Technical Change and Total Factor Productivity Growth for Swedish Manufacturing and Service Industries

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Abstract

This paper presents alternative specifications of the production functions of a large panel of Swedish firms for the period 1992-2000. The period can be characterized as a transition when long-run productivity growth in the Swedish economy improved from being among the weakest to one of the strongest within the OECD. In order to present a detailed exploration of this dramatic change, the time trend and general index models are applied to estimate total factor productivity (TFP) growth, rate of technical change and returns to scale. The models are extended to allow for firm-specific as well as time-varying technical change. The parametric TFP measures are also compared with the non-parametric Solow residual, and several hypotheses are tested to explain the growth patterns in the Swedish economy. It is found that the improved growth rate, initially starting in large exporting manufacturing firms, after a deep economic crisis at the beginning of the 1990s, spilled over to the rest of the economy, both manufacturing and services.

Keywords: Technical change, total factor productivity growth, manufacturing, service, enterprise panel data.

JEL codes: C23, C52, C67, D24, L25, L60, L80, O30

1. Introduction

Since the beginning of the 1990s, growth in labor productivity in the Swedish manufacturing sector has been among the highest within the OECD.[1] Sweden is also considered as a leading innovative country according to the European Innovation Scoreboard (Hollanders and van Cruysen, 2008). The performance of the Swedish economy in recent years is in sharp contrast to the period of stagnation of 1960-1990. From the beginning of the 1960s to the end of the 1980s the average annual growth rate in labor productivity of the manufacturing sector decreased from a high level of 6-7% to a low level of 1-2%. It is undeniable that falling trend in labor productivity growth was an international phenomenon during the 70s and 80s. But Sweden represents an extreme case.

It is well known that sustainable improvement in supply of factors plays an important role in increasing total factor productivity (TFP). The increase in TFP growth yields a high long-run growth of an economy. The supply factors include product and process technology, skill and innovativeness. The gradually deteriorating productivity of the Swedish economy reflects failure in this respect. It also influences the demand side. Notable is that 1/5 of Sweden's international market share was lost between 1977 and 1992 despite a 50% depreciation of the Swedish krona against the currencies of other key industrialized countries.

This paper examines productivity growth of an Swedish economy during the period between 1992 and 2000. This period constitutes a dramatic change in the Swedish long-run productivity performance and a turning point that coincides with the international recession of 1990-1993. During this three-year period, the average GDP in OECD-Europe grew by only 1.5%. The corresponding figure for Sweden, however, was a 5% contraction. It was not until 1995 that the Swedish GDP passed the pre-recession 1990-level. Between 1990 and 1993, gross fixed capital formation and employment declined by 27% and 13%, respectively.

The 1990-crisis started with a dramatic fall in industrial production and many exporting companies faced serious financial problems. However, there were obvious potentials to overcoming the crisis, which includes new technologies, development and implementation of innovations, outsourcing and offshoring available to firms. The recovery in productivity growth started in 1993 and two years later the total manufacturing production was more than 10% larger despite the substantial reduction in the workforce.[2]

The initial productivity improvement was closely linked to increased demand from the foreign markets and firms' export intensity. Like many other countries, Swedish exports are highly concentrated to a small fraction of firms. Thus, the 20 largest firms account for more than one third of the total export value and multinational firms for 90% of the exports. Small manufacturing and service firms supplying only on the

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[1] Annual percentage labor productivity growth in manufacturing 1990-2007: Korea 9.1, Sweden 6.1, Taiwan 5.7, U.S. 4.8, Singapore 4.6, France 3.8, Germany 3.7, Japan 3.5, The Netherlands 3.4, U.K. 3.3, Belgium 2.9, Canada 2.6, Denmark 2.4, Australia 2.2, Spain 2.0, Norway 1.7 and Italy 1.5. Source: U.S. Department of Labor.

[2] Within a couple of years employment in the manufacturing sector decreased by 20%.

home-market faced hard conditions because the demand from the home-market contracted by 8% for the period between 1991 and 1994.

Based on the above historical overview on the Swedish economy two hyphotheses can be made. One hypothesis to be tested is that large corporations led the productivity improvements in an economy during the period between 1992 and 2000, which yields gradual spillover to other firms and sectors. A second hypothesis is that the potential to increase productivity growth was larger in high technology manufacturing than in low technology firms and services. High technology firms are characterized by extensive R&D-investments, innovative products, skilled and global labour markets.

Methodologically, we employed a parametric production function approach to examine the TFP growth and its decomposed sources. By decomposing the TFP growth we obtained the rates of technical change, returns to scale and input biases among others. The data consists of 5,893 unique manufacturing and service firms observed during 1992-2000 and the total number of observations is almost 38,000.

We used various setting-ups in expressing technical change in our models. As a starting point we employed a simple time trend (TT) model in investigating technical change. Since the time trend model has been criticized that a time-trend expression of technical change only represent our ignorance, we also employed the general index (GI) model of Baltagi and Griffin (1988). The two basic models are extended to allow for firm-specific as well as time-varying technical change,each of which yields two extended models. The parametric TFP measures are also compared with the non-parametric Solow residual serving as a benchmark.

The empirical results show that improvements in productivity growth in the Swedish economy were not restricted to large exporting firms.[3] The positive and high growth rate spilled over to a broad network of manufacturing and service firms irrespective of their size, R&D and technology intensity. We also investigate determinants of TFP growth as well as the scale properties of the observed firms regarding input elasticities, returns to scale, and input and scale biases calculated from competing models.

The rest of the paper is organized as follows. The theory of productivity analysis is outlined in Section 2. Data on the Swedish manufacturing and service industries are described in Section 3. Section 4 provides the theoretical framework for modelling TFP growth, technical change, input elasticities, returns to scale, and input and scale biases. Section 5 discusses the estimation methods and Section 6 presents the specification tests and empirical results along with a comparison of the performance in the different model specifications. Finally, Section 7 concludes briefly.

2. The Theory of Productivity Analysis

It has long been recognized that modeling of production functions plays an important role in analyzing returns to scale, technical change and the rate of total factor productivity (TFP) growth. Attempts in the modelling has been one of the interesting

[3] In a previous study on the micro and small Swedish firms, Heshmati (2001) and Johansson (2005) estimate relevant growth measures based on a large firm-level data sets. See also Monte and Pagagni (2003) for for analysis of R&D and the growth of firms in Italy.

research topics in both theoretical and applied research. Moreover, a rich set of panel data in the field of empirical industrial economics enables sophisticated specifications in modelling production functions.

Due to the great efforts recently devoted to quantifying the rate of TFP growth, technical change and their relevant components, the following four main strands have been built up: (i) econometric estimation of production functions, (ii) the Divisia index, (iii) exact index numbers and (iv) non-parametric methods using linear programming (Diewert, 1981). This section briefly reviews the last three methods. The econometric estimation will be discussed in the next section.

Solow (1957) specifies a general index of technical change as a residual of production activities, in which output is produced by input factors and disembodied technology. In measuring the rate of technical change, three restrictive assumptions are required: constant returns-to-scale, Hicks-neutral technical change and perfect competition. Under these conditions, the rate of technical change is equivalent to the percentage growth in total factor productivity (TFP). The growth rate of TFP can be calculated as the difference in the percentage growth in outputs less the percentage change in a Divisia index of inputs.

Although the Solow residual approach has long been regarded as a pioneering tool for measuring technical change and TFP growth, its assumptions are considered too restrictive. For example, if an economy exhibits increasing returns to scale, the growth in TFP may be attributable to movements along the production function rather than upward shifts in production. The Hicks-neutrality and perfect competition are also considered too restrictive, as discussed in Hulten (2000). Diewert (1976) shows that there exists a class of superlative index numbers which corresponds to various production technologies based on second-order approximation, and that the Tornquivist index, offering a discrete approximation to the Divisia index, is based on a translog technology. By using the translog cost function, it is shown that the percentage change in costs depends on the share-weighted change in input prices. In his approach, increasing, constant and decreasing returns to scale can be assumed. Moreover, the condition of perfect competition can also be relaxed by allowing imperfect competition in input factor markets.

In sum, the Tornqvist index not only provides a very convenient mechanism for measuring technical change without estimating the production function, but also requires fewer assumptions than the Divisia index approach. As indicated by Denny and Fuss (1983), however, the exact index number approach can yield a biased measure for technical change if employed in analyzing industries with increasing returns to scale. They also claim that if the technology is not translog or if the second-order translog parameters differ across firms, the Tornqvist index can result in substantial distortion. When encountering these situations, econometric estimation needs to be employed.

Caves, Christensen, and Diewert (CCD, 1982) provide a non-parametric method using linear programming as an alternative for measuring technical change and TFP growth. By measuring deviations between the benchmarking frontier and decision making units (DMUs), the methods can yield TFP growth rates and their decomposed sources such as efficiency change and technical change. Färe, Grosskopf, Norris and Chang (1994) analyze the TFP growth and technical change of OECD countries for the period between 1979 and 1988, and show that Japan has caught up with the world frontier technology and that the US has innovated the world frontier technology. For this, they use the Malmquist productivity index by extending and augmenting the methods of CCD and Nishimizu and Page (1982).

Despite its wide use in measuring TFP growth and its decomposed components, the non-parametric approch also has been criticized for the following reasons: (i) It is not free from outlier problems. Since constructing a benchmarking frontier is highly affected by even a single outlier, TFP and decomposition can be biased. (ii) As Hulten and Isaksson (2007) argue, it suffers from a form of simultaneous equation bias implicit in the endogeneity of capital. A shift in the production function at a given capital-labour ratio leads to an increase in output per worker and some of this extra output is saved, leading to more output, more saving and so on.

3. The Data

We used the firm-level panel data, covering the period 1992-2000. The initial data set consists of 39,301 observations on manufacturing and service firms in Sweden. The data is stratified with the sampling conditions based on the representative target population for a national Swedish Innovation Survey conducted in 1999. We have removed the outliers from our data set in order to obtain robust estimation results. The criterion of the truncation is a growth rate of ±80% of value added. After this truncation, the final data set consists of 37,838 observations for unique 5,893 firms.[4]

Several variables are used in the empirical investigation of the production functions and computation of TFP growth. The value-added of each firm is used as a measure of output (Y). Capital stock and labour (K and L) are used as input variables. Capital stock has been computed by the perpetual inventory method, $K_t = (1-\delta)K_{t-1} + I_t$, where K_s and I_s are capital stock and amount of investment in time period s, respectively. The depreciation rate, δ, is assumed to be constant over the whole period and set at 0.10. Capital stock in the first year, K_1, is set to be equivalent to the amount of fixed assets. As a measure of labor input (L), we use the number of workers. Value-added and capital stock are deflated by the consumer price index. All the variables are transformed to logarithmic form when estimating the production functions.

The firms are categorized into several groups based on their size and technological levels to investigate the productivity growth patterns stemmed from these firm characteristics. We group them into five size classes by the number of employees: less than 10 (micro), 10-50 (small), 50-100 (small-medium), 100-300 (medium), and over 300 (large) employees. The criteria for the technological levels are obtained from

[4] Even though there is no a generally accepted and precise definition of the outlier, it is often referred to as an observation which is inconsistent with the remainder of the set of data (Barnett and Lewis, 1995). Among the reasons for being an outlier, errors when compiling the data set are considered the most likely source. Hence, a robustness can be obtained by removing those errors (or outliers). Quite strict rules for detecting and removing outliers exist in the field of frontier analysis studies, since they play an important role in estimating the models. The approaches of Simar (2003) and Fox, Hill and Diewert (2004) are good examples. The calculation result of TFP growth without the outlier removal can be retrieved from the authors on request.

OECD (2003). The manufacturing firms are categorized into four technological levels: high tech, high-medium tech, medium-low tech and low tech.

Table 1 provides summary statistics of the data for the input and output variables used in this study. The fact that all variables have mean values larger than the median indicates that the distributions of all the variables are skewed to the right. This implies that a large number of firms have operated with small inputs and small output levels and only a few firms have operated with large inputs and large output levels. The skewness of value added, capital stock and labour are 29.1, 28.7 and 26.8, respectively.

The first part of Table 2 gives the descriptive statistics of variables by size. Value added, capital and labour increase as firm size increases. For all the three variables, large discrepancies can be found between large and smaller firms. The average value added of large firms is at least six times larger than that of smaller counterparts. The capital stock and labour of large firms are somewhat larger than those of smaller firms. Although around three quarters of our sample are categorized as small and medium firms, their shares in output labour of the totals are only 32.1% and 35.4%, respectively.

The second part of Table 2 shows the descriptive statistics of variables by sector and technological level. Nearly 2/3 of the observed firms operate in the manufacturing sector. As expected, the average output of the high-technology manufacturing sector is larger compared to the medium- and low- technology manufacturing sectors.

Table 3 provides descriptive statistics of the variables over time. The mean value added fluctuates and the highest values are attributed to 2000 (93.3) and 1994 (90.9). There is no positive relationship between the level of the mean and its dispersion. The dispersion around the mean value is increasing and highest around 1998-2000. Capital stock also varies over time and reaches its highest values in 1999 and 2000. The dispersion of capital formation around the mean value is similar to that of value added. The change in employment size shows declining pattern. The dispersion in employment is largest during the period 1994-1995 and it reaches its lowest level in 1999.

4. The Empirical Models

We used a parametric translog production function to measure the rate of TFP growth and its components. Two specifications, the time trend (TT) and the general index (GI) models, are used as the starting point of the specification of technical change. Despite frequent use of TT and GI models, they still have a drawback in that they do not provide firm-specific measures under the following conditions: (i) If technical change is neutral, (ii) the firms face the same input and output prices. Thus, firm-specific effects in the two models play no role in TFP growth and its decomposition if one of the above conditions arises. The other drawback of the basic TT and GI models is that only intercepts are firm-specific with these specifications. This might not be enough to capture the economically meaningful firm-specific heterogeneity. Hence, implicit restrictions need to be alleviated in order to obtain more flexible modelling of production technology. We alleviated the restrictions imposed on the TT and GI models through their gradual extensions. These extensions generate rates of technical change and TFP growth which are not only time-variant but also input- and firm-specific. The parametric growth measures are further compared with the non-parametric Solow residual, which serves as a benchmark.

4.1 Productivity and technical change

We assume that production in manufacturing and service industries is specified as the following production function:

(1) $$Y = f(X, t)$$

where Y is a scalar output, X is a vector of inputs $(j = 1, \cdots, J)$, and t is the time trend variable. Here producers are assumed to maximize output given the inputs and technology available. Taking the total differential of equation (1) gives us the following equation:

(2) $$\dot{Y} = \sum_j \frac{f_j X_j}{Y} \dot{X}_j + \frac{f_t}{Y} = \sum \varepsilon_j \dot{X}_j + \frac{f_t}{Y}$$

where the "dot" over a variable represents its growth rate, f_j is a marginal product of the j^{th} input, and ε_j is the corresponding input elasticity.

Under the assumptions that the firms minimize cost and the input markets are competitive, the relationship in equation (2) can be rewritten as follows:

(3) $$\dot{Y} - \sum_j S_j \dot{X}_j = \frac{f_t}{Y} + (RTS - 1) \sum_j S_j \dot{X}_j$$

where S_j is the cost share of input j, and $RTS = \sum_j \varepsilon_j$ is the returns to scale. The left-hand side of equation (3) is referred to as the Divisia index of total factor productivity growth (TFP), expressed as

(4) $$TFP_{DIV} = \dot{Y} - \sum_j S_j \dot{X}_j$$

If price data are available, the above TFP growth can be calculated without an econometric estimation. If not, econometric estimation of a production function is necessary.

The main advantage of using a parametric approach over the non-parametric approach of the Divisia index is that one can avoid the strong assumption of constant returns to scale and can decompose TFP growth into technical change (f_t/Y) and scale $((RTS - 1)\sum_j S_j \dot{X}_j)$ components as indicated in equation (3).

4.2 Time Trend (TT) and General Index (GI) Models

For illustration of the basic models and their generalizations we assume the following standard specification of a production model with panel data:

(5) $$y_{it} = \beta_0 + \mathbf{x}_{it}\beta + u_{it}$$

where y_{it} is the log output of the producer i $(i = 1, \cdots, N)$ at time t $(t = 1, \cdots, T)$, x_{it} is the corresponding matrix of J inputs and β is $J \times 1$ vector of unknown parameters to be estimated. In this study the error term, u_{it}, is specified as a two-way error component model written as:

(6) $$u_{it} = \mu_i + \lambda_t + v_{it}$$

where μ_i, λ_t and v_{it} represent firm-specific effects, time-specific effects and statistical noise, respectively. Effects such as advantages or disadvantages in the location of the firm, access to (skilled) labour, measurement errors in the dependent variables and left-out explanatory variables, which cannot be controlled by the producers, are captured by the error term, v_{it}. We assume that this error term is independently and identically normally distributed with zero mean and constant variance, σ_v^2. The firm-specific effect, μ_i, is a factor representing producer efficiency, and the time-specific effect, λ_t, is a factor representing the exogenous rate of technical change (Heshmati, 2002). In order to avoid over-parameterization of the model the individual firm-specific effects, μ_i, are replaced by industry-specific effects, η_d. This accounts for between-industry-specific variations, which are important from a policy perspective. Also, we assume a translog form of the production since it provides a good second-order approximation to a broad class of functions (Kneller and Stevens, 2003).

In the time trend (TT) model, the trend variable is used as a regressor along with the x input variables. The time-specific effect is specified as a linear function of time trend, t. Hence, the basic time trend (TT1) model can be written as:

(7) $$y_{it} = \beta_0 + \beta_t t + \frac{1}{2}\beta_{tt}t^2 + \sum_j \beta_j x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_j \beta_{jt} x_{jit} t + \eta_d + v_{it}$$

where y and x are defined as above, and t is a single time trend representing the exogenous rate of technical change. The η_d is fixed industry-specific effects to be estimated. We named the model in equation (7) the TT1 model. Our TT1 model is assumed to satisfy the symmetry and convexity conditions.

In the general index (GI) model of Baltagi and Griffin (1998), the trend variable t is replaced by $A(t)$, where $A(t)$ $(t = 1, \cdots, T)$ is a vector of time-effects parameters to be estimated. Hence, the corresponding production function assuming the general index representation of technical change is given by:

(8) $$y_{it} = \beta_0 + \sum_j \beta_j x_{jit} + A(t) + \frac{1}{2}\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_j \beta_{jt} x_{jit} A(t) + \eta_d + v_{it}$$

where the time trend and its square terms are replaced by $T-1$ fixed time-specific effects $A(t)$. We name the model in equation (8) the GI1 model. The GI1 model is also assumed to satisfy the symmetry and convexity conditions.

