Journal of Productivity Analysis, 8, 431–446 (1997)
© 1997 Kluwer Academic Publishers, Boston. Manufactured in The Netherlands.

Estimating Technological Change Using a Stochastic Frontier Production Function Framework: Evidence from U.S. Firm-Level Data

RAJEEV DHAWAN*
Business Forecasting Project, Anderson Graduate School of Management, University of California at Los Angeles, 110 Westwood Plaza, Los Angeles, California 90095

GEOFFREY GERDES
Department of Economics, University of California at Los Angeles, 405 Hilgard Avenue, Los Angeles, California 90095

Abstract

This paper presents a methodology for estimating an index of technological change using firm-level data in a stochastic frontier production function model that takes into account time-varying technical inefficiency. In contrast to the Solow divisia index approach, econometric estimation of the index with panel data allows the researcher to separate technical progress from the stochastic measurement error. Applying the econometric methodology to a panel of 908 publicly-traded U.S. firms from the COMPUSTAT database, we find evidence of a significant downturn in general technological change for the period, 1970–1989, whereas the divisia index methodology applied to the same data shows stagnation. When the sample is divided into *Manufacturing*, *Services*, and *Miscellaneous* categories we find that estimates of technological change for the three groups display markedly different stochastic behavior and that the *Services* group is the source of the downturn.

Keywords: Solow residual, stochatic frontier, technical inefficiency, technological change, production function

1. Introduction

Economic growth can be characterized as the outcome of a process in which agents strive to catch up with the leaders. Harberger (1990) hypothesized that most growth in the economy occurs as firms strive to catch up with those closer to the technological frontier. Thus, the measurement of technological change has a natural association with a production possibility frontier. Estimation of the stochastic frontier production function (SFPF), first proposed

* A previous version of this paper under a different title was presented in November of 1995 at the Conference on Efficiency and Productivity at the University of New England at Armidale, Australia. The authors wish to thank Petre Badulescu, Trudy Cameron, Joseph Ostroy, and Simon Potter for helpful conversations and suggestions, and the participants at the conference for their comments. We would also like to thank Peter Jochumsen for his help with computer programming. Special thanks are due to George Battese and Tim Coelli, the editors of the special edition of the journal, and to two anonymous referees for suggestions and comments that substantially improved this paper. Of course, any errors belong to the authors.

by Aigner, Lovell and Schmidt (1977), allows for the existence of an idealized production possibility frontier with firm-specific one-sided deviations from the frontier, referred to as technical inefficiency. The SFPF model, which includes a zero-mean random error added to the negative technical inefficiency effect, can be used to identify the separate effects of technological change, factor substitution and firm-specific inefficiencies. Recently, Bauer (1990) and Kumbhakar and Hjalmarsson (1995) used the SFPF approach to estimate technological change in a panel data context. However, their studies were limited to analyzing particular industries. We apply the SFPF model of Battese and Coelli (1992) that allows for simultaneous estimation of firm-specific and time-varying inefficiency, and an index of technological change (in the form of time-specific intercepts) to firm-level data from a broad collection of industries in the U. S for 1970–1989.

We compare the Solow residual methodology, or divisia index approach, to the SFPF methodology because the Solow methodology is the basis of almost all macroeconomic studies that focus on the measurement of technological change. In his influential paper, Solow (1957) demonstrated a methodology for extracting a residual measure from aggregative national income data through the use of certain assumptions which allowed it to be identified with technological change.[1] Notable among these assumptions are that production in the economy can be described by a single constant returns to scale (CRS) production function, capital and labor inputs are paid their marginal products, and technological change is Hicks-neutral.[2] The Solow residual is calculated by subtracting a weighted sum of the growth rates of capital and labor inputs from the growth rate of output where the weights are taken to be the share of these inputs in national income.

A consequence of the divisia approach is that any deviation from the assumptions will result in measurement error being incorporated into the Solow residual index. Thus, where possible, application of appropriate statistical techniques that enable the researcher to simultaneously estimate an aggregative production function and technological change, and also to objectively assess the reliability of the estimates, is warranted. Unfortunately, when limited to the use of a single aggregative time-series of data, standard econometric techniques do not allow for the separate identification of input substitution, shifts in the production function, and the stochastic error. This occurs because the resulting number of parameters to be estimated in the model exceeds the number of data points. However, when panel data are available, estimation of time-specific intercepts is possible. To illustrate the difference between the aggregative approach and that of using firm-level data, we compare the estimation of an aggregative Solow residual divisia index with the statistical estimation of technological change within an SFPF model for our panel data set. The SFPF estimation is also applied separately for three broadly-defined industrial sub-categories of our data.

The paper is organized as follows. Section 2 discusses Solow's methodology for the measurement of technological change and some arguments for using panel data to measure technological change. The econometric framework of this paper is described in Section 3. The data set employed is described in Section 4. Section 5 reports the results of estimation, compares the full sample technology index with the Solow residual index, and compares technical progress estimates across the three broadly-defined industry groups. Section 6 explores the autoregressive properties of our technological change index. Section 7 summarizes and concludes the paper.

2. Technological Change Measurement

In Solow's model of economic growth, increases in output per worker are obtained through increases in the amount of employed capital per worker. With increases in capital per worker the marginal product of capital declines, suggesting the eventual convergence of capital per worker to a constant ratio which leads to a cessation in the growth of output per worker. However, output per worker has been increasing at a fairly constant rate in the U.S. since 1874. This property of the data suggests that an additional factor in the production function is operating that accounts for the constant growth. To deal with this fact, Solow (1957) introduced a multifactor productivity index of technological change into the production function and developed a methodology for extracting a measure of it from the U.S. National Income and Product Accounts (NIPA) data. Thus, there are two forces that can result in increases in output growth: 1) substitution of capital for labor which produces movements along the production function from increases in capital accumulation over time, and 2) technological change which produces shifts in the production function. However, without knowing the precise functional form of production one cannot identify the relative proportion of the growth in output that can be imputed to these two effects. Thus, some simplifying assumptions which allow for the separation of these two major sources of growth in the data are required.

