 2000). These authors emphasize the importance of technological progress *embodied in the form of new capital goods*.[27]

For simplicity and to focus on the essential aspects of the models of investment-specific technology change, we assume that (value-added) output is produced according to the constant-returns-to-scale aggregate production function:

$$V = G(K, L).$$

Note that there is *no* neutral technological progress, unlike the model presented in Section II. We assume that output can be used as usual for both consumption and investment. However, capital accumulation equation takes a form that differs from the standard one:

$$\dot{K} = IA - \delta K,$$

where I is gross investment and d is the depreciation rate. Here, A represents the current state of the technology for producing new capital goods: as A rises, more new capital goods can be produced for a unit of forgone output or consumption. This form of technical change is *specific* to the investment goods sector of the economy; hence, an increase in A is called investment-specific technology change. As Greenwood and Jovanovic (2001) emphasize, there must be investment in the economy to realize the gains from this form of technology change.

In a competitive equilibrium, the relative price of new capital goods, P_I, will be given by

$$P_I = 1/A.$$

This equation shows how much in consumption goods must be given up to accumulate one unit of capital. Note that we can easily identify investment-specific technology change by calculating changes in the actual relative price of new capital goods.

Table 11 and Figure 10 show the estimates of investment-specific technology change for the Japanese economy. Clearly, there is no evidence that investment-specific technology growth slowed in the 1990s. Hence, even if one allows for embodied technology change in addition to neutral technology change, explaining Japan's lost decade as a period of low technology growth remains implausible.

27. Greenwood and Jovanovic (2001) survey various growth models of investment-specific technical change. Fisher (2002) stresses the shock to investment-specific technology as the underlying driving force of business cycles.

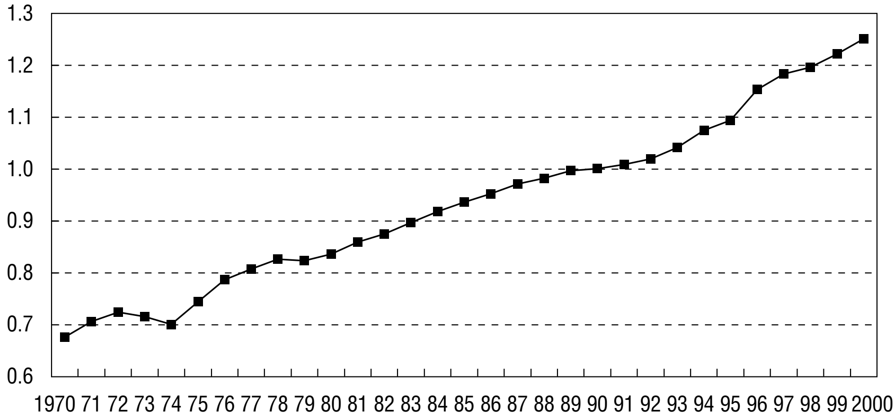
Table 11 Investment-Specific Technology Change

Percent per year

	1960s	1970s	1980s	1990s
Investment-specific technology change	3.7	2.1	1.8	2.2

Note: Investment-specific technology change is measured as the inflation rate of the consumption deflator minus the inflation rate of the investment deflator. Data on deflators are from the Japanese National Accounts.

Figure 10 Investment-Specific Technological Progress



Note: Investment-specific technological progress is measured as the inverse of the real price of investment goods (i.e., consumption deflator/investment deflator). Levels of the series are normalized to equal one in 1990. Data on deflators are from the Japanese National Accounts.

VII. Conclusion

In this paper, we measured aggregate technology change for the Japanese economy by correcting the aggregate Solow residuals for increasing returns, imperfect competition, varying utilization of capital and labor, and reallocation effects. We reached a robust conclusion: the productivity slowdown observed in the 1990s is *not* a slowdown in the rate of technological progress. Our results thus call into question a real-business-cycle explanation of Japan's lost decade.

Future research should refine our estimates of aggregate technical change for the Japanese economy. Owing to our primary interest in economy-wide aggregates, we used the industry-level data covering the entire Japanese economy. In principle, our exercise could be repeated for the manufacturing sector with a large firm-level data set, such as the Development Bank of Japan (DBJ) database. Such projects are likely to shed new light on the source and nature of the decade-long Japanese slowdown.[28]

28. For example, the firm-level data set would allow one to investigate the implications of "within-industry" reallocations that we do not deal with here.