Since technical change is defined as the log derivative of output with respect to time $(\partial y / \partial t)$, the rate of technical change (TC) in the TT1 model is given by:

(9) $$\mathrm{TC}_{\mathrm{TT1}} = \beta_t + \beta_{tt} t + \sum_j \beta_{jt} x_j .$$

The corresponding rate of technical change in the alternative GI1 model specification is given by:

(10) $$\mathrm{TC}_{\mathrm{GI1}} = \{A(t) - A(t-1)\}\left\{1 + \sum_j \beta_{jt} x_j\right\}.$$

Technical change expressed in equations (9) and (10) can be decomposed into components associated with pure time-variables (neutral) and input-variables (non-neutral). These components in the TT1 model are $\beta_t + \beta_{tt} t$, and $\sum_j \beta_{jt} x_j$, respectively. In the GI modelthese components are $\{A(t) - A(t-1)\}$ and $\{A(t) - A(t-1)\}\sum_j \beta_{jt} x_j$, respectively. It is worth noting that there are some problems inherent in the nature of technical change in the TT1 model. First, the rate of technical change either indefinitely increases $(\beta_{tt} > 0)$ or decreases $(\beta_{tt} < 0)$ linearly as a function of time. Second, with unbalanced panel data, it is not clear whether the trend variable, t, for a firm entering in period τ $(1 < \tau < T)$ should start from τ or be replaced with unity. Third, in the case when the time span is relatively narrow, a time trend model might not appropriately represent the exogenous rate of technical change. Finally, the two neutral and non-neutral components of technical change are modelled independently. All of these problems are avoided in the GI1 model by estimating one parameter for each time period in $A(t)$.

Technical change can be biased towards a particular input. This can also be measured. For input j, bias (B_j) in technical change is measured by $B_j = \partial S_j / \partial t$. A positive (negative) value of B_j implies that technical change is relatively jth input-using (saving). A zero value of B_j indicates that technical change is not biased towards any particular input, *i.e.*, technical change is neutral (Kumbhakar and Hjalmarsson, 1993, and Kumbhakar and Heshmati, 1996). In the TT1 model, $B_{\mathrm{TT1},j} = \beta_{jt}$ which is a constant over time, and its sign is simply determined by the sign of β_{jt}. Hence, input bias in technical change derived from the TT1 model is firm- and time-invariant. In the GI1 model, however, input bias varies over time since $B_{\mathrm{GI1},j} = \beta_{jt}[A(t) - A(t-1)]$. This implies that the sign of $B_{\mathrm{GI1},j}$ in the GI1 model is determined by the sign of β_{jt} and $A(t) - A(t-1)$.

Like the input bias, scale bias in technical change can also be derived from $SB = \partial RTS / \partial t$, where $RTS = \sum_j \varepsilon_j$. In the TT1 model, the scale bias is given by $SB_{TT1} = \sum_j \beta_{jt}$, while in the GI1 model the scale bias is given by $SB_{GI1} = [A(t) - A(t-1)]\sum_j \beta_{jt}$. The scale bias in the TT1 model is firm- and time-invariant, while in the GI1 model it is time-varying.

Using equations (3) and (9), total factor productivity growth in the TT1 model can be calculated as follows:

(11) $$\text{TFP}_{\text{TT1}} = \text{TC}_{\text{TT1}} + (\text{RTS}_{\text{TT1}} - 1)\sum_j \varepsilon_j \dot{x}_j,$$

where $\varepsilon_j = \partial y/\partial x_j = \beta_j + \sum_k \beta_{jk} x_k + \beta_{jt} t$, and $RTS = \sum_j \varepsilon_j$. If RTS is greater than (equal to or less than) one, then there are increasing (constant or decreasing) returns to scale. Similarly, TFP growth in the GI1 model can be expressed as follows:

(12) $$\text{TFP}_{\text{GI1}} = \text{TC}_{\text{GI1}} + (\text{RTS}_{\text{GI1}} - 1)\sum_j \varepsilon_j \dot{x}_j,$$

where $\varepsilon_j = \partial y/\partial x_j = \beta_j + \sum_k \beta_{jk} x_k + \beta_{jt} A(t)$, and $RTS = \sum_j \varepsilon_j$.

In the above two TFP growth rate measures, the only difference between TFP growth and technical change is RTS . If the production technology exhibits constant returns to scale, then TFP growth rate is identical to the rate of technical change. It should be noted that, if cost shares are available, then TFP growth rate can be obtained using a non-parametric Divisia approach under the assumption of constant RTS.

4.3 Extensions of Time Trend Model

Although technical change in the TT1 model (TC_{TT1}) is firm- and time-specific because input variables vary across firms, technical change is not firm-specific when the components related to input variables are all zero. It is important to obtain firm-specific neutral components. In this sense, The restrictive feature can be removed by extending the TT1 model in much more flexible ways. . Using the model proposed by Cornwell, Schmidt and Sickles (1990), the extended time trend model (hereafter, TT2 model) can be specified as:

(13) $$y_{it} = \beta_{dt} + \sum_j \beta_j x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_j \beta_{jt} x_{jit} t + v_{it},$$

where β_{dt} denotes industry- and time-specific intercepts. By replacing β_{dt} with a flexible parametric function of time, the TT2 model considers the industry-specific effects inherient in technical change. The model for the intercept (β_{dt}) given in this study is specified as follows:

(14) $$\beta_{dt} = \eta_{1d} + \eta_{2d} t + 1/2 \eta_{3d} t^2,$$

where η_{1d} , η_{2d} and η_{3d} are unknown industry-variant parameters to be estimated. Hence, in the above specification β_{dt} is a quadratic function of time trend and varies across industries. The temporal pattern of β_{dt} is flexible and no further assumption is required. Technical change in the TT2 model is expressed as follows:

(15) $$\text{TT}_{\text{TT2}} = \eta_{2d} + \eta_{3d} t + \sum_j \beta_{jt} x_j .$$

Thus, TC_{TT2} is industry-specific and it also changes over time even when all input variables are zero. The pure component of technical change $\eta_{2d} + \eta_{3d} t$ is both industry-specific and time variant. However, the industry-specific effects are not incorporated in the non-neutral technical change component, $\sum_j \beta_{jt} x_j$. In the same way as before, total factor productivity growth of the TT2 model can be obtained from:

(16) $$\mathrm{TFP}_{\mathrm{TT2}} = \mathrm{TC}_{\mathrm{TT2}} + (\mathrm{RTS}_{\mathrm{TT2}} - 1)\sum_j \varepsilon_j \dot{x}_j,$$

where $\mathrm{RTS}_{\mathrm{TT2}}$ and ε_j are returns to scale and elasticity of input j, respectively.

Although the TT2 model is successful in making the pure component of technical change industry-specific, non-neutral technical change is still restrictive as in the TT1 model. Now, we consider another extension of the TT2 model, the TT3 model, which allows industry-specific non-neutral technical change. The production function in the TT3 model is expressed as:

(17) $$y_{it} = \beta_{dt} + \sum_j \beta_j x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_j \zeta_{jd} x_{jit} t + v_{it},$$

where β_{dt} is the same as in the TT2 model, ζ_{jd} $(j = 1, \cdots, J)$ are industry-specific unknown parameters to be estimated.

Technical change from the TT3 model is given by:

(18) $$\mathrm{TT}_{\mathrm{TT2}} = \eta_{2d} + \eta_{3d} t + \sum_j \zeta_{jd} x_j .$$

TFP growth of the TT3 model is the same as in equation (16) except that the subscript $TT2$ is replaced with $TT3$.

Input bias and scale bias in the TT2 model are the same as in the TT1 model. Input bias and scale bias in the TT3 model, however, are industry-specific. For input j, $B_{\mathrm{TT3},j} = \zeta_{jd}$. Its sign is simply determined by the sign of ζ_{jd}. Scale bias is expressed as $SB_{TT3} = \sum_j \eta_{jd}$.

4.4 Extensions of General Index Model

Under the specification of the GI1 model an implicit restriction on the temporal pattern of technical change across industries is imposed. This means that technical change varies over time but it is the same across different industries if the components related to the input variables are all zero. This undesirable feature of invariant technical change across industries can be removed in such a way that the rate of technical change is industry-,time- and firm-specific. We have eliminated the restriction in two ways. In the first extended model, GI2, following Lee and Schmidt (1993), we make pure technical change industry-specific by specifying the production function as follows:

(19) $$y_{it} = \eta_d A(t) + \sum_j \beta_j x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_j \beta_{jt} x_{jit} A(t),$$

where η_d denotes industry-specific parameters. In equation (19) two vectors, η_d and $A(t)$, are unknown parameters to be estimated. Thus, technical change in the GI2 model is expressed as:

(20) $$\mathrm{TC}_{\mathrm{GI2}} = \eta_d[A(t)-A(t-1)] + \sum_j \beta_{jt} x_j [A(t)-A(t-1)].$$

In equation (20), the industry specific effect is inherent in the pure component of technical change, $\eta_d[A(t)-A(t-1)]$. The non-neutral component of technical change is $\sum_j \beta_{jt} x_j [A(t)-A(t-1)]$. Note that industry-specific effects are not incorporated in the non-neutral component of technical change of the GI2 model. However, the two components are not independent, implying that no non-neutral technical change can take place without attaining a pure rate first. Also note that, unlike the extensions of time trend models, no functional form of technical change is assumed, which is useful and reasonable when the time span of panel data is narrow.

The GI2 model can be further extended when every $A(t)$ in equation (8) is replaced by industry-specific general indexes. The production function in the GI3 model is expressed as

(21) $$y_{it} = \eta_d A(t) + \sum_j \beta_j x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} x_{jit} x_{kit} + \sum_j x_{jit} \zeta_{jd} A(t),$$

where ζ_{jd} denotes unknown parameters to be estimated. The rate of technical change in the GI3 model is obtained as:

(22) $$\mathrm{TC}_{\mathrm{GI3}} = \eta_d[A(t)-A(t-1)] + \sum_j x_j \zeta_{jd} [A(t)-A(t-1)].$$

The GI3 model is much more flexible than the GI1 or GI2 models in that the industry-specific effects are inherent in both the pure component and the non-neutral component of technical change.

Input bias and scale bias in the GI2 model are the same as in the GI1 model. In the GI3 model, however, input bias and scale bias are industry- and time-specific. These measures are obtained as:

(23) $$\begin{aligned} B_{\mathrm{TT3},j} &= \zeta_{jd}[A(t)-A(t-1)] \\ BS_{\mathrm{TT3}} &= \sum_j \zeta_{jd}[A(t)-A(t-1)]. \end{aligned}$$

4.5 The Non-parametric Approach

This sub-section provides a traditional measure of the TFP growth rate, the Solow residual approach. We begin with the following production function:

(24) $$Y = Af(K,L),$$

where A is a Hicks neutral technology index, which allows for shifts of the production function. By totally differentiating equation (24) and dividing it by Y, we have the following growth equation:

(25) $$\dot{Y}/Y = \varepsilon_k \dot{K}/K + \varepsilon_l \dot{L}/L + \dot{A}/A,$$

where ε_k and ε_l represent elasticities of output with respect to capital and labour. By assuming constant returns to scale, ε_l can be replaced with $1-\varepsilon_k$ and equation (25) can be expressed as follows:

(26) $$SR = \dot{Y}/Y - (1-\varepsilon_k)\dot{L}/L - \varepsilon_k \dot{K}/K,$$

where the Solow residual SR is equivalent to the estimate of TFP growth, represented by $(\dot{A}/A)$. It is often considered as a benchmark in empirical studies.

5. Estimation Methods

In panel data literature, the estimation processes of error component models shown in equations (7), (13), (17), (8), (19) and (21) have been developed in different directions. Applying a static formulation, as in our case, the models are mainly estimated using fixed and random effects. The fixed effects (FE) model assumes that μ_i and λ_t are fixed and correlated with the explanatory variables, while in the random effects (RE) model both error terms are assumed to be purely random. Efficiency, unbiasedness and consistency are the properties affecting the choice of FE and RE models.

We employ the following steps for choosing an appropriate estimation process: (a) in TT1 and GI1 models, the industry-specific intercepts, η_d, are substituted by firm-specific intercepts, η_i, (b) the least-squares dummy variables (LSDV) method and the maximum likelihood estimation (MLE) method are employed in estimating the two models with FE and RE, respectively, (c) The Hausman test is applied to choose an appropriate estimation process for both of the model specifications, and (d) the chosen estimation processis assumed to be applicable to the extended models.

The assumption in (d) above is necessarily imposed due to the fact that (i) with many observations in our data set, it is quite a time consuming task if firm-specific intercepts, η_i, are incorporated in the non-linear model specifications such as the GI2 and GI3 models, and (ii) with our large data set, observing fixed effects of individual firms is not meaningful. The above strategy reduces the excessive number of firm-specific unique parameters and is employed in estimating all the six models. One loss is the within-industry variation, but it maintains the between-industry variations. The amount of information loss is reduced by appropriate classification of industries such that it is useful for policy analysis.

Results of the Hausman test signify that the FE model captures the nature of our data set better than the RE model. Hence, we use only the FE-type models when calculating the components of TFP growth and reporting the results. The TT1, TT2, TT3 and GI1 models are linear and estimated using LSDV methods, while GI2 and GI3 models are nonlinear and estimated by MLE methods. In each model, we assume that $v_{it} \sim i.i.dN(0,\sigma_v^2)$,independent of the explanatory variables.

As discussed above, industry dummy variables are included to capture industry-specific features of TFP growth and rate of technical change. Fifteen industry dummy variables are used for this purpose, eleven of which are manufacturing sectors and four of which are service sectors. The classification follows the international industrial classification system, which is listed in the Appendix.

6. Empirical Results

6.1 Specification Tests and Model Selection

The six model specifications (TT1, TT2, TT3, GI1, GI2 and GI3) presented in Section 5 are used to estimate the productivity growth and its decomposed components of Swedish firms for the period 1992-2000. In all the models the null hypothesis of constant returns to scale is rejected in favour of variable returns to scale at the 1% level of significance. It suggests that a parametric approach to TFP measurement is to be preferred to the Solow residual approach. The R^2 values are quite high, around 0.9, in all the models. Due to the large size of parameters estimated and rejection of some models by a model selection procedure described below, the estimates of the parameters of the models are omitted from this paper in order to save space[5].

Although different assumptions of behaviour of technical change are inherent in each of our six models, it is essential to take into consideration which of these six competing models are appropriate for our data set and whether the corresponding results from such models are reasonable or not. One main obstacle to choosing appropriate models is that our six models are not nested in a single super model. The TT1 is nested in the TT2 and TT3, and the TT2 is nested in the TT3. The GI1 is not nested in the GI2 or GI3, whereas the GI2 is nested in the GI3. Furthermore, the TT models are not nested in the GI models, and *vice versa*. Because of this, we perform two non-nested tests (J test and Cox test) to examine the appropriateness of different non-nested models. For the nested models, we use a log-likelihood ratio test (LR test) for choosing appropriate models.

The result of the LR test on the TT1 and TT2 models rejects the TT1 at the 1% level of significance in favour of the TT2. The results of the LR test on the TT2 and TT3 models reject the TT2 in favour of the TT3. Thus, the test results give us conclusive evidence that the TT3 is the best model among time trend model specifications.

As discussed above, the GI1 is not nested with the GI2. The results of J test and Cox test show that the GI1 is preferred to the GI2, and the GI2 is not preferred to the GI1. However, the J test and the Cox test on the GI1 and GI3 models show that neither of the models is preferred. This is quite a well known problem with the J test and the Cox test and is not necessarily associated with our model specification or data set. The LR test on the GI2 and GI3 models shows that the GI2 is rejected at the 1% level of significance in favour of the GI3 model. Hence, among the GI models, the GI1 and GI3 are chosen as being the best models for describing our data.

In a final step, we test the preferred time trend model, TT3, against the two GI models, GI1 and GI3. The J test and the Cox test on these model selections are inconclusive. Then, we test each of the two GI models against the TT3 model, the results of which also yield inconclusiveness. Thus, these tests do not help us to choose the single best model among the TT3, GI1 and GI3 models.

Although the above statistical methodologies does not enable us to select a better model between the two GI models, the rationale extending the basic GI model (GI1) to the GI2 and then to the GI3 helps us to choose an appropriate model in a heuristic manner.

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[5]Interested readers can obtain the estimation results of the six models from the authors.

Since the industry-specific technical change is included in the GI2 and the GI3 models and the GI3 produces a better fit than the GI2, we conjecture that the GI3 is more appropriate than the GI1. In the following our presentation is mainly focused on the results of the TT3 and GI3 models. The complete estimates can be obtained from the authors.

6.2 Input Elasticities and Returns to Scale

The elasticities of output with respect to each of the inputs of capital and labour, ε_j, are calculated from $\varepsilon_j = \partial y / \partial x_j$, which measures the percentage changes in output in response to the percentage changes in inputs. The returns to scale (RTS), measuring changes in output in response to proportional changes in all inputs, are calculated from the sum of the two input elasticities. These input elasticities and returns to scale vary over time and across firms.

In Table 4 we report elasticities and RTS with respect to year of observation, industrial sector, firm size, and technology classification for the whole sample. Since the t-statistics based on the estimated elasticities and their standard errors are over 2, the hypotheses of zero input elasticities are rejected for inputs in both models.

The capital elasticities of the TT3 and GI3 models are 0.197 and 0.193, respectively. The corresponding labour elasticities are 0.816 and 0.821, respectively. The fact that the labour elasticity is larger than the capital elasticity reflects the fact that the increase of labour is more effective than the increase of capital in producing more output. However, both models show that the capital intensity increased somewhat between 1992 and 2000. Returns to scale of the two models are almost identical, indicating that the production technology exhibits increasing returns to scale. Returns to scale of the two models are almost identical, 1.010 and 1.011 for TT3 and GI3, respectively. The fact that RTSs of the two models are larger than unity signifies that the production technology exhibits increasing returns to scale. On average, Swedish firms in our sample are found to be of sub-optimal size.

In the upper part of Table 4, both models reveal a tendency for the capital elasticity to increase over time, while the trend is the opposite for labor elasticity. The mild downturn in the business cycle in the mid 1990s is reflected in a temporary decrease of RTS in the TT and the GI models. Notable is that the time trend model reports a growing RTS during the observed period. This trend cannot be found in the GI model.

Looking at the elasticities and RTS by industries, it is found that the input elasticities differ considerably across models but are mostly of reasonable sizes.[6] Compared to services, manufacturing firms generally have higher capital elasticity, lower labour elasticity and higher returns to scale.

The relationships between the sizes and elasticities are also presented in Table 4. *A priori*, one would expect the degree of capital utilization to increase as the size of a firm increases. This is confirmed by the empirical results. By contrast, labour elasticities decrease as the size of a firm increases. These trends suggest that it is

[6]Acronyms of industries are provided in the Appendix.

relatively more efficient for smaller firms to exploit the labour force rather than the capital stock, and *vice versa* for larger firms. Another interesting finding is that the returns to scale correlate positively with firm size. Only small firms operate close to their technically optimal size. Both models indicate that micro firms operate below their optimal scale of production while small-medium**,** medium or large firms have the potential to increase their efficiency by adjusting their scale downwards.

The average capital elasticity among firms belonging to the R&D and human-capital-intensive high technology is lower than for other firms and the labour elasticity is higher. This result, shown in both models, indicates the particular importance of well-educated, well-trained and skilled workers for value added activities in knowledge intensive firms. In firms characterized by standardized production it is more efficient to substitute workers with machines.

6.3 Rate of Technical Change

Technical change is reflected in a neutral shift in production function as a result of technological advancement for given input utilization. A positive rate indicates technical progress like improvement of production processes and learning by doing, while a negative rate of technical change indicates technical regress. Table 5 reports results for the TT3 and the GI3 models.

The average rates of technical change in all the models are positive, indicating technical progress. The overall mean rate of technical change is almost the same for all the models, around 2% per year increase in the level of output for given level of inputs used in production. Although figures are not tabularzed in this paper, it is found that there is a systematic difference between all the TT models and the GI models. all the TT models have a downward trend, explained by a reduced growth rate of the pure technical change. No corresponding pattern can be found among the GI models.