To obtain his measure, Solow assumed an aggregate Cobb-Douglas production function that converts capital (K_t) and labor (L_t) inputs into output (Y_t). Technological change is assumed to be Hicks-neutral so that shifts in the level of output do not change the marginal rates of substitution of the inputs. With the additional assumption of CRS, the Cobb-Douglas production function takes the form $Y_t = A_t K_t{}^{\alpha} L_t{}^{1-\alpha}$ where A_t is a measure of the cumulative effect of technological change over time, and $\alpha \in (0, 1)$ is the share of capital in production. The production function Y_t may be written in per-capita terms in the following way:

$$\frac{Y_t}{L_t} = A_t \left(\frac{K_t}{L_t} \right)^{\alpha}. \tag{1}$$

Letting $y_t = Y_t/L_t$ and $k_t = K_t/L_t$, Solow showed that $\Delta A_t = \Delta y_t - \alpha \Delta k_t$, where the operator Δ indicates a percentage change. Consequently, the Solow residual is the difference between a weighted sum of the growth rates of capital and labor inputs and the growth rate of output where the weights are taken to be the share of these inputs in national income. For each period t, data on the share of capital in income, output per unit of labor, and employed capital per unit of labor are used to obtain ΔA_t. To compute the index of technical change, the initial value A_1 is fixed to be equal to some constant—usually one. Successive values are calculated recursively using the relation $A_t = (1 + \Delta A_t) A_{t-1}$. Under the assumptions of CRS and perfect factor markets, the ratio of aggregative capital income to aggregative output is equal to capital's share in production. Hence, the slope parameter α may be taken as given rather than having to estimate it along with ΔA_t, avoiding the identification problem of simultaneous estimation of α and ΔA_t.

Researchers, such as Summer (1986), Hall (1987, 1988), Mankiw (1989), and Evans (1992) have argued that the Solow residual is afflicted with various measurement errors.

For example, Summers (1986) argues that the Solow residual is contaminated by the phenomenon of labor-hoarding. Hall (1988) on the other hand shows that the Solow residual is not a proper estimate of technological change in the presence of non-constant returns to scale due to market power. In particular, Ohta (1975), Denny, Fuss and Waverman (1981) and Bauer (1990) have shown that in the presence of non-constant returns to scale, the Solow residual is equal to true technological change plus a bias term that adjusts for the degree of departure from CRS.[3]

In response to these criticisms, researchers such as Morrison (1992) attempted to correct the aggregative Solow residual measure for scale effects. Finn (1995) calculated an adjusted version of the Solow residual that accounts for varying rates of capital utilization.[4] Additionally, Denny, Fuss and Waverman (1981), Hall (1988), and Domowitz, Hubbard and Petersen (1988) investigated the impact of markup behavior on the Solow residual.[5] Bauer (1990) demonstrated how changes in cost efficiency over time can affect Solow residual measurement. He then adjusted the measured Solow residual both for changes in returns to scale and technical inefficiency.[6]

These researchers either used national income or aggregative industry-level data to implement their corrective methodologies. We believe that one potential and significant source of measurement error is the use of aggregative data itself to calculate an index of technological change. The aggregative specification implicitly assumes that an exogenous technology process affects the production function of every firm in the economy identically, and that every firm has the same production structure.[7] However, empirical evidence (Mansfield (1989, 1993), Romeo (1975, 1977)) has shown that firms adopt new technological innovations at different rates.[8]

If differences among firms are significant, an econometric-based estimate of an index of technological change with panel data would thus seem to be preferred to the divisia index approach. Nelson and Winter (1982) have suggested the use of panel data to identify the two sources of output growth specified in the first paragraph of this section. The SFPF framework admits a production function which not only accounts for differences in technical inefficiency across firms as well as over time, but also allows for the existence of non-constant returns to scale, freeing the model from the possibly restrictive assumptions required by the divisa index approach. The SFPF framework contains firm-specific effects that are modeled as one-sided deviations from the production frontier.[9] The SFPF model used in this paper is formally described in the next section.

3. Econometric Methodology

We utilize the time-varying SFPF model of Battese and Coelli (1992) with the additional assumption of time-specific intercepts to represent the index of neutral technological change Z_t. In this model, given a sample of N firms for T time periods, the firms are assumed to produce a single output (Y_{it}) from inputs of capital (K_{it}) and labor (L_{it}). With the inclusion of Z_t, the model becomes

$$Y_{it} = e^{Z_t}\ F(K_{it}, L_{it}; \beta)\ e^{V_{it}}\ e^{-U_{it}} \tag{2}$$

where

$$\begin{aligned} U_{it} &= e^{[-\eta(t-T)]}U_i \\ i &= 1, 2, \ldots, N \\ t &\in \tau(i) \\ U_i &\sim \text{i.i.d.}N^+(0, \sigma^2) \\ V_{it} &\sim \text{i.i.d.}N(0, \sigma_v{}^2). \end{aligned}$$

In the specification above, $\tau(i)$ is the set of time periods with observations for firm i. The distribution of U_i is taken to be the positive truncation of the normal distribution.[10] The scalar parameter η is the rate of change in technical inefficiency. A positive value ($\eta > 0$) is associated with the improvement of technical efficiency of firms over time. Thus, this specification assumes a particular parameterization of the distribution of technical inefficiency across firms.[11]

Taking logarithms and following the translog specification in Griliches and Ringstad (1971), Equation 2 can be written as:

$$\begin{aligned} \ln(Y_{it}/L_{it}) = Z_t \ + \ & \beta_K \ln(K_{it}/L_{it}) + \beta_L \ln(L_{it}) + \beta_{KL} \ln(K_{it}) \ln(L_{it}) \\ & + \beta_{KK}(\ln(K_{it}))^2 + \beta_{LL}(\ln(L_{it}))^2 + V_{it} - U_{it}. \end{aligned} \tag{3}$$

Following the suggested parameterization in Battese and Coelli (1992) we define $\sigma_S^2 \equiv \sigma^2 + \sigma_v^2$ and $\gamma \equiv \sigma^2/\sigma_S^2$ and estimate $\sigma_S^2, \gamma, \eta, \mu$, the vector $\beta = \{\beta_K,\ \beta_L,\ \beta_{KL},\ \beta_{KK},\ \beta_{LL}\}$, and the Z_t's by maximum-likelihood estimation (MLE) methods.