APPENDIX 1: DERIVATION OF THE UTILIZATION PROXY IN BASU AND KIMBALL'S (1997) MODEL

This appendix describes the derivation of the utilization proxy, following Basu and Kimball (1997, appendix A) and Basu, Fernald, and Kimball (2002, section I.B).

We assume the firm faces adjustment costs in both investment and hiring, so that both the amount of capital, K, and employment, N, are quasi-fixed. Basu, Fernald, and Kimball (2002) provide a convincing argument for the necessity of quasi-fixity for a meaningful model of variable factor utilization. We assume that the number of hours per week for each worker, H, can vary freely with no adjustment cost (through changes in nonscheduled hours in the context of the Japanese economy). In addition, both capital and labor have freely variable utilization rates. For both capital and labor, the benefit of higher utilization is its multiplication of effective inputs. Basu and Kimball (1997) argue that there are two kinds of costs for increasing capital utilization, S: (1) firms must pay a "shift premium" (a higher base wage) to compensate employees for working at night, or at other undesirable times; and (2) higher capital utilization leads to quicker depreciation through extra "wear and tear" on the capital. For simplicity, here we consider only the shift premium, which is supported by many empirical studies (see, for example, Shapiro [1996]). The cost of higher labor utilization, E, is modeled as a higher disutility on the part of workers that must be compensated with a higher wage.

We consider the following dynamic cost minimization problem for the firm:

$$\min_{A,E,H,I,M,S} \int_0^\infty e^{-\int_0^t r d\tau}[WNG(H,E)V(S) + P_M M + WN\Psi(A/N) + P_I KJ(I/K)]dt,$$

subject to

$$\overline{Y} = F(SK, EHN, M, Z),$$

$$\dot{K} = I - \delta K,$$

$$\dot{N} = A. \tag{A.1}$$

At a point in time, the firm's costs are total payments for labor and materials, and the costs associated with undertaking gross investment I and hiring net of separations A. $WG(H, E)V(S)$ is total compensation per worker. W is the base wage; the function G specifies how the hourly wage depends on the length of the working hours H and effort E; and $V(S)$ is the shift premium. P_M is the price of materials. $WN\Psi(A/N)$ is the total cost of changing the number of employees; $P_I KJ(I/K)$ is the total cost of investment. d is the depreciation rate of capital. We assume that Ψ and J are convex. Defining the function F as $\log G(H, E) = \Phi(\log H, \log E)$, we assume the convexity of F to guarantee a global optimum. Moreover, we assume the normality of F, i.e., $\Phi_{11} > \Phi_{12}$ and $\Phi_{22} > \Phi_{12}$, for optimal H and E to move together. We omit time subscripts for clarity.

The first-order conditions relevant for our derivation are intra-temporal ones with respect to choices of S, H, and E:

$$WNG(H, E)V'(S) = \lambda F_1 K, \tag{A.2}$$

$$WNG_H(H, E)V(S) = \lambda F_2 EN, \tag{A.3}$$

$$WNG_E(H, E)V(S) = \lambda F_2 HN. \tag{A.4}$$

Here, λ is the Lagrange multiplier on the constraint (A.1), which can be interpreted as marginal cost. Combining (A.3) and (A.4) yields

$$\frac{HG_H(H, E)}{G(H, E)} = \frac{EG_E(H, E)}{G(H, E)}. \tag{A.5}$$

That is, the elasticity of labor costs with respect to H and E must be equal. Given the assumptions on G, (A.5) implies a unique, upward-sloping E-H path, so that we obtain

$$E = E(H), \quad E'(H) > 0. \tag{A.6}$$

Equation (A.6) expresses unobserved labor effort E as a function of the observed number of hours per worker H. Thus, defining $\zeta \equiv H^* E'(H^*)/E(H^*)$ as the elasticity of effort with respect to hours, evaluated at the steady state, we obtain a proxy for the growth rate of labor utilization:

$$de = \zeta dh. \tag{A.7}$$

Next, to find a proxy for capital utilization S, we combine (A.2) and (A.3):

$$\left[\frac{G(H, E)}{HG_H(H, E)}\right]\left[\frac{SV'(S)}{V(S)}\right] = \frac{F_1 SK/F}{F_2 EHN/F} = \frac{c_K}{c_L}. \tag{A.8}$$