In the TT3 model, the overall mean rate of technical change decreased during the study period. Since the pure technical change continuously decreased and the non-neutral technical change is negligible the decreasing trend of technical change is mainly influenced by the pure technical change. In the GI3 model, instead of showing a smooth uniform pattern, the rate of technical change fluctuates during the study period. Although the rate of technical change was decreasing in 1996 influenced by the a mild cyclical downturn, it rapidly began to regain a favourable rate of growth. An obvious pattern cannot be found in the relationship between the pure technical change and the non-neutral technical change components.

The rates of technical change averaged by each of industrial branches are also listed in Table 5. The extent of technical change varies somewhat across industries, ranging from close to zero percent in the food industry to above 3% in machinery and equipment. However, the majority of industries (11 in the TT-model and 14 in the GI-model) have a growth rate above 1%. Contrary to our expectation, no systematic link is found between firms belonging to an export-oriented industry and technological change.

Turning now to the technical change relating to the size, if one ignores the fact that the estimates for micro firms are somewhat deviating (1.3) in the GI3 model, the results are very close (1.8-2.1) for small, small-medium, medium and large firms. The rate of technical change is almost identical for all size classifications in the TT3 model. Hence, we find no evidence supporting the hypothesis of superior technological advancement in large firms.

This paper also studies the relationship between the rate of technical change and technology classification. Looking first at manufacturing versus services, the rates of technical change are almost the same in the TT3 model, while the GI reports 2.1% for manufacturing and 1.6% for services.

Consider then manufacturing firms were classified into four different classifications according to technology intensity defined by R&D and human capital. *A priori* one would expect the positive relationship between the technology intensity and technical change since technological advancement is mainly led by technology-intensive industries. This is partly confirmed by the results. The TT3 model shows that the magnitude of the technological change is lower in low and medium-low tech firms than in high tech and high-medium tech firms. However, in the GI3 model no difference can be found among the high, medium-low and low technology industries. The annual growth rate of these industries is about 2%. The corresponding figure for the typical high-medium technological firms is 2.6%.

6.4 Technological Bias Effects

Technological change can be biased towards certain inputs or have different impacts on different factors such as the wages of labour of different skills. Such change will induce changes in the proportion of inputs used in production. A negative sign indicates input-saving, while a positive sign indicates input-using technological change. The sum of the input biases is labelled as scale bias. Unlike returns to scale, which are the sum of expected positive input elasticities, the scale bias might turn out to be zero as a result of different input biases with opposite signs cancelling out each other when summed.

The overall capital and labour biases for all six models are presented in Table 6. Note that the standard deviation of input and scale biases of the TT1 and TT2 models are constant for all firms over time (See the first and second rows) This is due to the inflexible way they are specified.

In general, the results are very much model-dependent. The patterns of factor using/saving biases are similar for five of the models except for the GI2 model. These five models show capital saving and labour using patterns. Compared to the TT3 model, the factor biases in the general index models vary widely across models.

The mean scale bias is also listed in Table 6. Note that the standard deviation of scale bias is zero by definition in the TT1 and TT2 models. Like the average input biases, the average rate of scale bias vary substantially among the competing models. The GI2 model has quite large scale bias, while the other models yield similar figures that are significantly different from zero (around 2%). It needs to be noted that although the magnitudes of the scale bias are comparably small in the other five models, due to cancellation effects, they are not necessarily irrelevant to the productivity growth.

6.5 Total Factor Productivity Growth

Table 7 presents the rate of total factor productivity (TFP) growth for all six models. The Solow residual approach is also presented in the table for comparison purposes.

The TFP growth over time, and by industrial branch, firm size, and technological levels are reported as sample means. See the bottom part of the table. The rate of TFP growth is almost identical in the GI models (around 2% per year). The corresponding figures for the TT models and the Solow residual are 1.3-1.5%. The result for all models shows a considerable improvement in TFP-growth compared to the period before the economic crisis in Sweden in the beginning of the 1990s. Comparing the result of the technical change with the TFP growth, it can be found that patterns of the rate of TFP growth in all the six models are very much similar to those of the technical change component. This implies that the main mechanism for the change in productivity growth is technical change.

Looking at the TFP growth by year, the upper part of Table 7 reports a systematic difference between the time trend models and the other two models. The TT models yield decreasing trends in the rate of TFP growth, whereas the rate of TFP growth of GI models does not show any trend pattern. The result of the Solow residual is similar to those of GI models. Both of the GI models and Solow residual reveal a slower growth rate in the middle of the observed period, coinciding with a cyclical downturn in the economy.

Interestingly, the results of the TT, GI and Solow residual of the productivity equations by industry suggest a common feature of relatively high growth rate in the Swedish economy during the 1990s. This finding coincides with the rate of technical change, discussed above. Though the growth rates differ among the specifications, our two preferred models, TT3 and GI3, show conflicting results only for a few industries. The TFP growth for the 15 different industries are mainly explained by technical change in both the time trend and the general index models.

The hypothesis that R&D investments are particularly important for high and sustainable growth in productivity has been suggested at a theoretical level by many authors, arguing that there is close linkage among R&D activities, technical change, innovation, competitiveness, market size and productivity. Since large manufacturing firms and high technology firms are considerably more R&D-intense than other firms, one would expect a systematic difference in TFP growth in our sample. Looking at the relationship between productivity growth and firms' size, the hypothesis is confirmed by the non-proffered TT and GImodels. However, the TT3 model reports high growth rates for micro (1.6%), small (1.3%), small-medium (1.6%) medium (1.8%) and large firms (2.1%). The correlation between size and productivity growth is even more narrow in the GI3 model; the range between micro and large firms is 1.8%-2.2%. No systematic relationship at all between these variables is shown in the Solow residual approach. We also see that the link between a manufacturing firm's technology intensity and TFP growth is non-existent. Moreover, our expected difference in TFP growth between manufacturing firms and services is not strongly supported by the results. Only the GI3 model and the Solow residual report larger growth rates for manufacturing firms.

6.6 Determinants of TFP Growth

We now identify different growth determinants of TFP growth and estimate their importance. The information aims to increase our understanding of conditions for firms' survival, profitability and growth. A total of six indicators are identified and used in the regression analysis. These are: capital intensity (CAPINT), market competitiveness (MKTCOM), human capital (HMNCAP), growth in human capital (HMNGRT), capital structure (CAPSTR) and wage growth (WGGRTH).

Firms with a higher level of capital intensity, where capital intensity is considered as a measure of the firm-specific knowledge embodied in the machinery and equipment in production, are expected to have high asset specificity and thereby potentially more variability in capital utilization. The possibility of increase in the rental cost of unused capital encourages firms to use their production resources efficiently (Jung, 1991). However, empirical studies show a somewhat mixed strand of the results for this hypothesis. For example, Lim (1980) and Sheehan (1997) give support to the positive relationship between the level of capital intensity and the firms' performance, whereas Ferrier, Klinedinst and Linvill (1998) and Mahadevan and Kalirajan (2000) report a negative effect of capital intensity on production. We measure the capital intensity of a firm by the ratio of capital to the number of employees and its growth rate is used as one of the determinants of productivity growth.

Regarding the relationship between the performance and the competitive condition of a market, two different points of view exist in the literature. Neoclassical economists support a positive association between the two measures arguing that the elimination of slacks promotes performance. In contrast, Schumpeterians and others assert a negative relationship, pointing out that monopoly rents induce entrepreneurs to invest in R&D activities and thus promote dynamic performance. In empirical tests, Nickell (1996), Aghion, Harris, Howitt and Vickers (2001) and Boone (2001) find some support for the view that competition improves performance, whilst Dasgupta and Stiglitz (1980) support the Schumpeterian view. In this paper, competition is measured by the Herfindahl index, $\sum_i s_i^2$, where s_i is the market share of i^{th} firm. It should be noted that a Herfindahl index close to unity indicates a less competitive market condition.

Human capital is widely recognized as an important source of economic growth. Modern growth theories such as those of Romer (1986) and Lucas (1988) emphasize how human capital can stimulate economic growth through technological development, uptaking and imitation of new technologies, invention and innovation. Yet, adequately measuring its stock at various levels of aggregation remains controversial. Three general approaches to human capital measurement are education-based, cost-based and income-based (For a literature review, see Le, Gibson and Oxley, 2005). Following the empirical neo-Schumpeterian, we use formal education as a proxy for human capital. Our observed measure is the number of employees who have at least a bachelor's degree in engineering or science studies, and we distinguish between level and growth rate of human capital. There is a vast empirical literature verifying a positive and statistically significant relationship between human capital and productivity and between R&D and productivity as well. Since the definition of human capital in this paper also includes R&D personnel, a positive correlation across firms can be expected. Klette and Kortum (2004) report, however, that the longitudinal (within firm, and across time) relationship between firm-level differences in R&D and productivity growth is often low and insignificant.

Corporate governance defines the ways in which the supplier of finance to corporations is assured of getting a return on investment in a firm. Various stakeholders such as debt holders, equity holders and their representatives define the firm's rules, incentives and goals. Capital and resources are efficiently allocated by these activities (Kim, 2006). Hence, the structure of corporate governance is often closely linked to the growth of a firm and productivity. In our case, the corporate governance is to be captured by the capital structure of firms, which is defined as the ratio of debt to total.

We also examined the relationship between wage costs and TFP growth. Considering that firms' labour demand is mainly determined by labour productivity, it is likely that wages will increase if an employee is more productive. We therefore expect a positive correlation between the wage growth and the growth of TFP.

In order to isolate the relationships between the above six variables and TFP growth, it is essential to control for other factors that are likely to affect TFP growth. This is important for dealing with the heterogeneity of the firms in our sample. Among the various firm-specific attributes that are shared by firms in our sample, we have chosen the following control variables: firm size dummy, year dummy and industry dummy variables.

Table 8 presents the fixed effects parameter estimates of the determinants of TFP growth. Somewhat surprisingly, all six models show a negative relationship between capital intensity and TFP-growth. One possible explanation is that a considerable fraction of the capital stock became obsolete during the 1990s, a period characterized by rapid technological change due to ICT and other new technologies.

Regarding the market competition, signs as well as significant levels differ across model specifications. Only the results of the time trend models support the hypothesis that higher competition increases the TFP growth.

Our expression of human capital as university educated employment is positively and highly significantly related with TFP growth at the *level* dimension in all six models. However, we find the link between *growth* in education and growth in TFP to be fragile. Only the GI3 model indicates that TFP is influenced by both the stock and flow of human capital.

The capital structure variable displays a positive coefficient in the TT1, TT2, TT3, GI1 and GI2 models, while the GI3 model yields a negative coefficient. None of the coefficients, however, are statistically different from zero.

Finally, we can observe a positive and statistically significant relation between wage growth and TFP growth among all the model specifications. Since we control for level of education, the growth of wages reflect the fact that the average employee has become more productive due to factors such as learning by doing, more efficient methods of organizing the work, outsourcing and downsizing of less productive activities.

7. Summary and Conclusions

This paper presents a detailed exploration of technical change and total factor productivity (TFP) growth of a large panel of Swedish manufacturing and service firms over the period 1992-2000. The period is characterized as a transitional one in which the long-run productivity growth in Swedish manufacturing improved from being among the weakest to one of the strongest within the OECD.

One hypothesis tested is that the initial productivity improvements in manufacturing industries dominated by large multinational corporations are gradually spilled over to other firms and sectors through supply links and other forms of networking, new technology, development and implementation of innovations and outsourcing.

A second hypothesis is that R&D investment is particularly important for high and sustainable productivity growth due to its impact on technological change, innovation, competitiveness and market size. Since large manufacturing firms and high technology firms are considerably more R&D-intense than other firms, we expect a systematic difference in TFP growth in our sample.

Methodologically, we employed a parametric production function approach. We analyzed the TFP growth and investigated the decomposed components such as the rates of technical change, returns to scale and different input biases. The time trend and general index models were extended to allow for firm-specific as well as time-varying technical change. The results were compared with the non-parametric Solow residual.

The results of model selection tests are somewhat mixed. However, the heuristic inherent in extending the basic models and the results of comparing with the non-parametric Solow residual approach help us to choose the best model among the six models. Amoht the six models, the GI3 model were chosen as the best model in describing our sample data.

The empirical results show that improvements in long-run productivity growth in the Swedish economy are not restricted to large exporting manufacturing firms and high technology firms. The positive and high growth rate is spilled over to a broad network of manufacturing and services firms irrespective of their size and technology intensity. Hence, the transition process towards an increased rate of productivity growth is a phenomenon that permeated the whole Swedish economy during the 1990s. The main mechanism for development was the increased rate of technical change.

References

Aghion, P., Harris, C., Howitt, P., Vickers, J., 2001. Competition, imitation and growth with step-by-step innovation. Review of Economics Studies 68, 467-492.

Anon Higon, D., forthcoming. The impact of R&D spillovers on UK manufacturing TFP: A dynamic panel approach. Research Policy.

Baltagi, B. H., Griffin, J. M., 1988. A general index of technical change. The Journal of Political Economy 96(1), 20–41.

Barnett, A., Lewis, T., 1995. Outliers in Statistical Data. Chichester: Wiley.

Boone, J., 2001. Intensity of competition and the incentive to innovate. International Journal of Industrial Organization 19, 705–726.

Caves, D. W., Christensen, L. R., Diewert, W. E., 1982. The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity. Econometrica 50 (6), 1393-1414.

Cornwell, C., Schmidt, P., Sickles, R. C., 1990. Production frontiers with cross-sectional and time-series variation in efficiency levels. Journal of Econometrics 46(1-2), 185–200.

Dasgupta, P., Stiglitz, J., 1980. Industrial structure and the nature of innovative activity. Economic Journal 90, 266–293.

Denny, M., Fuss, M., 1983. A general approach to intetemporal and interspatial productivity comparison. Journal of Econometrics 23 (3), 315-330.

Diewert, W. E., 1976. Exact and superlative index numbers. Journal of Econometrics 4 (2), 115-145.

Diewert, W. E., 1981. The theory of total factor productivity measurement in regulated industries. Academic Press, New York.

Ferrier, G. D., Klinedinst, M., Linvill, C. B., 1998. Static and dynamic productivity among Yugoslav enterprises: Components and correlates. Journal of Comparative Economics 26(4), 805–821.

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. Americal Economic Review 84 (1), 66-83.

Fox, K. J., Hill, R. J., Diewert, W. E., 2004. Identifying outliers in multi-output models. Journal of Productivity Analysis 22 (1) 73-94.

Heshmati A., 2001. On the Growth of Micro and Small Firms: Evidence from Sweden. Small Business Economics 17(3), 213-228.

Heshmati, A., 2002. Productivity measurement in Swedish departments of gynecology and obstetrics. Structural Change and Economic Dynamics 13(3), 315–336.

Hollanders H., A. Van Cruysen, A., 2008. Rethinking the European Innovation Scoreboard: A New Methodology for 2008-2010. Pro Inno Europe Innometrics.

Hulten, C. R., 2000. Total Factor Productivity: A Short Biography. NBER working paper series 7471. National Bureau of Economic Research, MA.

Hulten, C. R., Isaksson, A., 2007. Why development levels differ: The sources of differential economic growth in a panel of high and low income countries. NBER working paper series 13469. National Bureau of Economic Research, MA.

Jerzmanowski, M., forthcoming. Total factor productivity differences: Appropriate technology vs. efficiency. European Economic Review.

Johansson, D., 2005. The Turnover of Firms and Industry Growth. Small Business Economics, 24(5): 487–495.

Jung, Y., 1991. Multinationality and profitability. Journal of Business Research 23(2), 179–187.

Kim, E., 2006. The impact of family ownership and capital structures on productivity performance of Korean manufacturing firms: Corporate governance and the "Chaebol problem". Journal of the Japanese and International Economies 20(2), 209–233.

Klette, T. J., Kortum, S., 2004. Innovating Firms and Aggregate Innovation. Journal of Political Economy 112, 896-1018.

Kneller, R., Andrew Stevens, P., 2003. The specification of the aggregate production function in the presence of inefficiency. Economics Letters 81(2), 223–226.

Kumbhakar, S. C., Heshmati, A., 1996. Technical change and total factor productivity growth in Swedish manufacturing industries. Econometric Reviews 15(3), 275–298.

Kumbhakar, S. C., Hjalmarsson, L., 1993. Technical Efficiency and Technical Progress in Swedish Dairy Farms. In Chapter 9, Oxford University Press, Oxford, pp. 256–270.

Le, T., Gibson, L. Oxley, L., 2005. Measures of Human Capital: A Review of the Literature, New Zealand Treasury Working Paper 05/10.

Lee, Y. H., Schmidt, P., 1993. A production frontier model with flexible temporal variation in technical inefficiency. Chapter 8 in Fried, H. O., Lovell, C. A. K., Schmidt, S. S. (Eds.), The measurement of productive efficiency: techniques and applications. Oxford University Press, Oxford.

Lim, D., 1980. The incentives and resource utilization in a small, less developed country. Australian Economic Papers 19, 22–30.

Lucas, R. R. J., 1988. On the mechanics of economic development. Journal of Monetary Economics 22, 3–42.

Mahadevan, R., Kalirajan, K., 2000. Singapore’s manufacturing sector’s TFP growth: A decomposition analysis. Journal of Comparative Economics 28(4), 828–839.

Monte, A. D., Pagagni, E., 2003. R&D and the growth of firms: empirical analysis of a panel of Italian firms. Research Policy 32(6), 1003–1014.

Nickell, S., 1996. Competition and corporate performance. Journal of Political Economy 104, 724-746.

Nishimitzu, M., Page, Jr., J. M., 1982. Total Factor Productivity Growth, Technological Progress and Technical Efficiency Change: Dimensions of Productivity Change in Yugoslavia, 1965-78. Economic Journal 92 (368) 920-936.

OECD, 2003. The Source of Economic Growth in OECD Countries. OECD, Paris, France.

Romer, P. M., 1986. Increasing returns and long-run growth. Journal of Political Economy 94 (2), 1002-1037.

Simar, L., 2003. Detecting outliers in frontier models: A simple approach. Journal of Productivity Analysis 20 (3), 391-424.

Sheehan, M., 1997. The evolution of technical efficiency in the Northern Ireland manufacturing sector. Scottish Journal of Political Economy 44(1), 59–81.

Solow, R. M., 1957. Technical Change and the Aggregate Production Function. Review of Economics and Statistics 39 (3), 312-320.