4. The Data

The data used in this study were obtained from Standard and Poor's annual COMPUSTAT database. COMPUSTAT contains income, balance sheet, cash flow, and related financial information for publicly held U.S. firms. The database contains firms that were traded on the New York, American, NASDAQ, and regional stock exchanges. The number of firms in the database varies for a given year. For example, it contains roughly 1400 firms for 1970, which increases to around 7000 firms for 1989, the terminal year of our study. Standard and Poor's collects financial and market-related information from 10-K reports and other relevant financial documents.

We define L_{it} to be the number of employees in firm i at time period t. Standard practice in this type of study is to define labor in terms of hours worked but this information is not available in COMPUSTAT. Capital (K_{it}) is defined as the market value of total assets using the adjustment proposed in Salinger and Summers (1983) and explained in detail in Whited (1992). We converted capital into real terms with the cost of capital deflator. Our definition of capital differs from that of studies using "productive" or "employed" capital in that it is broadly defined to include the value of all assets owned by the firm. This definition is consistent with the notion in the literature that financial factors matter for productive and investment purposes.[12] Output Y_{it} is taken to be value added, defined as sales less cost of goods plus inventories, and is converted into real terms with the GDP deflator.[13]

Table 1. Data summary statistics.†

Variable	*Firms*	*Obs.*	*Median*	*Std. Dev.*	*Min*	*Max*
Full Sample	908	7105				
Y			571.30	5591	0.013	64050
K			732.10	9958	0.041	152500
L			9.40	85.010	0.0020	876.80
K/L			71.90	394.90	2.66	13320
Manufacturing	497	4459				
Y			964.60	6144	0.013	55320
K			1072	9221	0.041	152500
L			14.70	93.48	0.0020	876.80
K/L			63.75	209.60	6.29	7769
Services	223	1101				
Y			65.90	3531	0.018	64050
K			94.45	7961	0.24	118500
L			1.37	43.97	0.0020	365
K/L			50.23	878.60	2.66	13320
Miscellaneous	188	1545				
Y			351	4755	0.18	57930
K			826.80	12770	0.44	149600
L			6.063	78.01	0.0050	854
K/L			142.10	153.40	11.96	1318

†Output (Y) and capital (K) are in millions of 1982 dollars and labor (L) is in thousands of employees.

Due to non-reporting of some data items required to calculate K_{it} and Y_{it}, quite a few COMPUSTAT firms had to be excluded from the estimation. For example, 10% of the firms in the database provide no sales information and 30% do not report a separate inventory figure. Additionally, the definition of cost of goods reported in the COMPUSTAT data includes the dollar value of labor inputs. As payments to labor are a component of the value added by a firm, the separately-reported labor expense component had to be added to the above calculation. This expense item is supplementary to the balance sheet, and a large proportion of firms fail to report it separately, necessitating their exclusion from the sample. In addition, firms that did not report inventories had to be excluded.[14] As non-reporting of these data items appears to be independent of firm size, type, and industry, we do not expect these exclusions to introduce any systematic bias into our analysis. Hence, after all exclusions, the total number of firms for which the required information is available is 908. The data on these 908 firms are referred to as the full sample.

COMPUSTAT also provides information about the major two-digit SIC categories to which the firms belong. Using these codes, we subdivide the data into three groups which we call *Manufacturing*, *Services*, and *Miscellaneous*. The *Manufacturing* group includes SIC manufacturing codes 20-39, *Services* includes SIC codes for the Services, Retail Trade, and Finance, Insurance, and Real Estate categories, and *Miscellaneous* includes firms classified under Transportation, Public Utilities, and Wholesale Trade.[15] Table 1 presents summary statistics on the data used in this study.

Table 2. Estimated production parameters.†

	Full Sample		*Manufacturing*		*Services*		*Miscellaneous*	
σ_S^2	0.853*	(0.054)	0.421*	(0.030)	1.564*	(0.166)	0.807*	(0.097)
γ	0.969*	(0.002)	0.960*	(0.003)	0.955*	(0.006)	0.977*	(0.003)
η	0.009*	(0.002)	0.006*	(0.002)	0.016*	(0.004)	0.001	(0.002)
β_K	0.380*	(0.009)	0.518*	(0.033)	0.538*	(0.074)	−0.145	(0.092)
β_L	−0.020	(0.019)	0.009	(0.012)	−0.032	(0.032)	−0.124*	(0.031)
β_{KL}	−0.047*	(0.005)	−0.005	(0.007)	−0.031	(0.016)	−0.119*	(0.023)
β_{KK}	0.022*	(0.001)	−0.002	(0.003)	0.014	(0.007)	0.060*	(0.010)
β_{LL}	0.026*	(0.003)	−0.009	(0.004)	0.029*	(0.011)	0.057*	(0.014)

†Asymptotic standard errors in parentheses. *Significant at 5%.