Note that the right-hand side of (A.8) is a ratio of factor cost shares. We define $g(H)$ as the elasticity of labor cost G with respect to hours H, and $\nu(S)$ as the elasticity of the shift premium V with respect to capital utilization S:

$$g(H) \equiv \frac{HG_H(H, E)}{G(H, E)},$$

$$\nu(S) \equiv \frac{SV'(S)}{V(S)}.$$

With these definitions, we can rewrite (A.8) as

$$\nu(S) = \frac{c_K}{c_L} g(H). \tag{A.9}$$

$g(H)$ is positive and increasing by the assumptions on G. $\nu(S)$ is also positive as long as there is a positive shift premium. We assume that the shift premium increases rapidly enough with S to make $\nu(S)$ increasing in S. Moreover, we assume that c_K/c_L is constant, which requires that the production function F be a generalized Cobb-Douglas in K and L, i.e.,

$$Y = F(SK, EHN, M, Z) = Z\,\Gamma\left[(SK)^{c_K}(EHN)^{c_L}, M\right],$$

where G is a monotonically increasing function.

Under these assumptions, log-linearizing (A.9) gives us

$$ds = \frac{\eta}{\omega} dh, \tag{A.10}$$

where η is the elasticity of g with respect to H and ω is the elasticity of v with respect to S.

Putting (A.7) and (A.10) together, equation (3) in the text can be expressed as

$$du = c_K^* ds + c_L^* de$$

$$= \left(c_K^* \frac{\eta}{\omega} + c_L^* \zeta\right) dh. \tag{A.11}$$

APPENDIX 2: METHOD OF AGGREGATION

In this appendix, we present our method of aggregation in detail, following the steps described in Basu and Fernald (2001, 2002).

The JIP database we employ uses the "double deflation" method to define *real* value added. That is, it normalizes the base-year (1990) prices of gross output and intermediate inputs to one, and defines double-deflated estimate of real value added, V_i, as

$$V_i \equiv Y_i - M_i. \tag{A.12}$$

Let s_{Mi} equal M_i/Y_i, the share of gross output going to materials in base-year prices.[29] Differentiating equation (A.12) and rearranging, we find that the growth rate of real value added is given by[30]

29. Note that the revenue share of materials s_{Mi} is not generally equal to the cost share c_{Mi}.

30. Basu and Fernald (2001, 2002) use the "Divisia" definition of value-added *growth*. The difference between the double-deflated index and the Divisia index is the weights used to subtract materials growth from gross output growth. The double-deflated index calculates the weights using constant base-year prices, whereas the Divisia index calculates the weights using current prices. See Basu and Fernald (1995, appendix) for details.

$$dv_i = dy_i - \frac{s_{Mi}}{1 - s_{Mi}}(dm_i - dy_i). \qquad \text{(A.13)}$$

In Section II.A, we obtained the following equation for gross-output growth:

$$dy_i = \gamma_i [c^*_{Ki}(ds_i + dk_i) + c^*_{Li}(de_i + dh_i + dn_i) + c^*_{Mi} dm_i] + dz_i.$$

This equation can be rewritten as

$$\begin{aligned} dy_i &= \gamma_i (1 - c^*_{Mi}) \left[\frac{c^*_{Ki}}{1 - c^*_{Mi}} dk_i + \frac{c^*_{Li}}{1 - c^*_{Mi}} (dh_i + dn_i) \right] \\ &\quad + \gamma_i (1 - c^*_{Mi}) \left(\frac{c^*_{Ki}}{1 - c^*_{Mi}} ds_i + \frac{c^*_{Li}}{1 - c^*_{Mi}} de_i \right) + \gamma_i c^*_{Mi} dm_i + dz_i \\ &= \gamma_i (1 - c^*_{Mi})(dx^V_i + du^V_i) + \gamma_i c^*_{Mi} dm_i + dz_i, \end{aligned} \qquad \text{(A.14)}$$

where

$$dx^V_i \equiv \frac{c^*_{Ki}}{1 - c^*_{Mi}} dk_i + \frac{c^*_{Li}}{1 - c^*_{Mi}} (dh_i + dn_i),$$

$$du^V_i \equiv \frac{c^*_{Ki}}{1 - c^*_{Mi}} ds_i + \frac{c^*_{Li}}{1 - c^*_{Mi}} de_i.$$