Appendix

A.1. Acronym of Industrial sectors

Table A. 1. Acronym of industrial sectors

Acronym	*Explanation*	*2-digits SNI*
FOOD	Food products beverages and tobacco	15-16
TXTL	Textile and textile products, leather products	17-19
WOOD	Wood and wood products	20
PULP	Pulp, paper, paper products; publishing and printing	21-22
COKE	Coke, refined petroleum products, chemicals, rubber and plastic products	23-25
NMTL	Non-metallic mineral products	26
METL	Basic metals and fabricated metal products	27-28
MCHN	Machinery and equipment n.e.c	29
ELEC	Electrical and optical equipment	30-33
TRAN	Transport equipment	34-35
MNEC	Manufacturing n.e.c	36-37
EGWS	Electricity, gas and water supply	40-41
WHOL	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	50-52
TSCO	Transport, storage and communication	60-64
ESTT	Renting and business activities	71-74

List of Tables

Table 1. Descriptive statistics of variables used in this study

	Mean	*Std.Dev*	*Median*	*Minimum*	*Maximum*
Y (unit in data /1000)	78.8	462.4	17.7	0	27790.5
K (unit in data /1000)	83.8	664.7	9.2	0	35641.2
L	159.3	729.9	44	1	41398
CAPINT	1.23e-01	3.36e-01	6.50e-02	-5.24e+00	7.38e+00
MKTCOM	3.23e-06	7.98e-05	8.99e-09	0.00e+00	9.07e-03
HMNCAP	1.08e+01	5.44e+01	2.00e+00	1.00e+00	2.16e+03
HMNGRT	-1.14e-01	6.58e-01	0.00e+00	-7.68e+00	5.27e+00
CAPSTR	6.41e+00	1.03e+02	1.74e+00	9.31e-04	1.52e+04
WGGRTH	8.97e-02	1.88e+00	6.98e-02	-1.00e+02	1.00e+02

Note: Y (value-added), K (capital stock), L (number of employees), CAPINT (capital intensity growth rate), MKTCOM (market competition index calculated by Herfindhal index), HMNCAP (number of employees who have at least bachelor's degree in science or engineering studies), HMNGRT (growth rate of HMNCAP), CAPSTR (captial structure calculated by the ratio of equity to total assets), WGGRTH (wage growth rate)

Table 2. Descriptive statistics by size and technology level

	Y		K		L		Number	Percent (%)	Cum Per. (%)
	Mean	S.D.	Mean	S.D.	Mean	S.D.			
A. By size									
Micro	12	1562.5	40.3	526.1	5.5	1539.7	373	0.99	0.99
Small	13.1	534.7	13.7	574.2	29.6	826.7	20643	54.56	55.54
Small-medium	29.9	164	27.2	161.2	69.9	332.9	7504	19.83	75.37
Medium	77.8	214.4	72.5	316.9	168.7	369.7	5903	15.60	90.97
Large	592.6	557.6	655.4	996	1140.1	948.3	3415	9.03	100.00
B. By Sector									
Manufacturing sector	77.9	401.4	69.7	378.2	162.1	5.8	24538	64.85	-
High tech	334.3	1562.5	162.9	526.1	556.3	1539.7	546	1.45	-
High-medium tech	117.6	534.7	96.8	574.2	230.6	826.7	6752	17.85	-
Medium-low tech	43.8	164	36.5	161.2	108	332.9	8288	21.91	-
Low tech	63.9	214.4	74.2	316.9	136.5	369.7	8952	23.66	-
Service sector	80.5	557.6	109.7	996	154.1	948.3	13300	35.15	-

Table 3. Descriptive statistics of variables used in this study by year

	Value added		Capital		Labor	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
1992	71.9	268.7	84.8	766.9	189.2	631
1993	72.2	288.1	82.9	681.7	171.4	559.7
1994	90.9	470.3	86.2	655.6	195.2	1034.9
1995	90	439.3	84.7	620.4	185.7	945.6
1996	63.6	402.2	68.4	568.8	139.8	815.3
1997	71.3	430.5	79.2	629.1	141.7	650.5
1998	76.9	438.3	85.1	659	147.1	621.6
1999	82.4	512.1	89.8	677.8	149.7	607.1
2000	93.3	665.6	94.8	749.8	156.2	664.7

Table 4. Elasticity and returns to scale: TT3 and GI3

	TT3			GI3		
	Capital	Labor	RTS	Capital	Labor	RTS
A. By year						
1993	0.195	0.813	1.005	0.190	0.832	1.017
1994	0.194	0.815	1.007	0.190	0.832	1.018
1995	0.196	0.816	1.009	0.191	0.828	1.016
1996	0.185	0.826	1.006	0.180	0.830	1.006
1997	0.194	0.818	1.009	0.191	0.821	1.009
1998	0.199	0.815	1.012	0.194	0.816	1.008
1999	0.205	0.812	1.014	0.201	0.811	1.010
2000	0.210	0.809	1.017	0.208	0.806	1.012
B. By industry						
FOOD	0.262	0.751	1.013	0.268	0.735	1.003
TXTL	0.200	0.800	1.000	0.186	0.818	1.003
WOOD	0.206	0.832	1.038	0.221	0.843	1.064
PULP	0.167	0.857	1.022	0.155	0.877	1.030
COKE	0.245	0.784	1.029	0.245	0.776	1.020
NMTL	0.245	0.776	1.019	0.239	0.763	1.000
METL	0.220	0.774	0.993	0.195	0.811	1.004
MCHN	0.127	0.904	1.026	0.116	0.910	1.022
ELEC	0.190	0.843	1.032	0.172	0.850	1.021
TRAN	0.166	0.851	1.014	0.160	0.854	1.011
MNEC	0.194	0.822	1.015	0.176	0.847	1.022
EGWS	0.346	0.669	1.016	0.366	0.647	1.013
WHOL	0.112	0.905	1.010	0.101	0.914	1.005
TSCO	0.201	0.815	1.011	0.214	0.802	1.013
ESTT	0.183	0.794	0.973	0.184	0.792	0.974
C. By size						
Micro	0.196	0.814	0.994	0.197	0.812	0.992
Small	0.187	0.822	1.006	0.183	0.828	1.007
Small-medium	0.196	0.817	1.011	0.192	0.823	1.013
Medium	0.210	0.806	1.014	0.205	0.813	1.016
Large	0.235	0.788	1.021	0.229	0.795	1.023
D. By sector						
Manufacturing industry	0.193	0.842	1.030	0.177	0.849	1.022
By technology						
High tech	0.170	0.859	1.026	0.160	0.863	1.020
High-medium tech	0.218	0.788	1.005	0.201	0.810	1.009
Medium-low tech	0.204	0.818	1.022	0.204	0.827	1.029
Low tech	0.193	0.808	0.996	0.198	0.802	0.996
Service industry	0.170	0.859	1.026	0.160	0.863	1.020
E. By sample						
Average	0.197	0.816	1.010	0.193	0.821	1.011
Standard deviation	0.078	0.078	0.023	0.078	0.079	0.025

Table 5. Rate of technical change and its components: TT3 and GI3

	TT3			GI3		
	Pure	Non-neutral	TCH	Pure	Non-neutral	TCH
A. By Year						
1993	0.025	0.001	0.026	0.003	0.021	0.025
1994	0.023	0.000	0.023	0.083	-0.001	0.082
1995	0.020	0.000	0.020	0.031	-0.016	0.016
1996	0.018	0.000	0.018	0.002	-0.023	-0.021
1997	0.015	0.000	0.015	-0.002	0.015	0.014
1998	0.013	0.000	0.013	0.044	-0.025	0.019
1999	0.011	0.000	0.010	0.008	0.008	0.015
2000	0.008	0.000	0.008	0.019	0.011	0.030
B. By industry						
FOOD	-0.048	0.052	0.003	0.021	-0.015	0.006
TXTL	-0.008	0.022	0.014	0.022	-0.005	0.017
WOOD	0.019	-0.015	0.004	0.021	-0.005	0.017
PULP	0.053	-0.035	0.018	0.023	0.007	0.031
COKE	-0.015	0.026	0.011	0.022	-0.007	0.015
NMTL	-0.025	0.043	0.018	0.021	-0.009	0.013
METL	0.007	0.011	0.018	0.021	-0.002	0.019
MCHN	0.075	-0.044	0.031	0.024	0.010	0.034
ELEC	-0.017	0.032	0.015	0.022	-0.004	0.018
TRAN	0.049	-0.022	0.026	0.023	0.003	0.026
MNEC	0.006	0.008	0.014	0.022	-0.001	0.021
EGWS	0.040	-0.032	0.009	0.023	-0.008	0.015
WHOL	0.064	-0.039	0.025	0.021	0.005	0.026
TSCO	0.011	-0.003	0.008	0.019	-0.005	0.014
ESTT	0.005	0.018	0.023	0.019	-0.004	0.015
C. By size						
Micro	0.016	0.005	0.020	0.017	-0.004	0.013
Small	0.015	-0.001	0.015	0.020	-0.002	0.018
Small-medium	0.017	-0.001	0.017	0.022	-0.002	0.020
Medium	0.018	0.001	0.019	0.023	-0.002	0.021
Large	0.018	0.004	0.021	0.023	-0.002	0.021
D.By sector						
Manufacturing industry	0.015	0.002	0.016	0.022	-0.001	0.021
By technology						
High tech	-0.009	0.028	0.020	0.022	-0.003	0.019
High-medium tech	0.035	-0.012	0.024	0.023	0.003	0.026
Medium-low tech	0.001	0.015	0.016	0.021	-0.003	0.018
Low tech	0.013	-0.002	0.011	0.022	-0.003	0.019
Service industry	0.020	-0.003	0.017	0.020	-0.003	0.016
E. By sample						
Average	0.016	0.000	0.017	0.021	-0.002	0.019
Standard deviation	0.035	0.029	0.018	0.025	0.033	0.038

Table 6. Overall input bias and scale bias

	Capital		Labor		Scale	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
TT1	-0.200	0.000	0.350	0.000	0.140	0.000
TT2	-0.200	0.000	0.480	0.000	0.280	0.000
TT3	-0.110	0.670	0.280	0.880	0.160	0.290
GI1	-0.160	1.050	0.320	1.090	0.160	1.100
GI2	0.980	1.040	0.990	1.320	1.970	0.670
GI3	-0.030	0.750	0.010	1.720	-0.020	1.090

Table 7. Mean rate of TFP growth: TT1, TT2, TT3, GI1, GI2, GI3 and Solow Residual (SR)

	TT1	TT2	TT3	GI1	GI2	GI3	SR
A. Measure by year							
1993	0.024	0.026	0.026	0.029	0.030	0.026	0.006
1994	0.022	0.022	0.023	0.083	0.083	0.083	0.067
1995	0.020	0.019	0.021	0.014	0.014	0.016	0.013
1996	0.017	0.015	0.018	-0.030	-0.030	-0.025	-0.021
1997	0.015	0.013	0.015	0.014	0.014	0.014	0.005
1998	0.013	0.010	0.013	0.017	0.017	0.019	0.010
1999	0.010	0.007	0.010	0.015	0.015	0.015	0.017
2000	0.008	0.004	0.008	0.031	0.031	0.030	0.025
B. Measure by industry							
FOOD	0.015	0.010	0.007	0.020	0.020	0.007	0.005
TXTL	0.016	0.011	0.011	0.019	0.018	0.017	0.012
WOOD	0.014	0.002	0.003	0.019	0.018	0.020	0.019
PULP	0.015	0.010	0.018	0.020	0.020	0.031	0.013
COKE	0.015	0.008	0.010	0.020	0.020	0.016	0.023
NMTL	0.016	0.019	0.020	0.021	0.021	0.013	0.023
METL	0.015	0.018	0.014	0.018	0.018	0.019	0.019
MCHN	0.016	0.018	0.025	0.020	0.020	0.035	0.022
ELEC	0.016	0.010	0.015	0.019	0.020	0.020	0.012
TRAN	0.016	0.015	0.024	0.020	0.020	0.026	0.022
MNEC	0.015	0.016	0.016	0.019	0.019	0.022	0.021
EGWS	0.010	0.003	0.010	0.017	0.018	0.016	0.009
WHOL	0.014	0.006	0.018	0.018	0.019	0.026	-0.002
TSCO	0.014	0.009	0.010	0.017	0.017	0.016	0.006
ESTT	0.015	0.022	0.023	0.019	0.020	0.012	0.011
C. Measure by size							
Micro	0.002	-0.009	0.016	0.011	0.011	0.018	0.249
Small	0.013	0.010	0.013	0.017	0.017	0.019	0.016
Small-medium	0.015	0.013	0.016	0.020	0.020	0.020	0.001
Medium	0.017	0.016	0.018	0.022	0.022	0.021	0.014
Large	0.019	0.020	0.021	0.025	0.025	0.022	0.020
D. Measure by sector							
Manufacturing industry	0.015	0.012	0.015	0.019	0.019	0.022	0.017
High tech	0.017	0.013	0.020	0.021	0.021	0.021	0.014
High-medium tech	0.016	0.014	0.020	0.020	0.020	0.027	0.020
Medium-low tech	0.015	0.016	0.014	0.019	0.019	0.019	0.020
Low tech	0.015	0.008	0.011	0.019	0.019	0.021	0.013
Service industry	0.014	0.013	0.016	0.018	0.019	0.016	0.007
E. Sample							
Average	0.015	0.013	0.015	0.019	0.019	0.020	0.014
Standard deviation	0.007	0.017	0.017	0.031	0.032	0.038	0.236

Table 8. Results of second regression on TFP (n = 31505)

	Expected sign	*TT1*	*TT2*	*TT3*	*GI1*	*GI2*	*GI3*
Intercept		1.32e-02***	2.31e-03*	1.77e-02***	2.43e-02***	2.37e-02***	1.33e-02***
CAPINT	(+/-)	-1.02e-03***	-3.08e-03***	-1.13E-04	-3.63e-03***	-3.70e-03***	-3.73E-04
MKTCOM	(+/-)	1.32e+00***	1.21E+00	3.09e+00***	-4.40e+00***	-3.98e+00***	1.55E+00
HMNCAP	(+)	8.70e-05***	1.15e-03***	1.01e-03***	2.01e-03***	1.72e-03***	5.30e-04***
HMNGRT	(+)	-2.31E-05	1.02E-04	1.67E-04	7.50E-05	1.09E-04	4.12e-04*
CAPSTR	(+)	6.22E-08	4.61E-07	9.76E-07	6.54E-07	6.65E-07	-8.30E-07
WGGRTH	(+)	1.59e-04***	2.85e-04***	2.01e-04***	2.30e-04***	2.24e-04***	2.55e-04***
Size dummy included		Yes	Yes	Yes	Yes	Yes	Yes
Year dummy included		Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy included		Yes	Yes	Yes	Yes	Yes	Yes
R2		0.645	0.341	0.273	0.695	0.672	0.654
Adjusted R2		0.645	0.34	0.273	0.695	0.672	0.652

Note: 1. The dependent variable of each regression model is the rate of TFP growth for each model specification.

Technical Change and Total Factor Productivity Growth: The Case of Chinese Provinces

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ABSTRACT

In the literature technical change is mostly assumed to be exogenous and specified as a function of time. However, some exogenous external factors other than time can also affect technical change. In this paper we model technical change via time trend (purely external non-economic) as well as other exogenous (external economic) factors (technology shifters). We define technology index based on the external economic factors which we call indicators of 'technology'. Thus our definition of production function is amended to accommodate several technology shifters which are not necessarily separable from the traditional inputs. That is, these technology shifters allow for non-neutral shift in the production function. In doing so we are able to decompose technical change (a component of TFP change) into two parts. One part is driven by time and the other part is related to producer specific external economic factors. These exogenous technology shifters are aggregated (via hedonic aggregator functions) into several groups (technology indices) for parsimonious parametric specification. The empirical model uses panel data on Chinese provinces. We identify a number of key technology shifters and their effect on technical change and TFP growth of provinces are examined.

Key words: technical change, total factor productivity growth, technology indicator, technology shifter, Chinese provinces,

JEL Classification Numbers: C33, C43, D24, O18, O47

1. INTRODUCTION

Measurement of technical change (TC) and total factor productivity (TFP) growth has been the subject of investigations in many empirical studies on industrial productivity (for example, Jorgenson, 1995). These studies have followed several well-known directions. The various approaches used in the literature have been classified by Diewert (1981) into: parametric estimation of production and cost functions, non-parametric indices, exact index numbers, and non-parametric methods using linear programming. In the non-parametric approach, the Divisia index has been widely used as a convenient measure of TFP growth over time and space as well. An important feature of the Divisia measure of TFP growth is that it coincides with the technical change when the underlying technology is homogeneous of degree one. However, constant returns to scale technology is rarely supported in empirical studies on production functions based on panel data. If this property does not hold TFP growth becomes a mixture of technical change and scale effects. In the case of non-constant returns to scale technology, decomposition of TFP growth into its sources requires knowledge of scale effects, which require econometric estimation of parametric functions.

In the parametric specification of technology using production/cost/profit functions, a widely used practice has been to use quadratic function of time trend to represent technical change. Notwithstanding its widespread use, the use of time trend is a mere reflection of our ignorance. Baltagi and Griffin (1988) has shown that if a panel data set is available, we could estimate a time specific parameter referring to the state of technology (general index of technical change) instead of using time trend. The method applied to analysis of manufacturing industry performance has shown evidence of erratic patterns of technical change which limits its usefulness in capturing technical change (see Kumbhakar and Heshmati, 1996; and Kumbhakar, Nakamura and Heshmati, 2000). Different generalizations of time trend (TT) and general index (GI) models of technical change have been developed and their performance and sensitivity using different datasets evaluated (see Heshmati and Nafar, 1998; Kumbhakar, Heshmati and Hjalmarsson, 1999; Kumbhakar, 2000; and Oh, Heshmati and Loof, 2009).

Econometric approach where technical change has been represented by a simple time trend or time dummies still dominates the empirical research. The popularity of time trend model comes from the fact that it is good in revealing long-run trends in technical change while general index model is good in capturing year to year variations (which may be caused by economy wide, sector-specific or firm-specific product or process innovations and demand or supply shocks). Despite of this popularity, the time trend model has been criticized because it reflects only our ignorance about the process. The general index overcomes the trend limitation by not imposing any systematic structure on the behavior of technical change, but it is by no means any better in explaining technical change. In both approaches TC is modeled entirely in terms of time and they fail to account for determinants of technological change and productivity growth. If two firms have the same inputs then their TC will also be the same. In the general index model determinants of TC are not directly used in the model. These are used in a second stage regression, therefore fails to take into account their direct or interactive effects with the traditional inputs.

In an attempt to remedy the above limitations, this paper is concerned with specification and estimation of technical change by utilizing observable determinants of technical change (TC). Here we argue that TC, given the inputs (X), is likely to be governed by some exogenous variables (Z) which are producer-specific. Time trend (time dummies) might be a component in it to reveal the long-run trends (year to year variations) in technical change. We generalize the concept and define an aggregator function, T(Z,t), and argue that this function becomes an argument in the production function. That is, with this technology index we can write the production function as Y=f(X, T(Z,t)) and calculate technical change treating T(Z,t) as a covariate in the production function. From this formulation we can separate out the impact of Z variables and time in TC. That is, TC defined in this way can be broken down to time-specific and Z-specific components. If Z variables are producer-specific, TC will be different for different producers even if the inputs (X) are exactly the same. If there are no Z variables in the model then our TC will be identical to TC in the TT model. If we put time dummies in the T(.) function and there are no Z variables, then our TC will be the same as Baltagi and Griffin's GI model of TC. Our present model allows estimation of TFP growth and its decomposition into technical change and scale components as well as marginal effects of the technology indices and their underlying components.

In modeling TC our focus is on various key external economic factors contributing to shift in production. These Z variables in our empirical model are related to human capital, information and communication technology, foreign direct investment and reform programs. These shift variables, in addition to yielding producer-specific technical change and factor bias (both in inputs and scale) in the overall TC measures, help us to estimate the contribution of the Z and t variables separately to TC and TFP growth. By using a flexible functional form and conducting sensitivity analysis we examine robustness of the estimates of TFP growth and its components.

Instead of using one aggregator function to define a single technology index T(Z,t), one can think of several aggregator functions $T_j(Z_j)$ which are indices of technology. These indices which are functions of the Z are used to define technology indices. Time variable can be one index of its own, T(t). With these technology indices, the production function can be written as $Y=f(X, T_j(Z_j), T(t))$. The advantage of the multiple index technology is that it is more flexible in separating the effects of different groups of technology shifters and important instrument in design and implementation of industrial technology policy. Note that the present formulation is more general and the previous formulation with a single technology index becomes a special case.