Table 3. Estimated time-specific intercepts.†

	Full Sample		*Manufacturing*		*Services*		*Miscellaneous*	
Z_{1970}	2.810	(0.016)	2.442	(0.104)	2.437	(0.212)	4.578	(0.252)
Z_{1971}	2.801	(0.028)	2.440	(0.103)	2.443	(0.211)	4.560	(0.249)
Z_{1972}	2.818	(0.025)	2.466	(0.102)	2.390	(0.213)	4.576	(0.247)
Z_{1973}	2.816	(0.030)	2.465	(0.103)	2.358	(0.211)	4.599	(0.249)
Z_{1974}	2.815	(0.020)	2.494	(0.102)	2.308	(0.205)	4.529	(0.245)
Z_{1975}	2.769	(0.028)	2.474	(0.100)	2.259	(0.199)	4.449	(0.237)
Z_{1976}	2.792	(0.027)	2.497	(0.098)	2.320	(0.194)	4.480	(0.232)
Z_{1977}	2.783	(0.021)	2.504	(0.097)	2.238	(0.197)	4.476	(0.228)
Z_{1978}	2.775	(0.031)	2.500	(0.096)	2.250	(0.189)	4.472	(0.225)
Z_{1979}	2.765	(0.027)	2.514	(0.094)	2.237	(0.187)	4.423	(0.220)
Z_{1980}	2.738	(0.028)	2.510	(0.093)	2.217	(0.185)	4.364	(0.214)
Z_{1981}	2.700	(0.029)	2.479	(0.091)	2.215	(0.181)	4.321	(0.208)
Z_{1982}	2.673	(0.030)	2.452	(0.090)	2.199	(0.180)	4.297	(0.203)
Z_{1983}	2.652	(0.026)	2.427	(0.089)	2.131	(0.174)	4.321	(0.203)
Z_{1984}	2.638	(0.021)	2.429	(0.089)	2.082	(0.173)	4.309	(0.203)
Z_{1985}	2.622	(0.030)	2.410	(0.090)	2.097	(0.175)	4.291	(0.204)
Z_{1986}	2.613	(0.016)	2.402	(0.091)	2.094	(0.177)	4.293	(0.206)
Z_{1987}	2.600	(0.018)	2.418	(0.092)	2.012	(0.178)	4.306	(0.208)
Z_{1988}	2.593	(0.022)	2.425	(0.092)	1.928	(0.178)	4.369	(0.210)
Z_{1989}	2.582	(0.029)	2.423	(0.092)	1.969	(0.179)	4.293	(0.209)

†All are significant at 5%. Asymptotic standard errors in parentheses.

5. Results of Estimation

Table 2 presents the estimated parameters of the production function, and Table 3 presents the estimated time-specific intercepts (Z_t's) from the MLE of Equation 3 for the full sample and separate MLE for each of the three broadly-defined industry sub-groups. Estimation was implemented using a program written in the GAUSS computer language.[16]

Table 4 presents the factor elasticity and returns to scale (RTS) estimates, calculated at the mean input values.[17] The hypothesis that the production function displays CRS at the mean cannot be rejected at the 5% significance level for the full sample nor for any of the three sub-groups. There is a significant difference between our estimates of the capital and

Table 4. Estimated mean factor elasticities and returns to scale.†

	Full Sample		*Manufacturing*		*Services*		*Miscellaneous*	
α_K	0.659	(0.020)	0.485	(0.057)	0.587	(0.068)	0.653	(0.141)
α_L	0.303	(0.038)	0.501	(0.062)	0.390	(0.077)	0.219	(0.167)
RTS	0.961	(0.041)	0.985	(0.080)	0.977	(0.054)	0.872	(0.206)

†Asymptotic standard errors in parentheses.

labor elasticities (α_K and α_L) and those obtained from NIPA. The estimated labor share of income from NIPA (under Solow's asssumptions) is 0.64 while our estimate for the full sample is about 0.30. An important reason for this difference is the nature of our sample which consists of only publicly-traded firms that are relatively more capital intensive and larger than the average firm in the economy. Another reason is the broader definition of capital employed in this study, which includes the current assets from the balance sheet as part of productive capital.

Figure 1 displays the estimated Z_t for the full sample and the calculated Solow residual from the U.S. National Accounts for the 1970–1989 time-period.[18] The graph clearly demonstrates the disparity between the behavior of the direct estimate of the technical change index from our sample of firms (Z_t) and the Solow residual index (A_t). Our estimate of technical progress suggests that during this period, for our firms, there was not merely a slowdown in productivity, but instead a downturn. Compared to a 4% growth in the A_t index, the Z_t index shows around an 8% drop. This difference is the result of using panel data and the SFPF model that allows for departures from the CRS assumption and accounts for the technical inefficiency differential across firms and over time. Thus, the importance of allowing for these factors, as emphasized in the work of Bauer (1992) and Finn (1995), is clearly evident.

Figure 2 displays four series: the estimated Z_t for the full sample using both the trans-log and Cobb-Douglas specifications, and a divisia index (A_t) calculated from aggregates of the same data using both 0.36 (obtained from MLE of the SFPF with Cobb-Douglas production) and 0.64 (obtained from the NIPA accounts) for labor's share. It can be seen from the graph that the estimated Z_t's from the two production function specifications are quite similar, but the Cobb-Douglas estimate is slightly higher than the trans-log estimate. The divisia index estimates of technical change (the A_t's), however, are quite different from the econometric estimates. For a labor share value of 0.64 the A_t index shows a stagnant technological change. In contrast, when the A_t is calculated using 0.36 for labor share, it shows a decline of about 20%.[19] Thus, the difference between the technical change estimates obtained from the two methodologies is evidently the result of correctly estimating the elasticities. Hence, correct estimation methods are critical in estimating technological change, assuming one has access to correct data.

We conducted various hypothesis tests of restrictions on the parameters of the production structure for the full sample and the different sub-groups. These generalized likelihood ratio statistics along with the asymptotic critical value are reported in Table 5.[20] A test of the restriction that Z_t was constant over time (Test 1) was rejected for the full sample,

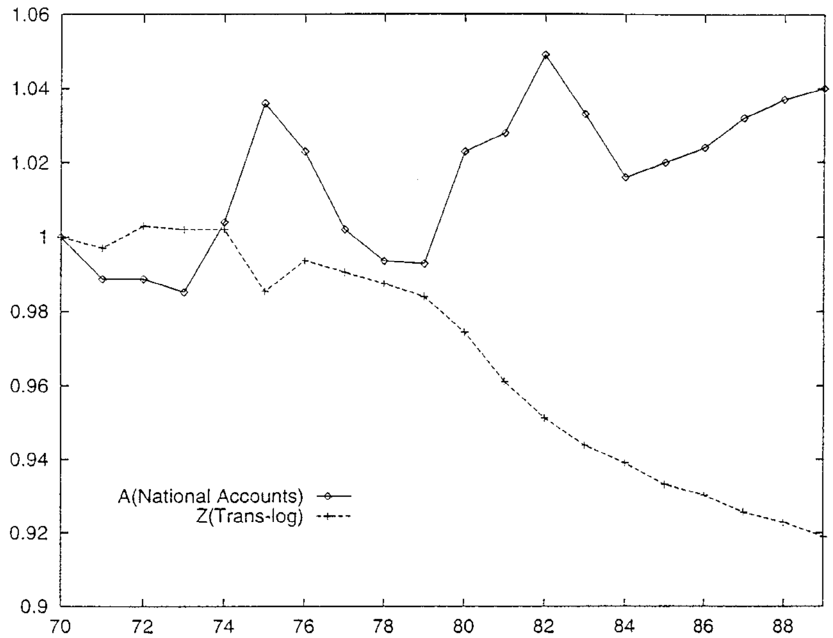

Figure 1. The Solow residual A_t from the NIPA accounts using 0.64 for labor's share, and Z_t from MLE. For comparison purposes, Z_t has been normalized to a starting value of 1.