Subtracting $\gamma_i c^*_{Mi} dy_i$ from both sides of equation (A.14) and dividing through by $1 - \gamma_i c^*_{Mi}$, we obtain

$$dy_i = \left[\frac{\gamma_i (1 - c^*_{Mi})}{1 - \gamma_i c^*_{Mi}} \right] (dx^V_i + du^V_i) + \left[\frac{\gamma_i c^*_{Mi}}{1 - \gamma_i c^*_{Mi}} \right] (dm_i - dy_i) + \frac{dz_i}{1 - \gamma_i c^*_{Mi}}. \qquad \text{(A.15)}$$

We now substitute (A.15) into the definition of value-added growth, (A.13):

$$\begin{aligned} dv_i &= \left[\frac{\gamma_i (1 - c^*_{Mi})}{1 - \gamma_i c^*_{Mi}} \right] (dx^V_i + du^V_i) + \left[\frac{\gamma_i (1 - c^*_{Mi})}{1 - \gamma_i c^*_{Mi}} \frac{c^*_{Mi}}{1 - c^*_{Mi}} - \frac{s_{Mi}}{1 - s_{Mi}} \right] (dm_i - dy_i) \\ &\quad + \frac{dz_i}{1 - \gamma_i c^*_{Mi}} \\ &= \gamma^V_i (dx^V_i + du^V_i) + \left[\gamma^V_i \frac{c^*_{Mi}}{1 - c^*_{Mi}} - \frac{s_{Mi}}{1 - s_{Mi}} \right] (dm_i - dy_i) + dz^V_i, \end{aligned} \qquad \text{(A.16)}$$

where γ_i^V is the "value-added returns to scale":

$$\gamma_i^V \equiv \frac{\gamma_i(1-c_{Mi}^*)}{1-\gamma_i c_{Mi}^*}, \tag{A.17}$$

and dz_i^V is the "value-added augmenting technology change":

$$dz_i^V \equiv \frac{dz_i}{1-\gamma_i c_{Mi}^*}. \tag{A.18}$$

The JIP database defines aggregate real value added, V, as the sum of industry-level real value added, V_i, evaluated at base-year prices:

$$V = \sum_i V_i.$$

Thus, aggregate value-added growth dv is a share-weighted average of industry-level value-added growth,

$$dv = \sum_i w_i dv_i, \tag{A.19}$$

where $w_i = V_i/V$.

Similarly, we define aggregate primary input growth as

$$dx^V = \sum_i w_i dx_i^V.$$

Substituting (A.16) into (A.19) yields

$$dv = \sum_i w_i \gamma_i^V dx_i^V + \sum_i w_i \gamma_i^V du_i^V + \sum_i w_i \left[\gamma_i^V\left(\frac{c_{Mi}^*}{1-c_{Mi}^*}\right) - \frac{s_{Mi}}{1-s_{Mi}}\right](dm_i - dy_i) + \sum_i w_i dz_i^V. \tag{A.20}$$

We define

$$du^V \equiv \sum_i w_i \gamma_i^V du_i^V,$$

$$R_M \equiv \sum_i w_i \left[\gamma_i^V\left(\frac{c_{Mi}^*}{1-c_{Mi}^*}\right) - \frac{s_{Mi}}{1-s_{Mi}}\right](dm_i - dy_i),$$

and

$$dz^V \equiv \sum_i w_i dz_i^V = \sum_i w_i \frac{dz_i}{1-\gamma_i c_{Mi}^*}.$$

dz^V is the aggregate technical change defined in Section II.B. With these definitions, we rewrite equation (A.20) as

$$dv = \sum_i w_i \gamma_i^V dx_i^V + du^V + R_M + dz^V. \tag{A.21}$$

Furthermore, we decompose the first term of (A.21) into the "average scale" effect and the effect of "reallocation" of inputs across industries with different returns to scale. That is, rearranging (A.21) gives us

$$\begin{aligned} dv &= \bar{\gamma}^V \sum_i w_i dx_i^V + \sum_i w_i (\gamma_i^V - \bar{\gamma}^V) dx_i^V + du^V + R_M + dz^V \\ &= \bar{\gamma}^V dx^V + R_\gamma + R_M + du^V + dz^V, \end{aligned}$$

where

$$\bar{\gamma}^V \equiv \sum_i w_i \gamma_i^V,$$

and

$$R_\gamma \equiv \sum_i w_i (\gamma_i^V - \bar{\gamma}^V) dx_i^V.$$

Thus, the aggregate Solow residual, dp, can be expressed as

$$\begin{aligned} dp &= dv - dx^V \\ &= (\bar{\gamma}^V - 1) dx^V + R_\gamma + R_M + du^V + dz^V. \end{aligned} \tag{A.22}$$

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