For the empirical analysis we use input and output data and production and technology characteristics for Chinese provinces observed for the period 1993 to 2003. The analysis is expected to improve our understanding of the causes and patterns of growth rate of provincial technical change and TFP growth in China. It enhances our knowledge on the causes and patterns of recent years of heterogeneous regional development in China. Information on differences in regional productivity growth is important for the government to formulate better policies of allocation and redistribution of productive resources to reduce the growing regional inequality in the country.

The present paper contributes to the literature in a number of ways. First, it tries to explain technical change based on actual observable exogenous external indicators or technology shifters that are not separable from the traditional inputs. These exogenous technology shifters are further aggregated into several technology groups. Second, we use panel data methodology and flexible functional form in which we control for province-specific effects that are not necessarily associated with technological change. Third, the growth rate is decomposed into time driven and technology shifter driven yet producer-specific components. Fourth, the model is applied to estimation of productivity growth in 30 Chinese provinces during the country's rapidly growth period of 1993 to 2003. Fifth, unlike other previous growth studies of China, which mainly apply the growth accounting approach (e.g. Chow, 1993; Borensztein and Ostry, 1996; World Bank, 1996; Hu and Khan, 1997; Maddison, 1998; Woo, 1998; Ezaki and Sun, 1999; Demurger, 2000; Wang and Yao, 2003; and Arayama and Miyoshi, 2004), this paper applies the panel data approach for estimation of the production function. The growth accounting approach which focuses on limited number of inputs, imposes strong assumption of constant returns to scale and uses fixed income shares over long period of time, tends to overestimate productivity growth. Sixth, we identify a number of key policy relevant technology shifters and their effects on TFP growth of provinces.

The rest of the paper is organized as follows. Section 2 reviews the earlier literature on Chinese provincial growth studies. Description of the Chinese provinces and the data are given in Section 3. The factors explaining TC and technological biases are described in Section 4. Specification tests and estimation issues are discussed in Section 5. Empirical results are discussed in Section 6. The concluding section summarizes the results of this study.

2. CHINESE PROVINCIAL GROWTH STUDIES

China's achievement of high economic growth since the adoption of the open-door policy in 1978 has been a source of admiration and a model for development policy. The average annual growth rate of real GDP over the past twenty-five years was 9.37% (Holz, 2005). This remarkable economic growth has led to a heated debate on whether the economic growth is a result of productivity growth or factor accumulation. Several studies have found that the country's high growth rate was brought about mainly by capital accumulation (e.g. Chow, 1993; Yusuf, 1994; Borensztein and Ostry, 1996; Hu and Khan, 1997; Sachs and Woo, 1997; Woo, 1998; Ezaki and Sun, 1999; Wu, 2004; and Arayama and Miyoshi, 2004). According to Krugman (1994), the massive accumulation of inputs will soon limit China's growth potential if there is little improvement in productivity. Indeed, the state's and province's stress of promoting productivity growth in the 90s led to dramatic increases in volume of research and development expenditure at different levels over the past decade. The Chinese productivity growth rate has almost sustained even under the 1997 Asian and current global financial crisis.

Other than the above mentioned analysis of sources of growth of TFP, a number of productivity studies on China's economy examined productivity differences by types of ownership (e.g. Jefferson, 1990; Dollar, 1992; Jefferson and Xu, 1994; Chen et al., 1998; Xu and Wang, 1999; Hu, 2001; and Zheng et al., 2003). A number of other categories of productivity research include the examination of sectoral productivity growth differences (e.g. Lin, 1992; Jefferson, Rawski and Zheng, 1992, 1996; Wu, 1995, 2000; Xu, 2000; and Zheng and Zheng, 2001) and the investigation of productivity difference among regions in China (e.g. Lee, 2000; Song et al., 2000; Cai et al., 2001; Demurger, 2001; Bao et al., 2002; and Demurger et al., 2002). A few of the datasets used in the above studies are at the firm level, while majority of them are at the aggregate national, sectoral, regional or provincial levels. Recently Maddison and Wu (2008) suggested that the official Chinese National Bureau of Statistics exaggerated GDP growth and recommended adjustment to conform to international norms.

The methodology used in the analysis of productivity in China is diverse. These include both non-parametric and parametric approaches. The non-parametric can be divided into growth accounting and Malmquist productivity indices. A handful of studies have applied the growth accounting approach (e.g. Chow, 1993; Borensztein and Ostry, 1996; World Bank, 1996; Hu and Khan, 1997; Maddison, 1998; Woo, 1998; Ezaki and Sun, 1999; Demurger, 2000; Wang and Yao, 2003; and, Arayama and Miyoshi, 2004). The growth accounting approach involves the subtracting of the growth of factor accumulation at a constant rate from the output growth to obtain the TFP measure. In this case with constant returns to scale, TFP is equivalent to technical change. Some of the studies above used Cobb-Douglas average production function (such as Chow, 1993; Ezaki and Sun, 1999; and Wang and Yao, 2003), while others (like Hu and Khan, 1997; and Arayama and Miyoshi, 2004) applied the translog production function. These studies focus on the estimation of factor input shares to be used in the computation of the aggregate productivity growth over time.

Chen (2001) and Zheng and Hu (2004) applied the Malmquist indexes of TFP growth. The Malmquist index measures the TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology. The TFP growth can be decomposed into two components, namely efficiency change and technological change. Chen (2001) found positive average TFP growth and technology improvement was found to be a larger component for TFP growth. Zheng and Hu (2004) found considerable average productivity growth, which was accomplished through technical progress instead of efficiency improvement. There are few studies which used the frontier production approach to measure TFP growth in China. Wu (1999) applied the stochastic frontier approach on Chinese provinces to examine productivity growth in China's reforming economy. Wu found positive TFP growth during the post-reform period.

A symposium published by European Journal of Comparative Economics, edited by Dougherty and Valli (2009), offers in-depth discussion of growth pattern of China and India and their influence in the world market. The essays and several other growth studies examine economic and human development indicators (Basu, 2009); culture (Kask, Auger and Li, 2004); resource misallocation (Hsieh and Klenow, 2007); complexities of economic transformation (Valli and Saccone, 2009); trade integration and changing specialization (Benisdoun, Lemoine and Unal, 2009); segmented global production process

(Lemoine and Unal, 2004); openness (Chen and Feng, 2000); industrial policy (Lu, 2000); technological learning and catch-up (Mu and Lee, 2005); macroeconomic policies and exchange rate regimes (Patnaik and Shah, 2009); and sources of high economic growth (Yang, 2009; Chen and Song, 2008; Meng and Li, 2002; Gao, 2004; Gholami et al., 2006; Heshmati and Yang, 2010).

In this study, in addition to the methodological contribution concerning the modeling exogenous determinants of technological change, we contribute to the existing research which focuses on the investigation of sources of economic growth in China. In particular, in addition to traditional inputs, we incorporate several indicators of technology. One such indicator is ICT investment as an infrastructure for economic development in China in the age of New Economy. Other indicators are human capital and its role in acquisition and absorption of new technology, skills and management. Our data allow us to consider productivity growth measures at the national, regional and provincial levels. Thus, we are able to have a more thorough understanding of the provincial and regional diversity of growth patterns in China.

We apply the panel data econometric approach for estimation of the production function, instead of using the growth accounting, Malmquist or frontier production function approaches. The growth accounting approach which focuses on limited number of inputs and uses constant returns to scale assumption and fixed income share over long period of time tends to produce biased and overestimated measure of growth. The Malmquist approach overcomes some of these limitations and allows decomposition of productivity growth but account only for few key production inputs. This study by applying the panel data models for parametric estimation of the technical change, allows to control for unobservable time invariant provincial effects. In addition technological change is modeled via exogenous factors and the production function specification is enriched by the introduction of non-traditional production factor inputs. These include factors such as ICT investment, inflow of FDI, human capital and economic reform measures which by experts are considered crucial for growth and development in general and to the Chinese economy in particular which has benefited from these factors in its emergence and catch up.

3. THE PROVINCE LEVEL DATA

In this paper, we use a combination of officially published and non-published provincial data of China, which provide information on the contributing factors to the development of technical change and TFP growth in China during the recent years of rapid economic growth.

The data for estimation of the translog production function and technological index comprises the following output, input and technology indicator variables for the 30 provinces during the period 1993 to 2003. Output is measured as aggregate gross domestic product (GDP) (in 100 million Yuan). The input variables include labor measured by the number of persons employed at year-end (in thousands) and capital stock (CAP) (in 100 million Yuan). The technology index is modeled using information and communication technology (ICT) investment (in 100 million Yuan), foreign direct investment (FDI) inflow (in 10,000 US$), percentage of highly educated labor (PCNT) (the ratio of number of graduates of regular institutions of higher education to population), and reform (REFORM) (the ratio of state-owned enterprises industrial value to total gross industrial value). These capture financial, technological, human capital and reform components of technology development, transfer and absorption by provinces in different years.

In specifying the technology index we tried a number of other indicators, but the model specification was highly nonlinear and difficult to further generalize. Other variables considered are road infrastructure (ROAD) (total length of highways in km), government consumption (GOV) (in 100 million Yuan), total domestic investment (INV) (in 100 million Yuan), household telephone subscribers (TEL) (in number of subscribers), and openness a proxy for globalization (OPEN) (the ratio of import plus export to GDP). In addition we use dummy variables to control for unobserved time-invariant province specific effects such as skills, planning and management differences, and location advantages/disadvantages of the provinces. A simple time trend (TRN) is added to the specification of the production function to capture possible trend in the use of inputs and output produced. It captures the unobserved exogenous components of technical change and productivity growth as well as province-specific effects such as central or local government economic policy effects.

All the input variables which are originally expressed in nominal prices are deflated using GDP deflator which varies across provinces and time. The nominal and real GDP indexes are derived based on data from various Chinese Statistical Yearbooks and calculated the GDP deflators accordingly. There were smooth increasing trends of the calculated GDP deflators and no abnormalities were found. The physical capital stock data from 1993-2003 is taken from Wu (2004). The authors extended the series to include 2003 data using the back casting method. It is calculated based on the assumption that the rate of depreciation is 4.0%. The series is expressed in 1952 constant prices.

The data is mainly taken from various issues of Chinese Statistical Yearbooks and the official Chinese government websites. The ICT investment data was supplied by the statistical department of Ministry of Information Industry (MII). The ICT investment includes investments in the production of radios, televisions, fixed telephones, mobile telephones, personal computers and communication equipments. The share of ICT investment to total investment was around 1% during the early 80s, but it has increased to approximately 5% in the late 90s and after 2000. The total number of observations (NxT) is 330. Table 1 shows the summary statistics of the deflated variables used in the paper, including average GDP, inputs, as well as other production and technology indicators.

Insert Table 1 Summary statistics of the variables about here

4. MEASUREMENT AND DECOMPOSITION OF PRODUCTIVITY GROWTH

We mentioned different approaches to measure productivity growth. Here we deal with the definition and measurement issues. In economics productivity is defined quite broadly. Here we focus on TFP as an appropriate measure of productivity. Production process can be a single or multi-output operation. In a single output case TFP growth $(\dot{TFP})$ is defined as $\dot{TFP} = \dot{Y} - \sum_j S_j \dot{X}_j$, where Y is output, X_j is a vector of inputs (j=1,2,…..,J), S_j is the share of input X_j in the total cost, $S_j = w_j X_j / \sum_j w_j X_j$, w_j being the price of input X_j, and a dot over a variable indicates its annual rate of change. If there are multiple outputs the TFP growth is expressed as $\dot{TFP} = \sum_m R_m \dot{Y} - \sum_j S_j \dot{X}_j$, where R_m is the output value share, $R_m = P_m Y_m / \sum_m P_m Y_m$, and P_m is the price of output Y_m (m=1,.....,M). Using the above definitions, the $\dot{TFP}$ measure can be computed from the observed data without any estimation. The resulting measure is called the Divisia index of TFP growth. It gives us information about output growth that is not explained by the growth of the factor inputs used in production.

The Divisia index is non-parametric and as such it does not provide information on the factors affecting productivity growth. The main advantage of the parametric or econometric approach is that we can both estimate and decompose TFP growth. The econometric approach can be based on primal (production) or dual (cost) or profit functions.[1] In this study we employ a production function approach. The main advantages with production function are that it does not require information on prices and it allows for non-constant returns to scale. It has several desirable properties such as: positive marginal product of inputs, non-emptiness of output, symmetry, monotonicity and convexity. In addition, the production function is assumed to be continuous at any point and twice-continuously differentiable. The translog production function with a time trend representing exogenous technical change can be written as:

$$\begin{aligned} \ln Y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \ln X_{jit} + \beta_t T_t + \tfrac{1}{2}\left(\sum_{j=1}^{J}\sum_{k=1}^{K} \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} T_t^2 \right) \\ + \sum_{j=1}^{J} \beta_{jt} \ln X_{jit} T_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where $\ln Y_{it}$ is the logarithm of output measure of total GDP of province i (i=1,2,...,N) in period t (t=1,2,….,T) and $\ln X_{it}$ is a vector of logarithm of J (j=1,….,J) inputs. The inputs include labor (LAB) and capital stock (CAP), T is a time trend and βs are unknown parameters to be estimated. The error term is decomposed into time-invariant province-specific effects (μ_i) and a random error term (v_{it}) , $\varepsilon_{it} = \mu_i + v_{it}$, with mean 0 and constant variance, σ_v^2 . The μ_i are assumed to be fixed parameters and are captured by N-1 province dummies.

The specification of technical change in (1) is represented by a simple time trend. Econometrically the production function in (1) can be extended to incorporate various ‘technology shifters’ that are functions of exogenous factors, viz.:

[1] Some of the earlier work can be found in the Cowing and Stevenson (1981) edited volume “Productivity Measurement in Regulated Industries”. See also Baltagi and Griffin 1988; Kumbhakar 1992; Bhattacharyya et al. 1997, among others.

$$\begin{aligned}
\ln Y_{it} &= \beta_0 + \sum_{j=1}^{J} \beta_j \ln X_{jit} + \beta_t T_t + \sum_{m=1}^{M} \delta_m T_m(Z_{it}^m) \\
(2) \qquad &+ 1/2\left(\sum_{j=1}^{J}\sum_{k=1}^{K} \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} T_t^2 + \sum_{m=1}^{M}\sum_{l=1}^{L} \delta_{ml} T_m(Z_{it}^m) T_l(Z_{it}^l) \right) \\
&+ \sum_{j=1}^{J} \beta_{jt} \ln X_{jit} T_t + \sum_{j=1}^{J}\sum_{m=1}^{M} \gamma_{jm} \ln X_{jit} T_m(Z_{it}^m) + \sum_{m=1}^{M} \theta_{tm} T_t T_m(Z_{it}^m) + \varepsilon_{it}
\end{aligned}$$

where $T_m(Z_{it}^m)$ are technology indices and Z^m are external economic factors (labeled as technology shifters). That is, given the traditional inputs, outputs can change depending on the level of the variables that can shift the production function. These shift variables can be grouped into various components (technology indices) $T_m(Z_{it}^m)$, where each component depends on a subset of mutually exclusive shift variables. Thus, we can specify $T_m(Z_{it}^m)$ as:

$$(3) \qquad T_m(Z_{it}^m) = \ln\left(\sum_{p=1}^{P_m} \gamma_p^m Z_{pit}^m \right), \sum_{p=1}^{P_m} \gamma_p^m = 1 \; \forall\, m$$

where P_m is the number of technology shifters in technology index $T_m(.)$. In this paper we use two technology indices, each based on two technology shifters. The first technology index ($T_1(.)$) is constructed from human capital and development infrastructure and it is based on percentage of labor with university education (PCN) and reform program (REFORM). The second index ($T_2(.)$) is constructed around financial market and is based on investment in information and communication technology (ICT) and inflow of foreign direct investment (FDI).[2] In defining each of the indices we restrict sum of the weights to be unity (identifying restrictions) so that we can interpret the weights as 'importance' of each shifter on the technology component. There are other ways of imposing identifying constraints on the γ_p^m parameters but none of them will have the easy and intuitive interpretation similar to the one we used.

The production model is estimated using fixed effect panel data approach with the specification of a translog functional form, by which the technology is represented in two ways by: (i) a time trend and (ii) a time trend and technology indices. We call the former the single Time Trend (TT) model whereas the latter is called the technology index (TI) model. The two models are nested and the former is a restricted version of the later.

Based on equations (2) and (3), the input elasticities (E) and the technical change (TC) can be calculated as follows for each of the two models:

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[2] We also tried to account for other determinants such as general provincial investment expenditure (INV), infrastructure like roads (ROAD) and telephone lines (TEL), provincial government expenditure (GOV), and provincial openness (OPEN), but these were exclude because the model become highly non-linear and not converging.

(4a) $E^{TT}_{jit} = \partial \ln Y_{it} / \partial \ln X_{jit} = \beta_j + \sum_{k=1} \beta_{jk} \ln X_{kit} + \beta_{jt} T_t$;

(4b) $E^{TI}_{jit} = \partial \ln Y_{it} / \partial \ln X_{jit} = \beta_j + \sum_{k} \beta_{jk} \ln X_{kit} + \beta_{jt} T_t + \sum_{m=1} \gamma_{jm} T_m (Z^m_{it})$;

(5a) $TC^{TT}_{it} = \partial \ln Y_{it} / \partial T_t = \beta_t + \beta_{tt} T_t + \sum_{j} \beta_{jt} \ln X_{jit}$; and

(5b) $TC^{TI}_{it} = \partial \ln Y_{it} / \partial T_t = \beta_t + \beta_{tt} T_t + \sum_{j=1} \beta_{jt} \ln X_{jit} + \sum_{m=1} \theta_{tm} T_m (Z^m_{it})$.

In similar way the elasticity for each technology index, here $T_m(Z^m_{it})$, is also calculated from:

(6) $E^{Z}_{mit} = \partial \ln Y_{it} / \partial \ln T_m (Z^m_{it}) = \delta_m + \sum_{l=1} \delta_{ml} T_l (Z^l_{it}) + \sum_{j=1} \gamma_{jm} \ln X_{jit} + \theta_{tm} T_t$

Note that purely exogenous technical change (TC^{TI}) in (5b) can further be decomposed into the pure $(\beta_t + \beta_{tt} T_t)$, non-neutral $(\sum_j \beta_{jt} \ln X_{jit})$, and technology index $(\sum_m \beta_{tm} T_m (Z^m_{it}))$ components. Pure technical change refers to neutral shift of the production function due to time alone, non-neutral technical change means input biased technical change, and technology index components is a results of effect of known exogenous technology shifters. Technical change is biased if the marginal rate of substitution between any two inputs measured along a ray through the origin is affected by technical change. It implies that technical change will tend to influence the relative contribution of each input to the production process.