Manufacturing, and *Services*, but not for the *Miscellaneous* group. A test of the restriction of constant efficiency over time ($\eta = 0$, Test 2) was rejected for the Full Sample and all of the sub-groups. A joint test of both of these restrictions (i. e. $\eta = 0$ and Z_t constant) (Test 3) was rejected for the Full Sample and for all of the three groups. A test that all the estimated parameters were common across all of the groups (Test 4) was rejected. Thus, separate MLE for the sub-groups is preferable to MLE of the full sample. Evidently, a significant degree of heterogeneity exists across these three groups, which is also apparent from the estimated values of the production parameters in Tables 2 and 4. Finally, a test of the Cobb-Douglas specification versus trans-log (Test 5) shows that the Cobb-Douglas is rejected in every case.

Figure 3 displays the estimated Z_t process for each category. The series are normalized to begin from a common value of one.[21] It is evident from the graph that most of the downturn in the technological change index for our sample can be attributed to the *Services* group as the indices for the other two groups remain relatively flat. This result is in conformity with the findings of Bauer (1992). Bauer analyzed the productivity slowdown for the same time period and attributed it to be a natural response to unbalanced growth, which shifts resources from sectors where the productivity growth rate is higher (manufacturing), to sectors where productivity growth is relatively stagnant (services).[22] A reason for the stagnant growth, as discussed by Bauer, is the inherent labor-intensity of the service sector,

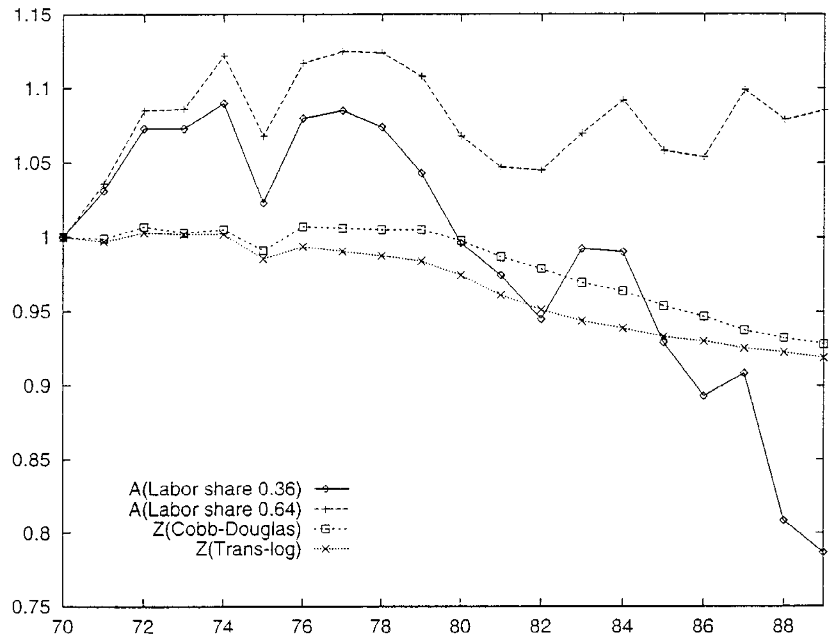

Figure 2. Comparison of two divisia index estimates (A_t), and two SFPF estimates of Z_t, all using the same data. For comparison purposes, the Z_t's have been normalized to a starting value of 1.

Table 5. Generalized likelihood ratio tests.

	Null Hypothesis	$\chi^2_{0.95}$	DF	*Full*	*Manf.*	*Serv.*	*Misc.*
1.	Z_t constant over time ($Z_t = Z\ \forall\ t$)	30.14	19	243.2*	206.0*	49.6*	63.4*
2.	No change in efficiency over time ($\eta = 0$)	3.84	1	45.8*	10.0*	14.2*	0.2
3.	Simultaneous test of Hypotheses 1. & 2.	31.41	20	253.4*	208.0*	50.2*	65.4*
4.	Shared parameters across groups	74.54	56	1657.4*	–	–	–
5.	Cobb-Douglas v. trans-log specification	7.81	3	81.6*	28.0*	12.2*	24.0*

*Rejected at the 5% level of significance.

which constrains the ability of firms to exploit productivity gains by substituting capital for labor. This is critical in light of technological improvements in the industrial sector over the last two decades. For example, Shephard (1982), Carlsson (1984, 1988), and Piore and Sable (1984) suggest that the development of numerically-controlled machines have made production techniques more flexible and have brought down the minimum efficient scale of production in the manufacturing sector since the 1970's.[23] Empirical evidence points toward a structural shift in the relative importance of services as a percentage of U.S. GNP. For the 1970–1985 period, the share of services in GNP grew 21%, retail and wholesale trade grew 10.3%, and finance, insurance and real estate grew 8.7%, compared with a 3.6% growth

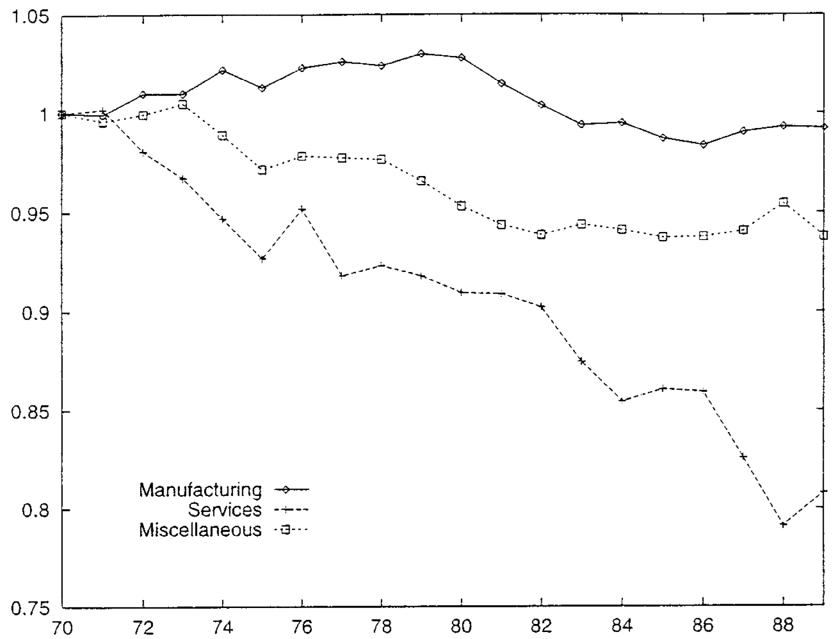

Figure 3. Maximum likelihood estimates of Z_t for the three industrial groups.

rate in the share of the manufacturing sector over the same period.[24] Given that the share of services has risen, a downward trend in this sector will bring the overall productivity down.

6. Time-series Behavior of Technological Change

A critical component of computable stochastic general equilibrium growth models is the nature of the technology shock process that affects the production possibility frontier. In these models, technological change is typically formulated as a highly persistent autoregressive process of order one, modeled in accordance with the behavior of Solow residuals obtained from the aggregative data. Business cycle proponents, notably Prescott (1986a,b), have suggested that technology shocks can account for a major proportion of U.S. GNP fluctuations. In this section we discuss the time-series behavior of the estimated Z_t.

We fit an autoregressive process of order one ($AR(1)$) with a time trend of the following form:

$$Z_t = \alpha + \rho Z_{t-1} + \theta t + e_t. \tag{4}$$

Traditionally the literature that discusses the general equilibrium implications of the Solow residual applies a linear model of this type. We are thus conducting a second-stage estima-

Table 6. Time series behavior of Z_t.†

	Full Sample	*Manuf.*	*Serv.*	*Misc.*	A_t(NIPA)	A_t(0.64)	A_t(0.36)
α	0.937*	0.564	1.825*	1.691	0.564*	0.617*	0.427*
	(0.411)	(0.308)	(0.598)	(0.943)	(0.221)	(0.186)	(0.192)
ρ	0.672*	0.777*	0.250	0.628*	0.431	0.441*	0.635*
	(0.143)	(0.124)	(0.243)	(0.205)	(0.223)	(0.173)	(0.172)
θ	−0.005*	−0.002*	−0.018*	−0.006	0.001	−0.001	−0.007*
	(0.002)	(0.001)	(0.006)	(0.004)	(0.001)	(0.001)	(0.002)
σ_e	0.014	0.017	0.035	0.038	0.013	0.025	0.035
R^2	0.975	0.821	0.945	0.888	0.594	0.308	0.873

†Estimation of the equation $X_t = \alpha + \rho X_{t-1} + \theta t + e_t$, where $t = 1 \ldots 20$, and X_t represents either the estimate of Z_t for the indicated sample, the Solow residual A_t(NIPA), or the sample Solow residuals A_t(0.64) and A_t(0.36).
*Statistically significant at 5%.

tion of an autoregressive process on the Z_t index which was previously assumed to be fixed. While the inclusion of the additional restriction imposed by Equation 4 within the maximum likelihood estimation would therefore be the preferred method, we found this approach to be intractable. However, this simpler second stage estimate is feasible. In addition, it allows for a direct comparison between the autoregressive properties of the Z_t estimates for the various groups and A_t. Table 6 presents the results of estimating Equation 4 on the different indices. For Z_t from the full sample, the autoregressive parameter ρ is 0.67 and is statistically significant. This value of ρ is different from the 0.95 value typically obtained from the NIPA by analyzing the Solow residuals for the 1950–1990 quarterly data. For the 1970–1989 time period, fitting an $AR(1)$ to the annual Solow residual from the NIPA (A_t(NIPA)) yielded an estimated value of ρ of only 0.43. This is much lower than the estimated ρ for our sample of firms. Researchers have found that the autoregressive parameter ρ drops and the variance of the error term e_t rises as one moves from quarterly data to annual.[25] Hence, accounting for non-constant returns to scale and technical inefficiency by using panel data has the effect of restoring the persistence level of the technical change index.[26] This result is useful for business cycle modelers, as the ability of their models to mimic the business cycle features is critically dependent upon the value of the autoregressive parameter ρ.[27] In the table, we also present the results of estimating an $AR(1)$ process on the sample-dependent Solow residual calculated using the 0.64 for labor's share from the NIPA estimate. This estimate has a value of ρ (0.44) which is very close to that of the Solow from NIPA, and smaller than the 0.67 value for the full sample. In contrast, when the correctly estimated value of labor share (0.36) obtained from the SFPF model is used to calculate the Solow residual from the same data, the autoregressive parameter ρ is 0.64. This value is closer to what is estimated for the index Z_t. Thus, these results support our hypothesis that correct modeling is critical for calculating the properties of technological change.

Fitting an $AR(1)$ process to the three different groups shows the heterogeneity evident in the value of the ρ parameter. The *Manufacturing* group exhibits a value of ρ (0.78) that is higher than that of the full sample, but the ρ for the *Services* group (0.25) is much smaller, and is statistically insignificant. Given that a higher value of ρ implies a more persistent process, the persistence level of the Z_t series differs substantially across these three groups. For the full sample, as well as the three groups, the estimated time trend coefficient θ is negative, but is insignificant for the *Miscellaneous* group.

7. Summary and Conclusions

The ability of computable general equilibrium models to explain fluctuations in economic aggregates depends critically on the stochastic properties of technological change. The properties of these changes are based on the behavior of the Solow residual, which has been criticized as a measure of technological change. To derive this residual from aggregative data, researchers have utilized a divisia index technique that assumes CRS, perfect factor markets, and that firms share a common production structure. These assumptions make it possible to separate growth induced by the substitution of labor for capital from growth due to technological progress. Numerous researchers have demonstrated that these assumptions do not hold in practice.