Returns to scale (RTS) is obtained by summing all of the input elasticities calculated in equation:

(7) $RTS^{TT}_{it} = \sum_{j=1}^{J} E^{TT}_{jit}$ and $RTS^{TI}_{it} = \sum_{j=1}^{J} E^{TI}_{jit}$

where E_{jit} is the elasticity of output for province *i* with respect to input *j* at period *t*. It measures the percentage change of output in response to a 1% increase in all inputs simultaneously. Technology is said to be exhibiting increasing, constant or decreasing returns to scale, respectively, if RTS greater than, equal to or less than 1. All input elasticities, returns to scale and technical change are computed at every data point. By using equations (4) to (8), the parametric TFP growth based on the translog production function for both TT and TI models can be obtained as follow:

(8a) $T\dot{F}P^{TT}_{it} = TC^{TT}_{it} + (RTS^{TT}_{it} - 1) \sum_{j=1}^{J} E^{TT}_{jit} \dot{X}_{jit} = TC^{TT}_{it} + SCALE^{TT}_{it}$ and

(8b) $T\dot{F}P^{TI}_{it} = TC^{TI}_{it} + (RTS^{TI}_{it} - 1) \sum_{j=1}^{J} E^{TI}_{jit} \dot{X}_{jit} + \sum_{m=1}^{M} E^{Z}_{mit} \dot{T}_m (Z^m_{it}) = TC^{TI}_{it} + SCALE^{TI}_{it} + TZ_{it}$

where TZ and TC^{TI} together measure the overall rate of technical change. The TC^{TI} part is due to time alone (purely external non-economic factor) whereas the TZ part is due to other external economic factors. In our application TZ is a weighted average of the two technology index components, where the weights are the marginal effects of the index components. The overall TZ index is the sum of the product of the technology elasticity and growth rate of technology index, viz.,

$$(9) \qquad TZ_{it} = \sum_{m=1}^{M} \left(\partial \ln Y_{it} / \partial \ln T_m(Z_{it}^m) \right) \left(\dot{T}_m(Z_{it}^m) \right)$$

Under constant returns to scale (CRS) and competitive output markets, TFP growth and technical change are identical (Solow 1957). In such a case it is not necessary to estimate anything econometrically, but computing Divisia index directly from the data. However, if the objective of producers is to minimize cost (given outputs) or maximize output (for given inputs), and the constant returns to scale and perfectly competitive output (input) market assumptions are relaxed, then it is possible to establish a relationship between the Divisia index and the TFP growth components (Denny et al. 1981). The TFP growth in (8a) and (8b) can be obtained from a parametric cost function or production function. The first component of TFP growth is TC and the second component is the *Scale* component, which is zero if RTS is unity. The last component is zero if either the marginal effect of every technology shifter is zero (i.e., they are not shifting the technology) or these shift variables are time-invariant. Note that in defining TFP change we are not taking into account the cost of these technology shift variables (assumed to be costless to change them).

It should be noted that even with a CRS technology, other factors that can explain productivity growth may exist. If these factors are observed, we can separate the contribution of factors that are under the control of the producers (external economic factors) and those that are exogenous to the firm (purely external non-economic factors) by estimating the underlying production technology econometrically. The external factors which define the environment where the producers operate, could affect profitability, survival and productivity growth of firms. These factors are usually taken into account in the endogenous growth literature. Morrison (1986) and Morrison and Siegel (1999) include these factors in the productivity growth analysis. They point out that such external factors affect the cost-output relationship of the firm and can be explicitly included into the model as non-neutral shift variables. See also Winston (1993) and Vickers (1995). Here we use them as technology shifter and in the context of technological change.

5. SPECIFICATION TESTS AND ESTIMATION

As mentioned in the data section, we specify and estimate a translog production function for Chinese 30 provinces observed for the period 1993-2993. Output is measured as aggregate gross domestic product (GDP). The vector of inputs includes labor measured as the number of employees (LAB) and capital stock (CAP). The technology index is modeled using information and communication technology (ICT) investment, foreign direct investment (FDI) inflow, percentage of highly educated labor (PCNT), and a reform (REFORM) variable. Several other production technology indicators (e.g. roads, government consumption, total investment, phone lines and openness) were also tried but removed from the specification due high degree of non-linearity and convergence problems. A simple time trend (TRN) is also added to the specification. In addition we use dummy variables to control for unobserved effects such as skills, planning and management differences, and location advantages/disadvantages at the provinces.

We investigate the issues of multicollinearity and confounded effects (see Table 2). The explanatory variables labor (0.646) and capital (0.714) are positively and highly correlated with GDP. There is also a positive association between GDP and trend (0.398). The labor and capital are weakly correlated (0.232). Labor is not correlated with time trend (0.021), but capital is (0.294). The correlation coefficient among the variables shows that there is no serious multicollinearity problem. FDI, ICT and REFORM variables are correlated with each other (0.326-0.672), but PCNT is lower correlated (0.115-0.300) with any of the other three technology indicator variables.

Insert Table 2 Pearson correlation matrix about here

Several model specification tests are possible. First functional form can be tested by testing a flexible translog form versus a simple Cobb-Douglas form. Second, one can test significance of the two technology components individually or jointly. Third, a test of single or multiple technology index component. The first test, based on F-test, showed that the translog form is accepted. The second test also shows that technology component index should be included in the specification. We could not perform the third test because the model with a single technology index with four shift (external economic) variables did not converge. The time trend model (1) is estimated using the PROC REG procedure and the technology index model (2) and (3) are estimated using the non-linear procedure PROC MODEL in SAS 9.2. Using the parameter estimates various measures (4) through (9) such as predicted indices, marginal effects of indices and individual index indicators, rate of technical change, input elasticities, returns to scale, TFP and its decomposition into technical change, scale and technology index components, and their respective share are computed. Each of these components is discussed in more details in the next section.

6. EMPIRICAL RESULTS

6.1 Parameter estimates

The estimation results for both of the time trend (1) and technology index (2) and (3) models are reported in Table 3. In the time trend model all slope parameters with the exception of capital and its interaction with trend and labor squared are statistically significant. A total of 22 of the 29 province dummies are statistically different from the Ancui province which serve as reference. The highest intercepts are associated with Cenan and Gansu, while the lowest to Shanghai and Tibet. The results suggest significant heterogeneity among the provinces in China. The fit of the model is very good.

Insert Table 3 Translog time trend and technology index parameter estimates about here

In the case of technology index model, 4 parameters are not significant at the 10 percent level of significance. These are: capital, index2, labor squared and index1 interacted with trend. Only 16 of the 29 province intercepts are significant at the less than 10 level of significance. The degree of heterogeneity is somewhat lower in this model compared to the time trend model. In terms of ranking the provinces by the level of intercept same inference as in case of time trend model can be made. The parameters of the two technology indices are of expected sign and all their interactions with two exceptions are statistically significant.

6.2 Elasticities and returns to scale

The input elasticities are estimated from the derivatives of the production functions with respect to labor and capital inputs (4a and 4b). In the case of simple time trend model, the first order capital coefficient and the interaction with labor are negative causing the overall labor elasticity to be negative. The negative interactive term suggest that the two inputs are substitutes. The sample mean elasticities of labor and capital are 0.545 and -0.230, respectively. The returns to scale computed from equation (7) shows decreasing returns to scale (0.315).

Insert Table 4 Pearson correlation matrix, unweighted TC index, marginal effects of indicators about here

The first order and second order capital coefficients in the technology index model are positive but the interaction with labor negative. Unlike in the time trend model where the regularity condition in case of capital was violated, the overall elasticities are positive. The two inputs interactions with the two technology indices are opposite. The two input elasticities are negatively correlated (-0.279) with each other. The input elasticities patterns again suggest that the two inputs are strongly substitutes. The sample mean elasticities of labor and capital are 0.267 and 0.289, respectively. The returns to scale computed from equation (7) is 0.553 suggesting decreasing returns to scale and is agreement with the time trend model. The mean input elasticities, returns to scale and marginal technology shifter effects across provinces, regions and over time are reported in Table 5.

Insert Table 5 Unweighted mean technology components by different characteristics about here

In both models the inputs elasticities and returns to scale measures, computed at each point, show large dispersions and in some cases show increasing returns to scale as well. In examining the differences across provinces, we observe that the mean labor elasticity is negative for Beijing, Jiangsu, Shandong, Shanghai and Lianing. It is highest for Tibet and Qincai. The capital elasticity is negative for Guangxi, Guizcou and Sichccon and highest for Beijing and Shanghai. The return to scale is increasing only in the case of Ningxi, Scaanxi and Tibet. In several provinces RTS is extremely low, below 0.20. The mean input elasticities and returns to scale are almost constant over time. However, they differ by regional location. The highest labor elasticity is attributed to West, the highest capital elasticity to East, while the highest combined effect in form of returns to scale to West.

6.3 Technology index and technical change

Technical change in the time trend production function model is computed using (5a). The first and second order coefficients are significant suggesting increasing growth but at a decreasing rate. The interactions with labor and capital suggest labor-using technical change in Chinese provinces. The non-neutral component provides information about possible input using/saving biased technical change. The sample average of technical change in the time trend model is 13.7% and ranges from 4.2% to 22.3%. It is the main contributor to TFP growth.[3]

In the technology index model, all of the time trend coefficients and their interactions with the exception of interaction of trend and technology index1 are statistically significant. The coefficients of technology index indicators/shifters are also statistically significant, but not the aggregate of the two indices by themselves. However, their squares and interactions with one exception are significantly different from zero. Technical change in the technology index model is computed using the formula (5b). Table 6 reports the correlation matrix of TC and TFP (0.172) components.

Insert Table 6 Pearson correlation matrix, weighted TFP components about here

Table 7 shows that purely exogenous (driven by time) technical change is 3.4% and its data point observations ranges from -9.0% to 15.4%. It is positively related with TFP growth, but negatively with the scale effect component. The provinces differ by their size and productivity growth rates. In reporting the results by certain common characteristics one should use weighted averages. The weighted average rate of technical change, using provinces share of national GDP, is computed and the weighted mean values for different provinces, regions and years are reported on Table 7.

Insert Table 7 GDP-based weighted mean technology components about here

The purely exogenous technical change varies greatly among the provinces. The highest mean rate is for Guangxi (4.7%) and Cunan (4.4%), while Shanghai (-2.4) and seven other provinces show a negative rate of technical change. Looking at the regional level, the Central region shows the highest rate followed by West and East regions. Since the purely exogenous technical change is represented by a time trend, the mean rate is steadily declining over time from +12.7% to -4.8%.

The technical change due to external economic factors is composed of two technology indices, index1 and index2. The first one is human capital and economic reform as infrastructures for purchase, attraction of and acquisition of technology, and technology transfer and learning capability of provinces. The second index is based on information technology and foreign direct investment. The parameter estimates show that the first index is weakly significant, but the second one is highly significant. Their interactive coefficient is negative suggesting a substitution relationship. However, their predicted values are positively, but marginal effects are negatively correlated (see Table 4).

[3] Not reported here to conserve space.

These two indices are used to compute an aggregate measure of technological change based on external economic factors using the expression in (9). The mean predicted indices are positive for each province, region and year. Unlike the mean marginal effect for index1 which is positive in all dimensions, the mean marginal index2 is negative at all levels (see Table 7). It suggests that contribution from additional units of ICT and FDI to technical change is negative, but those of human capital and reform are positive.

6.4 TFP growth and its decomposition

The total factor productivity growth for the time trend production model (1) is computed using the formula in (8a). It is then decomposed into technical change and scale components. The technical change component is further decomposed into neutral and non-neutral components. The sample average TFP growth rate is 12.6%. Contribution of technical change is positive (13.7), while scale component has a negative (-1.2) contribution to the TFP growth. The TFP growth is computed at each point of the data. It ranged from 4.3% to 35.5%.[4]

The TFP growth based on the technology index model is computed using the formula (8b). It is then decomposed into its three main components, namely, the technical change component which is dominated by the time trend effect, the scale component and the technology index component. Each component is further decomposed into several sub-components such as contributions from different technology shifters (indices).

The TFP growth obtained from the technology index model is much lower than the simple time trend production model. The weighted sample average TFP is 7.6%. The contribution of scale, technical change and aggregate index components are 0.7% (6.6), 3.4% (23.3) and 3.5% (77.3), respectively (see Table 5). The number in parenthesis is their shares (after removing a few extreme observations). Each component varies substantially. The dispersion in the technology index component is the largest with standard deviation of 12.7% and ranged from -41.9 to +48.3%. The correlation between TFP growth and its underlying components show that each component is positively correlated with TFP, but the technical change is negatively correlated with scale and technology index components (see Table 6). Note that the contribution from the scale component is negligible.

The difference in the economic size of the provinces and its heterogeneous changes over time implies TFP to be weighted. The weighted average TFP growth varied substantially across provinces. The highest growth rates are observed for Cobei, Guangdon, Fujian and Guangxi, while Qingcai, Ningxia, Beijing and Jiangxi show lowest growth rates. The source of growth differed across provinces, primarily due to the technology index component. The regional difference in TFP growth is small, but the Eastern region had the highest rate and Western region had the lowest. The development of TFP growth over time is quite pronounced. The growth rate reached its highest rate in 1994 (16.1%), dropped to -0.9% in 2001, and then increased to 15.1% in 2003 (see Table 7). The main contributor to

[4] In order to conserve space these are not reported here, but can be obtained from the authors upon request.

the large variations is technical change in the first part of the study period, while the technology index impacted most in the latter part. Again the scale effect is negligible.

In order to show that the estimated rate of TFP growth is technology driven, we plot the TFP growth and its components over time and across regions. Figure 1 show close relationship between the TFP growth and technology index component. Technical change modeled as time trend does not match the erratic pattern of TFP growth. The East region has on the average the highest mean values.

Insert Figure 1 Development of mean values of TFP and its components over time and across regions about here

6.5 Provincial and regional heterogeneity

The sustainable economic growth of China in recent decades combined with its enormous population, labor force, production and trade capacity and market size has turned the country into a major player in the global economy and a force not to be ignored. During the recent global recession China has emerged as one of few major economies registering continuous high growth rates. Despite its ongoing fragile structural reform program China is seen as a major force that can help to bring the world economy out of the current deep recession. China's active reform and state intervention-led growth model can be of use even to major transition and developing market economies. The gradual removal of different interventions has affected the flow of resources to increasingly productive areas and growing competition and leading role of state which has enabled the growth rate to accelerate. The gradualist approach and currency and capital account control seemed sensible and effectively sheltered China from the 1997 financial crisis and full effect of 2008 crisis. However, despite significant progress China is criticized for being weak in the state's pro-poor actions to favor the poorest part of its population in redistribution of achieved economic growth.

Coming down from the aggregate level to the province and region level, one gets a very different picture. There are significance differences in all the indicators across regions and provinces. The Eastern region is the driving force behind the rapid economic development and high economic growth in China, while the Western region is the laggard. Regional income inequality and higher concentration of poverty are evidence of the increased gap. Massive investment in public infrastructure and inter-provincial equalizing investment plans has reduced the regional disparity but it has not been very successful in bridging the gap and enhancing growth and development among the regions to desirable levels.

Again in order to show that the estimated rate of TFP growth is technology driven, we plot the TFP growth and its components across regions and provinces. Figure 2 shows the within and between regional variations in TFP growth and its components. Again the technology index component is the main contributor to the TFP growth. With few exceptions technical change is also a positive contributor. The East region has on the average the highest mean values.

Insert Figure 2 Within and between regional heterogeneity in TFP growth and its components about here

7. SUMMARY AND CONCLUSIONS

This paper was concerned with specification and estimation of technical change by utilizing observable internal and external determinants of technological change. We estimate total factor productivity growth and its decomposition into technical change, scale economies and technology index components. Marginal effects of technology indicators on productivity growth are also estimated. In modeling technical change our focus is on various key factors associated with it. These technology shifters are investment in human capital and information and communication technology, flow of foreign direct investment and state initiated reform programs.

For the empirical analysis we used a balanced panel data on output and inputs and production and technology characteristics for Chinese provinces observed for the period 1993 to 2003. The analysis is expected to improve our understanding of the causes and patterns of provincial technical change and TFP growth in China. It enhances our knowledge on the recent years of unbalanced regional development in China. Information on differences in regional productivity growth is important for the central and regional governments to formulate coordinated policies of allocation and redistribution of productive resources to reduce the growing within and between regional inequalities.

This study contributed to the literature in a number of ways. First, it specified the technical change in terms of purely exogenous factor (time trend) and exogenous economic technology shifter factors. Second, we use panel data methodology and flexible functional form in which we control for effects not necessarily associated with technological change. Third, the model is applied to estimation of productivity growth in Chinese provinces during the country's rapid and continuous growth period. Fourth, unlike other previous growth studies of China which mainly used growth accounting approach, this study applies the panel data econometrics approach for estimation of the production function and thereby able to control for unobservable province effects.

The estimation results showed that the technology index model is the preferred specification in modeling production technology. The fit of the models is very good. The parameters of the two technology indices were of expected sign. Various input elasticities and growth measures are estimated. The return to scale is low, suggesting decreasing returns to scale. The capital and labor elasticities are negatively correlated, indicating that the two inputs are substitutes. The inputs elasticities and returns to scale measures have large dispersion across provinces and regions but are almost constant over time.

The time driven part of technical change varied significantly across the provinces and regions and its impacts on TFP steadily declined over time. The technology index based rate is composed of two technology indices. They represent infrastructure and carriers of technological change. The margin contribution from ICT and FDI is negative, but those of human capital and reform positive to rate of technological change. Their interactive coefficient is negative suggesting a substitution relationship.

The total factor productivity growth is decomposed into technical change (which is purely time driven), the scale and the technology index components. Each component is further decomposed into several sub-components such as contribution from different technology shifters. Each component varies greatly and the dispersion in the technology index component is the largest. The correlation between TFP growth and its underlying components show that each component is positively correlated with TFP, but the technical change is negatively correlated with scale and technology index components. The weighted average TFP growth varies across provinces. The sources of growth differ across provinces and are mainly attributed to differences in the technology index component. The regional difference in TFP growth is small, but the development of TFP growth over time is quite large. The main contributor to the large variation is technical change in the early years, while the technology index impacts in the latter years. The scale effect is negligible.

REFERENCES

Arayama, Y. and K. Miyoshi (2004). “Regional Diversity and Sources of Economic Growth in China.” *The World Economy* 27, 1583-1607.

Baltagi, B.H. and J.M. Griffin (1988). “A Generalized Error Component Model with Heteroscedastic Disturbances.” *International Economic Review* 29, 745-753.

Bao, S., G.H. Chang, J.D. Sachs and W.T. Woo. (2002). “Geographic Factors and China's Regional Developments under Market Reforms, 1979-1998.” *China Economic Review* 13, 89-111.

Basu S.R. (2009). “Comparing China and India: Is the dividend of economic reforms polarized?”, *European Journal of Comparative Economics* 6(1), 57-99.

Bensidoun I., F. Lemoine and D. Ünal (2009). “The integration of China and India into the world economy: a comparison”, *European Journal of Comparative Economics* 6(1), 131-151.

Bhattacharyya, A., Bhattacharyya, A., Kumbhakar, S.C. (1997). “Changes in Economic Regime and Productivity Growth: A Study of Indian Public Sector Banks”, *Journal of Comparative Economics* 25, 196-219.

Borensztein, E. and D.J. Ostry (1996). “Accounting for China’s Growth Performance.” *American Economic Review* 86, 224-228.

Cai, F., Dewen, W., Yang, D., (2001). ”Labor Market Distortions and Economic Growth: Examining Institutional Components of Regional Disparity in China”. Working Paper no. 10, Center for Human Resource Studies, Chinese Academy of Social Sciences.

Chen, Y., (2001). “Evidence of the Effect of Openness Policy on TFP and its Components: The Case of Chinese Provinces”. Paper presented to the 3rd International Conference on Chinese Economy, “Has China become a Market Economy?”, Clermont-Ferrant, France, May 2001.