To circumvent the strong assumptions required of the Solow residual, we have proposed an alternative methodology for deriving an index of technological change. This index is directly estimated in the context of panel data by using a SFPF approach which controls for firm-specific and time-varying technical inefficiency. Applying the technique to a large panel of U.S. firms, we find evidence of a significant decline in the technological index over the 1970–1989 time period. Subdividing our sample into three broadly-defined industrial groups, we find that this downturn can be attributed to a decline in the *Services* group. Estimating an autoregressive process on the separate technological change indices reveals varying degrees of persistence across the three groups. Compared with the divisia index approach, these results have the implication that simultaneously estimating technical efficiency along with other production parameters in a panel data context gives markedly different behavior for estimated technological change.

Notes

1. See Griliches (1996) for historical background.
2. The first two assumptions characterize perfect competition. Technological change is assumed to be Hicks-neutral in the sense that the marginal rate of substitution between inputs is unaffected by shifts of the production function.
3. Additionally, according to Hall (1990), under the assumptions of perfect competition and CRS, the Solow residual should be uncorrelated with any variable that is uncorrelated with the rate of growth of true productivity. Using annual data at the industry level, Hall found that the Solow residual was highly correlated with the growth of military expenditures and changes in world oil prices, instruments reasonably thought to be exogenous. He concluded that the failure of the invariance property was due to an increasing returns to scale production function.
4. The rate of capital utilization is one aspect of technical inefficiency.
5. Domowitz, Hubbard and Petersen (1988) and Hall (1988) use aggregative industry-level data.

6. See Bauer (1990), Equation 24.
7. By *production structure* we mean not only the relationship between inputs and output(s), but also technical inefficiency, and any firm-specific attributes such as managerial quality, advertising strategy, intangible resources of the firm, etc.
8. Empirical literature on the diffusion rate of technological innovations finds that different industries react very differently to the same innovation. For example, according to Mansfield (1989), the diffusion rate of industrial robots was 12 years for the overall economy, but ranged from 3 years in the steel industry to 15 years in automobiles. In addition, Mansfield (1993) found that small firms adopted technological innovations later than large firms.
9. In the SFPF framework a firm is specified to be a one-period expected profit maximizer where certain idiosyncratic effects such as the weather or global economic conditions are not necessarily under its control. According to Greene (1993), one can view each firm in the model as facing its own frontier which is randomly placed by any number of stochastic elements that might affect output but cannot be controlled by the firm.
10. In the model of Battese and Coelli (1992), the U_i's are assumed to be independent and identically distributed non-negative truncations of the $N(\mu, \sigma^2)$ distribution. For this data, inclusion of μ in the likelihood function prevented precise estimation of the other parameters because the function is quite flat in the dimension of μ. See Greene (1993) for a discussion of this point.
11. A detailed specification would potentially allow the time-varying component of technical efficiency to depend on firm-specific attributes as well. For an example see Battese and Coelli (1995).
12. See Gertler (1988) and Jaffe and Stiglitz (1990) for a literature survey that emphasizes the role of balance-sheet and liquidity position for production. Numerous panel-data studies (e.g. Fazzari, Hubbard and Peterson (1988), Gilchrist (1990), Whited (1992), Dhawan (1997)) provide empirical support for this assertion.
13. The use of value added in the estimation of this production function, which includes only capital and labor inputs, means that changes in non-specified inputs such as the quantities and prices of materials used in production will be measured as changes in technical efficiency or Z_t.
14. Inventory is used to calculate value added. At the suggestion of a referee we examined the implications of including firms in the estimation that did not have a separate inventory figure. This increased the number of observations by 20%. Including them slightly reduced the autoregressive properties of the Z_t estimates without changing substantially other properties of the model. This reduction in autocorrelation is to be expected since the level of inventories for a given period are closely related to the level of value added in adjacent periods. Since including these firms involves a mis-specification of value added and affects the estimates in a dimension important to this paper, we have chosen to exclude them.
15. Italics are used to distinguish the broadly-defined groups of our sample from other definitions.
16. The program is available from the authors upon request. It requires `GAUSS` version 3.1.1 and the accompanying `OPTMUM` optimization package.
17. Due to the trans-log specification of production, the elasticity and RTS estimates will vary for different input combinations.
18. The Solow residual was calculated using 0.64 for labor's share. For comparison purposes, the estimated Z_t parameters in this and subsequent figures have been normalized by dividing by the initial Z_1.
19. We use the Cobb-Douglas specification based estimate of labor share instead of the trans-log estimate as it is consistent with the Solow residual methodology. However, using the trans-log based estimate of labor share, a similar decline is evident.
20. The test results are based on the asymptotic critical values which assume the existence of a large sample. Thus, tests on groups with a greater number of data points are less likely to be subject to a Type I or Type II error than those with fewer data points.
21. This was done by dividing each series by its initial value.
22. An exception is the high productivity growth in the telecommunication industry which is part of the services sector.
23. In addition, the emergence of new computer-based technology has improved quality of small-scale production relative to standardized mass production techniques.
24. 1990 Economic Report of the President, Table C-11.
25. See Christiano and Eichenbaum (1992).

26. The persistence of an $AR(1)$ process is higher, the higher the value of ρ.

27. See Prescott (1986b).

References

Aigner, D. J., C. A. K. Lovell and P. Schmidt. (1977). “Formulation and Estimation of Stochastic Frontier Production Function Models.” *Journal of Econometrics* 6, 21–37.

Battese, G. E. and T. J. Coelli. (1992). “Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India.” *Journal of Productivity Analysis* 3, 153–169.

Battese, G. E. and T. J. Coelli. (1995). “A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data.” *Empirical Economics* 20, 325–332.

Bauer, P. W. (1990). “Decomposing TFP Growth in the Presence of Cost Inefficiency, Nonconstant Returns to Scale, and Technological Progress.” *Journal of Productivity Analysis* 1, 287–299.

Bauer, P. W. (1992). “Unbalanced Growth and the U.S. Productivity Slowdown.” *Economic Commentary (Federal Reserve Bank of Cleveland)* Jan, 1–4.

Carlsson, B. (1984). “The Development and Use of Machine Tools in Historical Perspective.” *Journal of Economic Behavior and Organization* 5, 91–114.

Carlsson, B. (1989). “The Evolution of Manufacturing Technology and its Impact on Industrial Structure: An International Study.” *Small Business Economics* 1, 21–38.

Christiano, L. J. and M. Eichenbaum. (1992). “Current Real-business-cycle Theories and Aggregate Labor-market Fluctuations.” *American Economic Review* 82, 430–450.

Denny, M., M. Fuss and L. Waverman. (1981). “The Measurement and Interpretation of Total Factor Productivity in Regulated Industries, with an Application to Canadian Telecommunications.” In Thomas G. Cowing and Rodney E. Stevenson (eds.), *Productivity Measurement in Regulated Industries*. New York: Academic Press.

Dhawan, R. (1997). “Asymmetric Information and Debt Financing: The Empirical Importance of Size and Balance Sheet Factors.” *International Journal of the Economics of Business* 4(2), 189–202.

Domowitz, I., R. G. Hubbard and B. C. Petersen. (1988). “Market Structure and Cyclical Fluctuations in United States Manufacturing.” *Review of Economics and Statistics* 70, 55–66.

Evans, C. L. (1992). “Productivity Shocks and Real Business Cycles.” *Journal of Monetary Economics* 29, 191–208.

Fazzari, E., G. Hubbard and B. Peterson. (1988). “Financing Constraints and Corporate Investment.” *Brookings Papers on Economic Activity* , 141–195.

Finn, M. G. (1995). “Variance Properties of Solow’s Productivity Residual and Their Cyclical Implications.” *Journal of Economic Dynamics and Control* 19, 1249–1281.

Gertler, M. L. (1988). “Finacial Structure and Aggregate Economic Activity: An Overview.” *Journal of Money, Credit, and Banking* 20, 559–588.

Gilchrist, S. (1990). “An Empirical Analysis of Corporate Investment and Financing Hierarchies Using Firm Level Panel Data.” Mimeo, Board of Governors of the Federal Reserve System.

Greene, W. H. (1993). “The Econometric Approach to Efficiency Analysis.” In Harold O. Fried, C. A. Knox Lovell and Shelton S. Schmidt (eds.), *The Measurement of Productive Efficiency*, New York: Oxford University Press.

Griliches, Z. (1996). “The Discovery of the Residual: A Historical Note.” *Journal of Economic Literature* 34(3), 1324–1330.

Griliches, Z., and V. Ringstad. (1971). *Economies of Scale and the Form of the Production Function: An Econometric Study of Norwegian Manufacturing Establishment Data*. North-Holland Pub. Co.

Hall, R. (1987). “Productivity and the Business Cycle.” In *Empirical Studies of Velocity, Real Exchange Rates, Unemployment, and Productivity*, Vol. 28 Carnegie-Rochester Conference Series on Public Policy, pp. 421–444.

Hall, R. (1988). “The Relation between Price and Marginal Cost in U.S. Industry.” *Journal of Political Economy* 96, 921–947.

Hall, R. (1990). “Invariance Properties of Solow’s Productivity Residual.” In Peter Diamond (ed.), *Growth Productivity Employment*. Cambridge: MIT Press, pp. 71–112.

Harberger, A. C. (1990). “Reflections on the Growth Process.” Manuscript, Department of Economics, University of California, Los Angeles.

Jaffe, D. and J. Stiglitz. (1990). "Credit Rationing." In B. Friedman and F. Hahn (eds.), *Handbook of Monetary Economics*. Amsterdam: North-Holland, pp. 838–885.

Kumbhakar, S. C. and L. Hjalmarsson. (1995). "Labour-Use Efficiency in Swedish Social Insurance Offices." *Journal of Applied Econometrics* 10, 33–47.

Mankiw, N. G. (1989). "Real Business Cycles: A New Keynesian Perspective." *Journal of Economic Perspectives* 3, 79–90.

Mansfield, E. (1989). "The Diffusion of Industrial Robots in Japan and the United States." *Research Policy* 18, 183–192.

Mansfield, E. (1993). "The Diffusion of Flexible Manufacturing Systems in Japan, Europe, and the United States." *Management Science* 39, 149–159.

Morrison, C. J. (1992). "Unraveling the Productivity Growth Slowdown in the United States, Canada and Japan: The Effects of Subequilibrium, Scale Economies, and Markups." *Review of Economics and Statistics* 74(3), 381–393.

Nelson, R. R. and S. G. Winter. (1982). *An Evolutionary Theory of Economic Change*, Harvard University Press.

Ohta, M. (1975). "A Note on the Duality between Production and Cost Functions: Rate of Returns to Scale and Rate of Technical Progress." *Economic Studies Quarterly* 25, 63–65.

Piore, M. J. and C. F. Sable. (1984). *The Second Industrial Divide: Possibilities for Prosperity*, New York: Basic Books.

Prescott, E. C. (1986a). "Theory Ahead of Business Cycle Measurement." *Federal Reserve Bank of Minneapolis Quarterly Review* 10, 9–33.

Prescott, E. C. (1986b). "Response to a Skeptic." *Federal Reserve Bank of Minneapolis Quarterly Review* 10, 28–33.

Romeo, A. A. (1975). "Interindustry and Interfirm Differences in the Rate of Diffusion of an Innovation." *Review of Economics and Statistics* 57, 311–319.

Romeo, A. A. (1977). "The Rate of Imitation of a Capital-Embodied Process Innovation." *Economica* 44, 63–68.

Salinger, M. A. and L. H. Summers. (1983). "Dividend Taxes, Corporate Investment, and *q*." *Journal of Public Economics* 22, 777–787.

Shephard, W. G. (1982). "Causes of Increased Competition in the U.S. Economy, 1939–1980." *Review of Economics and Statistics* 64, 613–626.

Solow, R. M. (1957). "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics* 39, 312–320.

Summers, L. H. (1986). "Some Skeptical Observations on Real Business Cycles." *Federal Reserve Bank of Minneapolis Quarterly Review* 10, 23–27.

Whited, T. M. (1992). "Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data." *The Journal of Finance* 47(4), 1425–1460.