Chen B. and Y. Feng (2000). “Openness and trade policy in China: An industrial analysis”, China Economic Review 11, 323-341

Chen Z. and S. Song (2008). Efficiency and technology gap in China's agriculture: A regional meta-frontier analysis, *China Economic Review* 19, 287–296.

Chen, K., Wang, H.C., Zheng, Y.X., Jefferson G.H., Rawski, T.G., (1998). “Productivity Change in Chinese Industry: 1953–1985”. *Journal of Comparative Economics* 12, 570-591.

Chow, G. (1993). “Capital Formation and Economic Growth in China.” *Quarterly Journal of Economics* 108, 809-842.

Cowing, T. G., Stevenson, R. E. (1981). “Productivity Measurement in Regulated Industries”, Academic Press, New York.

Démurger, S. (2000). “Economic Opening and Growth in China.” OECD Development Centre Studies, Paris, March.

Démurger, S. (2001). “Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China?” *Journal of Comparative Economics* 29, 95-117.

Démurger, S., Sachs, J.D., Woo, W.T., Bao S., Chang, G., Mellinger, A., (2002). “Geography, Economic Policy, and Regional Development in China”. NBER Working Paper No. 8897.

Diewert, W. E. (1981). “The theory of total factor productivity measurement in regulated industries”. In T. G. Cowing and R. E. Stevenson (eds*). Productivity measurement in regulated industrie*s. Academic Press, New York.
Dollar, D., (1992). “Outward-oriented Developing Economies Really Do Grow More Rapidly: Evidence from 95 LDCs, 1976-1985”. *Economic Development and Cultural Change* 40, 523-544.
Dougherty S. and V. Valli (2009). “Comparing China and India: an Introduction”, *European Journal of Comparative Economics* 6(1), 53-55.
Ezaki, M. and L. Sun (1999). “Growth Accounting in China for National, Regional, and Provincial Economies: 1981-1995.” *Asian Economic Journal* 13, 39-71.
Gao T. (2004). “Regional industrial growth: evidence from Chinese industries”, *Regional Science and Urban Economics* 34, 101–124.
Gholami R., Tom Lee S-Y. and A. Heshmati (2006). “The Causal Relationship Between Information and Communication Technology and Foreign Direct Investment”, *The World Economy* 29(1), 43-62.
Heshmati, A. and N. Nafar (1998). “A Production Analysis of the Manufacturing Industries in Iran.” *Technological Forecasting and Social Change* 59, 183-196.
Heshmati, A. and W. Yang (2010). “Contributions of ICT to the Chinese Economic Growth”. In “*Business, Finance and Economics of China*”, eds. Lian Guo and Fai Zong (eds). New York: Nova Science Publishers.
Holz, C., (2005). China's Reform Period Economic Growth: Why Angus Maddison Got It Wrong and What That Means. Development and Comp Systems 0504012, Economics Working Paper Archive at WUSTL.
Hsieh C-T. and P.J. Klenow (2007). “Misallocation and manufacturing TFP in China and India” NBER Working Paper Series 2007:13290.
Hu, A.G.Z., (2001). “Ownership, Government R&D, Private R&D, and Productivity in Chinese Industry”. *Journal of Comparative Economics* 29, 136-157.
Hu, Z.L. and M.S. Khan (1997). “Why is China Growing so Fast?” IMF Staff Papers. Washington, DC: International Monetary Fund.
Kash D.E., R.N. Auger and N. Li (2004), “An exceptional development pattern”, *Technological Forecasting & Social Change* 71, 777–797.
Jefferson, G.H., (1990). “China’s Iron and Steel Industry: Sources of Enterprise Efficiency and the Impact of Reform”. *Journal of Development Economics* 33, 329-355.
Jefferson, G.H., Rawski, T.G., Zheng, Y., (1992). “Growth, Efficiency, and Convergence in China’s State and Collective Industry”. *Economic Development and Cultural Change* 40, 239-266.
Jefferson, G.H., Xu, W., (1994). “Assessing Gains in Efficient Production Among China's Industrial Enterprises”. *Economic Development and Cultural Change* 42, 597-615.
Jefferson, G.H., Rawski, T.G., Zheng, Y., (1996). “Chinese Industrial Productivity: Trends, Measurement Issues, and Recent Developments”. *Journal of Comparative Economics* 23, 146-180.
Krugman, P. (1994). “The Myth of Asia’s Miracle”. *Foreign Affairs* 73, 62-78.
Kumbhakar, S. C. 1992. “Allocative Distortions, Technical Progress, and Input Demand in U.S. Airlines: 1970-1984.” *International Economic Review* 33(3), 723--737.

Kumbhakar S. (2000), Estimation and Decomposition of Productivity Change when Production is not Efficient: A Panel Data Approach, *Econometric Reviews* 19, 425-460.

Kumbhakar S.C. and A. Heshmati (1996), "Technical Change and Total Factor Productivity Growth in Swedish Manufacturing Industries", *Econometric Reviews* 15(3), 275-298.

Kumbhakar, S.C., A. Heshmati and L. Hjalmarsson (1999). "Parametric Approaches to Productivity Measurement: A Comparison among Alternative Models." *Scandinavian Journal of Economics* 101, 405-424.

Kumbhakar S.C., S. Nakamura and A. Heshmati (2000), "Estimation of Firm-Specific Technological Bias, Technical Change and Total Factor Productivity: A Dual Approach", *Econometric Reviews* 19(4), 493-515.

Lee, J., (2000). "Changes in the Sources of China's Regional Inequality". *China Economic Review* 3, 232-245.

Lemoine F. and D. Unal-Kesenci (2004), "Assembly Trade and Technology Transfer: The Case of China", *World Development* 32(5), 829–850.

Lin, J.Y., (1992). "Rural Reforms and Agricultural Growth in China". *American Economic Review* 82, 34-51.

Liu (2000)

Liu Z. (2002), "Foreign Direct Investment and Technology Spillover: Evidence from China", *Journal of Comparative Economics* 30, 579–602.

Lu D. (2000), "Industrial policy and resource allocation: implications on China's participation in globalization", *China Economic Review* 11, 342-360.

Maddison, A. (1998). *Chinese Economic Performance in the Long Run*. Paris: OECD.

Maddison, A., Wu H.X. (2008), "Measuring China's Economic Performance", *World Economics* 9(2), 13-34.

Meng, Q. and M. Li (2002). "New Economy and ICT Development in China." *Information Economics and Policy* 14, 275–295.

Morrison, C. (1986), "Productivity Measurement with Non-Static Expectations and Varying Capacity Utilization: An Integrated Approach", *Journal of Econometrics* 33, 51-74.

Morrison, C., Siegel, D.S. (1999). "Scale Economies and Industry Agglomeration Externalities: A Dynamic Cost Function Approach", *American Economic Review* 89, 272-290.

Mu Q. and K. Lee (2005), "Knowledge diffusion, market segmentation and technological catch-up: The case of the telecommunication industry in China", *Research Policy* 34, 759–783.

Oh D-H., A. Heshmati and H. Lööf (2009), "Total Factor Productivity of Korean Manufacturing Industries: Comparison of Competing Models with Firm-Level Data", CESIS Electronic Working Paper Series 2009:201.

Patnaik I and A. Shah (2009), "The difficulties of the Chinese and Indian exchange rate regimes", *European Journal of Comparative Economics* 6(1), 157-173.

Sachs, J.D., Woo, W.T., (1997). “Understanding China's Economic Performance”, Harvard Institute of Economic Research Working Papers 1793, Harvard - Institute of Economic Research.

Solow, R.M. (1957). “Technical Change and the Aggregate Production Function.” *The Review of Economics and Statistics* 39, 312-320.

Song, S., Chu, G.S.F., Chao, R, (2000). “Inter-city Regional Disparity in China”, *China Economic Review*11, 246-261.

Valli V. and D. Saccone (2009), “Structural Change and Economic Development in China and India”, *European Journal of Comparative Economics* 6(1), 101-129.

Vickers, J. (1995). “Concepts of Competition”, *Oxford Economic Papers* 47, 1-23.

Winston, C. (1993). “Economic Deregulation: Days of Reckoning for Microeconomists”, Journal of Economic Literature XXXI, 1263-1289.

Wang, Y. and Y. Yao (2003). “Sources of China's Economic Growth 1952-1999: Incorporating Human Capital Accumulation.” *China-Economic-Review* 14, 32-52.

Woo, W. (1998). “Chinese Economic Growth: Sources and Prospects.” In *the Chinese Economy*, ed. Michel Fouquin and Françoise Lemoine. London: Economica.

World Bank. (1996). *The Chinese Economy: Fighting Inflation, Deepening Reforms*, Washington D.C..

Wu, Y. (1999). “Productivity and Efficiency in China's Regional Economics in Economic Efficiency and Productivity Growth.” In *the Asian-Pacific Region*, ed. Tsu-Tan Fu et al., Edward Elgar.

Wu, Y., (1995). “Productivity Growth, Technological Progress, and Technical Efficiency Change in China: A Three-Sector Analysis”. *Journal of Comparative Economics* 21, 207-229.

Wu, Y., (2000). “Productivity Growth and Economic Integration in the Southern China Region”. *Asian Economic Journal* 14, 39-54.

Wu, Y. (2004). *China's Economic Growth: A Miracle with Chinese Characteristics*. London: Routledge Curzon.

Xu, X., (1999). “Agricultural Productivity in China”. *China Economic Review* 10, pp.108-121.

Xu, B. (2000). “Multinational Enterprises, Technology diffusion, and Host Country Productivity Growth.” *Journal of Development Economics* 62, 477-493.

Xu X. and Y. Wang (1999). “Ownership structure and corporate governance in Chinese stock companies”, China Economic Review 10(1), 75-98.

Yang C.H. (2009). “Technological Sources and Regional Productivity Growth in China”, *China Economic journal* 2(1), 73-92.

Yusuf, S., (1994). “China's Macroeconomic Performance and Management During Transition”. *The Journal of Economic Perspectives* 8, 71-92.

Zhang, X., Zhang, S., (2001). “Impact of Ownership and Competition on the Productivity of Chinese Enterprises”. *Journal of Comparative Economics* 29, 327-346.

Zheng, J., Hu A., (2004). “An Empirical Analysis of Provincial Productivity in China, 1979-2001”. CCS Working Paper Series, Tsinghua University, No. 1, February 26.

Zheng, J., Liu, X. and Bigsten, A., (2003). “Efficiency, Technical Progress, and Best Practice in Chinese State Enterprises (1980-1994)”. *Journal of Comparative Economics* 31, 134-152.

Table 1. Summary statistics of the variables (total number of observations is 330).

Variable	Mean	Median	Std Dev	Minimum	Maximum	Coeff. of Variation
Year and location variables						
YEAR	1998.00	1998.00	3.17	1993.00	2003.00	0.16
EAST	0.37	0.00	0.48	0.00	1.00	131.63
WEST	0.37	0.00	0.48	0.00	1.00	131.63
CENTRAL	0.27	0.00	0.44	0.00	1.00	166.08
Output, input and trend						
GDP	2743.91	1967.51	2480.24	37.28	13625.87	90.39
LAB	2091.01	1812.69	1529.42	112.00	6335.30	73.14
CAP	80933.29	54020.49	81340.48	2690.36	536026.79	100.50
TRN	6.00	6.00	3.17	1.00	11.00	52.79
Technology shifters used						
ICT	153825.70	111977.57	148379.77	1964.47	961897.12	96.46
FDI	4871194.50	1536090.93	8077427.63	2808.99	43012460.57	165.82
PCNT	0.09	0.06	0.08	0.02	0.57	90.33
REFORM	0.49	0.45	0.19	0.11	0.91	39.47
Other technology shifters						
ROA	46237.95	43655.50	30312.83	3677.00	183341.00	65.56
GOV	11764.90	8534.80	11168.32	283.25	84104.73	94.93
INV	31094.90	21413.21	29557.02	926.90	190985.40	95.05
TEL	3630381.30	2372959.00	3891388.67	22168.00	20595000.00	107.19
OPEN	0.28	0.13	0.34	0.04	2.05	121.29
Other variables						
TRA	46335245.51	9015423.68	106352735.34	354156.86	912397287.07	229.53
DEF	1.11	1.10	0.09	0.88	1.40	8.33
CPI	200.69	192.80	62.94	107.60	378.00	31.36
POP	4110.35	3695.25	2812.10	232.00	11830.40	68.42
HIGH	32855.03	28328.00	23814.74	764.00	137048.00	72.48

Glossary of variables:
GDP: gross domestic product, LAB: labor, CAP: capital, TRN: time trend, ICT: information and communication technology, FDI: foreign direct investment, PCNT: share of highly educated labor, REFORM: reform, ROA: roads, GOV: government expenditure, INV: investment, TEL: telephones, OPEN: openness, TRA: trade, DEF: GDP deflator, CPI: consumer price index, POP: population, HIGH: number of people with university degree.

Table 2. Pearson correlation matrix (NT=330 observations).

	YEAR	ICT	LAB	GDP	CAP	INV	FDI	PCNT	Open	Reform
YEAR	1.000									
ICT	0.422	1.000								
	(0.000)									
LAB	0.021	0.407	1.000							
	(0.700)	(0.000)								
GDP	0.398	0.836	0.646	1.000						
	(0.000)	(0.000)	(0.000)							
CAP	0.294	0.686	0.232	0.714	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)						
INV	0.360	0.818	0.448	0.912	0.869	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
FDI	0.054	0.672	0.246	0.673	0.658	0.775	1.000			
	(0.329)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
PCNT	0.259	0.300	-0.258	0.163	0.576	0.377	0.270	1.000		
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)			
Open	0.004	0.534	-0.064	0.395	0.525	0.559	0.806	0.495	1.000	
	(0.945)	(0.000)	(0.249)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Reform	-0.203	0.327	0.391	0.474	0.368	0.464	0.556	0.115	0.464	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.037)	(0.000)	

Note: p-values in parenthesis

Glossary of variables:
YEAR: year of observation, ICT: information and communication technology, LAB: labor, GDP: gross domestic product, CAP: capital, INV: investment, FDI: foreign direct investment, PCNT: share of highly educated labor, OPEN: openness, REFORM: reform.

Table 3. Translog time trend and technology index parameter estimates.

Linear translog time trend model					Non-linear translog technology index model				
Parameter	Estimate	std err	t-value	Prob.	Parameter	Estimate	std err	t-value	Prob.
-	-	-	-	-	PCNT	0.9779	0.0091	107.980	0.001
-	-	-	-	-	ICT	0.7198	0.1441	5.000	0.001
Intercept	-2.0698	5.6289	-0.370	0.713	Intercept	-7.8292	4.9977	-1.570	0.118
Lab	3.5844	1.0084	3.550	0.000	Lab	2.8759	0.8392	3.430	0.001
Cap	-0.8518	0.6144	-1.390	0.167	Cap	0.3289	0.6255	0.530	0.600
Trn	0.1615	0.0534	3.020	0.003	Trn	0.2129	0.0609	3.490	0.001
-	-	-	-	-	Index1	-0.8482	0.4421	-1.920	0.056
-	-	-	-	-	Index2	0.0446	0.1565	0.280	0.776
LabxLab	-0.0322	0.0564	-0.570	0.569	LabxLab	-0.0167	0.0472	-0.350	0.723
CapxCap	0.1141	0.0338	3.380	0.001	CapxCap	0.1075	0.0351	3.060	0.002
TrxxTrn	-0.0061	0.0006	-9.480	0.000	TrnxTrn	-0.0080	0.0007	-11.810	0.001
-	-	-	-	-	Ind1xInd1	-0.0791	0.0367	-2.150	0.032
-	-	-	-	-	Ind2xInd2	0.0220	0.0071	3.080	0.002
LabxCap	-0.2476	0.0558	-4.440	0.001	LaxxCap	-0.2599	0.0554	-4.700	0.001
LabxTrn	0.0200	0.0052	3.880	0.001	LabxTrn	0.0320	0.0050	6.450	0.001
-	-	-	-	-	LabxInd1	-0.1334	0.0402	-3.320	0.001
-	-	-	-	-	LabxInd2	0.0371	0.0182	2.030	0.043
CapxTrn	-0.0090	0.0062	-1.450	0.148	CapxTrn	-0.0270	0.0066	-4.090	0.001
-	-	-	-	-	CapxInd1	0.1746	0.0505	3.460	0.001
-	-	-	-	-	CapxInd2	-0.0628	0.0221	-2.840	0.005
-	-	-	-	-	TrnxInd1	0.0012	0.0057	0.210	0.836
-	-	-	-	-	TrnxInd2	0.0114	0.0026	4.360	0.001
-	-	-	-	-	Ind1xInd2	-0.0386	0.0225	-1.720	0.087
c2	-0.1145	0.1015	-1.130	0.260	c2	0.0763	0.1093	0.700	0.486
c3	0.2055	0.1740	1.180	0.239	c3	0.7937	0.1826	4.350	0.001
c4	0.3271	0.1113	2.940	0.004	c4	0.7129	0.1317	5.410	0.001
c5	0.3347	0.1127	2.970	0.003	c5	0.3508	0.1049	3.340	0.001
c6	0.8465	0.1875	4.510	0.001	c6	1.2871	0.1876	6.860	0.001
c7	0.4294	0.1493	2.880	0.004	c7	0.9898	0.1680	5.890	0.001
c8	-0.0162	0.1157	-0.140	0.889	c8	0.4903	0.1614	3.040	0.003
c9	0.7345	0.2211	3.320	0.001	c9	1.2969	0.2137	6.070	0.001
c10	0.8355	0.1892	4.420	0.001	c10	1.3037	0.2011	6.480	0.001
c11	-1.0065	0.1490	-6.750	0.001	c11	-0.2260	0.1830	-1.230	0.218
c12	-0.9572	0.2456	-3.900	0.001	c12	-0.2912	0.2649	-1.100	0.273
c13	-0.6672	0.1079	-6.180	0.001	c13	-0.0371	0.1539	-0.240	0.810
c14	-0.7168	0.1043	-6.870	0.001	c14	0.0106	0.1580	0.070	0.947

c15	-0.4997	0.1029	-4.860	0.001	c15	0.0172	0.1434	0.120	0.905
c16	-0.0847	0.1123	-0.750	0.452	c16	0.4903	0.1509	3.250	0.001
c17	-0.6137	0.1738	-3.530	0.001	c17	0.1339	0.1905	0.700	0.483
c18	-0.7570	0.1291	-5.870	0.001	c18	-0.0718	0.1676	-0.430	0.669
c19	-0.0239	0.2319	-0.100	0.918	c19	0.6687	0.2245	2.980	0.003
c20	-0.0229	0.1468	-0.160	0.876	c20	0.5283	0.1664	3.180	0.002
c21	-0.5238	0.1807	-2.900	0.004	c21	0.1640	0.1943	0.840	0.399
c22	-0.1526	0.2650	-0.580	0.565	c22	0.5547	0.2470	2.250	0.026
c23	-1.8508	0.1429	-12.950	0.001	c23	-0.8967	0.1873	-4.790	0.001
c24	-0.9974	0.1405	-7.100	0.001	c24	-0.1475	0.1782	-0.830	0.409
c25	-1.6623	0.6464	-2.570	0.011	c25	-0.6020	0.5860	-1.030	0.305
c26	-0.7854	0.1178	-6.670	0.001	c26	-0.2650	0.1495	-1.770	0.077
c27	-1.1930	0.1076	-11.080	0.001	c27	-0.4854	0.1592	-3.050	0.003
c28	-1.4326	0.3969	-3.610	0.001	c28	-0.4870	0.3797	-1.280	0.201
c29	-1.4483	0.3169	-4.570	0.001	c29	-0.6500	0.3114	-2.090	0.038
c30	-0.5521	0.1291	-4.280	0.001	c30	0.1083	0.1721	0.630	0.530
Obs	330				Obs	330			
R^2 adj	0.9956				R^2 adj	0.9974			
RMSE	0.0737				RMSE	0.0573			
Iterations	1				Iterations	24			

Glossary of variables:
Dependent variable: GDP: gross domestic product,
Inputs: LAB: labor and CAP: capital,
Technology indicators: TRN: time trend; Index1 (PCNT: share of highly educated labor, and REFORM: reform), and Index2 (ICT: information and communication technology, FDI: foreign direct investment).

Table 4. Pearson correlation matrix, unweighted TC index, marginal effects of indicators (330 obs)

	Index1	Index2	ME index1	ME index2	ME-ICT	ME-FDI	ME-Pcnt	ME Re form	Elas-Lab	Elas-Cap	RTS
Index1	1.000										
Index2	0.714	1.000									
	(0.001)										
ME-index1	-0.066	0.010	1.000								
	(0.230)	(0.854)									
MEiindex2	-0.263	-0.003	-0.340	1.000							
	(0.001)	(0.961)	(0.001)								
ME-ICT	0.275	0.440	-0.440	0.244	1.000						
	(0.001)	(0.001)	(0.001)	(0.001)							
ME-FDI	0.275	0.440	-0.440	0.244	1.000	1.000					
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)						
ME-Pcnt	0.225	0.139	0.876	-0.388	-0.457	-0.457	1.000				
	(0.001)	(0.011)	(0.001)	(0.001)	(0.001)	(0.001)					
ME-Reform	-0.585	-0.270	-0.013	0.192	0.155	0.155	-0.495	1.000			
	(0.001)	(0.001)	(0.808)	(0.001)	(0.005)	(0.005)	(0.001)				
ElasLab	-0.518	-0.447	0.048	0.433	-0.477	-0.477	-0.017	0.120	1.000		
	(0.001)	(0.001)	(0.390)	(0.001)	(0.001)	(0.001)	(0.759)	(0.029)			
ElasCap	0.744	0.617	0.376	-0.527	0.004	0.004	0.583	-0.530	-0.279	1.000	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.939)	(0.939)	(0.001)	(0.001)	(0.001)		
RTS	0.070	0.042	0.318	0.010	-0.434	-0.434	0.411	-0.278	0.712	0.476	1.000
	(0.202)	(0.444)	(0.001)	(0.852)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	

Note: p-values in parenthesis

Glossary of variables:
Index1 and Index2: technology indices: Index1 (Pcnt and Reform) and Index2 (ICT and FDI)
ME-index1 and ME-Index2: marginal effects with respect to technology Indix1 and Index2.
ME-ICT, ME-FDI, ME-Pcnt and ME-Reform: marginal effects with respect to technology indicators ICT, FDI, Pcnt and Reform.
ElasLab, ElasCap and RTS: elasticities of labor, capital and returns to scale.

Table 5. Unweighted mean technology components by different characteristics (NT=330 obs)

A. Province:	Index1	Index2	ME-index1	ME-index2	ME-ICT	ME-FDI	ME-Pcnt	ME-Reform	Elas-Lab	Elas-Cap	RTS
Ancui	0.062	0.071	0.492	-0.265	-0.054	-0.021	0.390	0.102	0.298	0.033	0.332
Beijing	0.403	1.759	0.492	-0.332	-0.029	-0.011	0.478	0.013	-0.098	0.836	0.738
Cainan	0.057	0.862	0.570	-0.188	-0.009	-0.004	0.464	0.106	0.688	0.287	0.975
Cebei	0.082	0.185	0.599	-0.302	-0.039	-0.015	0.495	0.104	0.018	0.246	0.264
Ceilongj	0.100	0.114	0.541	-0.306	-0.079	-0.031	0.494	0.047	0.208	0.329	0.537
Cenan	0.062	0.059	0.561	-0.300	-0.060	-0.024	0.436	0.124	0.101	0.078	0.179
Cubei	0.106	0.170	0.495	-0.289	-0.040	-0.016	0.436	0.059	0.134	0.245	0.379
Cunan	0.077	0.100	0.430	-0.254	-0.043	-0.017	0.361	0.069	0.290	0.027	0.317
Fujian	0.091	0.892	0.448	-0.203	-0.008	-0.003	0.360	0.087	0.332	0.153	0.484
Gansu	0.067	0.053	0.623	-0.319	-0.150	-0.058	0.549	0.073	0.315	0.328	0.644
Guangdon	0.086	1.418	0.508	-0.213	-0.008	-0.003	0.398	0.110	0.061	0.115	0.176
Guangxi	0.055	0.111	0.452	-0.223	-0.028	-0.011	0.355	0.097	0.462	-0.040	0.422
Guizcou	0.048	0.024	0.495	-0.263	-0.129	-0.050	0.416	0.079	0.553	-0.013	0.541
Jiangsu	0.112	0.951	0.570	-0.274	-0.010	-0.004	0.481	0.089	-0.114	0.300	0.187
Jiangxi	0.070	0.161	0.508	-0.258	-0.034	-0.013	0.440	0.068	0.328	0.141	0.469
Jilin	0.123	0.145	0.514	-0.307	-0.060	-0.023	0.478	0.036	0.236	0.408	0.645
Liaoning	0.140	0.460	0.566	-0.309	-0.029	-0.011	0.516	0.050	-0.025	0.451	0.426
Mongolia	0.062	0.059	0.660	-0.321	-0.126	-0.049	0.567	0.093	0.321	0.361	0.681
Ningxia	0.061	0.057	0.641	-0.302	-0.163	-0.063	0.573	0.068	0.667	0.469	1.137
Qingcai	0.052	0.043	0.599	-0.280	-0.168	-0.066	0.539	0.060	0.834	0.363	1.197
Scaanxi	0.118	0.117	0.518	-0.315	-0.063	-0.025	0.479	0.039	0.152	0.354	0.506
Shandong	0.082	0.315	0.576	-0.282	-0.018	-0.007	0.466	0.110	-0.041	0.185	0.144
Shanghai	0.287	3.329	0.651	-0.339	-0.014	-0.005	0.621	0.031	-0.242	0.890	0.649
Shanxi	0.078	0.077	0.603	-0.321	-0.094	-0.037	0.521	0.082	0.235	0.340	0.575
Sichccon	0.061	0.057	0.512	-0.284	-0.067	-0.026	0.406	0.106	0.137	-0.008	0.129
Tianjin	0.232	1.856	0.508	-0.279	-0.010	-0.004	0.474	0.034	0.183	0.686	0.869
Tibet	0.040	0.078	0.579	-0.214	-0.101	-0.039	0.481	0.098	1.103	0.288	1.390
Xinjiang	0.077	0.043	0.641	-0.338	-0.207	-0.081	0.584	0.057	0.373	0.457	0.830
Yunnan	0.049	0.036	0.542	-0.279	-0.120	-0.047	0.467	0.075	0.405	0.063	0.468
Zcejiang	0.087	0.403	0.564	-0.270	-0.030	-0.012	0.437	0.127	0.082	0.234	0.316
B. Region:											
Central	0.085	0.112	0.518	-0.287	-0.058	-0.023	0.445	0.073	0.229	0.200	0.429
East	0.151	1.130	0.550	-0.272	-0.018	-0.007	0.472	0.078	0.077	0.399	0.475
West	0.063	0.062	0.569	-0.285	-0.120	-0.047	0.492	0.077	0.484	0.238	0.722
C. Year:											
1993	0.073	0.420	0.549	-0.314	-0.029	-0.011	0.450	0.100	0.222	0.322	0.543
1994	0.076	0.436	0.541	-0.307	-0.059	-0.023	0.441	0.100	0.248	0.300	0.548

1995	0.092	0.448	0.510	-0.299	-0.056	-0.022	0.429	0.081	0.256	0.298	0.553
1996	0.095	0.488	0.511	-0.291	-0.059	-0.023	0.423	0.088	0.269	0.286	0.555
1997	0.096	0.532	0.521	-0.279	-0.057	-0.022	0.427	0.094	0.281	0.268	0.549
1998	0.094	0.523	0.548	-0.275	-0.066	-0.026	0.454	0.094	0.285	0.270	0.555
1999	0.091	0.435	0.581	-0.270	-0.080	-0.031	0.516	0.065	0.290	0.262	0.552
2000	0.094	0.365	0.588	-0.269	-0.087	-0.034	0.523	0.065	0.288	0.268	0.556
2001	0.102	0.492	0.584	-0.258	-0.087	-0.034	0.520	0.064	0.291	0.263	0.554
2002	0.126	0.496	0.568	-0.260	-0.071	-0.028	0.516	0.051	0.268	0.288	0.556
2003	0.170	0.499	0.534	-0.268	-0.078	-0.030	0.497	0.037	0.234	0.332	0.566
D. Sample:											
Mean	0.101	0.467	0.549	-0.281	-0.006	-0.026	0.472	0.076	0.267	0.289	0.553
Std Dev	0.082	0.762	0.072	0.046	0.064	0.025	0.082	0.040	0.289	0.231	0.316

Glossary of variables:
Technology indices: Index1 and Index2
Marginal Effects with respect to technology indices: ME-index1 and ME-Index2
Marginal effects with respect to technology indicators: ME-ICT, ME-FDI, ME-Pcnt and ME-Reform
Elasticities of Labor, Capital and returns to scale: ElasLab, ElasCap and RTS

Table 6. Pearson correlation matrix, weighted TFP components (NT=330 observations)

	Scale	TC	Index	TFP	Share Index1	Share Index2	Share Index	Share TC	Share Scale
Scale component	1.000								
TC component	-0.255	1.000							
	(0.001)								
Index component	0.032	-0.275	1.000						
	(0.564)	(0.001)							
TFP	0.002	0.172	0.896	1.000					
	(0.970)	(0.002)	(0.001)						
Share Index1	-0.360	-0.117	0.176	0.092	1.000				
	(0.001)	(0.033)	(0.001)	(0.096)					
Share Index2	0.360	0.117	-0.176	-0.092	-1.000	1.000			
	(0.001)	(0.033)	(0.001)	(0.096)	(0.001)				
Share Index	0.043	-0.280	-0.021	-0.151	0.109	-0.109	1.000		
	(0.439)	(0.001)	(0.705)	(0.006)	(0.050)	(0.050)			
Share TC	-0.106	0.310	-0.025	0.113	-0.115	0.115	-0.933	1.000	
	(0.056)	(0.001)	(0.655)	(0.042)	(0.038)	(0.038)	(0.001)		
Share Scale	0.189	-0.082	0.055	0.035	-0.091	0.091	-0.188	0.260	1.000
	(0.001)	(0.139)	(0.317)	(0.533)	(0.102)	(0.102)	(0.001)	(0.001)	

Note: p-values in parenthesis

Glossary of variables:
Scale: scale; TC: technical change; Index: technology index components; of TFP: total factor productivity.
Share Index1; share of index1; Share Index2; share of index2; of the Index: overall technology index.
Share Index: share of technology index; Share TC: share of technical change; and Share Scale: scare component share of TFP.

Table 7. GDP-based weighted mean technology components by different characteristics (330 obs)

A. Province:	Scale	TC	Index	TFP	Sindex1	Sindex2	Sindex	STC	SScale
Ancui	0.004	0.037	0.054	0.095	0.471	0.529	0.816	0.168	0.016
Beijing	0.015	-0.012	0.032	0.035	0.208	0.792	0.406	0.739	-0.145
Cainan	0.001	0.016	0.062	0.078	0.077	0.923	0.816	0.183	0.000
Cebei	0.019	0.015	0.095	0.129	0.355	0.645	0.991	-0.016	0.025
Ceilongj	0.007	0.013	0.069	0.089	0.482	0.518	0.873	0.185	-0.058
Cenan	0.006	0.029	0.072	0.107	0.521	0.479	1.167	-0.188	-0.192
Cubei	0.016	0.024	0.042	0.082	0.384	0.616	1.301	-0.112	-0.284
Cunan	0.002	0.044	0.037	0.083	0.435	0.565	0.161	0.825	0.014
Fujian	0.014	0.035	0.062	0.111	0.106	0.894	0.501	1.151	0.463
Gansu	0.009	0.002	0.059	0.070	0.565	0.435	1.908	0.020	0.520
Guangdon	0.012	0.040	0.071	0.124	0.068	0.932	0.397	0.455	0.148
Guangxi	0.001	0.047	0.063	0.111	0.364	0.636	0.594	0.316	0.015
Guizcou	0.002	0.033	0.021	0.056	0.630	0.370	1.411	-0.420	0.008
Jiangsu	0.028	0.023	0.041	0.092	0.106	0.894	0.390	0.059	0.462
Jiangxi	0.006	0.029	-0.013	0.023	0.319	0.681	0.934	0.089	-0.024
Jilin	0.010	0.008	0.064	0.081	0.476	0.524	0.091	0.676	0.233
Liaoning	0.018	0.011	0.026	0.054	0.243	0.757	0.847	-0.288	0.441
Mongolia	0.009	-0.006	0.077	0.080	0.514	0.486	1.031	0.005	-0.036
Ningxia	-0.005	-0.016	0.039	0.018	0.530	0.470	0.749	0.228	0.023
Qingcai	-0.007	-0.008	0.023	0.007	0.564	0.436	0.630	0.283	0.087
Scaanxi	0.013	0.013	0.059	0.085	0.513	0.487	0.982	-0.191	0.208
Shandong	0.016	0.026	0.036	0.078	0.208	0.792	0.797	0.038	0.165
Shanghai	0.029	-0.024	0.035	0.039	0.083	0.917	1.363	-0.561	0.197
Shanxi	0.009	0.006	0.023	0.038	0.513	0.487	0.770	0.236	-0.006
Sichccon	-0.002	0.035	0.055	0.089	0.544	0.456	1.672	-0.801	0.129
Tianjin	0.007	-0.007	0.052	0.051	0.124	0.876	0.838	0.038	0.123
Tibet	-0.015	-0.009	0.057	0.032	0.348	0.652	1.450	-0.096	-0.354
Xinjiang	0.005	-0.012	0.068	0.061	0.649	0.351	0.977	-0.016	0.039
Yunnan	0.004	0.028	0.032	0.064	0.579	0.421	0.971	-0.018	0.047
Zcejiang	0.020	0.021	0.044	0.085	0.181	0.819	0.560	0.235	0.206
B. Region:									
central	0.008	0.026	0.048	0.082	0.454	0.546	0.834	0.182	-0.075
east	0.019	0.019	0.050	0.088	0.160	0.840	0.669	0.164	0.230
west	0.003	0.022	0.054	0.079	0.533	0.467	1.231	-0.256	0.101
C. Year:									
1993	0.000	0.127	0.000	0.127	0.258	0.742	0.000	1.000	0.000
1994	0.002	0.112	0.047	0.161	0.279	0.721	0.254	0.750	-0.004

1995	0.005	0.097	0.053	0.155	0.293	0.707	0.418	0.555	0.027
1996	0.011	0.080	0.020	0.112	0.304	0.696	0.514	0.491	-0.005
1997	0.015	0.063	-0.038	0.041	0.286	0.714	0.510	0.238	0.100
1998	0.018	0.043	-0.010	0.051	0.283	0.717	0.317	0.306	0.245
1999	0.017	0.022	-0.016	0.023	0.278	0.722	1.478	-0.004	-0.023
2000	0.012	0.004	0.048	0.064	0.290	0.710	0.747	0.117	0.136
2001	0.013	-0.013	-0.009	-0.009	0.277	0.723	0.844	0.028	0.253
2002	0.017	-0.030	0.133	0.120	0.311	0.689	1.103	-0.376	0.273
2003	0.015	-0.048	0.184	0.151	0.367	0.633	1.289	-0.418	0.129
D. Sample:									
Mean	0.007	0.034	0.035	0.076	0.366	0.634	0.773	0.233	0.066
Std Dev	0.011	0.059	0.127	0.124	0.200	0.200	1.243	1.133	0.519

Glossary of variables:
Scale: scale; TC: technical change; Index: technology index components; of TFP: total factor productivity.
Sindex1; share of index1; Sindex2; share of index2; of the Index: overall technology index.
Sindex: share of technology index; STC: share of technical change; and SScale: scale component share of TFP.

Figure 1: Development of TFP growth and its components over time and across regions

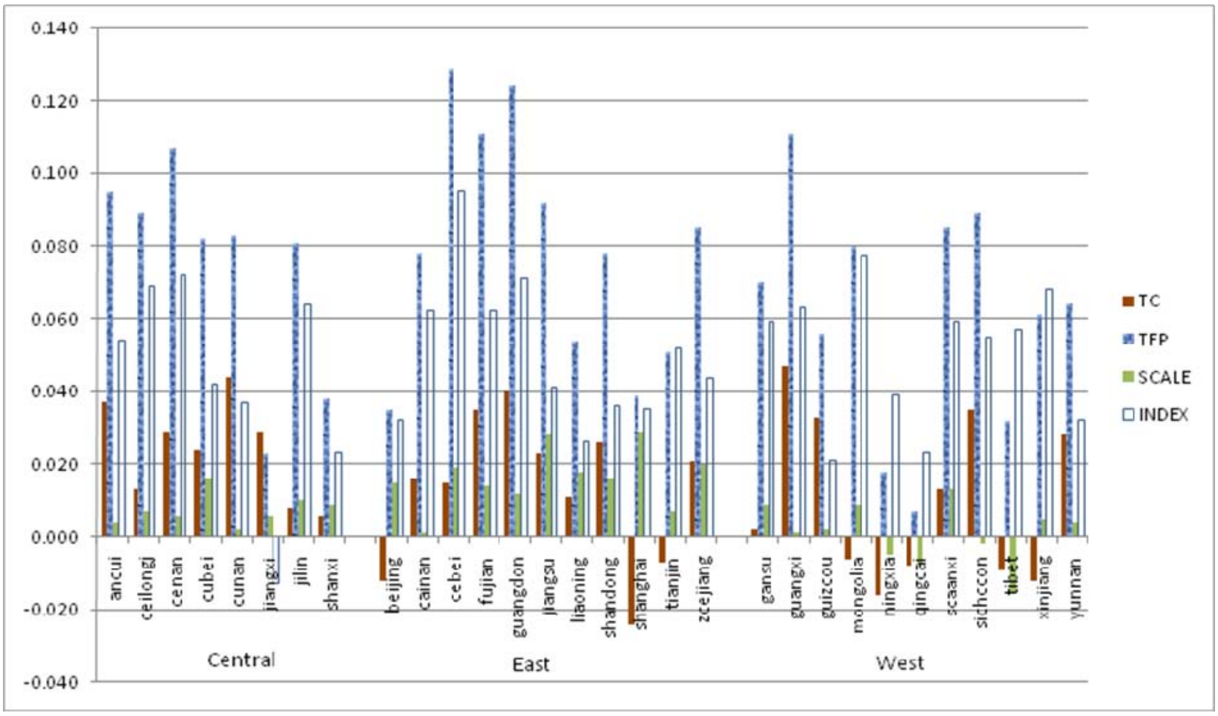

Figure 2: Within and between regional heterogeneity in TFP growth and its components